How Artificial Intelligence Reshapes Technical Work: A Task-Based Analysis and Implications for Vocational Education

Yin-Zhen Huang, Ming-Hsiu Tsai*

Graduate Institute of Technological & Vocational Education,

National Taipei University of Technology

Abstract

Artificial intelligence (AI) is extending automation from routine tasks to more complex technical work, including diagnosis, design, and decision support. For middle- and high-skilled technical workers, AI is more likely to reorganize tasks within occupations than replace entire jobs. This article examines how AI changes technical work and its implications for vocational education. Using industrial equipment maintenance as a case, it analyses how predictive maintenance affects inspection, fault diagnosis, maintenance decisions, repair, and documentation. In addition, an example from PwC's AI-enabled auditing and risk management practices is briefly discussed to illustrate how AI reshapes professional tasks beyond technical occupations. Based on task-based technological change theory and research on AI-enabled maintenance, the study compares different tasks according to their level of digitalization, standardization, ease of verification, and dependence on physical action and professional judgement. The findings show that routine inspection and documentation are more likely to be automated, while complex diagnosis, maintenance decisions, and physical repair still require human expertise. Meanwhile, new tasks are emerging, including data checking, alert validation, and AI-assisted decision making. The main employment challenge is therefore not occupational replacement, but changes in entry-level work and skill requirements. The article argues that vocational education should respond through continuous curriculum adjustment, practical training, and closer links with workplace changes. Instead of creating separate AI programs, vocational institutions should integrate AI-related skills into existing technical fields and strengthen students' ability to work effectively with intelligent systems.

Keywords: Artificial Intelligence; Technical Workers; Task Restructuring; Predictive Maintenance; Vocational Education

1. Introduction

AI is changing the labor market beyond clerical work and repetitive production. Its influence can now be seen in software development, engineering analysis, healthcare technology, financial services, and industrial maintenance. Eloundou et al. (2024) estimate that large language models may affect at least 10% of the tasks performed by around 80% of workers in the United States. However, AI exposure does not mean that jobs will disappear. An occupation usually includes different types of tasks. AI may replace some routine activities. It may also support workers in more complex tasks and create new responsibilities, such as checking AI outputs. Similar task transformations can also be observed in professional financial services. For example, PwC has discussed how generative AI can support risk management practices (PwC, 2024). Traditionally, risk assessment and auditing tasks involve extensive data review, transaction checking, compliance analysis, and professional judgement. With AI-enabled tools, some information-processing tasks can be increasingly supported by intelligent systems, including anomaly detection, large-scale data analysis, and risk identification. However, financial professionals remain responsible for interpreting AI-generated results, evaluating potential risks, addressing ethical and regulatory concerns, and communicating decisions with clients and organizations. This example further demonstrates that AI-driven transformation is characterized by changes in task composition rather than the disappearance of occupational roles. Task-based technological change provides a useful way to understand these changes. Autor, Levy, and Murnane (2003) argue that computerization mainly replaces routine tasks based on clear rules. At the same time, it can support tasks that require problem solving and judgement. Generative AI has expanded into some cognitive tasks, but AI exposure is still different from job replacement. Felten, Raj, and Seamans (2021) show that occupations with higher AI exposure do not always face greater replacement risks. Pizzinelli et al. (2023) also find that AI may both replace and support human work. The final impact depends on several factors. These include the reliability of AI results, the cost of errors, the need for physical work, and how organizations introduce new technologies.

These changes bring new challenges for vocational education. Adding a basic AI course is not enough. Vocational institutions need to understand which tasks are declining, which tasks are supported by AI, and which new tasks are appearing. This can help schools adjust learning objectives, practical training, and assessment methods. Otherwise, programs may spend too much time teaching skills that are easier to automate, such as routine data processing, standard technical drawings, basic reports, and fault-code matching. However, courses that focus on specific AI tools may also become outdated quickly. This article examines how AI affects middle- and high-skilled technical work and how vocational education can respond. It first discusses AI-related changes from a task perspective. It then uses industrial equipment maintenance as a case study. This occupation includes data analysis, technical diagnosis, physical repair, and safety responsibility. It therefore provides a useful example for understanding why AI exposure does not always lead to job replacement.

