Occupation and Professional Education Vol. 3 No. 5, 2026

Managing Generative AI Dependence in Vocational Education: An Institutional Governance Perspective

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Abstract: Generative AI is finding its place in vocational education, not just for students seeking help accessing information, translating content from other languages, and organizing report structures, but in writing assignments as well. This presents a threat beyond plagiarism and shake-me-up-words, if vocational institutions have to decide what kind of error-ridden, messy assistance is appropriate, how to confirm mediated evidence,. how to sort out teacher assistance provided to students, and how to assure quality. Once again, the suggestions come down, more or less, to managed dependence, recommending that we take risks on two sides.

Keywords: Generative Artificial Intelligence; AI Dependence; Vocational Education; Institutional Governance; Assessment Credibility; Quality Assurance

1. Introduction

Generative AI has shifted from a niche technology to a commonplace learning tool. People no longer meet it only in purpose-built digital learning environments. They encounter it in search engines, writing aides, translation tools, coding assistants, and chatbots. For many students, the first thing they do when faced with a challenging assignment is consult an AI system for an explanation, outline, example, or draft. This makes sense! GenAI is fast, patient, and present when learners feel stuck. Chan and Hu (2023) report that students view GenAI as a positive source of help in terms of learning support and academic tasks. Ilieva et al. (2023) suggest that generative chatbots can make it easier for students to step into challenging materials and unfamiliar academic language.

The same convenience that gave birth to the problem has also transformed educational settings in ways that further complicate governance. The line between student work and those who get help becomes blurry in this convenient world. One student queries the AI to better understand a concept. Another reorganizes a weak paragraph. A third student asks the AI to produce a report of some kind, or a reflection, teaching plan, business proposal, or technical explanation. The final product might be difficult to distinguish in these three cases. The work that produced it is not similar, and therein lies the governance problem.

The sharpening of the problem by vocational education settings may be evident. In vocational education, written and documentary work are often proxies for field competence. An intern"s logs may document "observations" of a work setting. A training plan may inform a "lesson." A "final report" may show "decisions made by the student," who explains "acceptable practice" and demonstrates "transferability to occupational constellations." From care plans to technical designs to our very pedagogical documents we speak as if they document the student"s learning. If the AI is a production mechanism hidden in this process, then surely the product provided for faculty assessment may no longer reliably reflect the learning of the student.

Even public reporting suggests that institutions see this problem. Australian universities "revised their arrangements" from "a system relying on take-home assessments," reported as print-and-grammar mark systems, to supervised pen-and-paper ones, amidst concern students were using generative AI-assisted chatbots to commit academic fraud (Cassidy, 2023). Higher ed reporting also reported on tests of AI-writing detection capability as duplicitious detections can create as many problems for students as elsewise for faculty via false positives as well as false negatives, without accounting for the punishment-focussed enforcement system schools so love to learn for us without interruption (D”Agostino, 2023). More recent reporting discusses a pivot that isn”t just endorsing a clear AI policy, it”s deploying agility techniques for ramp-policy-work, including clarity, pen-and-paper use, verbal assessment “to better inform their gradebook,” along with course-level statements and new quality controls for take-home work (Gecker, 2025). We don”t report these citations here as a causal factor but rather simply high level examples of institutions being pushed to change routines they thought were settled.

This article looks at the question through the lens of a more common form of AI dependence. I use the term here in an educational and managerial sense. I don”t mean clinical addiction. I mean the dependency on AI as a standard way of completing and handing in academic, work, or assessment-related tasks. This dependency may not always be inappropriate. It may enable understanding, or help students who are not native speakers of the language of the material available, or improve access to difficult material. It is a management problem if the university cannot tell if AI has supported their learning, or if an AI has substituted for the learning effort the task was designed to demand.

This article is written as a conceptual paper to help vocational education institutions. Rather than report original empirical findings, I use research, policy documents, and other public examples to develop the argument. Essentially, my main claim is very simple. Education institutions should not stop with detecting AI-generated text in order to address AI dependence. They should build capacity to manage AI-supported learning, and changes in assessment of AI risk. Capacity built on risk classification, clear rules, disclosure routines, and clearer process evidence, teacher support, student AI literacy, and quality assurance that looks very much at evidence credibility and much less at paperwork.

