Construction and Comparative Analysis of AI Skill Systems under the Nationalization of Vocational Education

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Abstract: Artificial intelligence skills development is a national priority which is now taken by governments in the world and vocational education is taking the center stage in this change. The paper constructs a four-layer AI skill model, which comprises foundation literacy, application practice, innovation creation, and governance ethics, and applies it to examine how five leading economies (European Union, China, the United States, Singapore and Germany) incorporate AI skills into their systems of vocational education. The discussion is based on national policy documents, standards of curriculum to review each system in seven dimensions (policy maturity, curriculum integration, industry alignment, teacher readiness, infrastructure investment, ethics governance, and student outcomes). Findings indicate that Singapore and the EU are leading in structured integration of curriculum, China has invested most in infrastructure and fallen behind in ethics governance and United States has been relying on market-based policies that bring about disparate access. The dual-system model in Germany is the most successful in terms of industry alignment but with very slow adoption of AI-specific content. This paper has noted three structural gaps that cut across the five systems: the gap between training AI tools and critical AI thinking, a lack of teachers who can train in AI in a vocational setting, and a lack of portable AI skill credentials that are cross-border. The suggested framework offers a viable blueprint to policy makers interested in creating AI skill systems that will be economically competitive and socially just.

1. Introduction

1.1 Research Background

Artificial intelligence is fundamentally transforming workplaces more rapidly than the education system is keeping up with the change. In 2023, the World Economic Forum also predicted that 44 percent of core skills of workers will be replaced, and AI-related competencies are now mentioned in job ads in all industries, including manufacturing and healthcare, logistics and agriculture. This change has the most impact on vocational education, since it does not have the buffer that university education offers to graduates with a longer study duration before they enter the labour market.

The urgent need is acknowledged by governments of nations. The European Union introduced the Digital Education Action Plan and revised the DigComp framework to 2.2, which has clear AI literacy indicators [1]. Between 2021 and 2025, China has announced its New Generation AI Development Plan and spent more than 50 billion yuan on AI education infrastructure. Singapore has developed a national system, SkillsFuture, which links AI competency certification to jobs. Germany has integrated digital skills into its dual-system apprenticeship standards. The US does not have a centralised education ministry; instead, its industry certifications and state-level efforts result in a patchwork quality. Regardless of this activity, there is no generally accepted framework to determine what AI skills vocational students indeed require.

The majority of the available frameworks are oriented towards university students or knowledge workers [2]. They focus on programming, algorithm design, and research skills—these are important to AI developers, but they lack what a factory technician, a nurse, or a logistics coordinator can use effectively to collaborate with AI systems. Kasneci et al. [3] demonstrated that large language models

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open opportunities and risks to education; yet their discussion of these opportunities and risks was limited to higher education in general, without considering the limitations of vocational education specifically: shorter education duration, greater connection to employer demands, and students who tend to favour practice over classwork.

1.2. Research Significance

For these reasons, three questions are tackled in this paper. First, what AI skills do vocational students need that can be structured into a coherent framework? Second, how do major national systems currently provide these skills, and in what contexts do they work well or poorly? Third, what structural gaps remain among these systems, and what would it take to close them?

We develop a four-level AI skills framework, extend it to compare five national systems, and examine the cross-cutting gaps which require concerted action. This framework is built upon a spectrum of knowledge: at one end, there is a level of digital proficiency and ethics control (the simplest form of AI usage), and at the other end, there is a multiplicity of positions occupied by vocational graduates in the contemporary economy, all built upon the same foundations.

2. A Four-Level AI Skill Architecture

Current competency models represent only some segments of the AI skill landscape but overlook the big picture. Digital competence in the framework of the EU is addressed in general, with AI being one of the many subtopics [1]. Ng et al. [4] created an AI literacy survey, which assesses affective, behavioral, cognitive, and ethical aspects but their measuring rod is aimed at general populations and is not occupation-related, unlike vocational learners who should master AI that is occupation-specific. Thornhill-Miller et al. [5] assessed 21st-century skills including critical thinking and collaboration but did not integrate AI-specific competencies into their model.

