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Competency Formation and AI-Enabled Teaching in Mechanical Manufacturing Technology: A Reform-Driven Study

Rensuo Li, Zhiguo Wang, Rui Wang, Xiaohua Xu

Guilin Aerospace Industry College, Guilin City, Guangxi, China 541004

Author to whom correspondence should be addressed.

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Abstract: As a core course in the mechanical engineering major, "Mechanical Manufacturing Technology" urgently needs to carry out systematic teaching reform. The motivation for reform stems from two aspects: the continuous rise in talent competency requirements from emerging engineering education, and the further strengthening of talent cultivation constraints by the 225 version of the Engineering Education Professional Accreditation Standards. This paper proposes a competency-oriented, AI-deeply-empowered course reform model, centered on a four-stage cyclic mechanism: industry demand perception, intelligent generation of competency goals, goal verification in digital twin scenarios, and adaptive optimization of teaching plans. A five-stage digital twin workshop is constructed to support virtual-real integrated teaching, and generative artificial intelligence is embedded into the top-level archite cture of the course rather than being used as an additional demonstration tool. The original nine chapters of the course are restructured into five major modules, with the intelligent process design module accounting for 40%. A three-level mapping relationship between graduation requirements, competency goals, and attainment levels is established, and a teaching reform practice is carried out with 586 students from 2. The results show that students' process and fixture design abilities are significantly improved, and the AI-assisted course evaluation demonstrates good reliability. This study can be a referenceable and adjustable implementation paradigm for similar engineering course reforms.

Keywords: Mechanical manufacturing technology; Revised engineering education accreditation; Competency formation; AI-enabled teaching

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1. Introduction

Intelligent manufacturing is moving fast, and engineering education is having trouble keeping up. Back in 2023, the Ministry of Education ran a survey that spelled out the problem plainly [1-2]. In conventional Mechanical Manufacturing Technology courses, competency targets rarely match what employers actually want. Grading still depends mostly on a single end-of-term exam. And when AI shows up at all, it tends to

be superficial — a demo here, a tool there, nothing systematic. So the question we started with was a simple one: how do we turn the principles of emerging engineering education into a competency objective system that reflects where industry is headed? This course matters. It is a cornerstone of the Mechanical Design, Manufacturing and Automation program, and students depend on it for both theory and hands-on skill. Its competency objectives have to serve two masters at once: the program's broader cultivation goals, and the demands of the moment — AI-empowered manufacturing, digital design and fabrication, intelligent process optimization. Getting the balance right is not optional.

The literature is pointing in one direction: intellectualization and cross-disciplinary integration. A CiteSpace analysis we ran for 2021–2023 found something striking — publications combining OBE-CDIO frameworks with AI-assisted instruction jumped by 320%. Sun Chunling and her colleagues looked at rebuilding competency standards for engineering cost programs amid intelligent transformation [3]. Ye Zhengting applied OBE-CDIO ideas to reforming "Fundamentals of Mechanical Design [4]." Good work, all of it. But three gaps remain, and they are gaps we wanted to address. First, most studies treat competency objectives as if they were set in stone — no mechanism for recalibration. Second, generative AI is usually a sidekick, not part of the course architecture. Third, the evidence base is thin: small samples, single cohorts, hard to generalize from. Our study tries to close all three. We built an AI-driven dynamic competency objective model, tested it across multiple cohorts, and distilled what we learned into a reform pathway that other programs can actually use.

2. Theoretical framework construction

2.1. The "Objective–Content–Assessment" trinity competency model

We started from OBE [1]. The idea is familiar enough — desired outcomes should drive curriculum design — but applying it well is harder than it sounds. What we built for Mechanical Manufacturing Technology is a "trinity" model: objectives, content, and assessment treated as one system, not three separate tasks. Think of it this way. OBE supplies the philosophy. Competency objectives give it shape. AI does the heavy lifting that makes the whole thing dynamic. Put them together and you get something that adjusts itself rather than waiting for an annual review. How does it work in practice? Three feedback loops, nested inside each other. The first — objectives to content — keeps the curriculum honest. The second — content to assessment — makes sure we are measuring competency, not memorization. The third — assessment back to objectives — feeds what we learn into the next round of refinement. AI is what makes these loops spin faster. It collects data automatically, analyzes it in near real time, and suggests adjustments. The old yearly review cycle? It compresses into something close to continuous improvement.

