

AI-Enhanced Educational Approaches and Soft Skills Development in Vocational Education: The Moderating Role of Metacognitive Ability

Jin Sun^{1,2}, Renee Shiun Yee Chew¹, Yachen Li^{1,2}, Song Buer³, Ping Li⁴

¹ Faculty of Education and Liberal Arts, INTI International University, Negeri Sembilan, Malaysia

² Shandong Polytechnic College

³ Xilingol Vocational College, inner Mongolia, China

⁴ Smart Learning Institute of Beijing Normal University

* Correspondence: Yachen Li (lily97lyc@163.com)

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ABSTRACT:

Artificial intelligence (AI) is increasingly embedded in vocational education through adaptive learning systems, large language model tutors, immersive simulation, and learning analytics. Yet the literature remains fragmented regarding whether AI-enhanced educational approaches consistently strengthen students' soft skills and under what learner-level conditions such effects emerge. This critical review synthesizes theoretical, empirical, contextual, and methodological scholarship concerning AI-enhanced education, vocational college students' soft skills, and metacognitive ability. Drawing on the literature corpus assembled in the original Chapter 2, the review integrates Cognitive Load Theory, Self-Regulated Learning Theory, and Social Cognitive Theory and critically compares complementary perspectives including the Expertise Reversal Effect, the Technology Acceptance Model, and UTAUT. Soft skills are organized into three interrelated dimensions: critical thinking and analytical skills, emotional intelligence and empathy, and psychological resilience. The synthesis indicates that AI may produce both enabling and constraining effects: personalized feedback, dialogue, simulation, and learning analytics can support higher-order and socio-emotional competencies, whereas cognitive offloading and excessive reliance may weaken independent judgment. Metacognitive ability is therefore proposed as a key boundary condition that can shape how learners select, monitor, evaluate, and regulate AI-supported learning. Particular attention is given to Chinese vocational education and the Shandong context, where industrial structure and digital vocational education policies create a distinctive setting for empirical examination. Four gaps are identified: contextual-regional evidence, integrated quantitative testing, qualitative mechanism explanation, and methodological

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integration. The review consequently supports an explanatory sequential mixed-methods design for testing the direct association between AI-enhanced educational approaches and soft skills and the moderating role of metacognitive ability.

Keywords: artificial intelligence in education, vocational education, soft skills, metacognition, mixed methods, education quality.

1. Introduction and Scope of the Review

The rapid diffusion of artificial intelligence into formal education has shifted the debate from whether digital tools should be used to how they reshape learning processes and student competencies. In vocational education, this question is especially consequential because programmes are expected to prepare learners not only for technically specified tasks but also for workplaces characterized by uncertainty, collaboration, emotional demands, and continuous technological change. The source literature defines soft skills as a set of intrapersonal, interpersonal, and higher-order cognitive competencies that complement occupation-specific hard skills and support long-term employability (Andrews & Higson, 2008; Tushar & Sooraksa, 2023). This distinction provides the starting point for examining whether AI-supported teaching can contribute to broader vocational competence rather than merely improve knowledge acquisition or procedural efficiency.

Existing scholarship does not support a simple technologically deterministic conclusion. Positive studies associate AI-supported learning with participation, efficiency, personalization, and selected cognitive or affective outcomes (Wu & Yu, 2024), while critical work highlights cognitive offloading, dependence on generated answers, and possible weakening of independent critical thinking (Essien et al., 2024; Gerlich, 2025). The coexistence of these findings suggests that the educational value of AI depends on boundary conditions related to the type of tool, learning task, instructional design, and learner characteristics. The present review focuses on metacognitive ability as one such boundary condition because it directly concerns learners' capacity to plan, monitor, evaluate, and regulate

their own cognition (Flavell, 1979; Schraw & Dennison, 1994).

The review has three objectives. First, it consolidates the conceptual development and empirical evidence concerning soft skills, AI-enhanced educational approaches, and metacognition. Second, it integrates Cognitive Load Theory, Self-Regulated Learning Theory, and Social Cognitive Theory to explain how AI-supported environments may influence vocational learners' cognitive, interpersonal, and adaptive competencies. Third, it identifies research gaps that justify an explanatory sequential mixed-methods investigation in Chinese vocational colleges, with particular attention to Shandong Province. In doing so, the review converts the thesis-oriented Chapter 2 into a journal-style synthesis organized around problem definition, literature review methodology, thematic findings, critical discussion, and research implications.

2. Soft Skills Competencies in Vocational Education

2.1 Conceptual Evolution and Dimensional Structure

The move from broad employability discourse to multidimensional soft-skill models also reflects a change in what vocational competence is expected to mean. In earlier manpower-oriented models, occupational readiness could be approximated through mastery of procedures, equipment, and standardized technical knowledge. Contemporary workplaces, however, increasingly combine technical tasks with diagnosis, coordination, communication, digital information evaluation, and adaptation to changing production systems. Under these conditions, soft skills are not peripheral personality attributes added after technical

training; they become part of competent performance itself. Critical thinking supports the diagnosis of non-routine problems, emotional intelligence and empathy support coordination with colleagues and clients, and resilience supports continued performance when tasks fail, requirements change, or feedback is negative. This functional interpretation is particularly appropriate for vocational education because it connects psychological constructs with observable demands in authentic occupational settings rather than treating them as abstract graduate qualities.

At the same time, the literature warns against treating the label 'soft skills' as conceptually self-evident. Different studies combine communication, teamwork, creativity, adaptability, leadership, problem solving, emotional intelligence, resilience, and critical thinking in different ways. Such heterogeneity makes direct comparison of effect sizes difficult and can produce apparently inconsistent findings that actually reflect different operational definitions. The present review therefore retains the three dimensions used in the source study because they capture complementary cognitive, socio-emotional, and adaptive functions, but it does not imply that these dimensions exhaust the soft-skills domain. Rather, they constitute a theoretically bounded representation suited to the research problem and the vocational context. This clarification is important for construct validity and for avoiding the common error of interpreting evidence about one narrow competency as evidence about soft skills as a whole.

