Determinants of Delegating AI-Exposable Occupational Tasks: A Scoping Review

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Abstract

Artificial intelligence (AI) is now capable of performing a wide range of job tasks, raising several questions about its role in the future of work. While research focuses on which tasks are technically automatable, little attention has been given to the wider question of whether these tasks should be delegated to AI in practice or not. This study addresses the central research question of what factors determine whether an AI-exposable occupational task should be delegated to AI systems. Deciding to delegate is not only a matter of technical feasibility; it is a complex analysis shaped by the interplay of expected performance gains, task characteristics, worker capabilities, and social and organizational constraints. Adopting a scoping review approach, this study systematically maps the key concepts and research gaps within this emerging field. The analysis organizes the determinants of AI delegation across six primary domains: AI-related advantages, such as workflow augmentation and automation logic; worker skills and adaptability, highlighting the tension between upskilling and the risk of skill decay; task characteristics, including the divide between routine analysis and emotional complexity; labour market effects, specifically regarding job polarization; human–AI interaction, centered on trust and algorithmic transparency; and organizational governance, which covers AI readiness and ethical risk management. By analyzing these six points, the review moves beyond the "technical replacement," identifying a "double-edged sword" effect in which efficiency clashes with professional autonomy and psychological well-being. Finally, this work provides a structured framework for understanding the multifaceted factors that determine the responsible integration of AI into occupational workflows.

1 Introduction

While the integration of Artificial Intelligence in the workplace is accelerating due to its capacity to augment worker performance, technical feasibility does not inherently justify implementation. Although AI may successfully execute an assigned occupational task, failing to meet a minimal precision threshold can render the intervention counterproductive, ultimately leading to operational inefficiencies and compromised output quality. In numerous instances, the premature introduction of an AI system has yielded adverse outcomes, including detrimental impacts on occupational health and psychological well-being. Consequently, it is essential to conduct a rigorous examination of the long-term implications of implementing an AI tool, ensuring that it satisfies established efficiency thresholds without compromising the physical or mental integrity of the workforce.

Despite the proliferation of studies on AI automation, current literature remains fragmented; research frequently focuses on the functional and efficiency-driven aspects of AI implementation, addressing only surface-level impacts without critically examining the more profound, long-term consequences. While pre-existent literature has identified various technical and economic variables, these factors are often studied in isolation. There is a notable lack of a cohesive structure that integrates these disparate elements into a unified decision-making model. This study was therefore undertaken to address the question of what factors determine whether an AI-exposable occupational task should be delegated to AI, where AI-exposable tasks are defined as those requiring cognitive or physical processing that can be modeled by current generative or narrow AI architectures. Consequently, a scoping review was identified as the most rigorous methodology for mapping this complex landscape because it can effectively survey the rapidly evolving field of AI integration and identify the essential determinants that must be satisfied before delegation is deemed viable. Drawing upon an in-depth analysis of 30 core papers, we developed a multidimensional framework that explores the impact of the intelligent agents in various fields, evaluates its advantages and functional characteristics, and categorizes the systemic challenges that constrain its implementation. The resulting framework serves as a diagnostic tool for organizational leaders to evaluate the viability of AI transition before resource allocation.

2 Method

To investigate how prior work has explored the implementation of AI tools in a work place, the effect it has on workers and on their relationship with artificial intelligence, together with its possible evolution of its impact on a task, we conducted a scoping review following a specific search strategy to ensure its relevance to the initial topic. Here, we detail how we went about choosing our sources, screening the papers for eligibility via inclusion and exclusion criteria and our method for data extraction and analysis. We started with the research question of what factors influence judgments that an AI-exposable task should or should not be delegated to AI, whether fully or partly. After identifying the key terms within it, we defined three search categories on which to base our search strings: artificial intelligence, tasks, and delegation. We then generated the search strings reported in the appendix and turned to multiple databases, including Scopus and Google Scholar. Scopus made it possible to combine the search terms effectively and order papers by citations, which later informed the screening process. We ran the initial search on 10/04/2026 and applied two filters to the retrieved records: publication date between 2015 and 2026, and a minimum threshold of 50 citations. We then screened English-language papers above that threshold against the inclusion criteria reported in the appendix, which had been defined collaboratively by multiple team members to reduce bias. Screening relied on titles, abstracts, and keywords, followed by a full-text accessibility check through open access or institutional credentials. Because this first stage relied on a single database and underrepresented practice-oriented sources, we expanded the corpus through Google Scholar.

