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The AI Pyramid: A Conceptual Model Outlining Workforce Capability

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Abstract

Artificial intelligence (AI) marks a major shift in technological change by extending cognitive labor rather than just automating routine tasks. Recent evidence shows that generative AI is impacting highly educated, white-collar jobs more than expected. This challenges traditional assumptions about which parts of the workforce are most vulnerable. As a result, conventional approaches to digital and AI literacy are no longer sufficient. This paper introduces "AI Nativity," the ability to seamlessly integrate AI into everyday thinking and decision-making. It also proposes the AI Pyramid as a framework for understanding workforce capabilities in an AI-driven economy. The pyramid includes three interconnected layers: AI Native, AI Foundation, and AI Deep capabilities. AI Native serves as a baseline for participation, while AI Foundation focuses on building and maintaining systems. AI Deep capability advances cutting-edge AI knowledge and innovation. The framework emphasizes capability development as ongoing infrastructure, shaping policy, education, and workforce strategies.

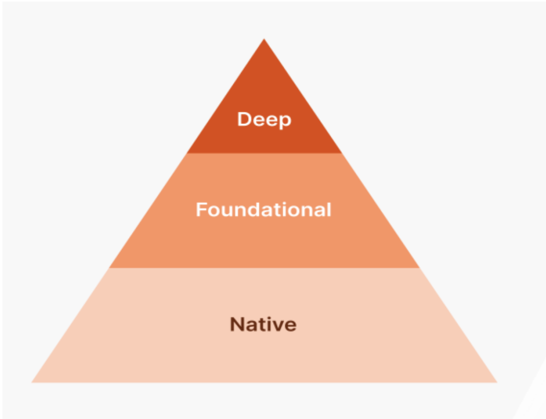
I. INTRODUCTION

Technological change has historically expanded different aspects of human capability. Industrial machinery enhanced physical strength and productivity. Digital computing accelerated our ability to process numbers and data. The internet enabled large-scale coordination and access to information. Artificial intelligence (AI), however, represents a fundamentally different shift. It extends cognitive labour rather than just supporting or automating physical and routine tasks. Modern AI systems can write, summarize, recognize patterns, and generate ideas. They also assist in communication, reasoning, and predictive decision-making. These capabilities were once considered exclusively human. Earlier research shows that automation mainly affected routine and repetitive work. In contrast, generative AI is now impacting highly educated, white-collar professions. This challenges long-held assumptions about which jobs are most at risk. It highlights the need to rethink how workforce skills and capabilities are developed. Traditional frameworks like digital literacy and AI awareness are no longer sufficient. Working with AI now involves collaboration, evaluation, and co-creation with systems that act as cognitive partners

To capture this emergent mode of interaction, this paper introduces the concept of **AI Nativity**. AI Nativity does not imply technical mastery or the ability to build AI systems. Rather, it describes the capacity to integrate AI fluidly into one's thinking, problem-solving routines, and everyday cognitive workflows, treating AI as part of the environment in which reasoning occurs. Building on this orientation, the paper proposes the **AI Pyramid**, a framework that both categorizes the capability segments societies require and guides how those capabilities can be systematically developed through training and infrastructure in an AI mediated economy.

The AI Pyramid Framework

Workforce planning in the AI era requires clarity about what different population segments need to know and do. This paper proposes the AI Pyramid, a framework that distinguishes three levels of capability required for an AI-ready workforce. The framework builds on Lepak and Snell's (1999) Human Resource



The pyramid's shape represents population scale and functional dependency, not value hierarchy. While visual convention might suggest the apex represents the "highest" achievement, our framework inverts this assumption: the base is the most critical layer. Just as ancient pyramids required massive foundations to support narrow peaks, AI-enabled societies require broad AI Native capability to support smaller populations of Foundation builders and Deep researchers. Without a stable base, nothing above it can function. The pyramid shows what is required for the whole system to work, not a ladder individuals should climb.

