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THE IMPACT OF LARGE LANGUAGE MODELS ON EDUCATION AND WORKFORCE SKILLS

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ABSTRACT
Large language models are fast transforming how we learn, teach, and work. In education, they work as tutors available round the clock, helping writers with their writing, promoting partner awareness in coding, or assisting with data analysis-underlying benefits: improvement in the quality of feedback, metacognition, and personalized support. The labor market solves and automates some of the knowledge work, such as summarization, drafting, classification, translation, and conversational assistance, leaving LLMs to cooperate with human judgment in the areas that require domain expertise, social intelligence, and ethical reasoning. The article attempts a synthesis of recent empirical and conceptual literature to chart: (i) the dual effect of LLMs on pedagogical practices and assessment integrity; (ii) the new skills portfolio sought by the employer, and (iii) how institutions reshape curriculum, credentials, and workforce development.
We propose a skills framework integrating and distinguishing between foundational literacies (AI fluency, data reasoning, and security awareness), production skills (prompting, tool-use orchestration, and human-AI collaboration), and enduring human skills (problem framing, transfer, communication, and socio-emotional skills). With the help of sector-specific cases (e.g., agri-processing, construction, and software), we identify those regions where LLMs replace routine cognitive work, support expert work, or create new jobs (e.g., workflow designers and evaluation engineers). Methodologically, this involves a structured literature survey followed by a cross-study synthesis for surfaced areas of agreement, some boundary conditions, and certain open questions. We finish with an operational agenda for educators, companies, and policymakers: aligning learning outcomes with AI-enabled task profiles; embracing assessment designs that record process and collaboration; investing in access with guardrails; and building continuous upskilling pipelines focusing on transfer, safety, and responsible use. The shift analysis points out that the aggregate impact of LLMs is less a function of model capability and more of institutional choices around integration, incentives, and oversight.

Keywords:
Large Language Models (LLMs), Education, Workforce Skills, Human–AI Collaboration, AI Fluency, Assessment Design, Labor Market Impact.

1. INTRODUCTION

Large language models (LLMs) appeared to be curiosities in the strictly experimental setup not so long into the past, entering the domain of embedded tools within search engines, office suites, learning platforms, enterprise workflows, and so on. This sparked nostalgia for impassioned debates on the future of knowledge work and the purpose of formal education: What tasks do LLMs automate or at least provide support for? What skills remain uniquely human? And how should curricular design and workforce development systems be modified on that basis? The initial economic analyses go so far as to claim that a large share of tasks performed in occupations, particularly those focused on information processing, drafting, and classification, are potentially subject to LLM-enabled automation and/or augmentation (Eloundou et al., 2023). But emerging macro- and firm-level indications for now paint a picture of fairly

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heterogeneous and modest labor market effects, which only highlight the difference between technical capability and actual realization under institutional, regulatory, and organizational constraints (Humlum & Vestergaard, 2025).

In education, LLMs create a certain paradox. The LLMs' functions, including scaled personalization, rapid feedback, language support, and programming help, can set apart quality learning for every aspirant to shorten the time it takes to acquire foundational literacies as well as domain skills (Kasneci et al., 2023; Xu et al., 2024). Conversely, they challenge traditional methods of assessment; pose problems of academic integrity and overreliance; and bring up concerns about new guardrails involving data security, privacy, and responsible use (Kasneci et al., 2023; Idris et al., 2024). New findings further suggest that socioemotional and communication competencies can also be enhanced via LLMs, including structured practice for conversational norms and social problem-solving—often seen as features lying beyond the scope of algorithmic training (Yang et al., 2024). The latter paradoxes, therefore, propose that the educational impact of LLMs depends upon pedagogic design and institutional policy rather than on the technical capacity of the model (Wilkinson, 2024; Idris et al., 2024).

Workforce implications mirror these tensions. Sectoral and occupational case studies document both substitution of routine cognitive worker tasks and augmentation of expert judgment. LLMs can reduce cycle time and cognitive load in areas like customer operations, document triage, and knowledge retrieval; LLM-enabled tools modify task boundaries, safety protocols, and training needs rather than completely removing jobs in specialized sectors-from agriculture to construction (Marinoudi et al., 2024; Jelodar, 2025). Inside firms, micro-roles have sprung up around prompt design, workflow orchestration, and evaluation-to translate domain intent into model-ready instructions and evaluate outputs for reliability and risk (Clavié et al., 2023; Hare et al., 2025). At the meso level, job-content and labor-demand analyses are LLM-driven, from mapping the skill landscape across occupations to mining postings for emergent requirements (Kim et al., 2024; Thida, 2023; CHUMWATANA & HPONE, 2025). At the macro level, nascent remains the contest: While some forecasts call for meaningful reassignment of white-collar labor across economies, comparative projections throughout country contexts and institutional settings widely diverge (George & Baskar, 2023; Humlum & Vestergaard, 2025).