We suggest a four-level model tailored to the vocational education settings (Figure 1). All levels are based on each other and vocational programs may be used to address various levels based on occupation and program length.

2.1. Level 1: Foundation and Literacy

This level identifies three clusters of competency. AI ideas and vocabulary helps students to know what machine learning, neural networks, training data, and model outputs mean in plain language—not mathematical abstractions, but functional concepts which they will work with at the workplace. Computational thinking and data literacy, by the way, teaches them to break things down step by logical step, to detect signals in data, as well as to appreciate how data quality impacts AI system performance. Tinmaz et al. [6] concluded that, as part of a systematic review, digital literacy remains unevenly defined across educational contexts, which makes this foundational level especially important for creating shared understanding. Competent use of digital tools equates to the basic software and hardware skills that all future AI learning requires.

2.2. Level 2: Application and Practice

Level 2 moves from comprehension to action. AI tool operation and prompt engineering gives students the tools and skills to work with generative AI tools and AI-powered software at work in relation to a job. A medical assistant learns how to work with AI-assisted diagnostic tools; a factory worker is trained on the operation of AI-driven quality inspection systems. Data analysis and visualization learns how to collect, clean and interpret data with access to tools—spreadsheets, dashboards, and low-code analytics platforms and not Python or R. Workflow automation learns how to find similar processes repeated, design automation systems using low-code platforms, and understand if automation really enhances results. Cetindamar et al. [7] found that employees' digital literacy is directly related to their acceptance of new technologies, which validates that Level 2 skills are the driving force of real world AI implementation in the workplace.

2.3. Level 3: Innovation and Creation

Targeting advanced vocational students and technicians. Training in AI-driven problem solving teaches students how to spot workplace issues that AI can help solve, word these problems in terms an AI system can analyze, and assess whether the AI solution actually outperforms existing methods. Human-AI collaboration design helps to design workflows through which humans and AI can effectively work together — which tasks the AI addresses, which tasks humans address, and how to handle handoff points. Industry-specific AI integration covers how AI transforms particular industries, to include predictive maintenance in manufacturing, precision agriculture, personalized patient care, or intelligent logistics routing. Morandini et al. [8] found that organizations require upskilling (the need to deepen skills that already exist) and reskilling (to build completely new competencies) in order to better integrate AI, and that which is reflected by this level as a double purpose: to improve pre-existing work or skills and develop new ones.

2.4. Level 4: Governance and Ethics

The upper tier features all that currently is being left by all vocational programs but which will become crucial in the spheres where AI systems will become consequential. The practical ethics of AI and AI usage go beyond theory to address practical situations in the workplace: What happens when a logistics worker monopolizes delivery paths given to them by an AI routing code due to discrimination? What would a doctor do to an AI suggestion that he/she believes to be wrong? Data privacy and security have the practical aspects of the processing of personal data, an understanding of consent efforts, and awareness of data breach. The policy interpretation with AI would practice the skills of reading and implementing AI regulations, the EU AI Act, or China algorithm governance rules or other sector-specific norms, in practice. In a study of the application of ethical principles to AI in education in 16 countries, Nguyen et al. [9] identified a big difference in the significance of transparency, fairness and accountability in practice across different cultures hence governance skills should be taught like cross-cultural skills rather than a single ethical concept.