The intellectual roots of soft-skills research can be connected to human capital theory, which broadened the economic understanding of education beyond narrow technical training. Schultz (1961) conceptualized education as investment in human capacities, while Mincer (1974) provided an empirical framework linking schooling and experience with labour-market returns. Later educational psychology and organizational research progressively transformed broad notions of non-technical competence into multidimensional constructs

that could be measured in educational and workplace settings.

For the present vocational context, three dimensions are especially salient: critical thinking and analytical skills; emotional intelligence and empathy; and psychological resilience. The first concerns the ability to gather, evaluate, and integrate information and to construct context-sensitive solutions to ambiguous problems (Andreucci-Annunziata et al., 2023). The second concerns recognition and regulation of one's own emotions together with appropriate understanding of others' emotional states, capacities that are central to teamwork, client interaction, and conflict management. The third concerns adaptive recovery and persistence under academic, training, and workplace pressure (Aryuwat et al., 2023). These dimensions should not be treated as isolated attributes. Their covariance reflects the fact that reasoning, affect regulation, and adaptive persistence often operate jointly in authentic vocational tasks.

2.2 Global Evidence, Developmental Mechanisms, and Unresolved Causal Questions

Across higher education research, soft skills are generally associated with engagement, academic outcomes, and employability, but the dominant evidence base remains correlational. Cross-sectional designs cannot establish whether stronger soft skills cause improved outcomes, whether supportive learning environments simultaneously produce both, or whether third variables such as socioeconomic background, institutional resources, teacher practices, and peer culture explain part of the observed relationship. Consequently, the literature supports the relevance of soft skills but is less decisive about developmental pathways.

Qualitative studies complement this evidence by emphasizing interactive, situated, and iterative learning experiences. Learners appear to benefit from opportunities for collaboration, problem solving, reflection, and authentic simulation rather than from lecture-only delivery. Such findings are particularly relevant to vocational education because soft skills are enacted in

practical contexts rather than demonstrated solely through decontextualized tests. However, the international literature remains disproportionately concentrated on general university populations, limiting direct transfer to vocational cohorts whose learning goals, prior academic preparation, and practical training intensity differ.

2.3 Soft Skills in Chinese Vocational Education and the Shandong Context

Chinese vocational education policy increasingly emphasizes comprehensive competence alongside technical skill. The National Vocational Education Reform Implementation Plan (Ministry of Education of the People's Republic of China, 2019) provides a policy basis for strengthening broader learner development. Within Shandong, the Digital Transformation Plan for Vocational Education (2023–2026) further situates AI and digital technologies within vocational reform. The source chapter argues that Shandong's manufacturing base, modern service industries, and emerging digital sectors intensify employer demand for teamwork, problem solving, and stress resistance. These contextual characteristics make the province a theoretically meaningful setting rather than merely a convenient sampling location.

Domestic research nevertheless remains weighted toward cross-sectional surveys and descriptive accounts. Studies have highlighted continuing curricular emphasis on professional knowledge and technical training, while systematic pathways for critical thinking, emotional intelligence, and resilience are less developed. The combination of strong policy momentum and limited mechanism-focused evidence creates a clear need to examine how AI-supported teaching is actually experienced and whether its association with soft skills varies across learners.

3. AI-Enhanced Educational Approaches in Vocational Learning

3.1 From Auxiliary Tools to Integrated Learning Environments

AI-enhanced educational approaches encompass multiple technologies embedded in curriculum design, classroom instruction, after-class tutoring, vocational simulation, and learning evaluation (Beloev et al., 2024). The literature reviewed in the source chapter distinguishes four functional categories: rule-based adaptive learning systems, large language model tutors, VR/AR immersive simulation platforms, and educational data mining or learning analytics. This functional distinction is important because different technologies afford different forms of learner activity and therefore should not be assumed to exert identical effects.

Adaptive systems can personalize sequencing and difficulty, but highly constrained adaptation may narrow opportunities for divergent reasoning. LLM tutors can sustain open-ended dialogue, explanation, and iterative questioning, potentially supporting analytical reasoning, while also creating risks of passive answer acceptance. VR/AR environments can approximate workplace scenarios and enable repeated practice of emotionally demanding or high-pressure situations. Learning analytics can make learning processes visible through feedback and longitudinal behavioral information. Thus, the independent variable is best understood as an integrated educational approach rather than a single undifferentiated technology.

3.2 The Enabling-Constraining Paradox of Educational AI

More recent synthesis research strengthens this dual-effect interpretation. Qian's (2025) systematic review of generative AI applications in higher education identifies emerging pedagogical uses related to creativity, critical thinking, autonomy, and prompt literacy, but simultaneously highlights the danger that efficiency-oriented use can outsource the cognitive and metacognitive processes that education is intended to develop. A 2025 meta-analysis of 57 studies and 97 effect estimates

likewise reported substantial average benefits of generative AI for several university learning outcomes, including higher-order thinking, while finding no statistically significant overall effect on metacognition (Chen & Cheung, 2025). This distinction is theoretically important: better immediate learning outcomes do not necessarily mean that learners have developed stronger capacity to regulate their own cognition. AI may improve task performance by supplying explanations, examples, feedback, or solutions while leaving the learner's independent planning and monitoring unchanged. Consequently, studies that evaluate only grades, completion, or short-term performance may overestimate the developmental value of AI for durable soft skills.