On 16/04/2026, we used Gemini to suggest authoritative publishers that could be entered in Google Scholar's `return articles published in:` field. We then screened results from publishers such as "OECD Employment Outlook" and "McKinsey Global Institute" using the same procedure. For the additional practice-oriented search, we relaxed the citation filter to avoid excluding recent but relevant material. On 19/04/2026, we also ran a targeted query on the effects of AI on work and workers and added six further sources that met the inclusion and exclusion criteria. Refer to the screening flow diagram in the appendix for the full record counts at each stage. The analysis of the papers followed this approach: each team member read one or more papers and extracted sentences that directly, or indirectly, referred to a set of general concepts (zip archive: Coding Scheme) that were determined with the approval of all members. After having extracted the data, we collectively coded the latter and categorized it under select general themes, with the help of Microsoft copilot (AI use disclosure in appendix). These themes will then go on to form the categories of our framework. After the first initial coding process and writing of the framework, we were left with six themes, but soon realized that some of the content within different themes overlapped. Therefore, we merged the overlapping content and obtained four general themes present in the framework.

3 Framework

The integration of Artificial Intelligence (AI) into production processes is more than a mere technological innovation; it represents a systemic transformation that is redefining the contemporary labor paradigm. The scientific literature analyzed in this review indicates that the adoption of these tools does not lead to a total replacement of the workforce, but rather to a profound reconfiguration of tasks and organizational structures. This contribution examines this phenomenon through a multidimensional perspective, organized into four key thematic areas. To observe both a schematic structure of the framework and a summary of the key takeaways, refer to Figure 1 and Table 1.

3.1 Organizational Changes and Labour Market Impact

Implementing an AI tool requires evaluating how it reshapes the structure of work across different levels of the labour market. Our review suggests that one of the defining characteristics of current AI systems is their limited ability to fully replace workers in most occupations; instead, they are especially effective at automating routine tasks [10].

At the worker level, the automation or augmentation of tasks changes how workloads are distributed. Human workers are often shifted toward positions involving tasks that require higher levels of emotional or cognitive expertise [18], which current AI tools are not yet able to perform reliably, or toward professional domains in which AI systems cannot operate at a sufficient level, or at all [23]. Another important effect is that AI can augment some mid-to-high-skill-ceiling tasks to such an extent that less skilled workers can perform them, thereby reducing the need for mid-skilled labour in highly repetitive sectors.

At the labour-market level, AI may make openings involving easily augmentable tasks accessible to low-skilled workers, while positions requiring high expertise continue to demand highly skilled individuals. This phenomenon is described in [7] as job polarization, namely the erosion of mid-level positions within the labour market. Moreover, jobs composed primarily of fully automatable tasks are exposed to the risk of complete automation regardless of the skill level previously required for their execution [4], potentially contributing to job displacement across entire sectors [4].

3.2 Human–AI Relationship, Worker Skills, and Training

Choosing whether to delegate tasks to AI tools requires balancing technical considerations with the lived reality of how workers collaborate with the technology. A central factor in this relationship is the worker's initial skill level [18], because it influences both the degree of trust placed in the AI system and the actual performance that the system can achieve. In many cases, AI tools need to be trained, calibrated, or supervised by human operators through supervised or reinforcement learning processes [4], and the quality of those processes depends heavily on the operator's expertise.