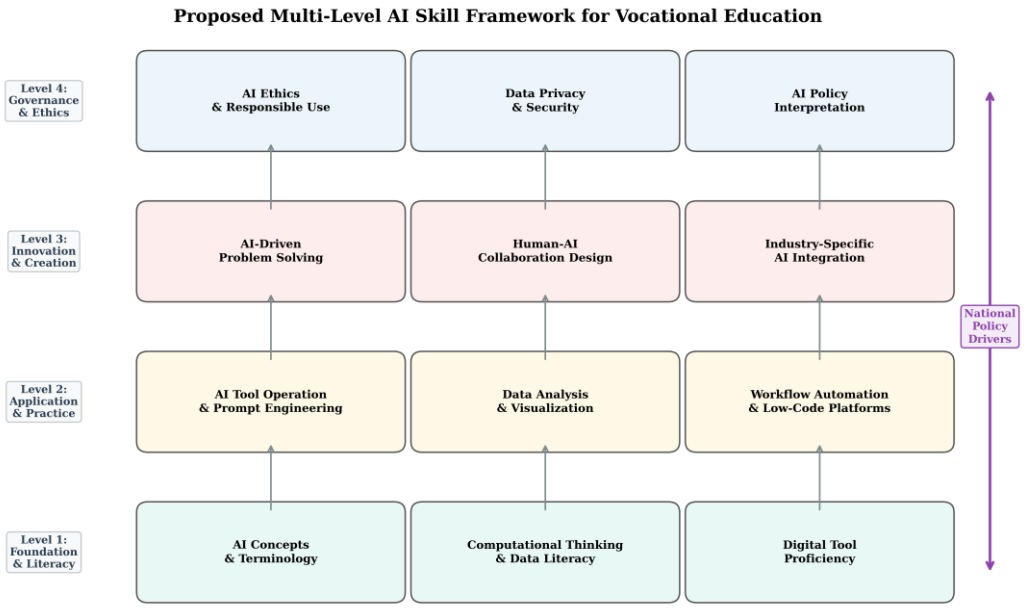

Figure 1: Proposed four-level AI skill framework for vocational education. Each level builds on the competencies below. National policy drivers shape requirements at every level, and occupation-specific pathways determine which levels a particular program emphasizes.

3. Five National Systems Under the Lens

We apply the four-level framework to evaluate five national systems. For each system, we analyze policy documents, curriculum standards, published evaluations, and empirical research. Table 1

summarizes the ratings across seven evaluation dimensions, and Figure 2 visualizes the cross-national comparison.

Table 1: Cross-national comparison of AI vocational education readiness (scores 1–10)

Dimension	EU	China	USA	Singapore	Germany
Policy Maturity	9	8	6	9	8
Curriculum Integration	8	7	7	9	8
Industry Alignment	7	9	8	8	9
Teacher Readiness	7	6	7	8	8
Infrastructure Investment	8	9	8	7	7
Ethics & Governance	9	6	7	8	8
Student Outcomes	7	7	8	8	7
Average	7.9	7.4	7.3	8.1	7.9