China and Malaysia are both informative systems for the purposes of exposition. China has a large higher vocational education sector, and a policy emphasis on reforming educational evaluation beyond a narrow set of outcome indicators (The Central Committee of the Communist Party of China and the State Council, 2020). Malaysia”s official TVET portal describes TVET as “education and training leading to employment and entrepreneurship”. (Malaysia Government, 2026) The Ministry of Education Malaysia (2023) and the Ministry of Science, Technology and Innovation Malaysia (2023) go on to talk about digital education and AI in the context of national development and skills. I do not suggest that the two systems are the same, but show that AI governance will be shaped by common technological pressures, and by the local institutional conditions it encounters.

2. Conceptual Orientation: From Tool Use to Governance

Early conversation around GenAI in education was whether the tool could help or hurt. That question is important, of course, but too general for the level of management we”re discussing. GenAI can help when it helps explain a hard idea, or gives feedback, or translates a hard technical phrase, or helps the student test their argument. It can hurt when it replaces independent thought, or skips authorship, or helps students superficially complete a task, or probable reasoning as if it were definitely so. Abbas et al. (2024) show that generative AI use by students produced both harmful and helpful consequences. Hadinejad et al. (2025) also report that students” experiences with GenAI include perceived benefits and ethical risks.

A governance perspective begins from a different question. Instead of asking, “Is AI good or bad?” we ask what will institutions put in place for when AI use becomes likely? That question matters because a swath of students will use AI whether institutions are moderately prepared, or not. If rules exist not, students make private decisions. If rules are vague, teachers interpret them inconsistently. If rules too restrictive, students hide uses which are in some sense legitimate. If rules too loose, the credibility of assessment can be eroded. Governance in this vision is not optional added dry layer of bureaucracy above some shiny new tool. It is what we construct to enable ourselves to use AI in integrity.

User acceptance research suggests how quickly students will spread use. Acceptance (adoption) of technology is determined by perceived usefulness, perceived ease of use, social influence, and facilitating conditions (Venkatesh et al., 2003). GenAI meets many of those conditions: easy to access, immediate response, apparently generically useful for many things we do, easily recommended (informally) by peers. When a normatively accepted tool (tool,

certainly) is available, depending on it can become habit not customized misconduct.
This governance issue and educational validity are closely related. Assessment of validity is not a property of a task; Kane (2013) suggests that it"s an issue with the inferences and uses we draw after the fact from the evidence, not the property of the assessment itself. Messick (1989) reframes validity as an evidentiary and interpretive problem -validity that is not property or property of a test. That vocational report is, credible (or can be) evidence, if it is truly the student"s own observation and reasoning and practice. That same report is weaker evidence if AI supplied most of the reasoning and the student did not explain it or deliver it. This is not to say that every AI assisted text is invalid. It"s just that governance presumably begins with an institution feeling the need for stronger evidential chains, if the final product alone is no longer evidence enough. This "orientation" in turn leads to the notion of managed dependence. Managed dependence acknowledges that depending on AI will happen and asks institutions to carve out the differences in use. In some sense, low-stakes learning support and high-stakes certification ought not be treated as the same transaction. Drawing that rough outline doesn"t mean outsourcing graduation report. Translating is not the same as replacing professional judgement. Thoughtful governance might delve and reward these differences, helping student and teacher craft rules they can abide.
This position also disentangles governance and surveillance. Surveillance asks the question of how an institution can catch someone misusing something after the fact. Governance asks the question of how the institution might design tooling such that legitimate use is easier to comprehend, and risky use is harder to hide. The difference is significant. Over-reliance on policing can erode trust - especially where detection tools are themselves uncertain, or students are using AI in ways that are permissible like translation, or editing. D"Agostino (2023) suggests the uncertainty and fairness issues that surround AI-writing detection. Luo says (2024) that assessment policy should reassess originality, and student work, in the light of GenAI. A governance approach does not ignore misconduct. It stands misconduct against the rest of the infrastructure of assessment design, teacher judgement, student literacy, and institutional accountability.
Managed dependence, therefore, facilities a principle of proportionality. Not every task needs the same level of control. A weekly vocabulary exercise, a formative note of a discussion, and a final portfolio of competence, each have different stakes attached to them. Accordingly the management response need differ. Kane (2013) ties assessment validity to the interpretation and use of results. Messick (1989) also emphasises the relation of the evidential base to the meaning of assessment outcomes. The more high-stakes the use of a result, the stronger the evidential chain should be. The more developmental the activity, the more the institution can decide to take chances, and to guide.
The approach engenders AI literacy as part of professional formation. Students need to learn how to challenge AI outputs, to verify technical information, to document being helped, and decide when human judgement has to override that of a machine. These are not solely academic skills. These are "workplace" skills. Future employers ought not only to expect students to use "AI tools" but still to be jurists, historians, and writers rendering their own judgement and decisions, and standing fully accountable for records and services. Miao and Holmes (2023) advocate a reliance on human agency, and for transparency in and responsible education use of GenAI. The OECD (2026) also warn how AI should assist learning, rather than substituting for students cognitive effort. Vocational institutions therefore need to help those students learn to use AI well, whilst nevertheless eschewing to allow AI to replace good, occupational judgement.

