Reframing career and technical education for the AI era: Metacognition and critical theory

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Abstract

As the AI-era continues to intensify, the traditional skill-based model of Career and Technical Education (CTE) will no longer serve the needs of society's workforce. There is a need for learners to regulate their thinking and critically evaluate the systems shaping that thinking so that they can operate effectively and responsibly in AI-mediated work environments . The proposed Cognitive–Critical Agency Framework, extends traditional skill development to include reflective, analytical, and system-aware capabilities. The proposition is that effective preparation for AI-mediated environments requires more than technical competence; it requires the ability to think about thinking and to question algorithmic systems. This reconceptualization positions CTE as a critical site for developing autonomous, informed, and responsible participants in an increasingly algorithmic world.

Keywords: AI in education, career and technical education, metacognition, critical theory, algorithmic power, cognitive agency

Introduction

Rooted in the historical need to align education with workforce demands, Career and Technical Education (CTE) programs typically emphasize technical proficiency, hands-on learning, and immediate employability (Rojewski, 2002). Fundamentally, CTE is about preparing individuals for participation in the labor market by equipping them with job-specific skills and competencies. What those job-specific skills and competencies are has evolved over time in consonance with changes in technologies, and despite technological advancements the of work has, on the whole, evolved steadily and remained relatively stable over time. In the last two decades digital technologies, it was the advent of the internet that brought disruption in how work is done but that disruption was mostly due to the global connectivity it brought about so that the nature of work became digitized, more collaborative and globalized. The model of CTE has proven effective in contexts up until now, where work is relatively stable and skill requirements are clearly defined. Up until now, digitization mostly automated tasks. Artificial intelligence (AI) technologies are changing all that. These technologies are not only automating routine tasks but also augmenting cognitive functions such as decision-making, problem-solving, and knowledge generation (Holmes et al., 2023). AI, quietly developing for decades in the background has broken free of technical domains and it is increasingly and rapidly being embedded into everyday life, and in professional and educational practices, influencing how individuals learn, think, and act within complex systems. The disruptive effect of AI technologies on work is beyond what has been seen before in human history, not only because of the sophistication of the technologies but because of the rapidity of its development. So rapid is the evolution of AI technologies, that has become difficult to predict what the nature of work will be like even in five years from now. The assumptions of the CTE model, work is relatively stable and when skill requirements clearly defined, are being called into question. Will the traditional skill-based models that are core of CTE remain sufficient?

The disruption due to AI tools is unique from other digital disruption because, other digital tools mostly change how the task is undertaken by the human – the relationship between human and digital tool is very clearly technology-user However, AI systems blur the boundary between human and digital tool. Machine learning algorithms mean that AI systems generate information, make recommendations and actively shape decisions. These systems influence not only outcomes but also the processes through which individuals interpret information and exercise judgment. For the human, the cognitive demand is now much greater than with previous digital technological tools. AI systems mean that the human must now do more than simply use the tool to achieve a task. Humans are positioned now as collaborators, evaluators and decision-makers. Humans must be able to critically assess algorithmic outputs, recognize bias, and navigate uncertainty in AI-mediated environments.

The technical-instrumental view of learning, focusing on skill acquisition and task performance is at odds with the requirements of working in an AI-mediated environment. The necessity of developing digital literacies is an element of more recent discussions of CTE but this is inadequate when AI is a system that shapes knowledge, distributes authority and strongly embeds values in its outputs (Selwyn, 2022). Discussions of digital literacies thus far mot the epistemic dimensions of AI.

The need for a fundamental rethinking of the aims and practices of CTE in the age of AI is sel-evident More than technical competence; students must be prepared for the world of work through the development of higher-order cognitive and critical capacities. Two educational frameworks can guide this development: Metacognition—the ability to reflect on and regulate one's own thinking—enables learners to monitor their interactions with AI systems and make informed decisions about when and how to rely on them. Together, these perspectives suggest a shift toward what can be termed *cognitive–critical agency:* *the* capacity to think independently, evaluate systems critically, and act responsibly within AI-driven environments.