2.2. Industrial large-model-driven demand mining

Here is the thing about competency objectives: if they do not reflect what industry actually needs, they are just wishful thinking. Expert opinion helps, but it is not enough. So we turned to the Huawei Pangu Large Model 3.0 and fed it job-posting data from 107 intelligent manufacturing firms in the Beibu Gulf Economic Zone [5]. The results were clear. Employers want cutting-edge skills — especially AI-supported process simulation and digital-twin operation and maintenance. And conventional courses? They barely cover these topics. 13% for AI process simulation. 9% for digital-twin O&M. That gap alone justified rebuilding the objective set. The mining also surfaced some competency clusters we had not expected to find so prominently: data-driven parameter

tuning, predictive maintenance using multi-sensor fusion, designing human–machine collaborative workflows, and even the ethical side of AI-augmented manufacturing. We should say a word about method here. Using a large industrial model for demand mining instead of relying on expert panels is not just convenient. It is a genuine improvement — faster, more granular, and less prone to the blind spots that come with asking the same small group of people every year [6].

3. Competency objective construction and teaching reform

3.1. Four-dimensional influence factor system

We found that four dimensions matter when competency objectives take shape under OBE. Societal demand comes first. Rather than relying on guesswork, we feed it directly from the large-model mining described above — real labor-market signals, technology forecasts, the whole picture. Graduation requirements form the second dimension. Each objective ties back to the program's graduate profile, so the course demonstrably contributes to every one of the twelve graduate attributes in the revised standards [7]. The third dimension is what makes this course distinctive. It sits at a crossroads — theoretical mechanics, materials science, process engineering, and hands-on workshop skill all meet here, and none can be left out without damaging the whole. The fourth dimension is the learners themselves. They arrive with different backgrounds, different thinking styles, different career goals, and the model has to accommodate that variety. In practice, we deployed Kimi, DeepSeek, and Doubao as AI teaching assistants through the Chaoxing platform. They ingest student feedback in real time and return optimized recommendations. It is that ongoing exchange — not any single feature — that gives the mechanism its dynamic quality .

3.2. Three-level mapping: Graduation requirements–competency objectives–achievement degrees

The curriculum matrix is where the rubber meets the road. It forces every course to answer a specific question: which competencies do you take responsibility for? Before getting there, though, it helps to see why this matters. Course-level objectives are concrete — you can test whether a student can apply specialized knowledge, demonstrate practical skill, think creatively, or work in a team. Graduation requirements are broader: engineering knowledge, problem analysis, design and development, and more. Bridging those two levels is what the matrix does. For Mechanical Manufacturing Technology - a professional core course — the answer centers on students' ability to work through complex engineering problems. That maps directly onto "Engineering Design and Implementation." The course design component that accompanies it builds hands-on fluency and teamwork, which lines up with "Project Management and Communication." The point is that this is not a one-time mapping exercise. Assessing achievement against each objective is what feeds the next round of improvement [8].

3.3. Curriculum system – job mapping

Course System Job Mapping is used to connect the logical chain between prerequisite courses, course competency objectives, enterprise job roles, and courses, accurately locating the integration points for artificial intelligence technology within the curriculum. The mapping logic is illustrated with two courses: "Mechanical Drawing" focuses on cultivating part analysis ability (Objective 1) and process design ability (Objective 2), corresponding to job roles in drawing review and process design; the course is sequentially linked to "Course

Design" and "CAD/CAM" courses, with the teaching process introducing DALL·E3 to assist in part model generation. "Theoretical Mechanics" and " Mechanics of Materials" focus on cultivating fixture and tool design ability (Objective 3) and machining error analysis ability (Objective 4), corresponding to tool design and fixture design job roles, with the course teaching introducing AI tools to assist in structural simulation analysis. This study does not pursue the undifferentiated overlay of AI tools across the curriculum, but insists on introducing AI in segments that can generate actual teaching benefits, achieving the gradual accumulation of AI-empowered competencies within the course cluster and avoiding AI teaching experiments [9].