At the same time, relying too heavily on AI tools may lead to skill decay [18]. When tasks are fully delegated over the long term, workers risk losing the very expertise needed to supervise augmented systems and to intervene when anomalies occur [10, 26]. Beyond technical competence, it is equally important to consider workers' mental health. The literature suggests that roles centred on constant AI supervision may cause psychological harm because of social isolation and the loss of a sense of purpose [24]. Similar concerns apply when AI is used to replace human emotional intelligence in sensitive roles. For this reason, responsible delegation must preserve human expertise while also protecting the long-term well-being of workers and users.

3.3 AI Advantages and Task Characteristics

The advantages of delegating a task to AI depend on the fit between the characteristics of the task and the strengths of the technology. A consistent finding in the literature is that AI excels at automating routine tasks governed by clear rules and standardized procedures [9]. However, even in work environments dominated by routine activities, complete automation is not always feasible or desirable. In high-stakes settings, where errors are unacceptable, the precision of AI tools in both routine and non-routine tasks remains a decisive parameter [26].

When AI systems achieve sufficient precision, they can significantly augment workflows by improving both efficiency and the quality of outputs [24]. Yet these advantages are bounded by clear functional limitations. Current AI systems are not yet able to perform highly emotionally sensitive tasks in a satisfactory manner [18]. Likewise, they display important limitations in genuinely creative activities, especially when they must navigate scenarios that go beyond the scope of their training data [23].

These functional limits are further compounded by the "black box" nature of many machine-learning systems. Because their internal logic is often opaque, hidden biases and errors may remain undetected, making continuous human supervision necessary to ensure accountability. In light of these intersecting benefits and risks, successful delegation requires organizations to redesign workflows proactively by separating work into three categories: tasks that can be fully automated, tasks that benefit from supervised AI augmentation, and tasks that should remain exclusively human [27].

3.4 Social and Ethical Issues

Technical feasibility alone is not sufficient to justify the implementation of AI into workplace workflows. It is also necessary to evaluate the related social and ethical constraints. A primary concern is responsibility, particularly identifying which stakeholders are accountable for tasks delegated to AI, especially in critical contexts where human supervision remains essential for safety and error prevention [7, 21].

Data management introduces further challenges. From a scalability perspective, AI systems require large quantities of data for effective processing and model training [22], which raises both financial and computational costs. From a security perspective, the adoption of AI tools can threaten data protection and, consequently, the privacy of users' information [22]. Trust also remains a fundamental condition for successful AI integration. From the workers' perspective, the quality of collaboration depends directly on the reliability and perceived quality of the system's outputs [20]. From the perspective of society, organizations that seek to integrate AI must also address public skepticism and fears of technological unemployment, both in public opinion and in the regulatory environment [7, 21].

4 Worked Use Case

4.1 Chosen Profession

Industrial and Commercial Designer

4.2 Use Case

Generating variants of 3D components using the help of an integrated AI tool in the used CAD software

4.3 Profession Characteristics

Within the field of Industrial and commercial design, a 3D CAD Designer is tasked with the creation of various versions of a product, a repetitive process that implies the elaboration of numerous projects that optimizes different geometry, materials and configurations. This activity responds to specific functional and esthetic requisites via an intense manual modelling process. According to our model, this activity presents a high level of complexity, making it ideal for a process of automation since it implies standardized procedures and rule based analysis. However, creativity and the ability to manage exceptional situations is needed, representing significant limits for an artificial intelligence model.

4.4 Performance and Transparency of the Proposed Technology

The proposed AI system, based on generative design and learning features integrated into CAD software, would offer noticeable performance improvements. By entering parameters such as weight limits and structural requirements, the AI model can autonomously generate hundreds of optimized versions. Despite these optimization capabilities, such models are often considered "black boxes" because the decision-making process used by the AI is not fully transparent. This lack of transparency makes it difficult for designers to understand how and why specific choices were made, thereby complicating the verification of a component's structural integrity.