AI as a Non-Neutral System: Technology, Power, and Knowledge

How often does one hear phrases like "The system doesn't allow for …" or 'The system tells us that…", "Using technology in the classroom improves student experience"….It is unfortunate that humans tend to attribute a certain neutrality to technologies. It seems the humans who design and develop technologies are frequently unacknowledged and the 'behavior' and attributes of the technology are intrinsic to the technology rather than the result of human design. This has important consequences: People use technology uncritically and remain unaware of what biases are implicit in the technology because of its design. Most people are unaware that inevitably, the biases and assumptions of those who made the technology are shaping the technology and their interactions with it (Take for example, a baby monitor application that has a rigid feeding routine for a young baby. The implication of this for the user is that it this is the *right* way /*only* way to do it. This is the assumption or belief of the designer, and it may not necessarily reflect the cultural or other circumstances in reality). Furthermore, without acknowledging technology as a human artefact, the power-distance between human and technology is made greater, with the technology holding the balance.

As Kranzberg (1986) reminds us:

"Technology it is said, has become autonomous and has outrun human control…the machines have become masters of men" (p. 545)

[Technology] merely opens a door, it does not compel one to enters. But an open door is an invitation. Besides, who decides which doors to open – and once one has entered the door, are not one's future directions guided by the contours of the corridor or chamber into which one has stepped?" (p.545).

AI systems, just like other tools, reflect the values, assumptions, and priorities of their designers, the data on which they are trained, and the environments in which they are deployed (Eubanks, 2018; Crawford, 2021).However, with AI the sense of power and neutrality of the technology are exacerbated. AI is a highly complex technology, and most do not possess even a broad understanding of how the algorithms work. This is a "black box" problem, limits the ability of users to understand or challenge algorithmic decisions, undermining transparency and trust (Burrell, 2016). Furthermore, AI has an unfortunate name – Artificial *Intelligence* – Intelligence is very human capability and that the word appears in the name of the tool Anthropomorphizes or gives a human quality to the technology. The anthropomorphic language used in AI (e.g. the AI is thinking) only serves to present AI not only as human but as something more powerfully human and much more authoritative. Unlike with other digital technologies, humans don't just consume information from AI. The outputs influence .

how individuals interpret information and make sense of complex phenomena, effectively participating in the construction of knowledge itself (Beer, 2017). In educational and workforce contexts, this means that learners and professionals are not merely consuming information but are engaging with algorithmically generated interpretations that may carry implicit biases or assumptions.

Users of AI may defer to algorithmic outputs without fully understanding how they were generated, leading to what has been described as "automation bias"—the tendency to overtrust machine-generated recommendations (Parasuraman & Manzey, 2010). This shift has profound implications for human agency, as decision-making authority becomes partially delegated to systems that are not easily interrogated.

The Transformation of Work in the Age of AI

The nature of work is invariably shaped by the tools employed in carrying it out. Throughout history there are numerous examples of how tools shape work. The industrial revolution enabled automation of much of the manual labour and thus required skillsets shifted from manual capabilities to the capability to use machines in a routine sequential manner, ensuring consistency of outcome each time. The advent of the personal computer and later the internet, changed again the nature of work. Mechanically automated worked entered the digital domain. This time, skills in communication, digital literacy and working within digital system became important. In the increasingly AI-mediated work environments of today, technology is not a smple replacement for a manual task. Technology is now replacing the more activities in the cognitive domain of humans such as cognitive activities such as pattern recognition, language processing, and decision support (Brynjolfsson & McAfee, 2017; Gmyrek & Bescond, 2023). Human labor is fusing with the work of machines. Still, the primary goal of AI is automation for efficiency but loss of transparency behind it's algorithms means increases the burden on the human to question, trust or override the machine generated outputs. What was once clearly professional autonomy in decision making is now being blurred by AI tools. On the one hand, AI tools can provide insights and reduce cognitive load and make for more informed decision making. On the other hand, humans may fall victim to algorithmic decision making especially when organizations might constrain autonomy by standardizing processes and limiting professional autonomy in effort to embed organizational priorities into the systems (Kellogg et al., 2020). Collaboration with AI requires a hybrid skill set that combines technical literacy with cognitive and social competencies, including judgment, adaptability, and ethical awareness (Dellermann et al., 2019).

Against the backdrop of the preceding discussion, new directions for CTE are emerging.