The contradiction becomes even clearer in critical-thinking research. Liu, Sihes, and Lu's (2025) systematic review found evidence for both enhancement and erosion of critical thinking: positive studies emphasized reasoning, evaluation, problem solving, creativity, and self-directed learning, whereas negative studies emphasized passive thinking, reduced analytical depth, and overreliance. A broader 2025 bibliometric and systematic review similarly identifies uncritical dependence, unequal digital literacy, opacity of AI systems, and institutional constraints as major challenges to preserving critical thinking in AI-integrated higher education. These findings suggest that the central research question should not be framed as whether AI is 'good' or 'bad' for cognition. A more defensible question is which patterns of AI use preserve learner responsibility for judgment and which patterns transfer that responsibility to the system. This reframing provides a stronger conceptual bridge to metacognition, because planning, monitoring, verification, and reflective evaluation are precisely the processes through which learners can maintain cognitive agency while benefiting from AI assistance.

The global literature reveals a central paradox. Meta-analytic and empirical work reports small-to-moderate positive effects of AI chatbots and related tools on learning outcomes (Wu & Yu, 2024), while other studies identify cognitive offloading and reduced independent critical

engagement under conditions of excessive reliance (Essien et al., 2024; Gerlich, 2025). Jose et al. (2025) describe this tension as a cognitive paradox: AI can extend learner capability and simultaneously displace the cognitive effort through which capability is developed. This contradiction is not necessarily a failure of the evidence; it may instead indicate that the effect of AI is conditional.

Interdisciplinary evidence reinforces this interpretation. Human-computer interaction research draws attention to trust, reliance, and user autonomy; educational data mining emphasizes behavioral traces and personalized feedback; and cognitive-load research highlights the fit between learner expertise and instructional support. Kalyuga's (2011) Expertise Reversal Effect is particularly relevant because support that benefits novices may become redundant or disruptive for more knowledgeable learners. In an AI context, the same logic implies that extensive scaffolding may help some students while encouraging dependence or unnecessary cognitive processing in others.

3.3 Pathways Linking AI-Enhanced Learning to Soft Skills

AI may influence soft skills through several pathways. Dialogue and problem-based prompting can create opportunities to articulate reasoning, compare alternatives, and critique evidence, which are relevant to critical thinking. Simulated social and workplace scenarios may permit repeated practice of communication, perspective taking, and emotional regulation. Adaptive feedback can reduce avoidable frustration and sustain engagement, potentially supporting resilience. At the same time, these mechanisms depend on how students interact with the technology. If learners delegate judgment, reflection, or decision making to AI, the same system may undermine the very competencies it is intended to develop.

4. Metacognitive Ability as a Boundary Condition

4.1 Conceptual Development of Metacognitive Ability

Metacognition was formally articulated by Flavell (1979) as knowledge and monitoring of one's own cognition. Brown (1987) emphasized executive control and self-regulatory processes, Paris and Winograd (1990) connected metacognitive monitoring with learning and instruction, and Schraw and Dennison (1994) provided a widely used measurement framework. Across these contributions, metacognition involves both knowledge about cognition and regulation of cognition through planning, monitoring, evaluation, and strategic adjustment.

4.2 Metacognition in AI-Supported Learning

The literature on self-regulated learning provides a useful way to specify this mechanism. In a conventional learning environment, metacognitive regulation involves setting goals, selecting strategies, monitoring comprehension, recognizing errors, and evaluating whether a strategy should be continued or changed. Generative AI adds a new layer because learners must regulate not only their own cognition but also their interaction with an external system that can produce plausible, immediate, and highly fluent responses. Effective regulation therefore includes deciding when AI assistance is necessary, formulating prompts that expose rather than conceal reasoning, checking the credibility of generated information, comparing alternative outputs, recognizing uncertainty, and determining when independent work should replace further AI assistance. In this sense, metacognition in AI-rich learning is not merely 'thinking about thinking'; it increasingly includes thinking about how one's thinking is being redistributed across a human-AI system.

Systematic review evidence supports this interpretation. Sardi et al. (2025), synthesizing studies published during the early ChatGPT period, reported that much of the literature links generative AI with improved self-regulated learning through personalized learning, adaptive feedback, and metacognitive support, while

simultaneously warning that technological overreliance can weaken learner independence. The important point is that AI support and self-regulation are not opposites. Well-designed AI can externalize cues that stimulate planning and reflection, whereas poorly designed or poorly regulated use can remove the need for those processes. This explains why metacognitive ability is a theoretically meaningful moderator rather than merely another positive predictor of learning. It can change the way the same technological affordance is used: feedback may become evidence to evaluate for one learner but an answer to copy for another; a conversational tutor may become a partner in Socratic questioning for one learner but a shortcut around problem solving for another.

In AI-supported environments, metacognition can determine whether technological assistance becomes a scaffold or a substitute for learner cognition. Recent studies reviewed in the source chapter indicate that learners with stronger metacognitive capacity are more likely to evaluate AI output critically and use it as a reference for reflection, whereas learners with weaker metacognitive capacity may be more susceptible to cognitive offloading and uncritical acceptance (Hou et al., 2025, 2026; Karaoglan Yilmaz & Yilmaz, 2025). This makes metacognition conceptually distinct from technology acceptance. Perceived usefulness or ease of use explains whether a learner adopts a tool; metacognition is more directly concerned with how the learner regulates cognition while using it.

4.3 Competing Regulatory Mechanisms

Two competing mechanisms deserve explicit consideration. A strengthening or complementary mechanism predicts that students with high metacognitive ability gain more from AI because they can select appropriate prompts, verify outputs, monitor understanding, and prevent dependence. A compensatory mechanism predicts that AI may provide structure and feedback that particularly benefits learners with weaker self-regulatory capacities. These mechanisms should be treated as empirical alternatives rather than resolved assumptions.

