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Competency Modeling in a Digital Age: Redefining Skills and Capabilities for a Technologically Evolving Workforce

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ABSTRACT

The rapid advancement of artificial intelligence (AI) and emergent technologies has revolutionized how tasks are performed across various domains (Dwivedi et al., 2021), in turn requiring a shift in the traditional competency model. These models now require more frequent updates to reflect the dynamic nature of technological evolution. In some contexts, AI surpasses human capabilities entirely (Zhang et al., 2020), consequently reshaping the landscape of required skills and knowledges for the tasks within the job and requiring a deeper focus on improved decision-making. This transformation introduces a dual challenge: identifying and emphasizing new competencies to support decision-making while simultaneously reassessing tasks that are either obsolete or augmented by AI systems. For example, in areas like aviation, emergent aircraft designs have created a shift in which tasks that were previously reliant on humans (Vempati et al., 2021) such as controlling 8-rotors on an electric vertical takeoff and landing (eVTOL) aircraft, are now feasible only through AI systems. These agents often achieve optimal performance levels unattainable by humans, rendering traditional training for these tasks unnecessary. Conversely, in fields where AI complements rather than replaces human capabilities, such as cyber and intelligence, new responsibilities and knowledge requirements are being appended to existing roles. These additional knowledge, skills, and/or task requirements can lead to increased cognitive and operational workloads for trainees (Strauch, 2017). This dichotomy highlights the importance of distinguishing between the roles where training could be minimized due to automation and those where training must be expanded to accommodate the new tasks due to these technologies. Competency models in this digital age need to adapt to consider tasks based on their relevance and the level of AI integration. Models should be updated to include more decision making and highlight collaboration with AI systems to address the balance between task automation and human involvement. These changes can help to ensure that training programs remain efficient and relevant. The current work explores these challenges and offers a framework for designing competency models that reflect the evolving technological landscape. Further we propose strategies for identifying and incorporating updated competencies, emphasize the need for continuous model refinement, and outline methods to balance training requirements with operational demands. Key considerations include integrating AI-awareness into competency frameworks, reducing redundant training efforts, and fostering skills that enhance human-AI collaboration.By addressing these evolving needs, competency models can better prepare individuals for the demands of the digital age while promoting efficiency and adaptability in training programs. The paper aims to provide actionable insights and key considerations for organizations and educators tasked with developing competency frameworks. Ultimately, this work seeks to bridge the gap between technological capabilities and human potential, empowering individuals to thrive in increasingly AI-driven environments

Keywords: Competency modelling, Training, Automation, Human-agent teams

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has transformed numerous industries by altering procedures and redefining human roles

(Madhan & Deeraj, 2023). As automation has proven to enhance efficiency, improve quality control, and reduce errors for specific manufacturing related jobs, occupations including assembly line workers who perform repetitive tasks may face high risk of job displacement (Gurav et al., 2024). However, this shift does not imply the complete replacement of humans in these roles. Instead, workers are transitioning from routine, manual roles to supervisory positions that require higher use of decision-making and problem-solving skills (Ge et al., 2021; Downey, 2021). Humans retain a critical role in overseeing automation, ensuring safe and optimized operations. This shift naturally fosters a collaborative partnership between humans and machines, requiring the human to learn additional knowledge, skills, and abilities, such as trusting the system, understanding system limitations, and knowing when to intervene appropriately (Paschkewitz & Patt, 2020).

There is an increasing reliance on technology across many occupations. For instance, tax preparers once relied on manual calculations using calculators, but now, software programs assist with computations, enabling faster and more accurate results. While these roles are not traditionally considered 'technology jobs,' future professionals in these fields must develop technological skills to efficiently perform their respective tasks. Similar transformations have occurred across various industries, where most modern occupations now require some level of technological proficiency. MacCrory and colleagues (2014) found that the skill content of occupations has changed so significantly that the knowledge and skills required before the digital age differ fundamentally from those needed today.

As machines become increasingly prevalent, there is a growing emphasis on understanding the knowledge and skills in which humans excel. While automation surpasses human capabilities in tasks such as arithmetic and pattern recognition (Dreyfus & Dreyfus, 1986), human oversight remains essential in handling unforeseen or abnormal situations that automation cannot anticipate or adapt to. Additionally, tasks requiring novel solutions and creative problem-solving are better suited to be performed by humans, as machines do not reliably generate new information (Traumer et al., 2017). Therefore as automation becomes more integrated into the workforce, skills like creative thinking, critical thinking, and problem-solving will become increasingly valuable for human operator roles.