Current CTE Models

The CTE model still emphasizes e procedural knowledge, hands-on training, and job-specific competencies aligned with industry needs. Such an approach was highly effective in industrial and early digital economies, where work processes were relatively stable and skills could be mapped directly onto predictable job functions (Rojewski, 2002). In an AI-mediated work environment these skills alone are insufficient. Despite growing emphasis on digital literacies in CTE, the ability to work effectively in AI-mediated environments is under-emphasized and in most cases excluded.

Many CTE programs still prioritize correct execution over critical engagement, leaving learners underprepared to navigate situations where there is no single "right" answer (Luckin et al., 2022). The operational competence of knowing how to get the correct output must now be replaced by competence in higher order skills required to critically evaluate (assess accuracy, detect bias, and understand limitations) tool outputs. Human judgement rather than technical competence is now emerging as the crucial employability capability. AI-capable learners are able to interrogate outputs, integrate contextual knowledge, and exercise independent judgment. The distinction between these two profiles is not merely academic; it has direct consequences for employability, adaptability, and ethical decision-making in the workplace (Ng et al., 2021).

Furthermore, the existing CTE model works for stable systems but AI technologies themselves are far from stabilized. New AI 'capabilities' are emerging almost daily and the power of AI is growing exponentially (consider how the capability of gen AI tools such as GPT in mid 2025 compared to beginning of 2026 !). Hence, workers must not only work with higher order cognitive skills, but they must also be adaptable in short timeframes.

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Addressing this misalignment requires a fundamental rethinking of CTE's educational objectivesA comparison of Traditional vs AI-era CTE learning model brings to the fore the gap between traditional work requirements and work requirements in AI-mediated contexts.

Table 1. Traditional vs AI-era CTE Learning Model

Dimension	**Traditional CTE Model**	**AI-Era CTE Model**

Focus of Learning	Task execution and technical skills	Cognitive–critical agency and judgment
Nature of Work Preparation	Stable, predictable job roles	Dynamic, AI-mediated work environments
Knowledge Orientation	Procedural and domain-specific knowledge	Interpretive, adaptive, and system-aware knowledge
Role of Technology	Tool for task completion	Co-agent shaping knowledge and decisions
Learner Role	User of tools	Interpreter and evaluator of AI outputs
Teacher Role	Instructor and content expert	Cognitive mediator and facilitator of reflection
Assessment Focus	Correct answers and task performance	Reasoning, judgment, and decision processes
Critical Thinking	Logic and problem-solving	Interrogation of systems, bias, and power
Metacognition	Self-monitoring of learning	Regulation of human–AI interaction
Outcome	Workforce readiness	Autonomous, adaptive, and ethical agency

The transformation of the CTE model must be from skill execution to cognitive–critical agency. This is required as the human-technology relationship changes in the AI era from human as user of tool (and therefore the human requires technical proficiency) to human as a co-agent in knowledge forming and decision making.

The transformation required means that within CTE, teaching and assessment must move from content delivery and mastery of technical skills to cognitive mediation, guiding reflection and critique. Assessment shifts from assessing on correct answers to the capability to reason, judge and make decisions.

There are two theoretical foundations which should be incorporated in the design of CTE: Metacognition and Critical theory.

Metacognition in AI-Mediated Learning

Metacognition, or "thinking about thinking," refers to the awareness and regulation of one's cognitive processes during learning and problem-solving. It encompasses the ability to plan, monitor, and evaluate one's understanding and performance, enabling learners to adapt strategies in response to changing demands (Veenman et al., 2006). Traditionally, metacognition has been conceptualized as an internal, self-directed process focused on improving individual learning outcomes. Within an AI-mediated environment, metacognition can be considered as a requirement for learners to engage with their own cognition but also to engage with the algorithmically generated outputs.

Metacognition has several dimensions. Self-regulation allows learners to set goals, select strategies, and adjust their approach based on feedback. Monitoring understanding involves continuously assessing whether one comprehends a concept or task, while evaluation entails reflecting on the effectiveness of chosen strategies after completing a task. These processes support adaptive learning, enabling individuals to respond flexibly to new information and challenges (Azevedo, 2020). Again, while traditionally these functions are inward facing, in AI-mediated environments these functions extend beyond self to include what is produced by the AI. Metacognition in AI-mediated contexts includes the assessment of accuracy, relevance and credibility of information produced by the AI system (Kasneci et al., 2023).