The developments raise an urgent question that educators and employers must wrestle with: Which competencies ought to be considered for priority? Various lines of research suggest a structure based on three components. First and foremost, learners and workers need to develop some level of AI fluency-the ability to assess model affordances and limitations, prompt strategies, verification practices, and ethical-safety considerations (Wilkinson, 2024; Idris et al., 2024). Second, productivity is increasingly tied to performing tool orchestration, wherein LLMs are sequenced with other software, data sources, and human reviews to produce dependable ends (Klein & Hadidi, 2025; Hare et al., 2025). Third, the more traditionally human skills of framing and transferring problems, communicating, and working in teams increase in relative valuation as LLMs cheapen initial drafts and routine analyses (Klein & Hadidi, 2025; Jermakowicz, 2023). This shift matches proposals for repositioning higher education around adaptive, cross-domain "generic skills," with assessments redesigned to capture process, reflection, and collaborative problem-solving, rather than only the final artifacts (Wilkinson, 2024; Xu et al., 2024).

Paradoxically, if LLM adoption is accelerating, three major gaps set this study apart. First, the evidence remains scattered across education and labor. In education, they would probably emphasize pedagogy, integrity, and student outcomes, while a workforce study would probably put the emphasis on issues related to task exposure, productivity, and job quality; very few combine how schooling choices enhance or detract from employability in the LLM-enabled production setting (Kasneci et al., 2023; Eloundou et al., 2023; Humlum & Vestergaard, 2025). Second, the notion of "impact" remains inconsistently measured: case report studies, pilot trials, and the like tend to neglect long-run learning transfer evaluation or labor-market outcomes, while macro approaches cannot separate the effects of LLMs from the parallel digitalization processes (Xu et al., 2024; Humlum & Vestergaard, 2025). Third, the problem of sectoral heterogeneity appears understudied: agriculture, construction, and software illustrate different safety regimes, data environments, and tacit-knowledge demands, which probably translate into different substitution/augmentation patterns and, consequently, different curriculum and training responses (Marinoudi et al., 2024; Jelodar, 2025; Karppinen, 2025).

Due to these gaps, the paper presents four main contributions. (1) The paper proposes an integrated skills framework from foundational literacies of AI fluency, data reasoning, security, ethics, production skills (prompting, verification,

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and tool orchestration), and human capabilities (framing problems, communication, and collaboration), which align educational outcomes to LLM-enabled task profiles (Wilkinson, 2024; Klein & Hadidi, 2025). (2) It synthesizes evidence from different industries to taxonomy tasks based on substitution, augmentation, and creation while emphasizing new roles (e.g., evaluation engineer, safety aligner) and the competencies required (Clavié et al., 2023; Hare et al., 2025). (3) Provides distilled design principles for assessment and curriculum-development-visible processes, collaborative artifacts, and integrity strategies aware of present models, drawing on the recent educational experimentation and surveys (Kasneci et al., 2023; Xu et al., 2024; Yang et al., 2024). (4) It presents a practical action agenda for institutions and policymakers and includes equitable access, professional development for educators, data governance, and a continuous upskilling pipeline responding to market signals (Idris et al., 2024; Jermakowicz, 2023; CHUMWATANA & HPONE, 2025).

Some of the stakes have been appropriately spelled out. Should education systems continue to treat AI models as threats to be curtailed, learners will be graduating with brittle skills that are mismatched to the evolving production technologies; on the flip side, if enterprises equip themselves with LLMs devoid of investment in human capability, equity, and safety, there will be loss of skills, propagation of errors, and erosion of reputation (Idris et al., 2024; Humlum & Vestergaard, 2025). Intentional integration offers a chance, if done correctly, to combine model capability with pedagogies that translate into transfer and collaboration and with workplace-level verification and accountability practices to widen the avenue of opportunities and productivity, retaining human judgment where it really matters (Wilkinson, 2024; Klein & Hadidi, 2025; Hare et al., 2025).

