

Transforming Vocational Pedagogy: A Quasi-Experimental Study on AI-Powered Job Sheets for Enhancing Critical Inquiry and Collaborative Dynamics in Metalwork Practice

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DOI: <https://doi.org/10.51584/IJRIAS.2026.11070203>

Received: 08 August 2026; Accepted: 14 August 2026; Published: 22 August 2026

ABSTRACT

Traditional instructional media in higher vocational education, particularly in metalwork and forging practice, often fosters passive learning, directive task execution, limited critical thinking development, and insufficient collaborative interaction. To address these gaps and align vocational training with current industry competency demands, this study designed and validated an AI-powered job sheet integrated into the practical engineering curriculum. This research evaluates the effectiveness of the AI-enhanced job sheet in improving students' Higher-Order Thinking Skills (HOTS) and collaborative competencies, compared to conventional instructional materials. A quasi-experimental non-equivalent control group pre-test-post-test design was employed, with participants assigned to an experimental group using the AI job sheet and a control group using traditional versions. Data were collected via validated assessment rubrics, then analyzed through normality and homogeneity tests, Normalized Gain (N-Gain) calculation, independent sample t-tests, and Cohen's d effect size measurement. Results show the experimental group achieved significantly higher gains across all measured competencies. For HOTS, the experimental group attained high-category N-Gain while the control group remained in the moderate category; the same pattern was observed for collaborative skills. The intervention demonstrates a statistically significant positive influence with an exceptionally large effect size. Integrating AI-powered job sheets transforms traditionally instructive workshop sessions into active, inquiry-oriented, and highly collaborative learning environments, offering a scalable, evidence-based framework for engineering and vocational educators.

Keywords: AI-powered job sheet, Higher-Order Thinking Skills (HOTS), collaborative learning, vocational pedagogy, metalwork practice, engineering education.

INTRODUCTION

The global imperative for technical and vocational education and training (TVET) to align with Industry 4.0 demands a fundamental shift from traditional instructional paradigms toward competency-based, inquiry-driven learning frameworks (UNESCO-UNEVOC, 2021; World Economic Forum, 2023). In manufacturing and mechanical engineering disciplines, practical workshop courses such as metalwork and forging serve as the cornerstone for developing technical mastery (Billett, 2020; Lucas & Spencer, 2021). However, conventional vocational instruction relies heavily on static, prescriptive job sheets designed primarily for algorithmic task execution (Kuo et al., 2022). While these traditional materials provide clear operational guidelines, evidence suggests they inadvertently induce passive learning behaviors, restrict creative problem-solving, and foster individualistic work habits (Bakhshi et al., 2020; Subrahmanyam, 2021). Students frequently execute tasks purely as passive instruction-followers rather than reflective practitioners, leading to elevated rates of operational error, suboptimal precision, extended task duration, and a marked deficit in essential interpersonal soft skills (Kuo et al., 2022; Winne, 2021).

This instructional limitation is particularly problematic given that modern industrial environments require engineers and technicians equipped with Higher-Order Thinking Skills (HOTS)—specifically critical inquiry, troubleshooting, and adaptive problem-solving—alongside robust collaborative dynamics (Chen et al., 2020; Hwang et al., 2020). Higher-order thinking enables technicians to analyze complex material behaviors,

evaluate process variables during thermal and mechanical deformation, and synthesize corrective strategies in real time (Lucas & Spencer, 2021). Concurrently, collaborative competence is crucial for modern team-based manufacturing setups, where peer interaction, clear technical communication, and cooperative troubleshooting dictate operational efficiency (Troussas et al., 2021). Despite the recognized importance of these dual competencies, traditional vocational media rarely incorporate structured mechanisms to nurture them during hands-on workshop practice (Luckin et al., 2021; Siemens et al., 2022).

Recent advances in artificial intelligence (AI) offer transformative opportunities to rethink vocational instructional design (Zawacki-Richter et al., 2019; Holmes et al., 2023). Integrating AI into educational media enables real-time scaffolding, dynamic problem generation, personalized feedback, and adaptive prompt engineering that shifts learning from passive execution to active inquiry (Chai et al., 2021; Winne, 2021). AI-powered job sheets can transform static step-by-step instructions into interactive problem-solving environments where students are prompted to evaluate parameter adjustments, predict material outcomes, and engage in peer-to-peer discourse prior to raw material manipulation (Hwang et al., 2020; Luckin et al., 2021). Despite the growing literature on AI in general engineering education, empirical studies examining the direct integration of AI-powered job sheets into physical, skill-heavy vocational domains—such as metalwork practice—remain scarce (Siemens et al., 2022; Subrahmanyam, 2021).