AI Native capability

AI Native capability forms the foundation of the AI Pyramid. It includes individuals who work in AI-mediated environments without building or engineering AI systems. This capability is not defined by technical expertise or domain knowledge alone. Instead, it reflects a behavioral orientation toward working with AI. It involves framing problems in ways that AI systems can effectively engage with. Individuals must also evaluate and interpret AI outputs critically. They integrate AI-generated insights into human judgment and decision-making. A key aspect is understanding AI's limitations, biases, and risks. This includes knowing when to question or reject AI outputs. AI Native capability is seen in how people use and manage AI in everyday tasks. It influences how teams collaborate and how organizations make decisions. It also shapes how institutions adapt to AI-driven environments. Research shows that AI affects highly educated, white-collar workers the most. Therefore, this capability must extend across the broader workforce, not just specialists. It can be assessed through how individuals interact with AI, especially in complex and uncertain situations.

AI Foundation Capability

AI Foundation capability forms the middle layer of the AI Pyramid. It includes individuals who design, build, and maintain AI-enabled systems. This group consists of engineers, developers, and applied data practitioners. They translate organizational goals into practical AI tools and workflows. Unlike AI Native capability, this level focuses on building systems rather than just using them. However, it does not require advanced or frontier-level research expertise. Its key strength lies in operationalizing AI effectively in real-world contexts. This involves integrating data, models, infrastructure, and business processes. It also requires attention to performance, scalability, security, and governance. AI Foundation capability is demonstrated through what individuals can create and sustain. A major challenge at this level is rapid skill obsolescence due to evolving technologies. Research shows that the value of technical skills can decline quickly over time. Therefore, static degrees or one-time training are not sufficient. Continuous learning and hands-on problem-solving are essential for staying relevant. This capability is best measured through real-world system implementation and integration outcomes.

AI Deep Capability

AI Deep capability represents the top layer of the AI Pyramid. It includes individuals who advance the frontiers of artificial intelligence. This group consists of researchers, scientists, and specialized engineers.

They develop new models, algorithms, and training methods. They also contribute theoretical insights that expand AI knowledge. In addition, they apply advanced AI to drive breakthroughs across domains. These domains include health, education, science, energy, and public policy. AI Deep capability focuses on creating new possibilities rather than just implementing systems. Unlike other layers, it is not required in every organization. Instead, it operates within research ecosystems and global innovation networks. Its impact spreads through spillovers to broader systems and users. These advances shape tools used by both builders and everyday AI users. Its importance lies in strengthening national and societal innovation capacity. Sustained investment in research infrastructure and resources is essential. This capability thrives in collaborative environments where theory and application evolve together.

Capability Distribution and the Infrastructure Challenge

The pyramid is not intended as a career ladder or a normative progression that individuals are expected to climb. Its structure reflects differences in scale, function, and dependency, not relative status or achievement. AI-enabled societies do not require all individuals or organizations to move toward higher layers of specialization; rather, they depend on a stable distribution of capabilities across layers. Broad AI Native capability enables effective participation in AI-mediated environments, Foundation capability enables systems to be built and sustained, and Deep capability generates frontier advances whose benefits diffuse outward. The pyramid therefore describes how capabilities must be distributed across a system, not how individuals should advance within it.

Workforce planning that overemphasizes one layer at the expense of others risks creating systemically imbalanced organizations and societies, with sophisticated research capacity but limited deployment expertise, or widespread tool adoption without the technical infrastructure to sustain it.

Problem-Based Learning for Capability Development

As AI capability development shifts toward continuous infrastructure, learning must support ongoing adaptation. Problem-based learning (PBL) plays a central role by aligning skills with real-world challenges. AI skills are not abstract knowledge but context-specific practices embedded in workflows.

PBL is effective because it focuses on solving the problems learners actually face. Research shows strong evidence supporting the effectiveness of PBL. Studies indicate it improves long-term retention, skill development, and learner satisfaction. It is particularly effective in building deep conceptual understanding. This type of understanding is essential for AI-augmented work environments. PBL reverses traditional learning by starting with problems rather than theory. AI concepts are introduced only when needed to solve specific tasks. Learners engage in cycles of experimentation, feedback, and refinement.