4.5 Worker Competences and Human–AI Collaboration

Relying on AI to generate multiple versions of a component changes the skills required from the worker, shifting the focus from manual 3D modelling to the management of automated systems. While productivity could increase substantially, this transformation also carries the risk of skill erosion, as the designer's professional abilities may deteriorate because of reduced practice. For this reason, it is crucial to establish a collaborative balance between the human worker and the AI system. The worker must preserve the expertise needed to manage uncommon scenarios that the AI model has not been trained to address.

4.6 Impact on Ethics and Reliability

The adoption of systems such as the one theorized here is accompanied by a potential crisis of trust. Designers may feel insecure if they are unable to foresee or explain the outcomes of a "black box" decision system. Furthermore, ethical concerns arise regarding responsibility: if a project created by an AI system fails, the lack of algorithmic transparency makes it difficult to determine who is accountable. Genuine human interaction and contextual intuition therefore continue to be preferable in tasks that involve human values and professional judgment.

4.7 Costs, Feasibility and Governance

From an administrative perspective, the use of these AI tools requires a substantial reorganization of work activities. It is essential to address governance and regulatory issues in order to guarantee privacy, accountability, and the scalability of the AI infrastructure. The feasibility of the transition toward AI-assisted design depends on balancing immediate productivity benefits with the long-term preservation of human skills.

4.8 Framework Evaluation

According to our framework, the tasks associated with the selected profession should be augmented rather than fully automated. AI should support the rapid generation of component variants through rule-based decision-making in order to improve efficiency, while the human designer should remain responsible for the final selection and refinement of the component. This division of roles ensures that human experience and professional judgment are not undermined by the opacity of the system, thereby safeguarding the overall quality of the project.

5 Gaps and Future Work

Building on the framework in Section 3, a synthesis of current literature reveals several limitations that hinder both our understanding and the practical use of AI task delegation. A major issue is that much of the research relies on generalized, predictive models to measure how AI affects work. While these provide a basic idea of which tasks might be automated, they often fail to capture the messy complexity of actual organizational environments. Furthermore, there is a lack of long-term evidence showing how AI delegation decisions change over time as both the technology and workplace habits evolve together. Additionally, existing studies frequently treat job tasks as independent units that can be easily separated for automation. This abstract approach ignores the fact that tasks are actually dynamic and highly dependent on one another. In practice, tasks are woven into broader workflows where suitability for AI delegation is shaped by a company's specific structure, collaboration habits, and technical infrastructure. The current body of research also suffers from a narrow focus, primarily centering on Western economies and "desk-based" knowledge work. While some studies explore how different cultures feel about AI, there is very little comparative evidence across diverse global institutions. This limited scope makes it difficult to apply current findings to a global context. There is also a significant gap between academic theory and real-world practice. Academic papers often focus on theoretical models of what AI can do, whereas industry reports highlight real-world adoption—often without explaining their methods clearly. This disconnect makes it difficult for leaders to turn theoretical insights into practical strategies, especially when trying to balance efficiency with the need for human oversight. Furthermore, we do not yet fully understand the proportions of the long-term impact of AI on human talent. While AI adoption can help people gain new skills, it can also lead to skill loss or reduced mental engagement depending on the situation. Evidence remains particularly thin regarding "soft skills"—such as professional intuition and emotional intelligence—which are harder to measure and often left out of empirical data. Finally, from a methodological standpoint, researchers lack a consistent way to define and measure AI-exposable tasks. Because different studies use different criteria and levels of detail, it is currently very difficult to combine their various findings into a single, unified framework. To address these limitations, future research should prioritize more context-sensitive and long-term approaches. The following research directions are particularly important:

- **RQ1:** How do cultural, institutional, and organizational factors shape the way people perceive, accept, and successfully use AI-assisted decision-making in different settings?
- **RQ2:** What are the long-term effects of delegating tasks to AI on skill development, the retention of tacit knowledge, and overall human expertise within companies?
- **RQ3:** How can organizations systematically track and evaluate changes at the task level to find the right balance between AI assistance and human oversight?