To address this critical pedagogical gap, this study designs, validates, and empirically evaluates an AI-powered job sheet embedded within a university-level metalwork practice course. By comparing the instructional outcomes of the AI-enhanced media against conventional static job sheets within a controlled quasi-experimental framework, this research seeks to answer four pivotal research questions:

RQ1: Does the implementation of an AI-powered job sheet significantly improve undergraduate vocational students' Higher-Order Thinking Skills (HOTS) and collaborative competencies compared to traditional job sheets?

RQ2: What is the extent of improvement (N-gain classification) achieved in HOTS and collaborative skills among students using the AI-powered job sheet?

RQ3: Is there a statistically significant effect of using the AI-powered job sheet on students' HOTS and collaborative performance?

RQ4: What is the magnitude (effect size) of the pedagogical impact exerted by the AI-powered job sheet intervention?

By answering these questions, this study provides empirical evidence on how AI-driven instructional media can reshape practical engineering workshop environments, bridging the gap between traditional vocational instruction and 21st-century industry expectations.

LITERATURE REVIEW

1. The Evolution of Vocational Pedagogy in Industry 4.0

Technical and vocational education and training (TVET) is undergoing a major paradigm shift to align with the technological demands of Industry 4.0 (Subrahmanyam, 2021; UNESCO-UNEVOC, 2021). Traditional vocational instruction in technical fields, such as metalworking and mechanical fabrication, has historically relied on behavioral, master-apprentice instructional models (Billett, 2020; Lucas & Spencer, 2021). In these setups, learning materials—primarily paper-based job sheets—serve as static, highly prescriptive directives that guide students through linear, step-by-step procedures (Kuo et al., 2022). While effective for basic technical operational training, recent studies highlight that over-reliance on static instructional media leads to passive execution, limits opportunities for critical inquiry, and minimizes interpersonal collaboration (Bakhshi et al., 2020; Winne, 2021). Modern industrial environments demand technicians who possess not only procedural expertise but also flexible problem-solving capabilities and strong collaborative dynamics (World Economic Forum, 2023). Consequently, modern vocational pedagogy must transition toward constructivist and

inquiry-driven approaches that foster active learning during hands-on workshop practice (Lucas & Spencer, 2021).

2. Higher-Order Thinking Skills (HOTS) and Collaborative Competencies in Practical Engineering

Developing Higher-Order Thinking Skills (HOTS)—specifically critical analysis, evaluation, and adaptive troubleshooting—is vital for vocational engineering students (Chen et al., 2020; Hwang et al., 2020). In practical workshop environments like metalwork and forging, HOTS enables students to analyze material deformation under thermal stress, evaluate parameter adjustments, and diagnose quality flaws in real time (Kuo et al., 2022). Furthermore, technical success in industrial setups rarely occurs in isolation; it requires collaborative competence, including task distribution, joint problem-solving, and clear technical communication (Troussas et al., 2021). Research demonstrates that integrating collaborative learning frameworks into technical instruction enhances peer-to-peer reflection, reduces task failure rates, and fosters collective critical inquiry (Troussas et al., 2021; Winne, 2021). However, conventional instructional media in engineering workshops lack embedded mechanisms to prompt peer interaction or critical reflection, often reinforcing individualistic and passive learning habits (Kuo et al., 2022).

3. Artificial Intelligence as a Pedagogical Catalyst in Technical Education

The integration of Artificial Intelligence (AI) into educational environments offers new opportunities to redesign instructional media in practical disciplines (Zawacki-Richter et al., 2019; Holmes et al., 2023). AI-assisted learning environments provide real-time scaffolding, personalized feedback, adaptive prompting, and dynamic scenario modeling (Chai et al., 2021; Luckin et al., 2021). Unlike traditional static media, AI-powered instructional media can act as an intelligent cognitive partner, prompting students to justify technical choices, predict manufacturing outcomes, and engage in reflective troubleshooting prior to physical execution (Hwang et al., 2020; Winne, 2021). While AI applications have gained traction in theoretical STEM education, empirical research evaluating AI-driven interactive job sheets within physical, hands-on TVET workshops—such as metalwork practice—remains scarce (Siemens et al., 2022; Subrahmanyam, 2021). Addressing this gap is critical to determining how AI-mediated instructional tools can systematically elevate HOTS and collaborative competencies in practical vocational settings.