3. Why Vocational Education Faces a Distinctive Risk

Vocational education is especially vulnerable to the problem of AI governance, because many of its assessment tasks are documentary representations of practice. Learners are asked to describe what they did, explain how they solved a problem, justify a choice of procedure, reflect on what they learned in workplace and simulation settings. Businesses find documents appealing because they are scalable and archivable, and documents are easy to grade with a rubric. They seem authentic because they touch on questions of professional practice.
Authentic assessment is important. It can help

make connections of classroom learning and life of work, support growth of reflective judgement, and encourage students to apply what they know beyond exams. Assessment that supports long-term learning has long been understood to be more educationally powerful than that which rewards only short-term performance (Boud & Falchikov, 2006). Digital technologies promise to strengthen authentic assessment even further, by providing capture of learning process, access to promptings, and evidence of progress (Hu et al., 2025).

Alas, the arrival of GenAI does not devalue authentic assessment. It does challenge the premise that anything with the look and feel of authenticity must have evidentiary weight. A workplace-style report can be generated without workplace understanding. An internship reflection can sound mature even if the young woman does not think deeply about her experience. A technical explanation can seem correct even when the high school student cannot transfer a principle to a new setting. The task remains authentic in theme, but the strength of its evidentiary weight drops steeply when the process is invisible.

It"s unwarranted to simplify the problem to "those brats are cheating me." Many students use AI because they are under time pressure, unsure what constitutes academic writing, anxious about grades, or at sea as to how to structure experience in a long form of formal language. Some use AI for translation or a grammar checker to make their own work that they have learned to speak, easier for readable audience. And students use AI because they don"t yet know where my legitimate support ends and my cheating begins. A governance system in which all AI use is assumption of cheating will fail to see these differences, and will do a poor job of catching differences. It"s likely to also create hardship conditions for students who hide their AI use from teachers. Today, unmoderated-time AI use surely seems likely to lose.

Unmoderated-time use of AI systems creates sufficient danger to deserve respect. If I can submit AI minutes of practice reflection, AI training report, AIshall act in good faith before beginning work on the patientcare and AI professional goals plan on line, I surely will not earn, honor, theory of habitual Taradiddle tips, with AI, I will give you fair about where your luscious cert is in the AI tool and cheat line, entitled chargé.

The solution is not to abandon written work, because documentation is an essential part of many occupations. Teachers write lesson plans; nurses record medical and observations. Engineers send memos—at least early ones do—and so forth. Vocational learners should learn to document. AI will likely be part of future workplace practice. The key is to make sure that documents are backed with data that students will come to understand, recognize as their own and defend.