Addressing these questions will require moving beyond purely theoretical or one-time studies toward real-world business settings. Long-term case studies, comparisons between different cultures, and mixed-method approaches (using both data and interviews) will provide a more complete understanding of how AI systems interact with human work over time. Ultimately, advancing this research will help create more reliable and evidence-based frameworks for AI task delegation. These frameworks should combine technical, organizational, and human factors, allowing for more informed and responsible decisions about the role of artificial intelligence in the workplace.

6 Results

The findings of this scoping review reveal that AI delegation is a complex negotiation between technological and human capability, which revolves around six determinant points. At the core there's a task-level logic, where AI is integrated not to replace entire jobs but to target specific occupational tasks. This process is expected to raise performance, particularly in high-precision areas like diagnostics, yet it is consistently moderated by the risk of skill decay. The suit of immediate productivity through AI delegation must be balanced against the preservation of human judgment. When complex cognitive tasks are outsourced to algorithms, there is a significant danger of skill degradation, leaving the workforce ill-equipped to manage the unique or unforeseen challenges that fall outside the AI's capabilities. Furthermore, the nature of the task itself dictates the logic of automation. While AI excels at standardized, rule-based data processing, it hits a "hard ceiling" when faced with tasks requiring creativity, fine manual dexterity, or emotional intelligence. This leads to a necessary redesign of workflows, where computational elements are handed to machines while humans retain responsibility for cognitively and emotionally complex scenarios. This transition also shapes the labor market, contributing to job polarization. The implementation of AI in workflows leads to a hollowing out of mid-level job entries, contributing to a labour market in which companies find themselves in need to hire either highly experienced professionals or low-skilled workers. Finally, the success of these systems depends heavily on human-AI trust and organizational governance. The "black box" nature of many algorithms creates transparency barriers that stifle adoption, particularly in relational professions where clients still demand authentic human interaction. Governance structures must therefore address privacy, data scalability, and accountability. Ultimately, the literature suggests that delegation is only sustainable when supported by a robust organization that accounts for "AI social gaps", ensuring that humans remain present to interpret, validate, and manage the outputs of autonomous systems.

7 Conclusions

In conclusion, delegating occupational tasks is a choice that involves different domains of consideration, spreading from technical feasibility to resilience of human skills. This review identifies the following dominant points of reflection when considering whether to delegate a task to an AI system:

- Does the task consist in something which is part of the AI system domain of expertise?
- If the task is of critical importance, can supervision be ensured?
- Does its delegation erode the necessary skills of the worker?

- Is the implementation of an AI system significantly advantageous?
- Does the adoption of the AI system result in the need of new workforce or the upskilling of the already existing one?
- Can privacy and compliance with regulations be ensured if a task is delegated to an AI system?

Figure 1: The model illustrates how the implementation of AI, ranging from operational tasks (core) through the human-AI relationship to macroscopic labor market outcomes (outer ring), is entirely influenced by the overarching framework of ethics and regulation. The color gradient distinguishes the dynamics resulting from a failed implementation (left, in red) from those of a virtuous implementation (right, in green).