3.4. Teaching content reconstruction

The old nine-chapter layout had to go. We replaced it with what we call a "process-flow spindle" — five modules instead of nine. Fundamentals and Frontiers takes 20%. Cutting Tool Design gets 5%. Machine Tool Fixture Design gets 15%. Intelligent Quality Analysis gets 20%. Intelligent Process Design and Optimization takes the biggest slice at 40%. That 40% was not arbitrary. In intelligent manufacturing, process design is where the action is, so it deserved the most space. Fundamentals and Frontiers is not just classical theory repeated. We wove in emerging developments so students see continuity rather than a rupture with the past. Cutting Tool Design was trimmed hard — down to 5% — but we could not drop it entirely. It remains the foundation everything else builds on. Fixture Design was reworked to use digital methods throughout. Intelligent Quality Analysis combines statistical process control, machine vision, and AI-based defect classification in one place. The capstone module, Intelligent Process Design and Optimization, is where everything converges: AI-assisted parameter recommendation, finite element simulation, digital-twin verification, and adaptive optimization, all in one learning arc.

3.5. Teaching method innovation

How we teach changed too. Lectures alone would not carry this. We shifted toward project-driven and scenario-simulated approaches, made possible by the digital-twin workshop and AI process assistants that blend virtual and physical experience. In project-based learning, students gather around real engineering tasks — it builds integrative skills and teamwork simultaneously. Scenario-simulated teaching drops learners into realistic work settings; understanding comes from doing, not from listening, and that translates into better readiness for real problems. **Table 1** shows how the competency objectives, content modules, and teaching methods line up.

Table 1. Relationship among teaching competency objectives, content integration, and pedagogical methods

Competency Objective	Teaching Content Module	Teaching Method	AI Integration
Manufacturing fundamentals application	Fundamentals and Frontiers (20%)	Flipped classroom + concept mapping	AI-generated knowledge graphs
Tool design and selection	Cutting Tool Design (5%)	Case-based learning	AI tool parameter recommendation
Fixture design capability	Machine Tool Fixture (15%)	Project-based learning	AI-assisted fixture design
Quality analysis and control	Intelligent Quality Analysis (20%)	Data-driven inquiry	AI defect classification
Process design and optimization	Intelligent Process Design (40%)	Digital-twin + simulation	AI process optimization + FEA

4. Teaching reform practice

4.1. Digital-twin workshop architecture

If you walked into our digital-twin workshop, what you would see is a five-layer setup. Start at the bottom with perception. We use a multi-modal sensor array — force transducers, vibration pickups, acoustic emission sensors, thermal imagers — and they stream live process signals up the stack. The data layer sits right above. Its job is unglamorous but essential: ingest, clean, fuse, store. Then you reach the model layer. This is where the digital counterparts live — every machine tool, workpiece, cutting tool, and fixture has one, and physics-based process models run alongside them. Above that is the application layer, which is where the useful stuff lives: process simulation, parameter optimization, fault diagnosis, quality prediction. At the very top is the interaction layer — the part students and instructors actually touch. Virtual reality headsets. Augmented-reality overlays projected onto workpieces. Desktop consoles. It is through these that the teaching process itself gets modeled and simulated digitally [6].

We run three kinds of virtual-real experiments, and each one teaches something different. The first is machine tool disassembly. We use a dual-track format here: every student works through it individually on an online virtual platform, and then the same students come together in teams to do physical disassembly in the workshop. Why both? The individual track builds personal understanding; the team track builds collaborative skill. The second kind is turning process optimization, which we run as a pipeline. AI suggests cutting parameters. Then finite-element-based optimization refines them [7]. Then online cutting simulation tests them. The strongest projects get selected for actual fabrication on the shop floor — which is a big motivator for students. The third kind is milling optimization, and we run it in parallel with the turning track. That is intentional. Running them side by side lets students see what the two processes share and where they diverge. If you step back, the whole sequence — AI recommendation, finite element analysis, digital verification — looks a lot like how intelligent manufacturing enterprises actually iterate.

On the generative AI side, we integrated large models — DeepSeek was one of them — into the Chaoxing platform. They handle three things: grading, question answering, and feedback. The AI grading component hit 94.7% accuracy, which took a real load off instructors and gave students feedback almost immediately. Based on performance patterns, the system also builds personalized learning pathways, though teachers still review them for quality. The AI question-answering function runs around the clock, which means instructors can spend less time answering routine questions and more on the kind of deep discussion and complex problem-solving that actually need a human.