Table 1. AI-related Risk in Vocational Assessment Tasks

Assessment task	Why the task matters	AI-related vulnerability	Governance safeguard
Training report	Shows understanding of procedures and practice outcomes.	AI can generate a fluent report from limited notes.	Require process notes, teacher questioning, and evidence of task completion.
Internship log	Connects workplace experience with reflection and professional growth.	AI can create generic reflection language that hides limited engagement.	Use workplace confirmation, reflective prompts, and short oral checks.
Project or design document	Demonstrates planning, judgement, and problem-solving.	AI can organise plans and justify decisions without student reasoning.	Add milestone reviews, draft comparison, and defence of key choices.
Graduation-related work	Supports final judgement of readiness and competence.	AI substitution can weaken certification credibility.	Use supervised components, oral defence, transfer tasks, and practical demonstration.
Routine formative work	Helps students explore ideas and improve expression.	Overuse may reduce independent effort and practice.	Permit AI support with guidance, disclosure practice, and verification habits.

4. Public and Policy Signals of Institutional Adjustment

Formal research develops more slowly than institutional practice. Public reports, then, can offer contextual signals. Reports on universities and schools alike show that AI has already forced test redesigns, course policy changes, debates over detection, and teacher advice. They are hardly substitutes for the peer-reviewed literature, but they can help us locate the practical problems that institutions are trying to solve.

One response that can be readily observed is a return to supervised or in-class assessment. When take-home writing is difficult to verify, institutions may begin to swing toward oral assessment, pen-and-paper work, closed book, or in-class examinations. The point is not a hunger to return to the past. Just to create moments when student reasoning can be observed with some directness. Cassidy (2023) reports that Australian universities have revised their assessment arrangements, citing greater reliance on supervised and pen-and-paper examinations. Gecker (2025) in a similar fashion described schools" move toward "clearer" AI guidelines, in-class writing and verbal assessment to determine what adult educators decide can be called "cheating" when it takes place using AI tools. A second response is detection, although detection is always a somewhat unstable pillar of governance. AI-writing detectors may provide useful signals but, by and large, are not strong enough to carry institutional signals on their own. False positives may damage students. False negatives might create a false sense of security. And detection simply cannot answer our deeper rhetorical question, "What learning has the student done?" D"Agostino (2023) reports flow to institutional interest clearly tinged with concern about the accuracy and fairness of AI-writing detection. A third response is to clarify policy. Students essentially need to know just what things are all right to do with AI in a given course and assessment. It will not suffice to say simply "Do not use AI to cheat." Students need examples. Can I use AI to brainstorm? Can I use it to translate? Can it revise my grammar? Can it rewrite this paragraph? Can it do this in an outline? Can it produce some of my code for me? Can it write a summary of this reading? Help me prepare this presentation? Questions of work and circumstance cannot be left to my private interpretation if my grade depends on it.

International organisations have not skimped on stress-falling responsible governance. UNESCO guidance prioritises human agency, transparency, ethical validation and data privacy, and truly conducive design of educational uses of GenAI for learners and teachers alike (Miao & Holmes, 2023). OECD work globally treats digital education and digital connectedness as ecosystem issues essentially touching on infrastructure, teachers, learners, governance, and evidence broadly and not as simple technology directly adopted by head of the class (OECD, 2023, 2026). In a nutshell, these players are saying, and rightly so in my opinion, that what is needed is concerned with AI in vocational education, or rather, AI in the teaching room, is not necessarily about tools.

However, while public examples are valuable, they need to be approached with care in educational writing. Public news reports capture the visible reaction of institutions, not the dynamics of policy development. A university falling back to supervised exams may be protecting the credibility of those exams; it may also be reacting to the panic of a deadline. A school writing AI in informs syllabi in relationship to its exam integrity, may be creating clarity; it may still be lacking in professional learning for every educator. For this reason, we should read public reporting against scholarly and policy sources rather than treating them as proofs in their own right. In this piece of writing, such reports show that the management problem for AI has become visible beyond the academic community.

Policy documents represent a second sort of evidence. They show how a government and institutions view AI as part of digital transformation, educational innovation, a risk management and quality assurance issue. However, this kind of language can remain too general for classroom practice. External statements about responsible use, human judgment, digital literacy, inform local needs on a school level where school procedures do not translate easily to classroom activities. Vocational institutions specify types of assessment instruments they need: task-risk categories, disclosure templates, rubrics for process evidence, moderation procedures for high-stakes assessment. The Ministry of Education Malaysia (2023) gives "direction" for digital education, while Miao and Holmes (2023) give international guidance for "Responsible GenAi use in education". Outside of useful local instruments, this kind of language can easily becomes symbolic rather than practicable.

