Research on the Construction Path of Digital-Intelligence Literacy for Science and Technology Talents in the Era of LLMs

Qian Cao, Meng Li*

Shandong Academy of Innovation and Development, Jinan, Shandong, China

*Corresponding Author Email: limenglim@shandong.cn

Abstract

When large language models become more and more powerful, the study aims at the gap trouble of science and technology talent education, and proposes a four-dimensional "Digital-Intelligence Literacy" framework. This framework includes four parts: Cognitive & Mindset, Core Skills, Science and Technology Ethics, and Collaborative Innovation. It will help humans make a shift from technology users to human-AI collaborators. We analyzed the gap between the troubles and typical examples, and built a path of a mix of education reform, dynamic evaluation, and institutional protection. The study will be a guide to meet the demand of cultivating new quality productive forces, and provides theoretical insights and practical guidance.

Keywords

Large Language Models, Science and technology Talents, Digital-Intelligence Literacy, Human-AI Collaboration, Competency Framework.

1. Introduction

We're living through a major shift-one that's happening fast. Large Language Models (LLMs) aren't just getting a little better each year; they're fundamentally changing how research and development work gets done. And that creates a real problem: the skills our current science and technology workforce has don't quite match what's now needed in modern R&D.Let's think about traditional STEM education for a moment. It's always put a heavy emphasis on deep domain knowledge-knowing your field inside out-and on hands-on experimental skills. That made perfect sense in the past. But generative AI has turned the nature of knowledge work upside down. Today's LLMs are genuinely good at pattern recognition, synthesizing large volumes of literature, and generating code. Those used to be tasks that took up a significant chunk of a researcher's cognitive load. Not anymore.Does that mean AI will make STEM professionals obsolete? No-that's not the argument we're making. What it does do is redefine what excellence looks like. The new benchmark is something we might call human-AI collaborative proficiency. That means knowing how to frame problems so that AI tools can actually help solve them, critically evaluating what those tools produce, extending their outputs where needed, and managing the ethical side of using AI in complex projects.Here's the issue: our current education and evaluation systems just aren't ready for this. Most academic curricula still treat digital tools as add-ons rather than central components. Professional assessments rarely reward sophisticated AI collaboration-if they even acknowledge it at all. So we end up with a workforce that might be highly skilled in outdated ways of working, but lacks the core literacy needed to use the most powerful tool of our era.This paper tries to address that gap. We aim to define, frame, and lay out a systematic path for developing what we call "Digital-Intelligence Literacy"-a set of integrated competencies that allow science and technology professionals to become strategic partners to advanced AI systems. The stakes are high. Closing this literacy gap isn't just nice to have; it's essential for building the new quality productive forces that drive national innovation and competitiveness[1][2][3].

2. The Four-Dimensional Digital-Intelligence Literacy Framework

We propose four interconnected dimensions. Think of them as layers that build on each other, starting from mindset and moving up to collaborative innovation.

2.1. Cognitive & Mindset

Let's start with the foundation. This dimension isn't really about learning a specific tool or technique. It's more fundamental than that-it changes how you see yourself as a professional and how you approach problems in the first place.The core here is what we call a Human-AI Collaborative Mindset. That means seeing AI not as a replacement for human thinking, but as a kind of "cognitive exoskeleton"-something that augments your intellect. You learn to delegate strategically: offload pattern matching, literature synthesis, and routine coding to the AI, while keeping higher-order reasoning, hypothesis generation, and value-based judgments for yourself.Underpinning all of this are two classic skills that now look different: critical thinking and systems thinking. With AI, you can't just trust the output. You have to maintain informed skepticism-actively checking for hallucinations, logical gaps, and hidden biases. And you also need to see the bigger picture: how an AI-assisted decision might ripple through a scientific process or an engineering project, affecting validity, safety, and ethical outcomes down the line[4].

2.2. Core Skills

If the first dimension is about mindset, this one is about turning that mindset into real, hands-on capability.

Start with the new human-machine interface: advanced prompt engineering. This is both an art and a science. It means crafting precise instructions, giving enough context, and using techniques like chain-of-thought prompting to reliably get useful, domain-specific outputs. Whether you're simulating an experiment or generating a data analysis script, good prompting is the difference between a helpful assistant and a frustrating one.