METHOD

Research Design

This study employed a quantitative quasi-experimental research design using a non-equivalent control group pre-test-post-test setup (Creswell & Creswell, 2018). This design is particularly suitable for educational and vocational workshop research where random assignment of individual students to classes is intact and unfeasible due to administrative class scheduling constraints (Cohen et al., 2018). The experimental group was instructed using the newly developed AI-powered job sheet, while the control group utilized conventional, static paper-based job sheets. Both groups followed the same course syllabus, total instructional hours, and fundamental practical assignments in metalwork and forging over a 16-week semester.

Participants and Sampling

The target population comprised undergraduate vocational engineering students enrolled in the Metalwork Practice course at a public vocational institution. A total sample of 93 students was selected using purposive sampling based on their enrolled in active practical workshop sections. The participants were assigned to two intact groups:

1. **Experimental Group:** $n = 48$ students (instructed with the AI-powered job sheet).
2. **Control Group:** $n = 45$ students (instructed with the traditional job sheet).

Intervention and Instructional Media

1. **Control Group (Traditional Media):** Students received conventional printed job sheets containing fixed technical drawings, linear step-by-step operational procedures, and static evaluation criteria. Instruction followed a direct demonstration model where students executed tasks imperatively.
2. **Experimental Group (AI-Powered Job Sheet):** Students utilized a digital, interactive job sheet integrated with generative AI scaffolding capabilities (Chai et al., 2021). Prior to raw material cutting and thermal forging, the AI media prompted students to analysed design parameters, predict potential material failures (e.g., thermal warping or dimensional deviation), and collaboratively formulate operational plans. The AI acted as a dynamic tutor, offering immediate diagnostic feedback, critical inquiry prompts, and real-time troubleshooting assistance during workshop practice (Winne, 2021).

Instruments and Data Collection

Data were collected using two primary measurement instruments before (pre-test) and after (pos-test) the instructional intervention:

1. **Higher-Order Thinking Skills (HOTS) Assessment:** A validated performance-based test evaluating critical inquiry, diagnostic problem-solving, process evaluation, and technical decision-making in metalworking scenarios (Kuo et al., 2022).
2. **Collaborative Skills Rubric:** A standardized observational assessment rubric evaluating peer communication, team problem-solving, task distribution, and cooperative execution during practical exercises (Troussas et al., 2021).

Instrument Validation

Both instruments underwent expert validation by subject matter experts in vocational pedagogy, technical engineering, and educational measurement. Content and construct validity were established, and reliability testing yielded Cronbach's alpha coefficients exceeding \$0.80\$ across all constructs, confirming high internal consistency (Field, 2018).

Data Analysis Technique

Data analysis was conducted using SPSS and statistical computing packages following a multi-step analytical workflow:

1. **Prerequisite Testing:** Data normality was verified using the **Shapiro-Wilk test** ($p > 0.0$), and homogeneity of variance across groups was tested using **Levene's test** ($p > 0.0$) (Field, 2018).
2. **Normalized Gain (N-Gain) Calculation:** To measure the magnitude of skill enhancement, Hake's normalized gain formula was computed for both HOTS and collaborative performance:
3. **Hypothesis Testing (Inferential Statistics):** An **Independent Samples t-test** on N-gain scores was performed ($\alpha = 0.0$) to determine whether statistically significant differences existed between the experimental and control cohorts.
4. **Effect Size Estimation:** To measure the practical significance and strength of the instructional intervention, **Cohen's d** effect size was calculated and interpreted according to standard conventions: Small ($d \geq 0.20$), Medium ($d \geq 0.50$), and Large ($d \geq 0.80$) (Cohen, 1988).

RESULTS

1. Test Analysis Requirements

1. Prerequisite Test Results

Prior to evaluating the main research questions, the data were tested to ensure compliance with parametric

statistical assumptions. Normality was verified using the Shapiro-Wilk test, and homogeneity of variance was assessed using Levene's test.

Table.1 Data Normality Test Results

Variable		Group	p value	Assumption Status
HOTS	Pre-test	Experimental	0.217	Normal
		Control	0.189	Normal
	Post-test	Experimental	0.243	Normal
		Control	0.166	Normal
Collaborative Skills	Pre-test	Experimental	0.301	Normal
		Control	0.228	Normal
	Post-test	Experimental	0.275	Normal
		Control	0.194	Normal

Note: All -values exceed , confirming that the data meet the assumptions of normality

Table 2. Homogeneity Test Results of Data Variance HOTS and Collaboration Skills (Levene's Test)

Variable	F count	p-value	Description
HOTS	1,890	0,172	Variance homogeneous
Collaborative Skills	2,150	0,145	Variance homogeneous

Note: $p > 0.05$ = homogeneous variance

3. Description and N-Gain Analysis (RQ1 & RQ2)

To answer Research Questions 1 and 2, descriptive statistics and Hake's Normalized Gain (N-gain) were calculated to assess student skill enhancement across both target competencies.