2. AI, Technical Employment, and the Vocational Education Response

2.1. How AI Changes Technical Tasks?

Research on technological change has shown that automation usually affects specific tasks rather than entire occupations. Autor, Levy, and Murnane (2003) argue that computer-based technologies mainly replace routine tasks that follow clear rules, while they complement non-routine tasks that require problem solving and judgement. More recent studies suggest that AI may extend automation into some cognitive tasks, but exposure to AI does not necessarily mean that workers will be replaced (Felten et al., 2021; Pizzinelli et al., 2023). The substitution effect of AI is stronger in tasks that are digital, standardized, and easy to evaluate. Examples include basic code generation, routine data processing, standard technical documentation, and information retrieval. In these areas, AI can complete part of the work with limited human input. However, such changes usually involve individual tasks rather than the disappearance of occupations (Acemoglu & Restrepo, 2019). AI can also increase the productivity of workers by supporting tasks that require professional knowledge and judgement. For example, AI systems can identify possible equipment failures, suggest solutions, and provide access to technical information. However, workers still need to evaluate the results and make decisions based on specific situations. This reflects the complementary relationship between technology and human expertise. Evidence from professional writing tasks also suggests that generative AI can improve productivity while keeping humans involved in the process (Noy & Zhang, 2023). At the same time, AI adoption creates new responsibilities within existing jobs. Workers may need to check data quality, evaluate AI outputs, and determine when automated suggestions should be accepted or rejected. These changes may not immediately create completely new occupations, but they can reshape existing technical roles. One important concern is the decline of entry-level tasks. Routine activities such as basic testing, documentation, and fault identification have traditionally helped new workers build experience. If these tasks become automated, vocational graduates may face higher requirements when entering the labor market.

2.2. Adjusting vocational education to changing tasks

AI-related changes in work create new requirements for vocational education. Previous studies suggest that technological change affects not only the demand for skills but also the way skills are developed and applied in workplaces (Autor et al., 2003; OECD, 2023). Therefore, vocational education should pay attention to changes in work tasks rather than only changes in occupational numbers. Vocational education should not close a program simply because the number of job vacancies decreases. It should also avoid creating new AI-related programs only because demand for AI skills is increasing. A better approach is to examine how workplace tasks are changing and how these changes influence skill requirements (OECD, 2026). Changes in job descriptions can provide useful signals. For example, employers may require less ability to record information, prepare standard documents, or complete routine technical work. At the same time, they may place more emphasis on interpreting data, checking AI results, and making decisions with technical judgement. Such changes may appear before major changes in job titles or employment numbers. Vocational curricula should maintain technical foundations and practical skills while adding abilities needed for AI-supported work. These include understanding data, checking AI outputs, handling unexpected situations, and making professional decisions. Assessment should also move beyond memorization and fixed answers. More attention should be given to practical projects, fault diagnosis, and explaining the reasons behind technical decisions. The following case shows how these ideas can be applied to industrial equipment maintenance.

3. Case Selection and Analytical Method

3.1. Occupational case and identification

This study uses a literature-informed task analysis to examine how AI changes technical work. The case selected is industrial equipment maintenance. This occupation is closely related to vocational fields such as advanced manufacturing and mechatronics. It includes several types of activities, including equipment inspection, fault diagnosis, repair, and maintenance records. The case was selected for two reasons. First, industrial maintenance combines digital information processing with physical operation and professional judgement. This makes it suitable for examining both the replacement and supportive effects of AI. Second, predictive maintenance has developed into an integrated technical process, including sensor data collection, condition monitoring, fault prediction, and maintenance decisions (Lee et al., 2018). Based on the maintenance workflow and previous research on predictive maintenance, this study divides maintenance work into five task groups: condition inspection, fault diagnosis, maintenance decision making, on-site repair, and maintenance documentation. These tasks represent different levels of interaction between AI systems and human workers.

3.2. Dimensions of task comparison

The analysis examines three possible effects of AI on tasks: task substitution, task augmentation, and the creation of new responsibilities. Following the task-based perspective on technological change (Autor et al., 2003; Acemoglu & Restrepo, 2019), five task groups are compared using four dimensions. The first dimension is digital executability, which refers to whether a task can be completed through digital information and computational processes. The second is procedural standardization, which considers whether a task follows stable rules or repeated patterns. The third is verifiability, which refers to whether AI results can be checked easily and reliably. The fourth is dependence on physical action and professional responsibility, including on-site conditions, safety risks, and the need for human judgement. This study does not calculate automation probabilities or assign numerical scores. Instead, each dimension is classified as low, medium, or high to show differences among tasks. Tasks that are highly digital, standardized, and easy to verify are more likely to be automated. Tasks involving physical action, uncertain conditions, and safety responsibility are more likely to be supported by AI rather than replaced.