5. A Managed-Dependence Model for Vocational Institutions

Managed dependence begins with a basic assumption that students will use AI in some fashion, and educational institutions need a more nuanced response than permissive or prohibited. The model that follows has five interlinked elements: task-risk classification, disclosure, process evidence, teacher support, and quality assurance. Each contributes towards a different weakness in current educational practice.

Task-risk classification is the first. Educational institutions should separate tasks into categories according to the consequences of substitution with AI. The low-risk tasks are mostly formative. They are prompts for students to explore ideas, learn language, or, receive feedback, and the use of AI may be permitted with some guidance. Medium-risk tasks affect grades and will require greater care of boundaries, but students should be permitted to use AI under some conditions, disclosing its role and providing process evidence. The high-risk tasks are those linked to certification, graduation from the course, judgment on internship, or suitable depth of study for professional preparation. Relying on the work turned in is not strong enough authentication.

Disclosure is the next element. Disclosure should be simple, routine and without punishments, if in fact, use of AI is permitted. A simple statement may suffice, asking if the student used AI to brainstorm, to assist in translation, to assist in editing, to assist in outlining, drafting, or answering a coding question or for explanations. Using the AI ought to not be a shameful act on the part of the student. Making boundaries of contribution visible is the purpose of the disclosure, and professional responsibility should be taught. In many cases, the issue will not be if AI was used, but whether its use was of the right kind and appropriate.

Process evidence is the next element. Traces of learning should inform a final product. Draft versions, annotated sources, practice notes, screenshots of project milestones, teacher feedback records, notes of work done or observations made of work environments, or even character sketches to explain a design mission. Process evidence doesn"t have to become bureaucratic. It should be proportionate to the level of task risk. Low risks for a weekly reflection may not require further evidence. Graduation project certainly requires more.

Teacher support is the fourth element. Teachers cannot be expected to figure out AI governance alone. They deserve institutional direction, shared examples, acknowledgment of their heavy workload and high stress, and cathartic professional development. When teachers are “at-risk populations” simply trying to survive, further teacher education is a hard sell. Research into GenAI acceptance by education shows that some factors contributing to positive embracing of the technology by educators are: AI literacy, pedagogical-technological knowledge, and trust (Al-Abdullatif, 2024). If teachers get told the circumstances, but not shown where to go for help, or how to monitor their responses, practice will run amok. Some teachers will ban AI foolishly. Some will ignore it. Some (especially initially) will rely on blind faith in detection tools. None of these responses alone is sufficient for good governance.

Quality assurance is the fifth element. Educational institutions must move beyond checking whether assessment files are turned in, and in an AI-dominated world, quality assurance will include whether the assessment design is substitution-vulnerable, whether the rules of AI-use are salient, whether a disclosure of some sort exists, whether high-stakes tasks include verification, and whether teachers have summarized the support they may need to apply the rules equitably. Quality assurance is not just a “box” to check for the school. It becomes evidence governance. Not “will I pass this class” but “can my grade and certificate be defended?”

Beyond the five key elements discussed above, the present study also identifies two additional objective governance considerations. The first is policy coherence. AI-related rules should not operate as a standalone or temporary add-on, but should be embedded within existing institutional systems, including academic integrity frameworks, assessment design, programme review processes, internship supervision, graduate competency standards, and staff development structures. Without such integration, AI governance risks becoming fragmented, producing inconsistent expectations across courses unless differences are explicitly justified and clearly communicated.

The second is reviewability. Institutional decisions involving AI-assisted work must remain explainable and traceable, particularly when they affect grades, progression, or graduation outcomes. Reviewability depends on documented criteria, transparent procedures, and verifiable evidence. It should not rely on surface-level text features or automated detection systems alone, given the well-documented risks of false positives, false negatives, and fairness concerns in AI-writing detection (D"Agostino, 2023). Empirical evidence further shows that chatbot-assisted writing complicates traditional academic integrity assessment (Gruenhagen et al., 2024). Accordingly, robust governance requires triangulating task-based evidence, process evidence, student explanation, and professional academic judgement.