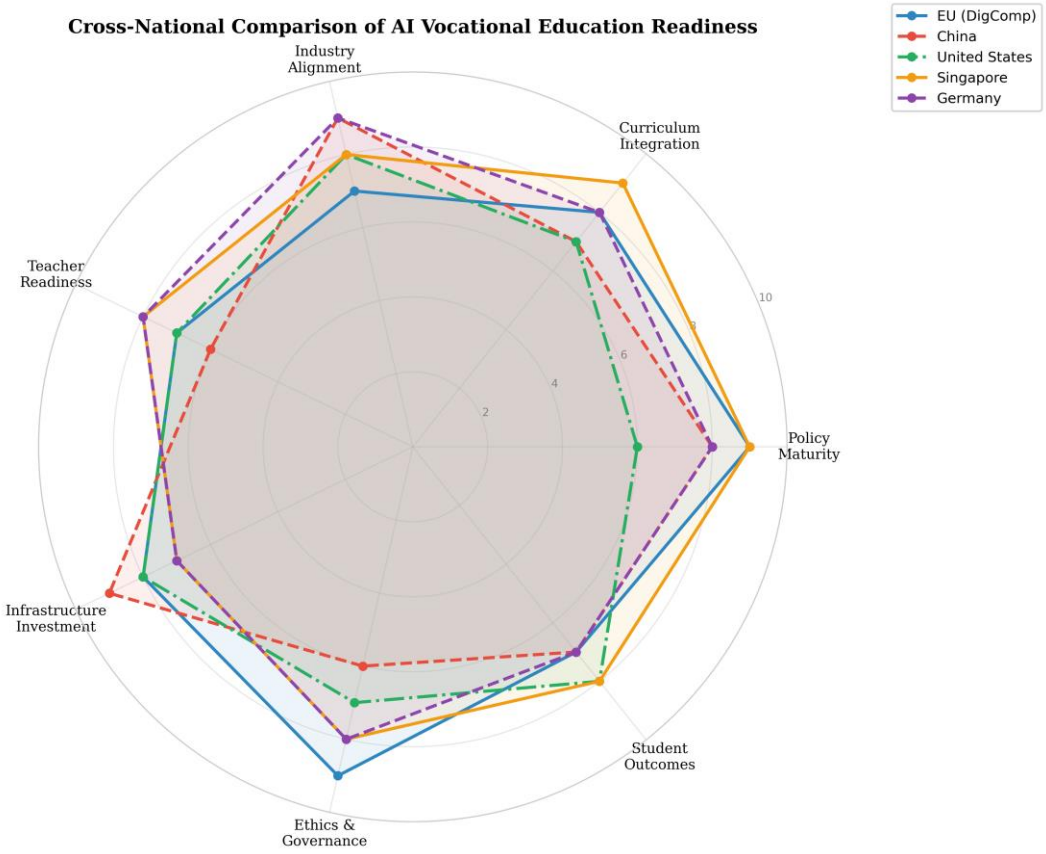

Figure 2:Radar chart of five national systems on seven dimensions of AI vocational education readiness. Singapore and the EU have the most balanced profiles whereas China and the US have more strength in disparity between dimensions.

3.1. European Union: Policy-Led Standardization

The EU builds its AI education strategy on the DigComp framework, which now includes AI-related descriptors across all five competence areas. This top-down design brings about some degree of consistency: The vocational institutions in the 27 member states have a common point of reference

in terms of curriculum development. Timotheou et al. [1] summed up the influence of digital technologies on the structure of educational systems and discovered that the policy instruments such as DigComp contribute much faster to adoption with funding and teacher training resources. The EU is better in ethics and governance since the AI Act has established legally binding requirements to be taught in vocational programs.

Nonetheless, the pace of implementation is also radically different among member states. Nordic countries implement AI content in vocational education within a few months after policy changes, whereas in Southern and Eastern European countries, two to three years is a common lag because of the insufficient teacher training infrastructure and budget limitations. Cattaneo et al. [10] determined the digital competence of Swiss vocational teachers, a non-EU country that applies similar frameworks, and discovered that age, subject area, and institutional support of teachers was the group that best explained the difference in digital teaching competence. This observation indicates that fine policy systems cannot work without concomitant investment towards the development of teachers.

3.2. China: Infrastructure-Heavy, Ethics-Light

The vision of AI vocational education in China is mass investment in infrastructure. Between 2020 and 2024, the government constructed more than 1,200 AI training facilities in vocational colleges, and joined forces with technology firms such as Baidu, Huawei, and Alibaba to create industry-focused curricula. The strategy generates high scores in terms of industry alignment since employers directly influence training material. The vice manifests itself in morality and political culture. Chinese Vocational AI education focuses on technical and industrial applications but spends little time discussing the privacy of data or bias in the algorithms or social aspects of the AI implementation. Li [11] highlighted reskilling in Industry 4.0 as an international requirement when he pointed out that besides technical training, workforce preparation at Industry 4.0 needs to be more of a critical thinking of how technology transforms social systems and power distribution. Through its vocational system, China has considered the technical aspect comprehensively and the critical thinking aspect whereby it is given the second priority.

3.3. United States: Market-Driven Fragmentation

The absence of a federal system on vocational education subjects the development of AI skills in the US to state processes, on one hand, community colleges, and business certification, on the other. Such market-based intervention yields innovation on the most elite level-community colleges in California, Texas, and Massachusetts have state-of-the-art AI courses but in rural and poor regions, AI learning is low. Bond et al. [12] performed a meta-review of AI in higher education and called for increased ethics, collaboration, and rigor. Most of their findings resonate, particularly in the context of vocational education, where programs are likely to implement AI tools also without students developing the skills to think critically and question the tools. Overall, the US has high student outcomes and industry alignment in regions with heavily funded programs, which is reflected in the national average, but which obscures enormous geographic inequalities.