This 'extended' metacognition means deciding when the AI can be trusted and having a basis of the decision to trust (or not) the AI. 'Having a basis for the decision to trust or not trust the AI, depends on at least a broad understanding of how AI algorithms work and the data on which they are operating. Over trust can result in automation bias, where users accept incorrect outputs without scrutiny, while under trust can lead to the underutilization of valuable tools (Bansal et al., 2021). Effective metacognitive regulation requires learners to develop a nuanced understanding of AI capabilities and limitations, enabling them to make informed decisions about when and how to rely on these systems.

Critical Theory and Algorithmic Power

Critical theory provides a powerful lens for understanding how knowledge, authority, and truth are shaped within technological systems. At its core, critical theory challenges the assumption that knowledge is objective and value-neutral, emphasizing instead that knowledge is socially constructed and deeply influenced by historical, political, and economic forces (Foucault, 1980). From this perspective, what is accepted as "truth" is not simply discovered but produced through systems of power that privilege certain voices, data sources, and interpretations over others. In contemporary digital environments, artificial intelligence (AI) has become a central mechanism through which such knowledge production occurs.

The relevance of critical theory to AI-mediated contexts is self-evident against the backdrop of the discussion of the perceived neutrality of technologies and the 'black box' nature of AI systems. Ai systems are trained on large datasets that often reflect existing social inequalities, leading to patterns of bias that can be reproduced and amplified at scale (Noble, 2018). The most often-experienced example of algorithmic bias is how search engines and social media systems select what the user sees based on the browsing habits of the user, resulting in a loss of agency of the user and restricting the user to a narrow field of information. Beyond bias, there is the question of organizational control over data and computations resources that AI systems use. These entities determine how algorithms are designed, what data is collected, and how outputs are distributed, effectively shaping the informational landscape within which individuals and institutions operate (van Dijck et al., 2018).

Critical theory with its emphasis on social construction of knowledge, authority and truth is brought to bear on AI systems, the socio-technical understanding of AI systems becomes prominent as does the human biases present in the AI systems themselves. Furthermore, through the lens of critical theory the human biases as embedded in the system become more explicit.

Through the lens of critical theory, users of AI have a framework for questioning who's knowledge? Whose interests are being served? This shift moves critical thinking from a purely cognitive activity to a socio-technical practice that engages with issues of power, representation, and equity (Williamson, 2023). For example, using the frame of critical theory, users may question not only the algorithms but also the data on which they draw.

Access to high-quality data is unevenly distributed across regions, institutions, and populations, leading to disparities in how AI systems are developed and deployed. Populations that are underrepresented in datasets may experience reduced accuracy in AI-driven decisions or be excluded altogether from the benefits of technological advancement (Crawford, 2021). At the same time, individuals often have limited control over how their data is collected and used, reinforcing asymmetries of power between data subjects and data controllers.

Integrating Metacognition and Critical Theory

Without a critical lens, metacognitive regulation may simply reinforce unexamined acceptance of these outputs, leading to a form of "efficient but uncritical" thinking (Azevedo, 2020).

Conversely, critical theory's emphasis on structural analysis can sometimes overlook the role of individual cognitive processes in navigating complex systems. While critical theory provides tools for interrogating power relations and uncovering hidden assumptions, it does not תמיד address how individuals develop the capacity to apply these insights in real-time decision-making. In educational contexts, this can result in a gap between awareness and action: learners may understand that systems are biased or inequitable but lack the cognitive strategies to respond effectively in practice (Selwyn, 2022).

Integrating these two perspectives addresses this gap by linking internal cognitive regulation with external system awareness. This integration can be conceptualized as **cognitive–critical agency**, defined as the capacity to regulate one's own thinking while critically evaluating the systems that shape that thinking. Cognitive–critical agency extends metacognition beyond self-reflection to include reflection on the sources, structures, and implications of knowledge. It also operationalizes critical theory at the level of individual practice, enabling learners to actively engage with and respond to systemic influences.