3.3. Qualitative comparison

Table 1 presents the qualitative comparison of the five task groups. The analysis first examines the technical characteristics of each task. It then considers how AI changes the division of work between systems and technicians. Finally, these changes are connected to curriculum design and practical training. The low, medium, and high classifications are based on existing research and qualitative analysis rather than statistical estimates.

They are intended to show relative differences among tasks, not to predict future job losses. The following sections provide detailed analysis of how predictive maintenance changes each task.

Table 1. Qualitative Comparison of AI Impacts across Industrial Maintenance Tasks

Task group	Digital feasibility	Procedural standardization	Verifiability	On-site action and responsibility	Main AI-related change
Condition inspection	High	High	High	Medium	Routine data collection can be automated, but on-site checking remains necessary
Fault diagnosis	High	Medium	Medium	High	AI suggests possible causes, while technicians verify the diagnosis
Maintenance decisions	Medium	Low	Medium	High	AI supports decisions, but responsibility remains with technicians
On-site repair	Low	Medium	High	High	Physical repair remains human-centered, with AI providing operational support
Maintenance documentation	High	High	High	Low	Report generation can be automated, while data accuracy and review become important

4. How Predictive Maintenance Restructures Equipment Maintenance Work

4.1. Data-based monitoring and documentation: from manual recording to data verification

Traditional maintenance relies on manual inspection, including checking instruments, measuring temperature and vibration, identifying abnormal sounds, and recording equipment conditions. With industrial IoT systems, equipment data can now be collected continuously, and AI-based anomaly detection models can identify possible problems by comparing current conditions with historical patterns (Lee et al., 2018). As a result, routine measurement, data recording, and report preparation tasks are increasingly automated or AI-assisted. However, automation does not remove the need for technicians. Sensor errors, poor data quality, or unusual operating conditions may lead to incorrect alerts. Technicians therefore need to check data quality, verify AI-generated signals, and connect digital information with actual equipment conditions. In this sense, the role of technicians is shifting from collecting information to ensuring the accuracy and reliability of maintenance data. Generative AI further extends this transformation by assisting with maintenance reports, work orders, and equipment summaries based on sensor data and repair records. However, automatically generated information requires human review because AI systems may produce inaccurate content or fail to distinguish between observed facts and generated conclusions (Dwivedi et al., 2023). Therefore, data verification becomes an increasingly important part of AI-supported maintenance work.

4.2. Fault diagnosis and maintenance decisions: from pattern matching to professional judgement

AI has been widely applied in predictive maintenance to analyze vibration signals, temperature changes, current variations, and other equipment data for fault detection and prediction (Carvalho et al., 2019). These systems can identify common failure patterns, provide possible causes, and support initial diagnosis. However, equipment failures are often influenced by multiple factors, including mechanical conditions, electrical systems, production environments, and operational changes. AI models may also perform poorly when facing new situations that are not represented in historical data. Therefore, AI mainly supports rather than replaces technicians in diagnosis and decision-making. Technicians need to evaluate AI suggestions, combine digital information with equipment knowledge, and determine appropriate actions. Maintenance decisions involve not only technical prediction but also safety risks, production requirements, repair costs, and organizational responsibilities. As human-centered AI research emphasizes, AI should support human decision-making, especially in high-risk situations (Shneiderman, 2020). This transformation changes the role of technicians from identifying known faults to interpreting AI outputs and making decisions under uncertain conditions. Vocational training should therefore strengthen students' abilities to question recommendations, evaluate evidence, and apply professional judgement.

4.3. On-site repair: limited substitution and continued importance of practical skills

Compared with data-related tasks, physical repair remains more difficult to automate. Maintenance work often requires technicians to disassemble equipment, replace components, adjust systems, and solve unexpected problems in complex environments. Unlike digital information processing, on-site repair is highly dependent on specific equipment conditions, workplace arrangements, and real-time judgement. Differences in equipment age, operating conditions, and installation spaces make it difficult to develop standardized solutions that can fully replace human workers. Industry 4.0 technologies, including AI assistants, remote support systems, and digital instructions, mainly provide information support and improve problem-solving efficiency rather than replace technicians (Frank et al., 2019). For example, AI-based systems can provide maintenance suggestions, display technical information, or help workers identify possible causes of equipment problems. These tools can reduce unnecessary trial and error and improve the efficiency of repair activities. However, they still depend on technicians who understand equipment structures and can evaluate whether digital recommendations are appropriate in specific situations. The continued importance of human involvement is also related to the physical and safety-related characteristics of maintenance work. A repair task may require workers to respond to unexpected conditions, such as damaged components, unclear failure causes, or changes in operating environments. These situations often cannot be fully predicted by historical data. Technicians must combine technical knowledge with practical experience to adjust solutions and ensure safe operation. Therefore, AI assistance does not reduce the importance of hands-on skills; instead, it changes how these skills are used. From a vocational education perspective, this means practical training should not be reduced simply because AI technologies are introduced into maintenance processes. Students still need to develop a strong understanding of equipment principles, operation procedures, and repair methods. At the same time, training should incorporate AI-supported maintenance scenarios, allowing students to learn how to use digital tools while maintaining independent judgement and problem-solving abilities. The future maintenance technician is therefore not a worker replaced by AI, but a professional who can combine practical expertise with intelligent technologies.