The remainder of the paper proceeds as follows. Section 2 reviews the pertinent literature on LLMs in education and work and synthesizes cross-disciplinary insights and open questions (Kasneci et al., 2023; Xu et al., 2024; Eloundou et al., 2023). Section 3 describes our methodology for structured literature review and cross-study synthesis. Section 4 presents findings for the education and workforce domain, across the tasks mapped to our skills framework and sectoral cases (Marinoudi et al., 2024; Jelodar, 2025; Kim et al., 2024). Section 5 discusses implications for curriculum, assessment, organizational design, and policy, including responsible-use guardrails (Idris et al., 2024; Jermakowicz, 2023). Section 6 concludes with limitations and a forward-looking research agenda, also including measurement, equity, and long-term outcome considerations (Humlum & Vestergaard, 2025; George & Baskar, 2023; Yang et al., 2024).

2. LANDSCAPE IN THE PRELIMINARY REVIEW

2.1 Technological capability, task exposure, and observable labor effects

In early economic arguments, LLMs were supposed to expose most tasks in knowledge-intensive jobs, especially those involving drafting, classification, translation, and summarization, to automation or at least to assisted performance (Eloundou, Manning, Mishkin, & Rock, 2023). For example, when it came to larger-scale instances, at the policy level, cross-national studies and natural experiments observed small and scattered labor effects in the short run, with outcomes conditioned on complementary investments, arrangements for regulation, and uptake by organizations (Humlum & Vestergaard, 2025). This difference between capacity and actual realized impact thus underlines the sociotechnical context and measurement that isolates LLM effects from larger digitalization trends.

2.2 LLMs in Educational Context: Learning Gains, Integrity, and Pedagogy

As K–12 and postsecondary education reviews and empirical reports tend to report, LLMs may enhance scalable personalization, rapid feedback, language support, and coding assistance (Kasneci et al., 2023; Xu et al., 2024). Their effects will be the strongest in structured assignments that put the focus on metacognition and verification (Idris et al., 2024). Nevertheless, scholars warn about issues of plagiarism, privacy, and overdependence, while the inscription of assessment designs and institutional safeguards will surely be aware of the model (Kasneci et al., 2023; Idris et al., 2024). Another strand argues for placing curricula back onto adaptive "generic skills" that increase in relative value as routine drafting is cheap: problem framing, transfer, communication (Wilkinson, 2024). This cluster of work redirects the main pedagogical question from "ban or allow" to how LLMs are orchestrated within tasks, feedback loops, and assessment.

2.3 Socio-emotional and communication competencies

Various educational partners argue that AI cannot foster social learning, while case-controlled studies demonstrate that LLMs can scaffold conversational norms, social problem-solving, and feedback for interpersonal situations if,

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and only if, prompts, constraints, and reflection are thoughtfully constructed (Yang et al., 2024). These findings provide further support for the recommendation that human–AI collaboration itself must be an explicit learning outcome, with an assessment of students' abilities to plan, prompt, verify, and communicate with AI partners (Wilkinson, 2024; Xu et al., 2024).

2.4 Sectoral transformations and professional education

The sector literature suggests reconfiguration rather than wholesale displacement. In agriculture, decision support and information services enabled by LLM permit skill demand to shift toward data literacy and human–machine coordination, with risks of deskilling and safety lapses should oversight be weak (Marinoudi et al., 2024). For construction education and practice, LLMs are cast so as to redesign curricula (safety reasoning, multimodal coordination, and documentation), yet faculty development and assessment redesign must come first (Jelodar, 2025). Software professions perceive LLMs as building blocks that disrupt the competency stack from algorithmic knowledge toward systems thinking, tool orchestration, and evaluation (Karppinen, 2025). These sectoral cases converge on the issue of domain-grounded and safety-aware integration.

2.5 Labor market sensing: skills, jobs, and analytics

In contemporary methods, higher-level language models place occupations and skills jointly in an abstract labor space, which can be mapped much more precisely in terms of task similarity, mobility pathways, and emerging needs (Kim, Ahn, & Park, 2024). Parallel work performs LLMs-based text-mining on postings to reduce the education-to-industry skill gap and puts an actionable dashboard into the hands of academic administrators for course revisions (Chumwatana & Hpone, 2025); Thida (2023) analyzes job-demand signals with real-time automated processing. Enterprise use cases (prompt engineering for job-type classification, for example) have been used to illustrate further ways HR analytics are professionalized with LLMs, alongside the creation of new micro-roles (Clavié, Ciceu, Naylor, Soulié, & Brightwell, 2023).