Table 1: Key Findings

	Organizational changes and labour market impact	Human-AI Relationship and Worker Skills/Training	AI Advantages & Task Characteristics	Governance, Ethics and Trust
1	AI primarily automates specific tasks rather than replacing entire roles, requiring a granular redesign of workflows. Human workers shift toward high-level cognitive, emotional, and specialized tasks where AI cannot yet compete.	AI effectiveness and training quality are directly proportional to the worker's initial skill level. Prolonged delegation causes skill decay, compromising the worker's ability to manage AI anomalies and failures.	AI excels in routine, rule-based automation, but overall success depends on high precision to avoid costly errors in sensitive environments. To fully leverage AI capabilities, companies must restructure and adapt their existing organizational workflows.	AI delegation requires clear responsibility structures, ensuring human oversight for safety and error prevention in critical tasks. High data demands for AI training create significant financial costs and elevate risks related to data privacy and potential security breaches.
2	AI lowers the barrier for complex tasks, potentially benefiting low-skill workers but hollowing out mid-level positions.	Constant AI supervision can lead to psychological harm due to social isolation and a lack of professional purpose.	AI capabilities are limited by a lack of genuine creativity and emotional sensitivity, restricting its use to pre-trained scenarios.	Internal trust is built through the perceived reliability and objective quality of the AI's output during human-AI collaboration.
3	Roles centered on routine-heavy tasks face a high risk of full automation, necessitating proactive workforce retraining.	Trust in AI tools is heavily rooted in the operator's expertise and their ability to oversee the automated task.	The "black box" nature of AI models hides intrinsic biases and errors, necessitating constant human oversight to ensure accountability.	Successful integration must address societal skepticism, fear of job loss, and evolving government regulations to ensure public acceptance.
KEY TAKE	*AI integration requires workflow redesign, shifting workers toward complex roles that require emotional and high-level thinking.*	*Success depends on keeping worker skills high. Organizations must prevent skill loss and mental health risks to ensure effective AI supervision.*	*Delegate routine tasks, but keep humans responsible. AI has limited creativity and its logic can be difficult to understand.*	*Long-term success depends on data management and responsibility rules. Organizations must follow ethics, privacy, and government regulations.*

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A Appendix

A.1 Search String and Strategy

The literature search was conducted using Scopus and Google Scholar. The initial search date was 10/04/2026.

The search strategy was developed to identify literature focusing on the practical criteria for task delegation to Artificial Intelligence. The search string was constructed by combining three core conceptual clusters with the Boolean operator `AND`.

- **Phenomenon (AI):** terms related to artificial intelligence and machine learning.
- **Context (Task):** terms related to occupational tasks and skills.
- **Outcome (Delegation/Exposure):** terms related to the automation, augmentation, or assignment of work.

Exact Scopus Search String.

```
("AI" OR "algorithms" OR "language model" OR "machine learning" OR "d
AND ("job task" OR "work task" OR "job assignments" OR "job skills" OR
AND ("automation" OR "augmentation" OR "assignment" OR "exposure").
```

Exact Scholar Search String.

```
("effects of AI on work and workers")
```

A.2 Team Information

Team Name. In ChatGPT We Trust.