5. An Extended Example: AI-driven Task Restructuring in Financial Risk Management

Although this study focuses on industrial equipment maintenance, similar patterns of AI-driven task restructuring can also be observed in professional service fields. Financial risk management provides an example of how AI changes the composition of work tasks rather than replacing entire occupations. PwC's discussion of generative AI applications in risk management shows that AI can support financial professionals by improving data analysis, risk identification, and decision support (PwC, 2024). Traditionally, financial risk management involves activities such as reviewing transaction records, analyzing historical information, identifying potential risks, and preparing reports. Many of these tasks require processing large amounts of structured and unstructured data. With AI technologies, some information-intensive activities can be increasingly automated or supported by intelligent systems. For example, AI models can identify unusual transaction patterns, assist risk detection, and improve the efficiency of data analysis. However, these applications mainly enhance the speed and scale of information processing rather than independently completing the entire risk management process.

Similar to industrial maintenance, human expertise remains essential in tasks involving judgement, responsibility, and contextual understanding. AI-generated results still need to be evaluated by professionals, particularly when decisions involve regulatory requirements, ethical considerations, and potential organizational risks. Financial professionals must determine whether AI outputs are reliable, explain decision rationales, and communicate recommendations to relevant stakeholders. From a task-based perspective, AI reshapes financial risk management in three ways. First, routine analytical activities, such as initial data screening and pattern identification, become increasingly automated or AI-assisted. Second, new responsibilities emerge, including validating AI outputs, monitoring data quality, and ensuring compliance with professional standards. Third, higher-level capabilities, such as professional judgement, explanation, and communication, become more important.

This example supports the broader argument of this study: AI-driven transformation should be understood as a redistribution of tasks within occupations rather than simple job replacement. Although industrial maintenance and financial risk management involve different knowledge domains, both demonstrate a similar pattern. AI is more likely to take over tasks that are digital, standardized, and data-intensive, while humans remain central in situations requiring judgement, responsibility, and practical understanding (Felten et al., 2021; Pizzinelli et al., 2023).

6. Implications for Vocational Education

Artificial intelligence does not require vocational education to simply add more AI-related courses. A more fundamental change is needed: programs should adjust according to how technical tasks are changing. Traditional program evaluation often focuses on employment numbers or job titles. However, AI usually changes the content of work before it changes the existence of an occupation. Therefore, vocational institutions need to pay attention to changes in specific tasks, such as the decline of manual inspection, the growth of data-based monitoring, and the increasing need for AI output validation. Curriculum adjustment should start from changing work tasks rather than from individual technologies. For example, if predictive maintenance reduces the need for manual vibration checks, this does not mean that vibration knowledge is no longer important. Instead, students need to learn how to interpret sensor data, identify abnormal signals, and verify whether AI-generated alerts match physical conditions. Technical foundations, practical skills, and professional judgement remain essential because AI cannot replace the need to understand equipment mechanisms and production risks. Practical training should also be redesigned around human–AI cooperation. A possible approach is to develop three progressive stages. In the first stage, students learn to diagnose basic problems without AI assistance and build fundamental technical understanding. In the second stage, students use AI tools to support diagnosis, while learning to check data quality, evaluate suggested solutions, and explain their decisions. In the third stage, students practice handling AI failures, such as false alarms, missing data, or incorrect recommendations. Through these tasks, students learn not only how to use AI, but also when and why they should question it.

This change is particularly important because AI may reduce some entry-level tasks that previously helped new workers gain experience. Vocational institutions therefore need to provide more structured practice opportunities. Case-based learning, simulation, and school–enterprise projects can help students experience different situations, including normal operation, common failures, complex faults, and AI errors. Students should gradually move from identifying problems to explaining causes, making decisions, and taking responsibility for outcomes. Close cooperation between schools and industry is also necessary. Enterprises can provide examples of real maintenance problems, equipment data, and AI application experiences, while teachers can transform these materials into training cases and assessment tasks. Assessment should focus less on whether students can follow an AI recommendation and more on whether they can explain the evidence behind a decision. AI can improve technical work only when workers are able to understand, evaluate, and appropriately challenge its outputs.