ADAPTING COMPETENCY MODELS FOR HUMAN-AI COLLABORATION

With AI integration expanding across industries, systematically identifying the evolving knowledge and skills needed for updated human roles is essential. The military, for example, has leveraged automation to reduce training time and costs, such as in unmanned aerial vehicle (UAV) training for automated landings and takeoffs (Cummings et al., 2019). By allowing the automation to conduct higher-workload phases of flight like landing, UAV operators with minimal flight experience can train for the MQ-1 Predator, significantly reducing training time (Blacke, 2009). Consequently, the instructional material must reflect these changes—placing less emphasis on manual takeoff and landing skills and focusing more on supervisory related tasks, which require an updated set of knowledge and skills.

Further, a shift in human operator tasks has been demonstrated through the Aircrew Labor In-Cockpit Automation System (ALIAS) program, developed by the Defense Advanced Research Projects Agency (DARPA) to reduce pilot workload in the flight deck. This system aimed to integrate higher levels of automation into existing aircraft, alleviating crew workload. Paschkewitz & Patt (2020) assessed ALIAS's effectiveness, particularly in scenarios where pilots were expected to compute energy requirements during landing with a failed engine, which is often taxing on the pilot-especially during a high workload phase of flight. The study found that the ALIAS effectively assisted the pilot in computing energy requirements, as the pilot handled the aircraft more safely and with greater ease. As ALIAS reduced the need for routine piloting skills, the system also highlighted the critical role of human pilots in managing unforeseen circumstances (Paschkewitz & Patt, 2020). While automation could handle standard piloting tasks, it could not replace the pilot's cognitive adaptability required in unpredictable and ambiguous situations. These factors are often overlooked in programming due to their endless variability. Ultimately, the study reinforced the necessity of human-machine collaboration, where automation supports pilots rather than replaces them. In order to facilitate the training of the capabilities required to work in this new digital age and collaborate effectively with technology, we need to understand what roles the humans play, and the requirements to successfully fulfill these roles.

Competency models serve as structured frameworks that define the knowledge, skills, abilities, and other characteristics (KSAOs) required for effective job performance (Schippmann et al., 2000). Unlike traditional job analysis, which inductively identifies job tasks and required KSAOs, competency modeling is more deductive, focusing on desired outcomes and working backward to determine necessary competencies (Campion et al., 2011). This approach allows organizations to align competencies with strategic objectives, ensuring that employees develop attributes essential for success in evolving job roles. Moreover, competency models facilitate a broader understanding of job performance by encompassing not only task-specific skills but also softer attributes such as adaptability, teamwork, and creative thinking (Rodriguez et al., 2002). The Air Force does this by distinguishing between institutional and occupational competencies, with the former being KSAOs that are applicable to all Airmen, and the later targeting technical and mission-specific expertise (Roberson et al., 2017).

A key advantage of competency modeling over traditional job analysis is the ability to include future-oriented requirements, making it particularly valuable in dynamic and evolving environments. For example, the U.S. Department of State's "Project Horizon," included the use of future-oriented scenario workshops to identify important competencies in a future where China and the rest of Asia dominate the world. In this initiative, subject matter experts (SMEs) analyzed alternative global scenarios and identified emerging competencies necessary for diplomatic effectiveness. The U.S. Army has also employed forward-looking competency modeling to define the skills required for 21st-century warfare, emphasizing adaptability, decision-making, and mission-essential competencies (Ford et al., 2000). The identification of these future-oriented competencies allows us to move beyond what current job performance requires and gain a better understanding of what training and development are needed to help servicemembers prepare for future situations.

In addition to applications in recruiting, selection, and performance appraisals, competency models can also be used to identify training gaps and guide learning and development programs toward well-defined outcomes. Unlike traditional training methods that emphasize course completion, competency-based training prioritizes the mastery of essential competencies. By systematically identifying the competencies needed for a job, one can ensure that learning resources align with the relevant KSAOs across competencies. This structured framework can also be used to categorize performance data into predefined standards, ensuring consistency in data collection and classification.

In contrast to traditional task-based models that emphasize discrete tasks and procedural knowledge, competency models provide a more comprehensive view by identifying the underlying knowledge and skills that drive effective performance (Schippmann et al., 2000). This broader perspective enhances flexibility and adaptability, preparing individuals to navigate evolving roles and unpredictable environments. As automation reshapes industries, competency models must remain dynamic, allowing instructional designers to identify emerging skill and knowledge requirements to proactively update competency models and training curricula. By incorporating emerging competencies and KSAOs while removing outdated ones, training programs remain relevant and comprehensive. This ensures that human operators are equipped with the necessary expertise to perform their jobs safely and effectively. For example, when operating an aircraft with newly installed automation, a pilot must be proficient in using the UI interface to monitor and manage automated systems safely. By integrating UI navigation skills into training curricula, instructional designers can ensure pilots receive consistent and comprehensive instruction, equipping them with the expertise needed to operate the aircraft safely and effectively.