The source chapter prioritizes a strengthening moderation hypothesis but appropriately recognizes that the observed pattern could weaken, disappear, or reverse depending on learner characteristics and instructional design.

5. Theoretical Integration: Explaining Regulated Human-AI Interaction

Cognitive Load Theory, Self-Regulated Learning Theory, and Social Cognitive Theory provide complementary explanatory levels. Cognitive Load Theory (Sweller, 1988) explains how instructional design and AI support may redistribute intrinsic, extraneous, and germane cognitive demands. Self-Regulated Learning Theory (Zimmerman, 2008) explains how learners plan, monitor, and adapt their strategies, thereby supplying the most direct theoretical basis for metacognitive moderation. Social Cognitive Theory (Bandura, 1986) expands the analysis beyond internal cognition by emphasizing reciprocal interaction among person, behavior, and environment, which is relevant to AI-mediated simulation, observational learning, feedback, and social-emotional competence.

The three theories are therefore not redundant. Cognitive Load Theory specifies processing constraints; Self-Regulated Learning Theory explains strategic learner control; and Social Cognitive Theory situates these processes within interactive environments. Together they support a conditional model in which AI does not mechanically generate soft skills. Instead, AI modifies learning opportunities and demands, learners regulate their engagement with those opportunities, and repeated interactions may contribute to cognitive, interpersonal, and adaptive outcomes.

Alternative technology-adoption frameworks such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2012) remain useful for explaining perceived usefulness, ease of use, and behavioral intention. However, they are less directly suited to explaining why two students who both accept and frequently use AI may experience different competency outcomes. For that reason, metacognitive ability offers a more proximal boundary condition for the present research question (Baskara et al, 2024).

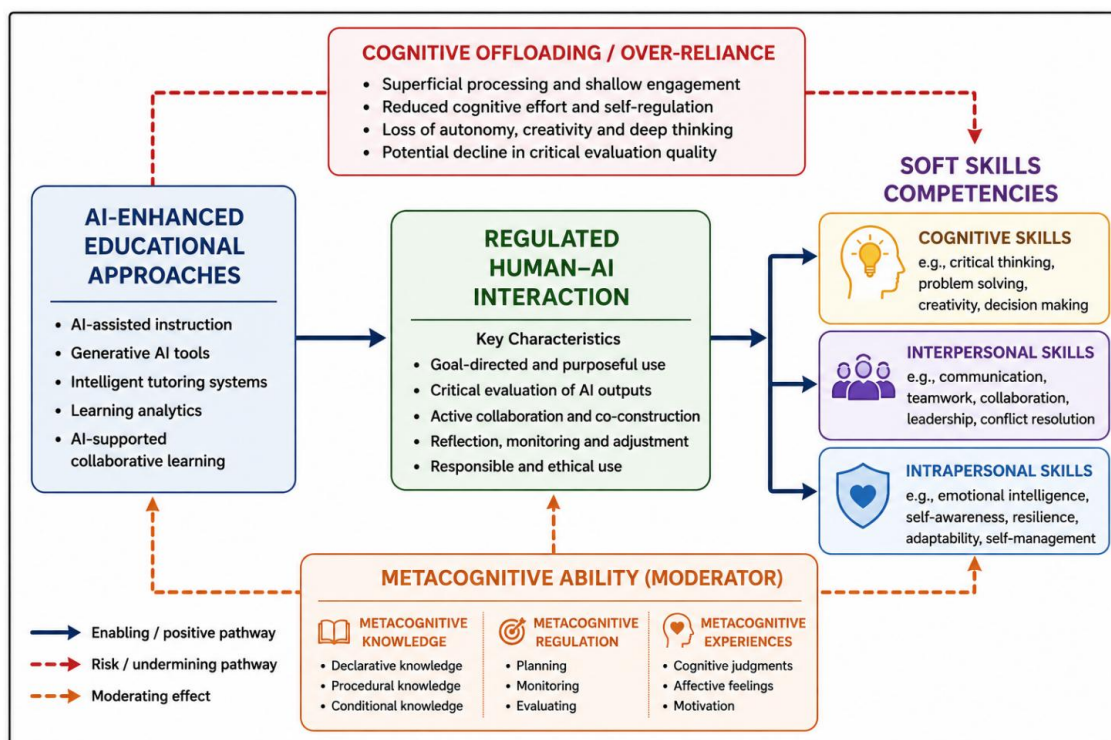


Figure 1 Integrated Conceptual Model of Regulated Human-AI Interaction and Soft-Skill Development

6. Generative AI, Learner Agency, and Critical Thinking

Learner agency offers a broader interpretive frame for these differences. Agency refers to the learner's capacity to make intentional choices, exercise judgment, and act on learning goals rather than simply respond to external prompts. Generative AI can expand agency by giving students immediate access to explanations, alternative perspectives, rehearsal opportunities, and personalized feedback that would otherwise be difficult to obtain. For vocational students, this may be particularly valuable when institutional resources are uneven or when learners require repeated low-stakes practice before participating confidently in authentic workplace tasks. Yet the same immediacy can narrow agency if students begin to treat the first generated response as authoritative, cease searching for alternatives, or allow AI to define the problem as well as solve it. The relevant distinction is therefore between AI as an agency-enabling resource and AI as an agency-substituting decision system.