Table 3. Descriptive Statistics and Normalized Gain (N-Gain) Summary

Variable	Groups	Average N-Gain	Upgrade Categories	t count	p-value	Cohen's d	Categories Influence
HOTS	Experimental	0.77	Height	11.638	0	1.25	Very Large
	Control	0.47	Medium				
Collaborative Skills	Experimental	0.83	Height	12.873	0	1.32	Very Large
	Control	0.39	Medium				

N-Gain Criteria: ≥ 0.70 = High; $0.30-0.69$ = Moderate; < 0.30 = Low. Cohen's criteria d: $0.20-0.49$ = Small; $0.50-0.79$ = Moderate; ≥ 0.80 = Large/Very Large. $p < 0.05$ = there is a significant difference.

Students in the experimental group instructed via the AI-powered job sheet achieved a Hight category mean N-gain in both HOTS (0.77) and Collaborative Skills (0.83). Conversely, the control group utilizing conventional static job sheets remained in the **Moderate** category for both HOTS (0.458) and Collaborative Skills (0.481).

DISCUSSION

The findings of this study demonstrate that the integration of AI-enhanced job sheets in the *Metalwork and*

Forging Practice course has produced substantial improvements in students' Higher-Order Thinking Skills (HOTS) and collaborative competencies compared to the use of conventional job sheets. These results confirm that the instructional approach previously in place was insufficient in fostering higher-level cognitive processes and social interaction among students, as also noted in preliminary observations where students tended to work passively, follow instructions mechanically, and showed limited willingness to collaborate or communicate effectively.

Improvement in Higher-Order Thinking Skills (HOTS)

The experimental group achieved an average N-gain score of 0.77, placing it in the *high improvement* category, whereas the control group attained only 0.47, corresponding to *moderate improvement*. The difference in improvement is statistically significant ($p < 0.05$) with a very large effect size (Cohen's $d = 1.25$). This indicates that the AI-enhanced job sheet is not merely delivering content but actively guiding students toward analysis, evaluation, and creative problem-solving—cognitive dimensions that were largely absent when students followed traditional, instruction-based worksheets. Instead of simply following step-by-step directions, students in the experimental group were encouraged to plan, evaluate work processes, and identify solutions independently, which directly contributed to the substantial growth in critical thinking ability.

Improvement in Collaborative Skills

For collaborative skills, the gap is even more pronounced: the experimental group recorded an N-gain of 0.83 (*high improvement*), while the control group reached only 0.39 (*moderate improvement*). The difference is highly significant ($p < 0.05$) with an effect size of 1.32, classified as *very large*. This outcome suggests that the AI-supported learning design successfully reduces the tendency to work individually and promotes interdependence, communication, and shared responsibility among students. Unlike traditional job sheets that emphasize individual completion of tasks, the AI-enhanced version appears to structure activities that require students to discuss, distribute roles, and negotiate solutions—naturally building collaborative competence.

Overall Impact and Implications

The very large effect sizes observed for both variables confirm that the AI-enhanced job sheet has a powerful practical impact, far exceeding the influence of conventional materials. This aligns with 21st-century vocational education goals, where technical proficiency alone is no longer sufficient; critical thinking and teamwork are equally essential competencies. The traditional media, which students described as passive, rigid, and time-consuming to use, appears to limit both cognitive and social development. By contrast, the AI-integrated design appears to scaffold learning more effectively, reduce unnecessary workload, and free students to focus on higher-order and collaborative activities.

LIMITATIONS AND SUGGESTIONS

While the results are highly positive, this study is limited to two variables (HOTS and collaboration) and one subject area. Future research should also examine communication skills and investigate long-term retention of competencies, as well as applicability across different vocational subjects. Nevertheless, the findings strongly support the use of AI-enhanced instructional materials in vocational practical courses to better prepare students for industry demands.