3.4. Singapore: The Compact Integrated Model

Singapore's SkillsFuture initiative is the most tightly integrated among the five systems in its approach to AI vocational education. At the government level, the government works directly with industry to set skill requirements, finances individual learning accounts that workers use for AI courses, and has a national skills taxonomy that ties AI competencies to specific job roles. Overall, Singapore scores highest because the smaller size means policy can be implemented quickly, industry-government coordination can be held close together, and there is consistent quality control. The problem is scalability: Singapore's approach is suited to a city-state of 5.9 million people but would be difficult to do in other, larger, more diverse countries. Ng et al. [13] examined teachers' AI digital competencies in a post-pandemic context, and they discovered that structured professional development programs help teachers incorporate AI into their teaching more effectively; Singapore provides this systematically but larger countries find it difficult to scale.

3.5. Germany: Dual-System Strengths and Digital Gaps

The dual-system apprenticeship framework in Germany integrates vocational training at workplaces, thus delivering good industry congruency. Apprentices get acquainted with AI tools in the same settings that they will be employed at after graduating. As Antonietti et al. [14] demonstrated, the digital competence of teachers affects the technology acceptance in vocational education, and the apprenticeship trainers in Germany, who are industrial practitioners and not vocational teachers, were more likely to demonstrate high practical digital competencies but reduced systematically-teaching AI concepts. Germany is very high on the readiness of the teachers due to the fact that the apprenticeship trainers come equipped with practical experience in the industry, but this advantage leads to another challenge which is that training is not concept-based but rather tool-specific. A learner could master an application of a particular AI-enabled welding inspection system without having the conceptualization of the general principles that will enable them to adopt a new AI system in his/her employment. This indicates an overarching conflict in dual-system models of short-term employer demands and skills transferability in the long run.

4. Structural Fractures That Cut Across All Five Systems

The cross-national comparison reveals three structural problems that appear in every system, regardless of political structure, economic development level, or educational tradition.

4.1. The Tool-Thinking Gap

Every system equips students to work with AI tools. No system adequately teaches students how to think critically about AI. Vocational training for students trains them to engage with ChatGPT, Copilot, or industry-specific AI software; they seldom develop the metacognitive skills required to know when AI outputs are wrong, biased, or inappropriate for a given context. Celik et al. [15] conducted a review of AI challenges for teachers and discovered that most educators focus on AI as a teaching tool rather than as a subject that demands critical examination. This trend carries over to the vocational education where educators instruct students to become proficient users of AI tools and not to become intelligent critics. The tool-thinking gap is important because vocational graduates end up in jobs where AI errors can directly impact them. A manufacturing technician that agrees to a wrong quality prediction by AI will deliver defective items. When a healthcare worker inaccurately triage with the recommendation of the AI, the worker postpones the urgent treatment. Since this gap needs to be bridged by changes in the curriculum, where critical AI understanding is taught in all practical tasks, not as an ethics course but as part of training on how to use the tool.

4.2. The Teacher Bottleneck

The vocational teachers who are able to teach AI effectively are seriously lacking in all the five systems. The issue has two facets. Firstly, there are still numerous vocational instructors who do not know much about AI technology themselves. Cattaneo et al. [10] noted that the digital competence of vocational teachers was significantly differing; many were below the necessary level of digital competence to handle digital topics. Second, industry positions to which AIskilled individuals can earn much more than teaching are a recruitment problem, which will grow more critical as the need for AI grows. Ng et al. [13] demonstrated that professional development programs should be organized in a systematic way, which in turn was suggested to enhance AI competences of teachers, yet it required along-term funding and organizational dedication that many other vocational systems were deprived of. The teacher bottleneck forms a vicious cycle: without skillful AI teachers, vocational programs will not produce AI curricula; without AI curricula, no demand will be created on AI teachers; no demand will ensure that AI teacher-training programs will be funded.

4.3. The Credential Portability Problem

The skills in AI taught in a vocational system in one country are of less importance in a different country. The competencies of an AI-related German apprentice, as certified by the dual-system test cannot be automatically accepted as valid in France, much less in China or the United States. This

unportability is a source of friction in global labour markets and fails to allow workers to take advantage of AI skills that they really have acquired.