But basic interaction isn't enough. True literacy includes customizing tools to your own work. That means skills in model adaptation and data curation-for instance, using retrieval-augmented generation (RAG) to ground an LLM in your own lab's internal research corpus, or fine-tuning a model on a specialized dataset. You also need to be comfortable with multimodal interaction: working seamlessly with AI across text, code, images, and structured data. And don't forget good old data and code literacy-you still have to ensure the quality and security of what goes in and what comes ou[5][6][7]t.

2.3. Science and Technology Ethics & Responsibility

As AI becomes a core research instrument, ethical stewardship stops being optional. It becomes part of the job.So what does this dimension ask for? First, proactive awareness of risks. That includes navigating algorithmic bias and fairness: understanding that training data shapes outputs in sometimes problematic ways, and learning how to mitigate potential harms. Second, academic integrity in the AI era. We need clear protocols for disclosing AI assistance in publications and properly attributing contributions-this is still a gray area, but we can't afford to ignore it.Most critically, this dimension demands safety and accountability. In high-stakes domains like biomedicine or critical infrastructure, you absolutely cannot take AI outputs at face value. Robust human verification is a must, and ultimate responsibility for any decision has to remain with the human professional. Not the model.

2.4. Collaborative Innovation

This is the top level-where you move from using AI effectively to using it as a catalyst for truly transformative work.What does that look like in practice? One piece is driving scientific and engineering innovation: using AI to explore novel research hypotheses, optimize complex system designs, or find new patterns in ambiguous experimental data. Another piece is orchestrating human-AI teamwork. The literate professional acts as a conductor-and sometimes as an "AI translator"-integrating AI agents into project workflows and clearly communicating their capabilities and limitations to interdisciplinary team members.When you get this right, you can tackle problems at a scale and complexity that were simply out of reach before. That's the real promise of human-AI partnership[8].

3. Current Challenges and Constructive Models

To be honest, the current system isn't in great shape. We face several major hurdles. There are no standardized competency definitions. Curricula are often disconnected from real-world AI applications. Evaluation metrics largely ignore AI collaboration. And ethics training, where it exists at all, tends to be superficial.That said, some promising models are already emerging. Let's look at three.

Integrated Curriculum Model:A few forward-thinking universities are moving beyond generic "AI 101" courses. Instead, they're embedding what they call "AI-for-Science" or "AI-for-Engineering" modules directly into core disciplinary classes. For example, a molecular biology course might include a lab session on using protein-folding AIs. A mechanical engineering design course might require students to use generative design algorithms. And when you couple this with university-wide micro-credentialing systems for digital-intelligence competencies, you get learning that's contextualized, applied, and actually sticks.

Workplace Credentialing Model:Some leading tech firms and R&D institutes have started building internal, competency-based certification pathways. These programs tie mastery of specific AI toolchains-like internal prompt libraries or proprietary RAG systems-directly to project performance metrics and career advancement. That creates a powerful incentive: learn this stuff, show you can use it, and you get promoted. Skills become directly aligned with organizational goals.

Ecosystem Partnership Model:This one is the most robust. Here, government agencies or industry consortiums define competency standards. Universities and training providers develop aligned curricula. Enterprises contribute real-world datasets and problem statements for capstone projects. And then independent bodies issue verifiable, portable digital badges that are recognized across the whole ecosystem. It's a virtuous cycle: education meets market needs, learners get clear value, and everyone wins[9].

4. A Systemic Implementation Strategy for Digital-Intelligence Literacy Development

Knowing what needs to be done is one thing. Actually doing it at scale is another. This section lays out a three-part implementation strategy[10].

4.1. Establishing a Dynamic Evaluation and Credentialing System

We need to move past the old model of static knowledge tests-the ones where you cram, take an exam, and forget everything a week later. Evaluating digital-intelligence literacy has to be different. It should be ongoing. It should be competency-based. And it needs to be woven into real professional development, not tacked on as a one-time check.