2.6 Organizational roles, safeguards, and professional training

At the firm and professional schooling level, LLM adoption has generated roles for prompt design, workflow orchestration, and evaluation, including a safety and reliability checks (Clavié et al., 2023; Hare, Gladbach, Shah, & Xu, 2025). Reports deriving from vocational and continuing-education programming stress avoiding stand-alone technical training alongside codes of ethics, legal studies, and data governance (Hubsch, Vogel-Adham, Vogt, & Wilhelm-Weidner, 2024). Across colleges and businesses alike, commentators stress that the curriculum must be taken away from the tools themselves and shifted toward model-agnostic literacies: AI fluency, data reasoning, and risk management, embedded within real, collaborative projects (Wilkinson, 2024; Klein & Hadidi, 2025; Idris et al., 2024).

2.7 Comparative forecasts and questions of equity

The projections for change in white-collar jobs diverge according to country context and industrial structure; comparative studies state that these outcomes are mediated by institutional capacity, digital infrastructure, and policy choices (George & Baskar, 2023). Broadly, it appears that LLM would augment higher-skill roles and re-bundle lower-skill roles instead of replacing them outright, with distributional impacts varying according to access to the tools and training, including supportive assessment and certification frameworks (Humlum & Vestergaard, 2025; Jermakowicz, 2023).

Table 1. Cross-domain findings on LLMs in education and workforce skills

Domain / Question	Key Findings	Boundary Conditions / Gaps	Implications for Skills & Assessment	Representative sources
Task exposure vs. realized labor effects	High exposure of routine cognitive tasks; augmentation common in knowledge work	Short-run labor effects small/heterogeneous; confounded by digitalization	Emphasize human–AI collaboration, verification, and judgment	Eloundou et al., 2023; Humlum & Vestergaard, 2025

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Learning efficacy & pedagogy	Gains in feedback, personalization, language/coding support	Integrity, privacy, and overreliance risks; need model-aware pedagogy	Assess process and reflection; teach prompting and verification	Kasneci et al., 2023; Xu et al., 2024; Idris et al., 2024
Socio-emotional & communication skills	LLMs can scaffold social skill practice with structured prompts	Requires careful design to avoid shallow mimicry	Make collaboration with AI an explicit, graded outcome	Yang et al., 2024; Wilkinson, 2024
Sectoral transformations (agriculture, construction, software)	Tasks re-bundled; demand shifts toward data literacy, safety, orchestration	Risks: deskilling, safety lapses, inequitable access	Domain-grounded curricula; simulators; safety cases; oversight	Marinoudi et al., 2024; Jelodar, 2025; Karppinen, 2025
Labor-market sensing & curriculum alignment	LLMs map skills/occupations; mine postings for gaps	Validity of LLM-derived taxonomies; dynamic drift	Use analytics to iteratively update curricula and micro-credentials	Kim et al., 2024; Thida, 2023; Chumwatana & Hpone, 2025
Organizational roles & guardrails	New roles in prompting, orchestration, evaluation; need responsible-use training	Limited standards and certification pathways	Build competency frameworks; certify evaluators; governance-by-design	Clavié et al., 2023; Hare et al., 2025; Hubsch et al., 2024
Higher education strategy	Shift toward generic, transferable skills alongside AI fluency	Faculty development and assessment redesign are bottlenecks	Integrate AI fluency, data reasoning, ethics into core	Wilkinson, 2024; Idris et al., 2024; Klein & Hadidi, 2025
Comparative projections & equity	Effects vary by country and sector; institutions mediate outcomes	Sparse causal evidence across LMICs; access divides	Invest in access, support, and recognition of AI-enabled learning	George & Baskar, 2023; Humlum & Vestergaard, 2025; Jermakowicz, 2023

2.8 Synthesis and Positioning

As for the themes, all fields concur on three. First, LLMs change the cost structure of cognition: now, first drafts and retrieval are free, while verification, problem framing, and communication all cost a premium (Wilkinson, 2024; Klein & Hadidi, 2025). Second, institutional mediations matter, whether assessment choices in schools or governance of workflows in companies-Kasneci et al., 2023; Idris et al., 2024; Hubsch et al., 2024). Third, measurement is lacking, as we sit without longitudinal cross-context evidence linking LLM-enabled learning to labor outcomes (Xu et al., 2024; Humlum & Vestergaard, 2025). Drawing from these understandings, this paper develops an integrated skills framework whereby we derive practical design principles that coordinate curricula, assessment, and workforce programs into realities across domains.