Table 2. Managed-Dependence Model for Institutional AI governance

Element	Management question	Weak practice	Improved response
Task-risk classification	What is the educational and certification risk of this task?	One AI rule is applied to all tasks.	Classify tasks as low, medium, or high risk and set rules accordingly.
Disclosure	Can teachers see how AI contributed to the work?	Students hide use or guess what is acceptable.	Use short disclosure statements and examples of permitted assistance.
Process evidence	Can the institution verify learning beyond the final product?	Polished submissions are treated as sufficient evidence.	Use drafts, notes, annotations, practical records, and short explanations.
Teacher support	Are teachers prepared to judge AI-assisted work fairly?	Individual teachers carry the whole burden.	Provide training, shared rubrics, departmental examples, and workload recognition.
Quality assurance	Can grades and certificates be defended?	Quality review checks files rather than evidence credibility.	Audit assessment vulnerability, safeguards, rule clarity, and verification practices.

6. China and Malaysia: Comparative Management Considerations

China and Malaysia are useful to think through AI governance in vocational education because both link skills development to some kind of national transformation.The comparison is not meant to rank systems; it just makes clear how some similar technological pressures may be filtered through different institutional arrangements.

In China, higher vocational education is large, policy demanded, and regionally anchored in industrial upgrading and local development. The National reform agenda on educational evaluation stresses that less attention should focus on narrowly defined outcome indicators, and more on capability, development and process (The Central Committee of the Communist Party of China and the State Council, 2020). GenAI makes this reform direction more urgent. If final documents can be produced or polished by AI, then institutions need to pay more attention to how students learn, how learning is demonstrated, and how it is defended.

Chinese higher vocational colleges may also face some implementation challenges. A large system can quickly drop normative expectations, but how are those translated into local interpretation? Different majors have different assessment tasks, and think of a preschool education student, a nursing student, a computing student, a mechanical engineering student: they would be using AI in very different ways. Central rules must be interpreted locally to be made field-salient, or the teacher and student would receive the same general policy but could literally face very different problems.

Malaysia offers further perspective. TVET is "educational experiences" and "training" which provides a base of knowledge and skills required for various types of employment and entrepreneurship (Malaysia Government, n.d.). Digital Education Policy mentions digital competence, infrastructure, content, partnership and governance (Ministry of Education Malaysia, 2023), while the National Artificial Intelligence Roadmap looks at AI as a part of broader innovation and transformation ecosystem (Ministry of Science, Technology and Innovation Malaysia, 2021). These policy conditions suggest that the ways that AI should be learned and cautioned against in vocational education should be as part of the institutional capacity-building process, rather than merely about student discipline.

An emergent multilingual and institutionally diverse landscape in Malaysia may lead to diverging ranges of AI use - students might avail themselves to AI more for translation, or academic English, or Malay-English movement, technical terms or workplace documentation. Such use might afford access but may also obfuscate authorship and thus governance should focus on discerning when translation is use and when concept substitution. Sort of a different world to sort is a student who AI has translated their reflection they"ve written out, to the student who for all intents and purposes asked AI to come up with a reflection.

Singapore provides a useful regional reference even if the main comparison in this article is not. The public education policy references AI as something that should be guided by pedagogy and the approach to student development, and responsible use, rather than merely dealt with as threat (Ministry of Education Singapore, n.d.). This mirrors a wider governance principle, that AI adoption should record, with educational purposes, rather than be left entirely to its own devices. Tools should never lead policy, learning goals should.

Across China and Malaysia, the main policy implication is similar. Institutions need to build practical governance capacity. Rules must be specific enough for classrooms and assessment tasks. Teacher development must be routine rather than optional. Students must be taught how to use AI responsibly. Quality assurance must examine the trustworthiness of evidence. These tasks require institutional coordination. They cannot be left to individual teachers alone.