This distinction has direct implications for critical thinking. Recent scoping work shows that critical thinking in generative-AI environments is increasingly operationalized in AI-specific terms, including detecting errors, evaluating credibility, and verifying sources, rather than only through classical measures of reflective judgment. This evolution is appropriate because AI-generated information changes the epistemic task facing the learner. Students are no longer simply evaluating textbooks, teachers, or peer arguments; they must assess outputs produced by systems whose fluency can mask uncertainty or error. For vocational education, this epistemic challenge is closely tied to workplace readiness. An apprentice technician, logistics worker, healthcare assistant, or service employee who uses AI-supported guidance must be able to distinguish plausible advice from reliable advice, and must know when contextual conditions invalidate a generic recommendation. Critical thinking under AI conditions therefore includes both traditional reasoning and AI-specific verification literacy.

Recent research published after the initial rapid adoption phase of generative AI strengthens the argument that educational outcomes depend less on simple access to AI than on the structure of human-AI interaction. A 2025 systematic review comparing vocational and undergraduate higher education found that vocational institutions tend to employ AI in competency-based and practice-oriented training, whereas universities more often emphasize theoretical exploration and higher-order cognition (Gao & Tan, 2025). This sectoral distinction is important for the present study because vocational learners encounter AI in settings where performance, simulation, workplace relevance, and immediate task completion are especially salient. Consequently, the mechanisms through which AI affects soft skills may differ from those observed in conventional university samples.

The emerging literature on critical thinking shows a similarly conditional pattern. A recent systematic review of pedagogical applications of generative AI in higher education concludes that GenAI is being used across tutoring, feedback, assessment, content generation, and collaborative learning, but its effectiveness depends on pedagogical integration rather than technological availability alone (Qian, 2025). More recent reviews of critical thinking research further indicate that GenAI can function as a scaffold when students are required to verify, justify, compare, and revise AI outputs, but may become a substitute for reasoning when use is frictionless and unregulated. This distinction sharpens the theoretical proposition of the present study: AI-enhanced education should not be represented as a uniformly positive exposure variable; its developmental value is contingent on the learner's active cognitive and metacognitive engagement.

A useful conceptual distinction is therefore between productive cognitive offloading and substitutive cognitive offloading. Productive offloading delegates lower-level or repetitive processes to AI while preserving learner responsibility for interpretation, evaluation, synthesis, and decision making. Substitutive offloading occurs when learners delegate

precisely those higher-order processes that educational activities are intended to cultivate. Quasi-experimental evidence suggests that structured AI-supported offloading can improve critical-thinking outcomes when students are required to critique, revise, and reflect rather than simply accept generated responses (Hong et al., 2025). In contrast, qualitative evidence documents students' perceptions of superficial engagement, reduced self-regulation of cognitive effort, and increasing reliance on AI-supported thinking under less structured conditions (Roy & Jony, 2026). These apparently contradictory findings are theoretically compatible once the quality of learner regulation is treated as a boundary condition.

7. Metacognitive Support and Self-Regulated Learning in GenAI Environments

The moderating role proposed for metacognitive ability receives additional support from recent GenAI-specific evidence. Xu et al. (2025) used a quasi-experimental design with explicit metacognitive support in a generative-AI learning environment and found that metacognitive prompting can strengthen self-regulated learning and improve students' learning experience. This evidence is especially relevant because it moves beyond a general association between metacognition and academic performance: it directly locates metacognitive regulation inside human-AI interaction. The implication for the present model is that metacognition may influence not only whether students use AI, but also the sequence of actions through which they interrogate, verify, revise, and internalize AI-supported learning.

A 2025 qualitative systematic review of AI-supported self-regulated learning similarly identified chatbots, adaptive feedback systems, serious games, and intelligent learning resources as mechanisms that can support learner autonomy, while also emphasizing the need for pedagogical guidance (Lan & Zhou, 2025). Taken together, this literature suggests that metacognition should not be reduced to a stable personal trait detached from instructional context. It can be understood as a regulatory

capacity whose expression is activated or suppressed by task design, feedback structure, teacher guidance, and AI affordances. This observation is important for interpretation of moderation results: a statistically significant interaction between AI-enhanced education and metacognitive ability would represent a person-by-environment relationship rather than a purely individual psychological effect.

This distinction also clarifies why TAM and UTAUT are insufficient as primary explanatory frameworks for the current research question. Technology-acceptance models can explain adoption intentions and perceived utility, but frequent or enthusiastic use does not guarantee cognitively productive use. Two students may report equally high acceptance of an AI tutor while differing substantially in source verification, prompt refinement, reflection, error detection, and willingness to challenge generated answers. Metacognitive regulation therefore operates closer to the hypothesized competency-development mechanism than perceived ease of use or behavioral intention.

8. Reconsidering Soft-Skill Development in AI-Rich Vocational Learning

The three soft-skill dimensions may also differ in their temporal relationship with AI. Critical-thinking changes can sometimes be observed during relatively short interventions because learners can be asked to compare arguments, evaluate evidence, or revise AI-generated responses within a course. Emotional intelligence and empathy may require longer periods of repeated social practice before changes become stable, particularly because competence in simulated interaction does not guarantee transfer to real relationships. Resilience is even more strongly developmental: it concerns patterns of adaptation across repeated difficulty, not simply satisfaction with an easier learning experience. Cross-sectional self-report studies therefore risk collapsing competencies with very different developmental timescales into one moment of measurement. A publishable interpretation should acknowledge that a common higher-order soft-skills factor can coexist with dimension-

specific developmental mechanisms and different sensitivity to intervention duration.

This temporal issue also helps explain why apparently beneficial AI experiences should not automatically be equated with resilience. If AI removes avoidable extraneous difficulty, it may free cognitive resources and allow students to persist with the substantive task. If it removes all meaningful struggle, however, learners may have fewer opportunities to develop strategies for coping with uncertainty, failure, and delayed success. The pedagogical goal is therefore not maximum ease but calibrated challenge. This principle aligns with Cognitive Load Theory and with the expertise-reversal perspective: assistance should be sufficient to prevent unproductive overload but should gradually recede as learners gain competence. In vocational settings, such calibrated support could be implemented through staged simulations in which AI initially provides extensive feedback and later shifts toward hints, reflective questions, or post-task debriefing rather than direct solutions.