7. Discussion and Conclusion

This study shows that the impact of AI on technical occupations is better understood at the task level rather than the occupation level. The case of industrial equipment maintenance demonstrates that AI can simultaneously produce task substitution, augmentation, and new task creation within the same occupation. Routine inspection, standard documentation, and familiar fault identification are more likely to be automated because they involve structured data and repeatable procedures. In contrast, complex diagnosis, maintenance decisions, and physical repair continue to require human judgement, practical experience, and responsibility. Therefore, AI reshapes the internal structure of technical work rather than simply replacing workers. High AI exposure should not be directly interpreted as a high risk of unemployment, as employment outcomes depend on technology adoption, organizational choices, and workplace conditions. Similar patterns can also be found beyond technical occupations. PwC's example of AI-enabled risk management shows that professional service work is also undergoing task redistribution rather than occupational replacement (PwC, 2024). In financial risk management, AI can support data screening, anomaly detection, and information analysis, while professionals remain responsible for evaluating results, considering contextual factors, and making decisions. This suggests that AI's impact should be analyzed through changes in task structures across occupations.

A key challenge for vocational education is the decline of traditional entry-level tasks. Activities such as manual inspection, standard reporting, and basic fault identification have provided important opportunities for beginners to develop practical knowledge. As these tasks become increasingly automated, vocational institutions need to provide more structured learning experiences through simulations, case-based training, and workplace projects. Students should learn not only how to use AI tools but also how to evaluate AI outputs, identify data problems, and make responsible technical decisions. These findings suggest that vocational education should avoid focusing on specific AI tools that may quickly become outdated. Instead, training should emphasize more durable capabilities, including technical understanding, data evaluation, AI output verification, problem solving, and professional judgement. AI should be integrated into authentic technical tasks rather than taught as an isolated skill. Although this study focuses on industrial equipment maintenance, the task-based framework can also be applied to other fields where AI changes the relationship between technology and human expertise.

This study has several limitations. The analysis relies mainly on occupational descriptions and existing research rather than direct workplace observations. Differences across industries, organizations, and stages of AI adoption require further investigation. Future research could combine workplace data, job advertisements, and employment information to examine how AI-driven task changes influence skill requirements and career development over time.

References

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics, 118(4), 1279–1333.

Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. P., Basto, J. P., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., ... Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International Journal of Information Management, 71, 102642.

Eloundou, T., Manning, S., Mishkin, P., & Rock, D. (2024). GPTs are GPTs: Labor market impact potential of LLMs. Science, 384(6702), 1306–1308.

Felten, E. W., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. Strategic Management Journal, 42(12), 2195–2217.

Frank, A. G., Dalenogare, L. S., & Ayala, N. F. (2019). Industry 4.0 technologies: Implementation patterns in manufacturing companies. International Journal of Production Economics, 210, 15–26.

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mechanical Systems and Signal Processing, 20(7), 1483–1510.

Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial artificial intelligence for Industry 4.0-based manufacturing systems. Manufacturing Letters, 18, 20–23.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192.

OECD. (2023). OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market. OECD Publishing.

OECD. (2026). Developing vocational education and training with artificial intelligence. OECD Publishing.

Pizzinelli, C., Panton, A. J., Tavares, M. M., Cazzaniga, M., & Li, L. (2023). Labor market exposure to AI: Cross-country differences and distributional implications. International Monetary Fund.

PwC. (2024, March 7). How GenAI can enhance risk management. PwC. https://www.pwc.com/us/en/industries/financial-services/library/gen-ai-and-risk-management.html

Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human–Computer Interaction, 36(6), 495–504.

Author Biography

1. Yin-Zhen Huang, PhD Candidate, Graduate Institute of Technological and Vocational Education, National Taipei University of Technology. Her main research interests include Strategic Human Resource Management (SHRM), AI-driven workforce transformation, and cross-domain talent development in vocational education.

2. Dr. Ming-Hsiu Tsai, Assistant Professor, Graduate Institute of Technological and Vocational Education, National Taipei University of Technology. His current research interests include generative AI for image and video creation, multimodal digital content generation, AI-enhanced teaching and learning design, human–AI collaboration and generative AI literacy, AI agents and educational workflow automation, and the impact of artificial intelligence on technological and vocational education and workforce development.

Acknowledgements

Special thanks go to Enterprise Mentor Mr. Hui-Ming Pao for his insightful advice and constructive feedback, which greatly enhanced the quality of this study.