4.2. Implementation results

Table 2 shows what the 2021–2022 cohorts — 586 students altogether — actually achieved. Process design compliance went from 72.3% to 88.6%, a gain of 16.3 percentage points. Fixture design compliance climbed from 68.5% to 84.2%, up 15.7 points. AI grading accuracy stayed at 94.7%. Student satisfaction rose from 78.2% to 91.4%. And the average time students spent on process design assignments dropped by about 28% — so AI tools did not just improve the quality of what they produced; they got them there faster. These gains span the cognitive domain (design quality), the psychomotor domain (hands-on compliance), and the affective domain (satisfaction). That breadth suggests the model is having a broad-based effect, not just moving one n.

Table 2. Comparative implementation results (n = 586)

Performance Indicator	Conventional Teaching	Reform Model	Improvement
Process design compliance rate	72.3%	88.6%	+16.3 pp
Fixture design compliance rate	68.5%	84.2%	+15.7 pp
AI grading accuracy	—	94.7%	—
Student satisfaction	78.2%	91.4%	+13.2 pp
Average process design time	Baseline	−28%	Efficiency gain

5. Conclusion

This paper constructs and implements a curriculum cultivation program centered on competency formation and AI empowerment, ensuring that curriculum objectives dynamically update in line with manufacturing. The new certification standards have raised the threshold for talent cultivation, while traditional courses face issues such as lagging objectives, single evaluation methods, and superficial AI application. The study draws three conclusions: First, the trinity system of OBE core AI-driven realizes the shift in teaching logic from knowledge transfer to competency generation; Second, demand mining using large models confirms the lack of cutting-edge content in traditional courses, supporting content reconstruction; Third, the four-stage cycle of "demand perception intelligent generation, digital twin verification, and adaptive optimization" ensures the dynamic iteration of competency objectives. The curriculum is integrated into five major modules, relying on digital twins for virtual-to-real experiments, while AI teaching assistants achieve the dual benefits of reducing teacher workload and enabling personalized learning. The limitations of this study are that the sample is drawn from only a single institution and relies on specific AI tools. Future work will involve multi-school joint practices to build a teaching framework decoupled from specific AI tools

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Disclosure statement

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References

[1] Wang HJ, Zhang HC, Zhong JL, et al., 2013, Construction of the "Fundamentals of Mechanical Manufacturing" Course Based on Engineering Capabilities. China Electric Power Education, 2013(1): 3.

[2] Sun CL, Zhang ZY, Yan L, 2025, Reconstruction of Engineering Cost Professional Capability Standard System for Intelligent Transformation: Based on Recruitment Data Mining and Case Analysis. Higher Engineering Education Research, 2025(2): 60–65 + 72.

[3] Sun CL, Zhang ZY, Yan L, 2025, Reconstruction of the Professional Competency Standard System for Engineering Cost Management Oriented Towards Intelligent Transformation—Based on Recruitment Data Mining and Case Analysis. Higher Engineering Education Research, 2025(2): 60–65.

[4] Ye ZT, 2025, Practice of Adult Teaching Reform in the Course of "Fundamentals of Mechanical Design" Based on OBE-CDIO Concept. Equipment Manufacturing Technology, 2025(2): 68–70.

[5] Li RS, Wang R, Zhang ZP, et al., 2022, Application of Virtual Simulation Technology in the Mechanical Manufacturing Technology Course. Equipment Manufacturing Technology, 2022(4): 208–210.

[6] Wang M, Xiong HQ, Mao ZS, 2024, "Four Domains and Ten Characteristics" of Virtual Simulation Experimental Course Development. Laboratory Research and Exploration, 43(6): 88–93.

[7] Wei XY, Li D, Cheng ZM, Qian MY, 2025, Teaching Reform of Artificial Intelligence-Driven Sensor and Detection Technology Course. Journal of Anhui University of Technology (Social Sciences Edition), 42(4): 56–58.

[8] Chanjuan L, Gao ZX, Wang RX, et al., 2025, Research and Practice of Big Data and AI-Empowered Personalized Teaching Mode for "Electrical Engineering and CAD" Course. Home Appliance Maintenance, 2025(9): 61–63.

[9] Wu F, 2025, The Construction of a Hybrid Teaching Mode for Mechanical Design Courses Empowered by AI and the Cultivation Path of Students' Innovative Abilities. Zhangjiang Science and Technology Review, 2025(12): 170–172.

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