Critical thinking is the dimension for which the AI literature is currently most developed, but even here construct definition is changing. Recent scholarship increasingly treats critical thinking in AI-rich environments not only as abstract reflective judgment, but also as the capacity to detect AI errors, evaluate credibility, verify evidence, identify bias, and justify why an AI-generated claim should or should not be accepted. This shift has measurement implications. Conventional self-report critical-thinking scales may capture dispositions, whereas performance tasks involving evaluation of AI output may better capture enacted critical thinking during human-AI collaboration. A robust empirical design should therefore interpret self-report associations cautiously and, where feasible, triangulate them with qualitative accounts of verification and reasoning practices.

For emotional intelligence and empathy, the evidence base is less mature and more heterogeneous. AI dialogue agents and immersive simulations can expose learners to multiple perspectives, emotionally charged scenarios, and

repeated communication practice; however, simulated interaction does not automatically produce authentic empathic competence. Empathy involves recognition of another person's state, perspective taking, context-sensitive response, and ethical interpersonal judgment. In vocational fields involving service, healthcare, logistics, customer relations, and team-based manufacturing, AI simulation may provide a low-risk rehearsal space, but transfer to real interpersonal settings remains an empirical question. The current study can contribute by examining whether students themselves perceive AI-supported activities as strengthening perspective taking and emotional regulation, rather than assuming transfer from technological exposure.

Psychological resilience likewise requires careful conceptual separation from short-term task persistence. Personalized AI feedback may reduce frustration, provide alternative explanations, and allow repeated attempts, thereby supporting persistence after failure. Yet excessive reliance may also reduce opportunities to experience and independently resolve productive difficulty. From a resilience perspective, the central question is therefore not whether AI makes learning easier, but whether it helps learners develop adaptive strategies that remain available when AI assistance is absent or insufficient. This issue is particularly relevant to vocational education, where graduates must ultimately cope with uncertain, time-sensitive, and socially complex workplace problems.

9. Construct Boundaries and Measurement Issues in Existing Research

The proposed model contains several measurement challenges that should be acknowledged at the literature-review stage. First, 'AI-enhanced educational approaches' is broader than use frequency. Exposure, intensity, perceived instructional integration, tool diversity, and pedagogical purpose are conceptually different. A student who uses an LLM for answer generation and another who uses a VR simulator for repeated workplace practice may both report high AI exposure while experiencing very

different learning processes. The operational definition should therefore align closely with the actual institutional AI-enhanced teaching practices represented in the sample.

Second, soft skills are higher-order latent competencies whose dimensions are related but not interchangeable. Treating critical thinking, emotional intelligence/empathy, and resilience as indicators of a single higher-order construct is theoretically defensible only if the measurement model demonstrates adequate factor loadings, discriminant validity, and higher-order structure. The quantitative phase should therefore test competing measurement models before interpreting structural paths. This is particularly important because overly broad aggregation could conceal a positive association with one dimension and a null or negative association with another.

Third, moderation analysis is sensitive to measurement quality. If metacognitive ability is measured unreliably, the interaction effect may be attenuated even when a genuine boundary condition exists. The Metacognitive Awareness Inventory developed by Schraw and Dennison (1994) offers a strong theoretical starting point, but adaptation to Chinese vocational learners should involve careful translation, contextual review, pilot testing, and confirmatory factor analysis rather than assuming that a scale validated in other populations will reproduce the same structure. The same principle applies to all soft-skill measures.

Finally, reliance on self-report data for predictor, moderator, and outcome variables collected in the same survey can inflate associations through common-method variance (Podsakoff et al., 2003). Procedural remedies may include anonymity, psychologically separating predictor and outcome sections, varying item formats, and reducing evaluative wording. Statistical checks can supplement but not replace sound survey design. The qualitative phase is valuable here because interview evidence can reveal whether statistically associated constructs correspond to recognizable learning behaviors and experiences.

10. Shandong Vocational Education as a Context for AI-Enhanced Learning

The regional argument becomes stronger when it is connected to the structure of vocational learning rather than to broad claims about provincial learner traits. Shandong's industrial economy creates many occupational contexts in which technical and non-technical competence are inseparable: intelligent manufacturing requires troubleshooting and team coordination; logistics requires rapid information judgment and communication across roles; modern services require emotional regulation and customer interaction; digitally transformed production environments require workers to learn new systems continuously. AI-enhanced vocational education can therefore be examined as part of a wider transformation of occupational competence, not simply as the introduction of a fashionable classroom technology. The province's digital-education policy direction provides institutional momentum, while its industrial structure supplies authentic scenarios in which the relevance of critical thinking, empathy, and resilience can be observed.

Nevertheless, regional specificity should not be overstated. The existing literature assembled in the source chapter does not establish that all Shandong vocational students share a distinctive psychological profile, nor does it justify deterministic comparisons with students in Jiangsu, Guangdong, or other provinces without direct comparative data. For publication, the more defensible position is that Shandong offers a theoretically relevant context in which the proposed relationships can be tested, while the external validity of the findings remains an empirical matter. This framing turns regionality from a descriptive claim into a boundary condition: if relationships are observed in Shandong, subsequent studies can test whether they replicate across provinces with different industrial structures, levels of digital infrastructure, institutional resources, and patterns of AI adoption.