COMPETENCY MODELLING APPROACHES

Competency models can be structured in various ways. In the current example, a competency model was organized hierarchically with the competencies at the top, segmented into tasks, and then further categorized into knowledge (essential information for skill and attitude development), skills (measurable task performance capability), and abilities (current action performance capacity) (AFH 36-2647, 8 Feb 2022). To develop a flexible competency model that could easily accommodate updates and modifications to the human role, a cognitive work analysis (CWA; Vincenti, 1999) approach was used in creating a competency model for pilots to operate an eVTOL aircraft under development. Given the novelty of the aircraft, CWA was the ideal method as it accounted for unpredictable, non-routine operations. The unique challenges of this emerging technology required a flexible, iterative approach to competency modeling to meet evolving demands.

The process of developing the competency model began with domain familiarization to gain a better understanding of the pilot role. To further explore the eVTOL pilot role, multiple knowledge elicitation (KE) sessions were conducted with stakeholders. The data gathered from these sessions enabled the team to identify specific tasks and KSAOs applicable to the human role while also establishing connections between competencies, tasks, knowledge, and skills while eliminating redundancies to enhance model accuracy. Extensive collaboration with SMEs was necessary to iteratively refine and validate the model, ensuring the model correctly represented the pilot role. Once the key competencies, tasks, and KSAOs were defined, the team synthesized the information into a structured framework, mapping tasks across competencies and aligning knowledge and skills with relevant tasks. This transition to a task-based approach provided a clear blueprint for instructional designers, allowing them to adapt the competency model as the aircraft evolved.

To keep competency models relevant in the digital age, organizations must engage SMEs and industry leaders in continuous refinement. SMEs provide valuable insights into the changing nature of work and ensure that competency frameworks remain aligned with industry standards. Regular consultation with professionals across diverse fields allows organizations to identify emerging trends and skills gaps before they become critical deficiencies. Additionally, adopting a modular and adaptive framework enables competency models to remain flexible and responsive to industry shifts. By structuring competencies in a hierarchical fashion and tying them to tasks, organizations can update their models incrementally without requiring a complete overhaul. Another important approach is integrating future scenario planning into competency model development. This proactive method ensures that workforce development strategies remain robust even in the face of rapid technological advancements. Future scenario planning allows organizations to prepare employees for a range of possible changes, equipping them with versatile skills that will remain valuable despite uncertainty.

Expanding competency models to include interdisciplinary skills is another critical step in keeping them relevant. As job roles become increasingly cross-functional, employees must develop competencies that span multiple domains. For example, cybersecurity professionals must not only have technical expertise but also an understanding of legal regulations and ethical considerations. Similarly, healthcare providers using AI-assisted diagnostic tools require both medical knowledge and digital literacy. Organizations that integrate interdisciplinary competencies into their models will ensure their workforce is better prepared to handle complex, multi-faceted job demands. Competency development should also be embedded into training and talent management programs. Aligning competency models with career progression pathways allows employees to develop the necessary skills in a structured and strategic manner. AI-driven personalization in training can help tailor learning experiences based on an individual's competency gaps, ensuring that employees receive targeted development opportunities that enhance their proficiency in key areas.

Organizations must continuously monitor industry trends and regulatory changes that impact workforce competencies. As new regulations, technological advancements, and economic shifts emerge, competency models should be revisited and adjusted accordingly. By maintaining agility in competency frameworks, organizations can remain competitive and ensure that their workforce is equipped to navigate a rapidly evolving professional landscape.

CONCLUSION

As human-AI teams become increasingly prevalent in defense and other high-stakes domains, competency modeling must evolve to account for the unique challenges of human-machine collaboration. Effective team performance depends on both taskwork—the execution of technical tasks—and teamwork—the integration of interpersonal, and cognitive skills necessary for coordination (Eccles & Tanenbaum, 2004; Salas et al., 1992). In other words, competency models for human-AI teams should define technical proficiencies to interact with AI systems, along with cognitive and adaptive skills necessary for dynamic teaming. By structuring training and assessment around these competencies, organizations can ensure that personnel are equipped to operate effectively alongside AI, leveraging human strengths in decision-making, creativity, and ethical reasoning while maximizing AI-driven efficiencies.

Ultimately, the success of human-AI collaboration will depend on organizations' ability to continuously refine competency models that support workforce adaptability. As job roles evolve alongside technological advancements, competency models must be updated to reflect these changes—removing outdated tasks, revising existing ones, and incorporating new technology-driven responsibilities. By leveraging AI to augment human expertise rather than replace it, industries can cultivate a resilient, future-ready workforce capable of thriving in complex, technology-driven environments.

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