7. Field-Sensitive Implications for Vocational Programmes

Perhaps you teach early childhood education and wonder how students will interact with AI as they draft lesson plans, mother-teacher communications, observations, or activities and reflections targeted toward young children and families. Certainly the AI"s suggestions may be helpful, but learning child development, classroom dynamics, safety, ethics, and responsive teaching strategies still matter. A professional-looking lesson plan isn"t enough. Ask students to explain why a particular activity is appropriate for children of a certain age and 2.5 is not the same as 3. To ask also how they would adapt those activities for children with different needs or how they might respond should the activity flop means the student has internalized responsibility.

You may teach a health-related programme, perhaps for nursing and allied health. AI may summarize texts, learn vocabulary and nuances of case-situated decision making, or draft patient education materials, but there is greater risk; it will be wrong or assume unverified information and might affect real people in very real ways. “Train” your students to compare AI outputs with previously authorized documents along the way, how to describe where the advice falls down, and how to recognise that their professional choices lie well beyond the code. We are not just confirming that the report is not plagiarized; we are necessitating the accountability for decisions.

You might prepare students for engineering technology or design. AI explanations may help, but make sure assessments require real-world problem solving. Students might be asked to diagnose the fault, justify their decision to repair rather than replace a part, or adapt a plan that"s now subject to an unanticipated constraint. A written technical explanation of the decision may be part of that evidence, but not all of it.

You may have a computing or electronic information programme. One of the special challenges of coding assistants in AI is the risk of being able to offload as much of the actual code as you generate, correct, or explain in a submission. Institutions might be tempted to confuse “I worked with AI on this” and “I just submitted the coding, but had no idea how this actually worked.” Assessment may entail code walkthroughs live alterations and debugging and justification of design decision costs and trade-offs. These forms of verification assist us in spotting when students have not made that knowledge transfer beyond the generated solution.

You may teach in a business or management programme. AI can generate a plausible local marketing plan, propose topics and write a business proposal or executive summary and presentation plan for the local banker. The great risk is plausibility but generic reasoning. Students may present these plans with only a wink and nod to exactly how the plan fits the local area. Teachers might respond by requiring them to bring data from the community, conduct at least one analysis of the incremental situation, defend a decision based on it, and to present their plan orally too. Rather than asking the students what the plan says, ask why it fits that particular problem.

Workplace learning needs special treatment. For work experience and employer tasks, records often receive less super-vision than classroom materials, yet represent powerful evidence. A well-written internship log suggests that a student has seen professional ways at work, thought about problems, and learned rules of thumb at work. AI will make the writing neater but not the observation. Programs, therefore, need to strengthen links among students, workplace mentor, and college teacher. As Boud and Falchikov (2006) comment, assessments that support the aims of long-term learning support not short-term performance. Hu et al. (2025) demonstrate that digital technologies may support authentic assessment that captures learning work and evidence of development. Short mentor confirmations and unexpected oral questions, authentic demonstrations of problem-solving follow-up, can keep internship documentation from becoming a form of text production.

8. Implementation Roadmap for Ordinary Vocational Institutions

Many vocational institutions do not have bands of AI risk governance staff ready to deploy. The managed-dependence approach needs to be practical. A phased roadmap allows ordinary institutions to begin moving from reaction to governance without having to wait for perfect culture change.

Phase one is institutional mapping: departments map what kinds of tasks they have that are most likely to be substitutable by AI. These will almost always include take-home reports, reflective writing, internship log/recording documentation, presentation scripts, project proposals/change management or project management documents and graduation documents, among others. Mapping the material does not require a lot of technology. Instructors will need to look at their assessment tasks with a simple question: could a student complete this task or something close to it without showing the ability that you want to see demonstrated? If so, then that task needs to be remediated or made to capture more evidence.

The second phase is rule-translation: translate X in institutional policy to near term tasks that offer up these examples. Floors and ceilings to use may not translate effectively without a good "rule translation" dive. Teachers and students alike need concrete language: "You can use AI to understand what that work means but you can"t generate the actual final reflection. You can use AI to edit your grammar, spelling and style if you tell me? Or not use AI to write things about your job that haven"t happened? Or things we will factually do in the course, and you will need to submit that one page summary for me?" These examples greatly mitigate the uncertainty we can find ourselves in.