The Shandong focus should be framed as an analytical context rather than a claim of provincial

exceptionalism. The source chapter identifies three relevant contextual features: a strong manufacturing and industrial base, provincial policy support for digital transformation in vocational education, and a vocational learner population characterized by strong practical orientation and heterogeneous academic preparation. These features create plausible reasons why AI-enhanced learning may interact with soft skills differently from general undergraduate settings. Nevertheless, claims about Shandong students being systematically weaker in autonomous learning than students in other provinces require direct comparative evidence and should not be presented as established fact unless supported by an appropriate source.

A stronger contextual argument is that vocational education itself changes the meaning of AI integration. Practice-oriented curricula provide opportunities for AI-supported simulation, troubleshooting, feedback, and scenario rehearsal that differ from text-dominant academic courses. At the same time, vocational institutions may vary substantially in digital infrastructure, teacher AI literacy, curriculum alignment, and student access. Gao and Tan's (2025) systematic comparison notes that vocational settings can be particularly vulnerable to infrastructure gaps and unequal learner readiness. These institutional differences should be recognized as contextual heterogeneity that may influence observed relationships.

Table 1 Synthesis of Major Literature Streams and Their Implications for the Present Study

Literature stream	Representative sources	Main contribution	Persistent limitation / tension	Implication for present study
Soft skills and employability	Alt et al. (2023); Tushar & Sooraksa (2023); Andreucci-Annunziata et al. (2023)	Positions critical thinking, interpersonal-affective competence, and adaptability as central to employability and long-term development.	Evidence is often correlational and dominated by general higher-education samples; causal direction and vocational transfer remain uncertain.	Treat soft skills as a multidimensional outcome and test both overall and dimension-specific associations.
AI-enhanced education	Crompton & Burke (2023); Wu & Yu (2024); Qian (2025)	Shows that AI can support personalization, feedback, dialogue, learning efficiency, autonomy, and higher-order learning when pedagogically integrated.	Technology type and instructional design vary greatly; positive task performance does not necessarily imply durable competence development.	Operationalize AI-enhanced education as an integrated instructional approach rather than simple frequency of AI use.
Critical thinking and cognitive offloading	Essien et al. (2024); Gerlich (2025); Liu et al. (2025)	Identifies a dual effect: structured AI use can support reasoning, while over-reliance may reduce analytical	Current evidence is context-sensitive and still heavily concentrated in higher education	Model AI effects as conditional rather than uniformly positive and examine learner regulation as a

		depth and independent thought.	and language-learning settings.	boundary condition.
Metacognition and self-regulated learning	Flavell (1979); Schraw & Dennison (1994); Xia et al. (2023); Xu et al. (2025)	Explains planning, monitoring, verification, reflection, and strategic adjustment during AI-supported learning.	Metacognition is sometimes treated as a general learner trait without considering how task design activates or suppresses regulation.	Test metacognitive ability as a moderator of the AI-soft-skills relationship and interpret it as a person-by-environment mechanism.
Vocational and Chinese context	Ministry of Education of PRC (2019); Shandong Provincial Department of Education (2023); Hong (2025); Ma et al. (2025)	Establishes policy and practical relevance of digital transformation, AI literacy, employability, and comprehensive competence in vocational education.	Regional evidence connecting AI, metacognition, and multidimensional soft skills remains limited, particularly in Shandong.	Provide context-specific evidence from Shandong vocational colleges while avoiding unsupported claims of provincial exceptionalism.

11. Integrated Literature Synthesis and Conceptual Proposition

Across the reviewed literature, the proposed model can be understood as a conditional competency-development model. AI-enhanced educational approaches provide affordances such as personalization, dialogue, simulation, feedback, and analytics. These affordances alter cognitive demands and learning opportunities. Metacognitive ability influences how learners regulate those opportunities through planning, monitoring, verification, reflection, and strategic adjustment. Repeated regulated engagement may then be associated with critical thinking, emotional intelligence/empathy, and resilience. Conversely, poorly regulated engagement may lead to cognitive offloading, dependence, or superficial task completion. This synthesis explains why a simple main-effect model is theoretically incomplete and why moderation is central rather than peripheral to the study.

The model also yields an important interpretive principle for the eventual results: a positive AI-

soft-skills coefficient should not be interpreted as evidence that AI itself develops soft skills. It would indicate that students reporting stronger exposure to or integration of AI-enhanced educational approaches also report stronger soft-skill competencies within the observed context. The moderation test can then examine whether this association changes with metacognitive ability, while qualitative follow-up can explore the learning practices that plausibly generate the statistical pattern. Such disciplined interpretation preserves the distinction between prediction, association, mechanism, and causality.

11.1 Convergent Findings and Persistent Tensions

The central conclusion of the literature is conditional rather than uniformly positive or negative. AI-enhanced education can expand access to feedback, dialogue, personalization, and simulation, but educational benefit depends on the cognitive work retained by the learner. This distinction is especially important for soft skills because such competencies require active

judgment, emotional regulation, reflection, collaboration, and recovery from difficulty. A system that makes tasks easier may improve immediate performance without necessarily strengthening the underlying competency. Accordingly, outcome evaluation should distinguish task completion from durable capability development.

The literature also suggests that soft skills should be modeled as a higher-order multidimensional construct while retaining dimension-specific

analyses. Critical thinking, emotional intelligence/empathy, and resilience share developmental conditions but may respond differently to AI affordances. For example, conversational AI may have a more direct relation to reasoning practice, whereas immersive simulation may be more relevant to emotional and resilience-related outcomes. Testing both an overall soft-skills construct and its dimensions can therefore reveal whether apparently positive aggregate effects conceal heterogeneous component-level patterns (Chew et al, 2025).