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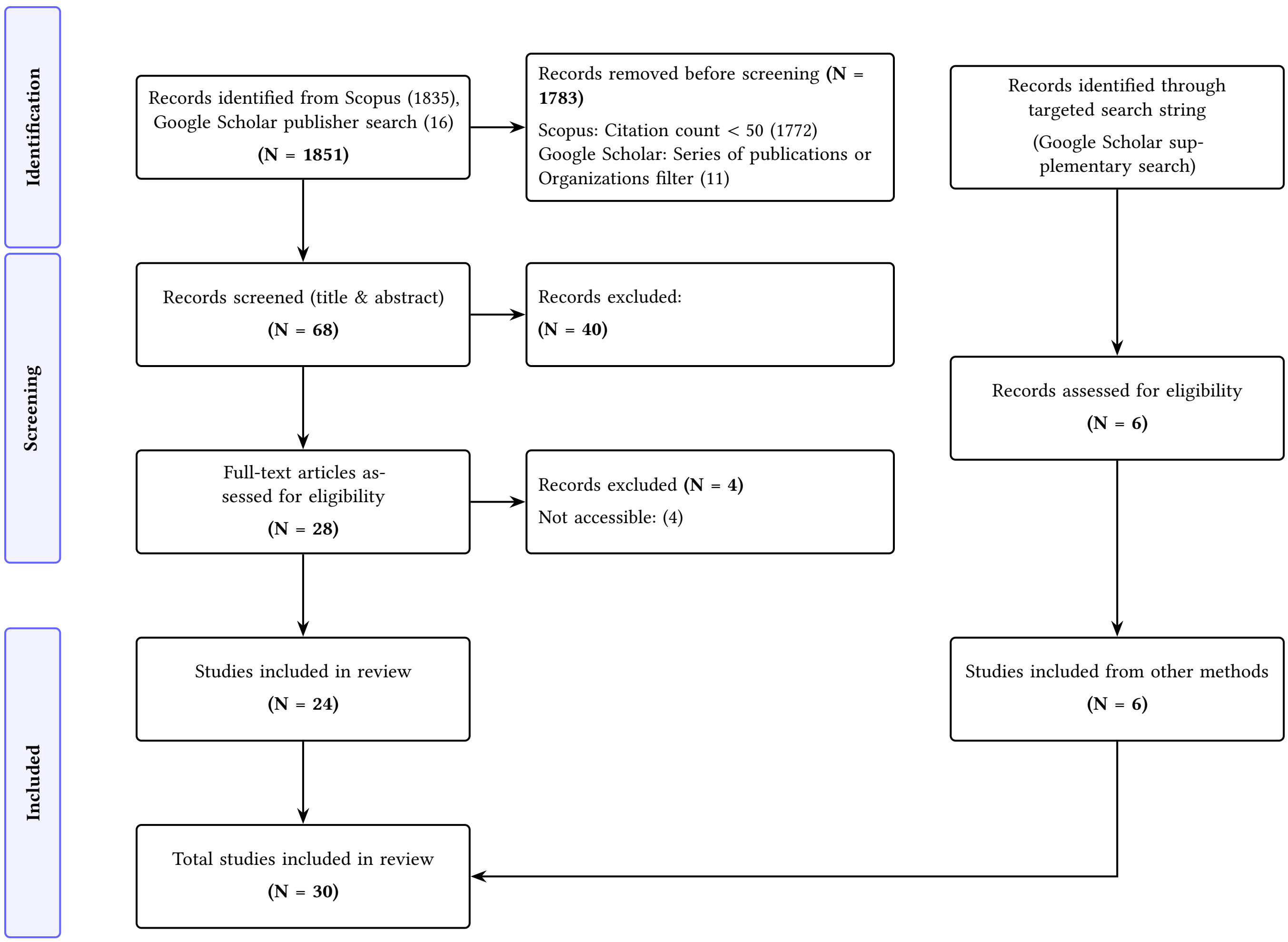
A.3 Reproducibility Material

The data extraction CSV and coding protocols are available in the supplementary ZIP archive at link.

A.4 Screening Flow Diagram



A.5 AI Disclosure

Verification. We confirm that all team members personally read, verified, and checked all cited sources. Also all AI suggestions were checked by team members.

AI tool	**Usage**
Copilot	Copilot was used to group extracted codes into broader themes, which were then used as paragraph headings in the scoping review. *Prompt used:* "In the B column of the second sheet of this table, there are a series of concepts: group together similar concepts under one theme and give me a table where the concepts are organized under these themes."

AI tool	Usage
Gemini	Gemini was used for spell checking, to help identify potential gaps in the reviewed papers, and to suggest authoritative international organizations and industrial research bodies that could provide relevant practice-oriented sources. It was also used to help draft graph structures and LaTeX formatting inside the paper. *Prompt used:* "Hello Gemini, you must scan the entire document, paying special attention to the section titled Gaps and Future Work, to identify possible gaps in the reviewed literature. Specifically, look for answers to these four questions: (1) were the factors studied only in one specific sector, occupation, or country? (2) are there claims or factors mentioned in theory that lack actual empirical support/data? (3) what contexts, populations, or worker demographics are missing from this study? (4) what specific future research do the authors recommend?" *Prompt used:* "Hello Gemini, could you list the main names of authoritative international and political organizations, as well as large industrial consultancy and research companies, that could provide sources with a practical component? By practice I mean authoritative sources that are not strictly academic, such as standards bodies, professional associations, major policy reports, or sector and industrial research."