So how do we do that? Start with a tiered indicator system, built directly on our four dimensions. For each dimension-Cognitive, Skills, Ethics, Innovation-you define specific, observable behaviors that people can demonstrate, at progressive levels: Basic, Intermediate, Advanced. For example, at the high stage of Core Skills, maybe you have a benchmark like "designing and implementing a RAG pipeline for a specialized research domain."

Digital micro-credentials-also called badges-form the operational core of the system. Learners complete structured modules to earn the badges, such as "Prompt Engineering for Scientific Literature Review" and "Ethical Risk Assessment for AI-Assisted Research," and then demonstrate their abilities through practical assessments. These credentials are verifiable and stackable. They map out a person's skill profile in a much more granular way than a traditional diploma.

Otherwise, every professional also has a dynamic talent document. The document can collect a lot of data from different channels, such as earned micro-credentials, project portfolios that include reflective statements on how to use AI, peer and mentor evaluations, and anonymous data from training platforms. It can be visualized with a radar chart in four dimensions. The document can show a person's talent and where they can improve.

4.2. Reforming Education and Professional Development Pathways

Cultivation has to span the entire career lifecycle, from university to continuing professional education.

In higher education, we recommend three levels of reform. First, a mandatory foundational course in the whole school, such as Generative AI and Responsible Research Practice. Second-and this is critical-disciplinary courses need to embed "AI-for-X" case studies and assignments. We can think of a chemistry course using molecular dynamics simulators with AI, or an engineering course requiring AI-optimized design work. Third, capstone projects and theses should explicitly require and evaluate the method of human-AI collaboration and detailed record what the AI did and how the student guided it.

For working professionals, we need a suite of modular, stackable training programs, catering to different roles and skill levels. These could range from short courses on specific toolchains (e.g., "Leveraging Copilot for Scientific Software Development") to advanced programs on "AI-Driven Research Paradigm Innovation." Completion should grant micro-credentials and recognized continuing education units (CEUs).

Practice-oriented platforms are also essential. Knowledge doesn't stick unless you apply it. Institutions or regional bodies should establish "Digital-Intelligence Innovation Workshops" that provide access to curated datasets, toolkits, and computing resources. Regular themed hackathons and challenges-like "AI for Climate Science"-would help people learn through collaborative, real-world problem-solving and build a genuine community of practice.

4.3. Strengthening Institutional Enablers and Policy Synergy

It will be not happened without supportive infrastructure and aligned incentives.

Standard setting and governance. National science and technology authorities can work with industry, formulate and publish a competency standard framework for digital-intelligence literacy. This offers everyone-universities, training providers, employers-a common reference point. It ensures coherence and quality across the whole system.

Incentive alignment. Here's the most powerful lever: integrate digital-intelligence literacy into formal talent evaluation mechanisms. That means professional title (academic rank) evaluations, research grant peer review, and hiring/promotion criteria should all recognize and value outputs created through proficient and ethical AI collaboration. Add a "Digital-Intelligence Literacy" dimension or portfolio requirement to assessment rubrics. Once you do that, you send a clear signal: this isn't optional. It's core to modern excellence.

Ethical infrastructure. Finally, organizations need to establish clear, practical guidelines and review processes for using AI in R&D. That includes defining authorship norms for AI-assisted papers, establishing data safety protocols for projects using sensitive data with AI tools, and creating lightweight ethics review checkpoints for high-risk applications. This infrastructure protects individuals and institutions alike.

5. Conclusion

Let's step back for a moment. Cultivating digital-intelligence literacy isn't just another educational update. It's a strategic investment in the very foundation of scientific and technological capability.

We've laid out a four-dimensional framework that maps the necessary competencies. We've proposed an implementation strategy that offers a viable path to instill those competencies at scale. If we systematically empower STEM talents to become sophisticated collaborators with AI, we won't just automate old tasks more efficiently. We'll unlock entirely new capacities for discovery, innovation, and problem-solving.

The ultimate goal is something we can call genuine human-AI symbiosis in science and technology. Human creativity, judgment, and ethics, amplified by machine intelligence. That combination can drive progress that's not only faster and more efficient, but also more profound-and more responsibly guided.

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