Table 2 Research Gaps and the Corresponding Contribution of the Proposed Study

Gap	What existing literature establishes	What remains unresolved	How the present study responds
Contextual-regional	AI and digital transformation are increasingly embedded in Chinese vocational education policy and practice.	Little integrated evidence explains AI-soft-skills relationships specifically in Shandong vocational colleges.	Uses Shandong vocational students as the focal population and interprets findings within local industrial and educational conditions.
Construct integration	Separate literatures exist on AI use, soft skills, metacognition, and self-regulated learning.	Few studies test AI-enhanced education, multidimensional soft skills, and metacognitive moderation within one coherent model.	Tests direct AI-soft-skills associations and moderation by metacognitive ability at overall and sub-dimensional levels.
Mechanism	Quantitative studies frequently report associations or intervention outcomes.	Statistical coefficients do not explain verification, reliance, reflection, emotional regulation, or persistence during AI use.	Uses qualitative follow-up to explain quantitative patterns and identify productive versus substitutive forms of AI use.
Methodological	Cross-sectional surveys are common; experiments and qualitative studies provide complementary but fragmented evidence.	Single-method designs cannot simultaneously provide population-level patterns and lived mechanism explanations.	Adopts an explanatory sequential mixed-methods design while explicitly limiting causal claims from observational evidence.
Measurement	Validated scales exist for metacognition and individual soft-skill dimensions.	Broad AI exposure and higher-order soft skills can be over-aggregated; common-method bias is a concern.	Requires measurement-model validation, dimension-specific analysis, careful scale adaptation, and procedural controls for common-method variance.

11.2 Research Gaps and the Contribution of the Present Study

The contextual gap is therefore more specific than the simple absence of Shandong studies. What is missing is evidence about whether findings derived largely from general higher education transfer to a practice-intensive vocational environment in which AI is embedded in simulation, troubleshooting, personalized practice, and employment-oriented training. Existing vocational-AI scholarship shows growing attention to personalization, curriculum development, automation, robotics, and practical training, particularly in manufacturing and logistics, but the link between these applications and multidimensional soft skills remains comparatively underdeveloped. The proposed study can contribute by connecting technological integration to competencies that matter beyond immediate technical task performance.

The theoretical gap concerns conditionality. Much of the early AI-in-education literature asks whether AI use predicts better outcomes, whereas the newer literature increasingly demonstrates heterogeneous effects across tasks, learners, and pedagogical arrangements. The original Chapter 2 correctly identifies metacognition as a candidate moderator, but the contribution becomes stronger when it is framed as an explanation of why identical AI affordances can produce different developmental consequences. Rather than adding metacognition as another variable to an already crowded model, the present study positions it as the regulatory mechanism that separates productive assistance from cognitive substitution. This creates a coherent theoretical reason for testing an interaction effect.

The methodological gap follows from the first two. Cross-sectional quantitative data can establish patterns of association and moderation but cannot reveal how students actually regulate AI use or whether a statistically significant interaction reflects verification, prompt revision, reflection, avoidance of dependence, or some other process. Qualitative follow-up is therefore not merely an optional supplement; it is necessary

for interpreting the meaning of the interaction. At the same time, qualitative narratives alone cannot determine the prevalence or strength of relationships across a larger student population. An explanatory sequential design is valuable precisely because the two strands answer different parts of the research problem. The contribution should therefore be presented as integrative explanation rather than as methodological novelty for its own sake.

Four gaps emerge from the synthesis. First, a contextual-regional gap persists because evidence specific to Shandong vocational colleges is limited despite distinctive industrial and policy conditions. Second, an integrated quantitative gap remains: relatively few studies test AI-enhanced education, multidimensional soft skills, and metacognitive moderation within one model. Third, a mechanism gap remains because statistical associations alone cannot explain how students interpret AI feedback, when they rely on it, or how they experience changes in reasoning, emotion, and resilience. Fourth, a methodological gap persists because much of the literature relies on a single method, particularly cross-sectional surveys, limiting the integration of breadth and explanatory depth.

11.3 Theoretical Contribution: From Technology Exposure to Regulated Human-AI Interaction

The theoretical contribution lies in shifting the unit of explanation from technology exposure to regulated human-AI interaction. Cognitive Load Theory explains why AI scaffolding can either reduce unnecessary processing or become redundant; Self-Regulated Learning Theory explains how learners actively control their engagement; and Social Cognitive Theory explains how behavior, cognition, and digitally mediated environments reciprocally shape learning. Metacognitive ability connects these levels by specifying a learner-side regulatory mechanism that can determine whether AI affordances become developmental resources or cognitive substitutes.

This integrated account also responds to the rapidly developing literature on learner agency.

Recent scoping work conceptualizes GenAI use as capable of producing both agency-supportive and agency-eroding patterns, with metacognition, self-regulation, critical thinking, trust, AI literacy, and pedagogical scaffolding functioning as key mechanisms or boundary conditions. The present model narrows this broad framework into a testable vocational-education proposition centered on metacognitive moderation and multidimensional soft skills.

11.4 Implications for AI-Enhanced Vocational Pedagogy

If the proposed relationships are supported, the practical implication is not simply to increase AI access. Vocational colleges would need to design AI-supported activities that preserve cognitive responsibility. Examples include requiring students to justify acceptance or rejection of AI suggestions, compare multiple solutions,

document prompt-revision processes, identify errors in generated outputs, alternate AI-assisted and AI-free task phases, and reflect on how feedback changed their reasoning. Such designs maintain productive cognitive friction while exploiting AI's capacity for rapid feedback and simulation.

For instructors, the literature implies a transition from controlling information delivery to designing and monitoring human-AI learning processes. Teacher development should therefore include not only technical tool training but also metacognitive prompting, assessment redesign, verification routines, and strategies for identifying over-reliance. For institutions, evaluation of AI initiatives should include competency-development indicators and equity considerations rather than adoption rates alone.

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