CONCLUSION

This study concludes that the use of AI-enhanced job sheets in the *Metalwork and Forging Practice* course significantly improves students' Higher-Order Thinking Skills (HOTS) and collaborative skills compared to conventional job sheets. The experimental group demonstrated a high level of improvement in both HOTS (N-gain = 0.77) and collaborative skills (N-gain = 0.83), whereas the control group using traditional job sheets showed only moderate improvement (N-gain = 0.47 for HOTS and 0.39 for collaboration). Statistical analysis confirmed that these differences are highly significant ($p < 0.001$), with very large effect sizes (Cohen's $d = 1.25$ for HOTS and 1.32 for collaboration), indicating that the AI-enhanced job sheets have a strong and

practically meaningful impact.

In summary, the AI-integrated learning materials successfully address the limitations of traditional instructional media—such as passive learning, limited critical thinking, and poor collaboration—by actively guiding students for evaluate information? Evaluate, solve problems, and work together. Therefore, AI-enhanced job sheets are recommended as an effective alternative to conventional materials in vocational practical courses, and are strongly encouraged to better equip students with the critical thinking and teamwork competencies required in the modern engineering industry.

REFERENCES

1. Bakhshi, H., Downing, J. M., Osborne, M. A., & Schneider, P. (2020). The future of skills: Employment in 2030. *Journal of Vocational Education & Training*, 72(4), 512–533.
2. Billett, S. (2020). Learning in the workplace: Strategies for effective practice. *Vocations and Learning*, 13(2), 173–191.
3. Chai, C. S., Lin, P. Y., Jong, M. S. Y., & Dai, Y. (2021). Perceptions of AI and AI pedagogical support in STEM education. *Computers and Education: Artificial Intelligence*, 2, 100018.
4. Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264–75278.
5. Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.
6. Field, A. (2018). *Discovering Statistics Using IBM SPSS Statistics* (5th ed.). SAGE Publications.
7. Hake, R. R. (1998). Interactive-engagement versus traditional methods in mechanics courses. *American Journal of Physics*, 66(1), 64–74.
8. Holmes, W., Bialik, M., & Fadel, C. (2023). *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Center for Curriculum Redesign.
9. Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, and trends in AI in education. *Computers and Education: Artificial Intelligence*, 1, 100001.
10. Johnson, D. W., & Johnson, R. T. (2019). *Cooperative learning and achievement: Theory and research*. (2nd ed.). Interaction Book Company.
11. Kuo, C. H., Wu, T. H., & Chen, Y. L. (2022). Re-engineering technical job sheets for enhanced problem-solving in vocational workshops. *International Journal of Technology and Design Education*, 32(3), 1421–1439.
12. Lucas, B., & Spencer, E. (2021). Remaking TVET coaching: Pedagogy for practical skills acquisition. *Empirical Research in Vocational Education and Training*, 13(1), 1–21.
13. Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2021). *Intelligence Unleashed: An argument for AI in education*. Pearson Education Research Report, 11(2), 45–68.
14. Prasetyo, B., & Jatmiko, B. (2023). Effectiveness of AI-enhanced learning materials in improving higher-order thinking skills in vocational engineering education. *Journal of Technical Education and Training*, 15(2), 89–97.
15. Richey, R. C., & Klein, J. D. (2014). *Design and development research: Methods, strategies, and issues*. Springer.
16. Siemens, G., Marmolejo, F., & Dawson, S. (2022). Digital learning transformation in higher education: AI and learning analytics integration. *Higher Education Quarterly*, 76(1), 89–108.
17. Sönmez, D., & Kocak, O. (2023). The impact of AI-supported worksheets on students' critical thinking and collaborative skills in hands-on engineering courses. *International Journal of Engineering Education*, 39(4), 987–998.
18. Subrahmanyam, G. (2021). Digitization in TVET: Preparing the workforce for Industry 4.0. UNESCO-UNEVOC International Centre, 4(2), 101–120.
19. Sugiyono. (2021). *Metode penelitian kuantitatif, kualitatif, dan R&D*. Alfabeta.
20. Troussas, C., Krouska, A., & Sgouropoulou, C. (2021). Collaboration and personalization in smart learning environments. *Computers in Human Behavior*, 115, 106612.
21. UNESCO-UNEVOC. (2021). *Innovating TVET education: Frameworks for digital transformation*. UNESCO Publishing.

22. Winne, P. H. (2021). Open research questions about self-regulated learning in AI-assisted digital environments. *Frontiers in Education*, 6, 680874.
23. Wahyudi, W., & Hartanto, S. (2022). Developing 21st-century skills in vocational metalwork practice: Challenges and opportunities. *International Journal of Vocational Education and Training Research*, 8(1), 37–48.
24. World Economic Forum. (2023). The Future of Jobs Report 2023. World Economic Forum Geneva.
25. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16(1), 39.