This integrated framework produces several key outcomes. First, it fosters reflective learners who are not only aware of their cognitive processes but also capable of questioning the validity and reliability of the information they encounter. Reflection, in this sense, becomes both inward and outward focused on understanding one's own thinking and the broader systems that inform it (Schraw et al., 2006). Second, it cultivates system-aware thinkers who recognize that knowledge is mediated by technological, social, and institutional structures. These learners are better equipped to identify bias, evaluate sources, and understand the implications of algorithmic decision-making (Coiro, 2021).

Third, and most importantly, cognitive–critical agency supports the development of autonomous decision-makers. Autonomy in AI-mediated environments does not simply mean independence from technology but rather the ability to engage with technology in a deliberate and informed manner. This includes deciding when to rely on AI, when to question it, and how to integrate its outputs with contextual knowledge and ethical considerations.

The integration of metacognition and critical theory therefore represents a necessary evolution in educational thinking. It acknowledges that effective learning in contemporary contexts requires both cognitive skill and critical awareness. By developing cognitive–critical agency, learners can move beyond passive interaction with AI systems toward active, informed engagement. This shift is particularly important for Career and Technical Education, where the goal is not only to prepare individuals for work but to equip them with the capacity to navigate and shape the systems in which they operate.

Proposed Framework: Cognitive–Critical Agency Model for CTE

Metacognition and Critical theory are two useful frameworks to guide CTE and the development capabilities necessary for the AI-Era, but they are most useful when the two frameworks are integrated. Metacognition supports awareness, monitoring and reflection. Critical theory supports reflection, awareness and monitoring of social construction of knowledge and power. Together these two theoretical frameworks serve to strengthen each other. This may be referred to as a Cognitive Critical Agency model (Figure 1.0) which offers a structured framework for preparing learners to function effectively in AI-mediated environments. This model moves beyond traditional skill-based approaches by emphasizing the development of layered competencies that support not only performance but also reflection, evaluation, and autonomous action.