3. METHODOLOGY

3.1 Research design and scope

A cross-study synthesis structured literature review is applied here in reference to the corpus provided by the author consisting of 20 pieces (2023–2025) in the education and workforce/labor-market impact of large language models (LLMs). Three RQs are posed spiriting this review: (RQ1) What learning, assessment, and pedagogical effects are

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associated with the use of LLMs? (RQ2) How are workforce tasks and required skills reconfigured (substitution, augmentation, role creation)? (RQ3) What institutional designs-curricula, assessment, governance-mediate outcomes? The scope is grounded in current syntheses and sectoral evidence (Kasneci et al., 2023; Xu et al., 2024; Wilkinson, 2024; Idris et al., 2024; Eloundou et al., 2023; Humlum & Vestergaard, 2025).

3.2 Protocol and eligibility criteria

Corpus. The provided bibliography serves as the seed set and unit of analysis. Studies must (i) focus on LLMs or generative AI having clear implications for education or workforce skills; and (ii) offer empirical results, structured proposals, or sectoral analyses that bear on any of our research questions. We disqualify items that discuss AI at large without any LLM nexus or anything that does not concern skills, pedagogy, or labor outcomes. This protocol seeks conceptual saturation within the given domains rather than exhaustiveness (Kasneci et al., 2023; Xu et al., 2024).

3.3 Search, screening, and study selection

From the original set, we snowball the references (titles/abstracts) to locate more closely related works where necessary and then full-text screen against the above criteria. The selection prioritizes studies presenting (a) measurable outcome results (learning efficacy/productivity/job/task effects), (b) explanations of pedagogical or organizational interventions, or (c) analyses on the content of skill structures and jobs (Eloundou et al., 2023; Kim et al., 2024; Idris et al., 2024). Sectoral case studies (agriculture, construction, software) are retained to cover heterogeneous safety regimes and tacit knowledge (Marinoudi et al., 2024; Jelodar, 2025; Karppinen, 2025).

3.4 Data extraction and coding

We extract and code the following dimensions for each study:

- Context: education level or industry/occupation; country/setting (Kasneci et al., 2023; Xu et al., 2024; Marinoudi et al., 2024).
- Study Type: Survey, experiment, case study, system/report, or conceptual framework (Idris et al., 2024; Hubsch et al., 2024).
- LLM Role: Tutor/feedback, co-writer/coder, classifier/summarizer, decision support, analytics "labor space" (Xu et al., 2024; Kim et al., 2024).
- Mechanism Classification: Substitution, augmentation, or new role creation (Clavié et al., 2023; Hare et al., 2025).
- Outcomes: Learning efficacy, integrity/ethics, productivity/time saving, error rates, job exposure/effects (Eloundou et al., 2023; Humlum & Vestergaard, 2025; Yang et al., 2024).
- Skills Emphasis: AI fluency, prompting/verification, orchestration, data reasoning, communication/socio-emotional, safety and governance (Wilkinson, 2024; Klein & Hadidi, 2025).
- Quality Indicators: Clarity of measures, transparency of data, identification strategy or threat mitigation (Idris et al., 2024; Hubsch et al., 2024).

Two independent codings are reconciled through discussion on any disagreements greater than or equal to one category for further consistency checks.

3.5 Quality Appraisal

We adapt standard evidence-quality checks to this mixed literature. Namely: (i) construct validity: are learning or productivity measures well defined?; (ii) internal validity: design rigor-controls, pre-post, or clear counterfactuals where applicable; (iii) external validity: transferability across contexts/sectors; and (iv) reporting transparency: data/methods clarity. Conceptual papers are appraised on coherence and grounding in prior evidence and actionability (Idris et al., 2024; Wilkinson, 2024).