Livingstone et al. [16] synthesized the findings that targeted the outcomes of digital skills acquisition among the young people they found out that formal credentials can have a profound impact in determining whether digital skills introduce benefits into employment opportunities or not. International mobility between vocational graduates will mean that they have to re-verify skills they already have, without portable AI credentials, which is a waste of time and discourages international mobility. Mutual recognition arrangements of the EU are a partial solution to the problem in Europe but there is no counterpart on the global scale.

5. Breaking Forward: What Genuine Progress Requires

Structural gaps noted above cannot be bridged by incremental enhancements of currently available vocational AI programs. The actually changed trajectory could be changed by three transformative changes.

Integrate AI urgency in all of practical exercises. Rather than just having standalone AI ethics courses that students view as a checkbox requirement, professional training can guide practical tasks by reorganizing them in such a way that critical reflection on artificial intelligence outputs cannot be dissociated with using the other tool. Whenever a student interacts with an AI system, an exercise must encourage at some point when students determine possible ways of failure, comparing results with other sources, and recording their explanations. The current tool thinking gap being discussed here develops the metacognitive processes. Kasneci et al. [3] contended that huge language models necessitate novel methods of pedagogy extending beyond customary information provision, and this concept of embeddedness is equally applicable to vocational AI education. Issue cross-border AI micro-credentials, with machine-verifiable evidence.

The second group of international conferences to reconcile the credential frameworks will not solve the issue of credential portability. Instead, vocational policies are to adopt micro-credentials with machine-coded manifestations of competence-recorded versions of AI tool use, portfolios of AI-assisted pieces of work, and standard evaluation results stored on digital systems that are interoperable. These qualifications follow the employee; can be verified by any employer anywhere and are accumulated over a career rather than becoming obsolete with just a single qualification. This approach avoids the time consuming government to government credential recognition operation and builds bottom-up reveal of AI capability.

Educate teacher AIResidencies Industry. Traditional professional development workshops will not get through the teacher bottleneck. Vocational systems ought to develop funded residencies where educators work three to six months in AI-intensive businesses, gaining practical experience with AI in real-production conditions. The industry in its turn needs to devote the same amount of time to teaching in vocational schools, introducing the latest AI applications to the classrooms. Such a two-way flow tackles the two aspects of the teacher issue: retraining existing teachers and bringing professionals of the industry into the teaching field. Morandini et al. [8] demonstrated that to train teachers better, more than lecture-based training is necessary, practice-based learning, which is based on immersion in the field and skills of AI, is essential, and the same applies to other employees. The problem of these three changes is a common sense: they transfer the development of AI skills not as an abstract system but as specific, verifiable, activities integrated into practice. These shifts that national vocational systems make will result in graduates who can not merely use AI tools but can also make critical evaluations of them, demonstrate competence to any employer, and be educated by teachers with a real experience of AI use in industry.

There are not merely stakes in a certain employability. The nations developing powerful AI professional training systems will get the most technologically advanced manufacturing, can have more people involved in the AI economy, and will also lower the risk of AI causing a two-career system with AI elites and replaced low-skilled AI employees. Those nations which perceived vocational AI education as an incidental consideration will follow the trajectory of observing the loss

of workforce and competitiveness of their industries as well as the social fabric stretched to its limits by technological displacement without appropriate preparation.

6. Conclusion

This paper examined how AI skills are incorporated into vocational education across five national systems and proposed a four-level framework to structure these competencies. The comparison shows that while each system has strengths, none achieves balanced development across policy, curriculum, industry alignment, and ethics governance. Three structural gaps—the tool-thinking gap, the teacher bottleneck, and the lack of credential portability—are found across all systems, indicating that current approaches remain incomplete. The proposed framework offers a structured way to organise AI skills and identify where improvements are needed. Ultimately, vocational AI education is not only about training students to use AI tools, but also about enabling them to think critically, adapt across contexts, and demonstrate skills in a transferable way.

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