The third phase is the place holder for assessment: schools don"t of course need to rush out to redesign most every task. But high stakes tasks: Ask how all of your graduation projects, internships, competence certifying examinations will have that need checking. Oral questioning? Checking of the "pre-writing" and speed rounding? "Do you know the style guide invariably by heart already?"; "Show me"; "Do you know this patient to your core?"; "Tell me that in your own words loud and clear"

The fourth stage is teacher development: Professional development on cases from your own house. Teachers not only need some awareness, they can help each other with the "yes but this is our real work…" "Here"s how I used AI to do this course, here"s what I wiped my hands off of as borderline and here"s where I squalled and didn"t put AI in my design". Forget the four hour mega offsite. Department level shorties might do better. Find the sweet spot connecting AI governance with assessment then design, not the session on Google or the A-A"I".

The fifth stage is quality assurance feedback: review in the light of whether rules are even getting understood or not and whether even the safeguards feel achingly bare, blanket or not manageable to students. Did you make that disclosure form too ugly so that no way will they pick that? Let"s make it shorter; otherwise it"s going to be impossible used. Will they open their mouth in oral defence or do we simply pile on from their final paper submission? If the students keep "slipping into the grading shrink pool" too randomly, where do they learn they"ve slipped and how do we finish? Quality assurance then learns to correct and refine itself.

Table 3. A Staged Roadmap for Institutional Implementation

Stage	Institutional action	Expected outcome
Mapping	Identify tasks most vulnerable to AI substitution.	A clear list of priority assessment risks.
Rule translation	Convert general AI policy into course-level examples.	Students and teachers share clearer boundaries.
Assessment redesign	Add process or performance evidence to high-	Grades are supported by more credible

	stakes tasks.	evidence.
Teacher development	Use field-specific cases and shared rubrics.	Teachers apply rules more consistently.
Quality feedback	Review workload, clarity, disclosure, and safeguards.	Governance improves through implementation experience.

9. Limitations and Future Research

This article has shortcomings. It is more a conceptual discussion than an empirically conducted study of a single institution or national system. It builds an institutional governance argument by drawing on research literature, policy materials, and public reporting. The model thus also requires further testing in classrooms, departments, internship settings, quality assurance processes, etc.

Going forward, it would be important to research how students understand and enact definitions of acceptable AI use, how teachers judge AI-assisted work, as well as how administrators translate example norms and guidance from national policy into local practice. Comparative research involving China, Malaysia, Thailand, Singapore, and other Asian contexts where AI governance is being developed would lead to rich insights about which governance mechanisms "travel" across these systems and which depend on local policy, language, infrastructure, and institutional culture. Research on AI governance in specific fields is also required. The challenges of AI dependence in early childhood education are fundamentally different from those in computing, nursing, engineering, business, and so on, each of which has different risks, requirements for evidence of competence, and forms of professional accountability. Finally, "how can this system of governance be adapted while maintaining institutional coherence?" would be a key question.

10. Conclusion

GenAI has changed the conditions under which vocational institutions make learning and assessment. The questions lie less in whether students are using AI, and more in whether institutions can still make judgements that people can credibly accept as judgements of student learning, practical competence and professional readiness, when AI is involved in the work that produces those judgements.

A simple ban will likely not be good enough. Unqualified adoption is also too unsafe. The more practicable the path is one of managed dependence: institutions embark upon the work of classifying things by risk, explaining rules through worked examples, normalising disclosure where AI use is permitted, uplifting evidence of process, supporting teachers in these matters, and linking quality assurance with evidence credibility; the better able they are to make AI something that helps students learn, rather than something that quietly weakens the trustworthiness of that assessment.

For China, Malaysia, and wider vocational systems, the central challenge of AI is, therefore, institutional rather than merely technological. Governance of AI is less about catching students in the act, and more about anticipating how to design an systems of assessment and tracking, of assessment and management, that can maintain fairness, accountability and public confidence in a funnelling global future of workplaces filled with AI.

Acknowledgments

This work was supported by Wei Zhang"s Doctoral Research Start-up Fund.

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