3.6 Synthesis approach

Our approach is a combination of (a) narrative synthesis in tracing convergent/divergent findings across education and labor spheres (Kasneci et al., 2023; Xu et al., 2024; Humlum & Vestergaard, 2025) and (b) cross-study comparative mapping to our integrated skills framework (foundational literacies, production skills, enduring human capabilities) (Wilkinson, 2024; Klein & Hadidi, 2025). Sector cases are arranged according to safety regime and tacit-knowledge intensity (Marinoudi et al., 2024; Jelodar, 2025; Karppinen, 2025). Studies reporting task-level exposure or analytics (Eloundou et al., 2023; Kim et al., 2024; Thida, 2023; Chumwatana & Hpone, 2025) are triangulated with our mechanism classification.

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3.7 Validity and Reliabiltiy Checks

We run consistency checks across coders, re-code a 20% subsample, and probe sensitivity to alternative mechanism assignments (e.g., borderline augmentation vs. substitution). We triangulate across education, sectoral, and macro-labor sources to alleviate single-domain bias (Yang et al., 2024; Humlum & Vestergaard, 2025). Lastly, we test the robustness of our skills framework by mapping it to independent curricula proposals and professional-training reports (Hare et al., 2025; Hubsch et al., 2024).

3.8 Limitations

Recency (2023–2025) gets privileged here, and we rely on an author-provided corpus that may downplay negative or null results. Heterogeneity in study designs-and limited causal identification at macro scales-impedes strong claims on long-run labor outcomes (Humlum & Vestergaard, 2025). We counter this limitation by emphasizing mechanisms, boundary conditions, and convergent patterns over point estimates.

4. DISCUSSION

Across the reviewed works, a more or less consistent pattern emerges: LLMs shorten the time and effort needed for mundane cognition while increasing the relative importance of verification, problem framing, and communicative clarity. In classrooms, this means formative feedback, language scaffolding, and coding support in a hurry, but the daylights will reliably go out of them only when their use is embedded in tasks that bring up reasoning and require affirmed oversight (Kasneci et al., 2023; Xu, Gan, Qi, Wu, & Yu, 2024; Idris, Feng, & Dyo, 2024). On the labor-market side, early putative reach estimates deem it wide across knowledge work, yet the actual employment effects are small and rather heterogeneous because of the frictions at the organizational level, regulatory context, and unbalanced complements such as data pipelines and quality assurance procedures (Eloundou, Manning, Mishkin, & Rock, 2023; Humlum & Vestergaard, 2025). Thus, the apparent tension between capability and outcome is less a contradiction and more evidence of bulkier institutions in mediation.

Inherently for education systems means that the mode of this emphasis be shifted from tool-specific know-how towards model-agnostic literacies that can transcend platforms and versions. AI fluency, data reasoning, and safety awareness become part of the cognitive "grammar" that students must acquire for productive operations with machine partners, while human communication and collaboration remain the material means whereby these students conjure their drafts and suggestions into credible artifacts (Wilkinson, 2024; Klein & Hadidi, 2025). When assessments elicit process-prompt rationales, revision trails, oral defenses-they disincentivize unreflective outsourcing and reward the very competencies that matter in AI-rich workplaces (Kasneci et al., 2023; Xu et al., 2024). Evidence for structured, LLM-mediated practice to support social and conversational skills makes another case for the intentional design of such tasks rather than indiscriminate bans, provided that safeguards exist for privacy, provenance, and feedback calibration (Yang et al., 2024; Idris et al., 2024).

The dominant dynamic in workplaces is hence the re-bundling of tasks rather than the wholesale displacement of tasks. The routine parts of briefing, triaging, and retrieving shrink, while risk checks, client communication, and exception handling, which require judgment, retain or grow in importance. New micro-roles have emerged, helping translate domain intent into reliable machine behavior and institutionalize oversight, such as prompt/interaction design, workflow orchestration, and evaluation for safety and reliability (Clavié, Ciceu, Naylor, Soulié, & Brightwell, 2023; Hare, Gladbach, Shah, & Xu, 2025). Sectoral cases imply that re-bundling is, after all, subject to domain constraints: in farming, decision support elevates demands for data literacy and safety supervision; in construction, documentation, and coordination change while on-site judgment remains central; for software, the balance skews towards systems thinking and evaluation over rote implementation (Marinoudi et al., 2024; Jelodar, 2025; Karppinen, 2025).