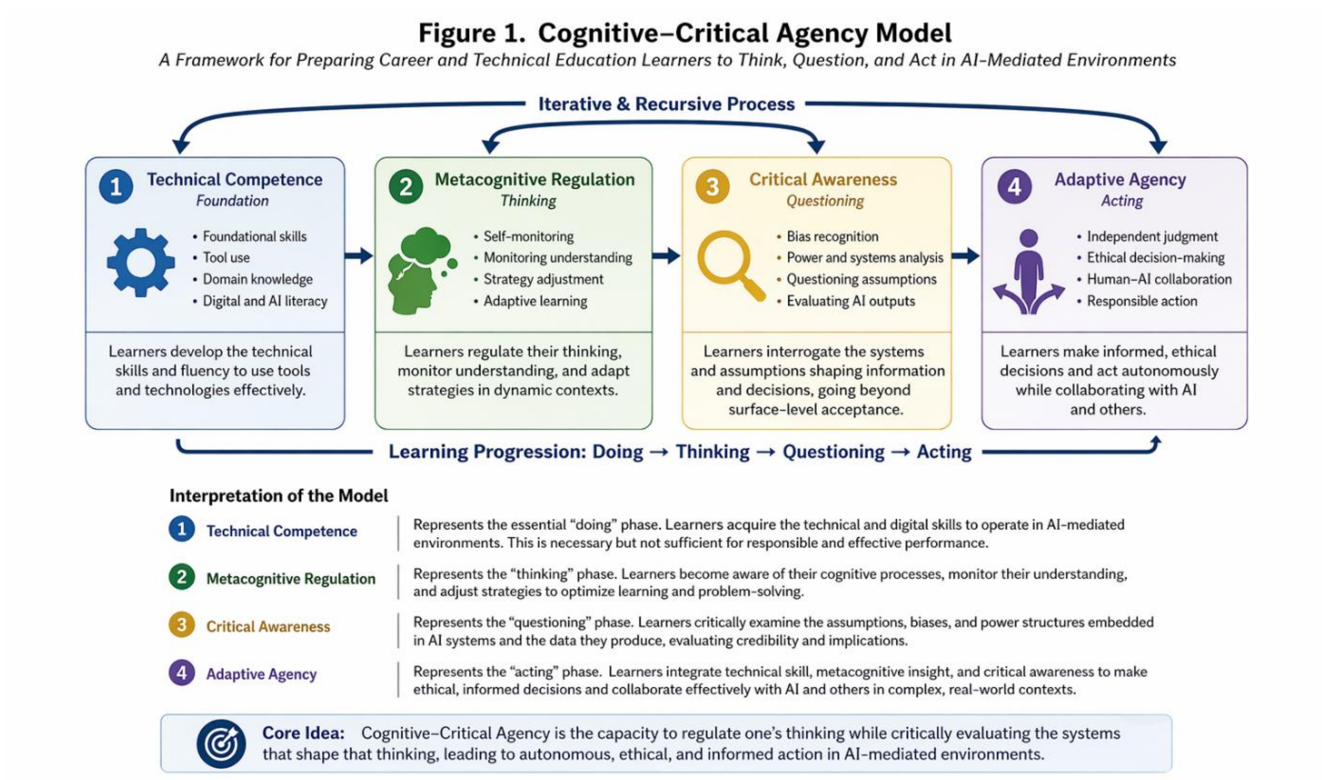

Figure 1 Cognitive critical agency model for CTE (AI-generated image).

Technical proficiency remains important but is an entry point rather than an endpoint for CTE. Technical competence enables participation but does not guarantee effective or responsible engagement with complex systems (Ng et al., 2021).

Metacognitive regulation means that learners must be able to monitor their understanding, evaluate their strategies, and adjust their approach in response to feedback as well as managing their own interactions with AI systems. This is critical for navigating environments characterized by uncertainty and rapid change (Azevedo, 2020).

Critical reflective awareness means recognition of biases and questioning of the assumptions in the AI system. The emphasis is not on how to use technology but on how technology shapes knowledge and outcomes and for who. In doing so, it equips learners to engage with AI systems as informed participants rather than passive users (Williamson, 2023). This component is particularly important for addressing issues of equity and accountability, as it enables learners to identify and challenge systemic limitations.

The culmination of the framework is adaptive agency, in which users have the capacity to interact effectively, independently and responsibly with AI systems., Workers operating with adaptive agency can integrate technical knowledge, metacognitive insight, and critical awareness to respond to novel situations and evolving demands (Jarrahi, 2018).

Implications for CTE Practice

Developing the competencies of the Cognitive-critical agency model for CTE requires a shift in the design of curriculum, assessment practices, redefining the role of the teacher and changes to the policies surrounding CTE. For the traditionally skill-based models of CTE this will require a significant transformation of philosophies and approaches. Curriculum most be grounded in higher order thinking skills rather than technical competencies.

Technical competencies will remain important but what they are will also need to change and be redefined. AI literacy extends beyond digital literacy understanding how systems function to include awareness of their limitations, biases, and societal implications (Ng et al., 2021).

The role of the teacher is more than a facilitator to one of cognitive mediator and learning will look more like a cognitive 'apprenticeship' than training in technical competencies. Teachers become orchestrators of thinking rather than transmitters of knowledge, helping students navigate the interaction between human judgment and machine intelligence (Holmes et al., 2023). This will necessitate professional development that ensures teachers also shift their conceptual frames about what teaching in CTE is about.

Assessment practices must also change. Process-oriented assessment methods, such as reflective journals, scenario-based tasks, and portfolio assessments, provide more comprehensive insights into learner capabilities (Baker & Hawn, 2022).

Conclusion

Traditionally grounded in acquisition of technical skills the model of CTE needs transformation so that CTE can continue to meet the core goal of meeting the needs of work in society. AI is not just changing the nature of work through automation; it is is changing the nature work because of the change of relationship between human and machine. While AI is certainly 'just a tool' it is a tool unlike any other. Whereas other digital tools merely automated tasks or made them simpler to do, the human as user needed to learn to how to use the tool, working in an AI-mediated system means that the human-machine relationship is redefined and there are higher level cognitive demands on the user to be able to question, interpret, judge the AI outputs.

In the present article, the case has been made for adopting a cognitive-agency model to guide CTE into the era of AI. Integrating metacognition and critical theory, the cognitive-agency model guides an approach to CTE which aligns with the necessity of developing critical thinking and judgement that is framed by understanding of the social construction of knowledge and power.

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