This leads to practical understanding rather than abstract memorization. The approach is grounded in situated learning theory. This theory emphasizes learning through participation in real-world contexts. For AI, this means embedding learning directly into everyday work. However, large-scale implementation requires competency-based assessment. Capabilities must be measured through performance, not course completion. This involves evaluating skills like judgment, task design, and responsible AI use. Skill ontologies provide a shared structure to map and track these capabilities. Together, PBL and competency frameworks enable continuous, scalable workforce development.

Building Capability Infrastructure Through the Pyramid

The AI Pyramid offers a framework for structuring capability development in an AI-driven world. It highlights that different workforce segments require distinct approaches to building skills. This aligns with the idea that varied human capital needs tailored development strategies. Across all layers, capability development depends on dynamic skill ontologies and competency-based assessment. AI skills must be evaluated through real-world performance rather than static credentials. This shared system enables continuous learning, measurement, and workforce planning at scale.

AI Native Level: Mass Accessibility and Behavioral Fluency

At the AI Native level, the shared competency-based infrastructure must be adapted for scale and accessibility across the general population. Here, problem-based learning is embedded directly into everyday work and civic contexts, enabling individuals to develop fluency in AI-mediated reasoning through routine task performance rather than formal instruction. The relevant competencies emphasize behavioral patterns, how people frame problems for AI systems, evaluate outputs, exercise judgment under uncertainty, and recognize risks or misuse, rather than technical knowledge. As a result, learning and assessment at this level prioritize continuous, low-friction integration into daily workflows, ensuring AI nativity functions as a baseline capability for participation in AI-structured environments rather than a specialized qualification.

AI Foundation Level: Role-Specific System Building Capability

At the AI Foundation level, the same competency-based infrastructure is applied to a narrower population with distinct functional responsibilities: individuals who build, integrate, and maintain AI-enabled systems on behalf of organizations. This includes engineers, applied data practitioners, technical generalists, and developers tasked with translating organizational objectives into deployable, governed, and sustainable AI workflows. Problem-based learning at this level centers on real implementation challenges, such as data pipeline design, model integration, workflow automation, system monitoring, and responsible deployment within organizational constraints. Competency assessment therefore emphasizes demonstrated system-building outcomes tied to specific roles and contexts, enabling continuous updating and re-verification of capability as tools and architectures evolve.

AI Deep Level: Research Ecosystems

At the AI Deep level, a small group advances AI through research and real-world breakthroughs. Learning occurs through solving open research problems and pushing theoretical and applied boundaries. This capability operates at national and global levels, with impact spreading through knowledge spillovers. Assessment focuses on research contributions, innovation, and broader ecosystem influence. The AI Pyramid highlights the need for a unified, competency-based learning and measurement system across all layers. Balanced investment across AI Native, Foundation, and Deep capabilities is essential for effective and inclusive workforce development.

II. CONCLUSION

The AI Pyramid provides a conceptual framework for understanding how societies can organize human capability in an era where cognition is increasingly shaped by machine systems. By distinguishing between AI Native, Foundation, and Deep capabilities, it clarifies which skills must be widespread and which should remain specialized, while emphasizing that these layers function as an interconnected system rather than a linear path. At its core, the framework highlights that effective AI adoption depends on a shared, competency-based infrastructure for learning, measurement, and credentialing that can be adapted across all layers.

However, important research gaps remain. The framework calls for empirical validation across organizations, industries, and national contexts to understand how different capability distributions affect productivity, resilience, and inclusion. It also raises questions about how these distributions vary across economic stages and how competency-based assessments can reliably measure real-world AI capabilities. As AI continues to spread across society, the ability to measure, develop, and distribute human skills will become critical, requiring sustained research, policy innovation, and collaboration to build effective capability systems at scale.

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