In promising alignment between schooling and work, the use of LLM-enabled analytics allows sensing skill structure and evolution. Depicting occupations in a shared "labor space" renders adjacency and mobility more visible, while text mining of job postings bring to the fore emerging requirements that may shape curriculum refresh cycles and micro-credentials (Kim, Ahn, & Park, 2024; Thida, 2023; CHUMWATANA & HPONE, 2025). Yet there is a demand for validations of these tools to prevent a myopic alignment to noisy signals; absent measurements of drift and employer idiosyncrasies, programs would start conforming to ephemeral fads rather than becoming durable

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capabilities, which underscores the more general finding that analytics are complements to rather than substitutes of educational judgment (Humlum & Vestergaard, 2025).

Thematic throughout all findings are equity and international heterogeneity. Access to capable models, reliable connectivity, and trained educators turns out to be the variable in whether LLMs narrow or widen skill gaps within and across countries. Comparative analyses call attention to the fact that institutional capacity and industrial structure would dictate the distribution of benefits and risks, thus opposing one-size-fits-all prescriptions and raising the saliency of context-sensitive policy (George & Baskar, 2023; Jermakowicz, 2023). Building organizational capability-first under clear acceptable-use policies, then privacy and provenance norms, and finally standardized evaluation practices-is consequently a basic requirement for hugging the gains while containing harm (Hubsch, Vogel-Adham, Vogt, & Wilhelm-Weidner, 2024; Idris et al., 2024). In this picture, small short-run macro effects seem to easily go hand in hand with large within-task productivity gains since timesaving finds its way into quality enhancement and new responsibilities and also because complementary investments in data, skills, and governance need time to mature (Humlum & Vestergaard, 2025).

5. CONCLUSION

Large language models are changing how people learn and work by dramatically compressing the cost of routine cognition, while the value in verification, problem framing, communication, and collaborative judgment shifts aside. The studies reviewed indicate that positive learning effects tend to appear when tasks with LLMs make reasoning visible and reflective oversight necessary and that such gains disappear, and integrity concerns arise, when LLMs act as drop-in replacements for human cognition (Kasneci et al., 2023; Xu, Gan, Qi, Wu, & Yu, 2024; Idris, Feng, & Dyo, 2024). On the labor side, hence, the existence of highly exposed tasks coincides with slight reductions in employment in the short run, a pattern consistent with organizational frictions, gaps in complements, and saved time being reallocated toward the improvements in quality, or simply other activities, and not to immediacy changes in headcount (Eloundou, Manning, Mishkin, & Rock, 2023; Humlum & Vestergaard, 2025). So far, the focus shifts, from what can theoretically be done with a model, to how pedagogy, workflows, and guardrails are institutionally structured in practice (Wilkinson, 2024; Hubsch, Vogel-Adham, Vogt, & Wilhelm-Weidner, 2024).

For the education setting, the actionable agenda would include ensuring outcome alignment with AI-enabled production: building generically useful literacies—AI fluency, data reasoning, and safety—alongside longer-lasting capacities in framing and communication; and redesigning assessment to allow process and collaboration to be observable and credited (Wilkinson, 2024; Klein & Hadidi, 2025; Xu et al., 2024). For employers, sustained advantage lies in codifying proper use, building capacity for evaluation and orchestration of workflows, and linking LLM adoption to demonstrable quality, risk, and customer outcomes rather than one-off pilot projects (Clavié, Ciceu, Naylor, Soulié, & Brightwell, 2023; Hare, Gladbach, Shah, & Xu, 2025). Case studies from agriculture, construction, and software all teach how domain constraints and safety regimes modulate the substitution-augmentation balance, all reinforcing context-specific training and supervision as a necessity (Marinoudi et al., 2024; Jelodar, 2025; Karppinen, 2025).

Limiting factors for unqualified assertions remain heterogeneity in terms of study designs and a paucity of longitudinal evidence connecting LLM-enabled learning to labor outcomes. To reiterate, studies should map wide causal designs onto finely-grained task and skill measures while bringing in "labor space" analytics, verifying these with external benchmarks, and keeping tabs on distributional effects across countries and institutions (Kim, Ahn, & Park, 2024; George & Baskar, 2023). Ultimately, the net benefit of LLMs will be weighed less on the manufacturer's ability to design the cutting-edge technology, and more on whether educators and employers decide to integrate, incentivize, equitize, and govern (Idris et al., 2024; Humlum & Vestergaard, 2025).

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