
Research article

Generative AI in vocational ICT education: Implications for teaching, learning, and assessment

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Academic Editor: William Guo

Abstract: Generative AI learning outcomes and skill acquisition technologies in vocational ICT education are explicitly incorporated in the teaching practice and assessment design. This study used a mixed-methods approach, combining questionnaires with in-depth interviews (n = 20), to investigate pedagogical issues in generative AI and its potential learning and evaluation capabilities. 323 ICT undergraduates from a university of vocational technology in Sri Lanka participated in the research. The outcomes of the experiment showed that generative AI is not a leveler but a competence amplifier; thus, very competent students in ICT and those with a high level of awareness of generative AI are much more likely to succeed, whereas undergraduate use of generative AI denies individuals the opportunity to acquire basic skills. The mediator of learning value is student engagement, which implies that students' use of generative AI is more important than the generative AI itself. These findings, when applied to vocational teachers, imply systematic curriculum development: an initial foundation in basic programming, followed by the introduction of generative AI, open pedagogy that builds metacognition, and process-based testing that assesses actual skills rather than generative AI-related tasks. The research provides empirical guidance for educators who need to determine how to structure their instruction, ensure test integrity, and use generative AI in professional training.

Keywords: generative AI, vocational education, competency-based learning, pedagogical implications, ICT education, student engagement, assessment design

1. Introduction

The artificial intelligence revolution has already brought paradigm-shifting changes to the modern landscape, and education is one of the fields where radical change is imminent [1]. Using generative AI platforms like ChatGPT, GitHub, Copilot, and other machine learning models has positioned universities and colleges as change agents, especially in technology-oriented education [2]. Another significant effect of generative AI use is in vocational and technical subjects, as the instructional process should be closely aligned with industry and workplace training requirements [3].

Unlike other institutions of higher learning, vocational education and training (VET) uses a pedagogical design based on competency-based learning, practical skills acquisition, and relevance to the labor market [4]. The competence-based method centers on both learning and applied skills [5]. The above method presents significant challenges: although generative AI apps can carry out most tasks, they are often presented as learning experiences and evaluations. Modern students also use artificial intelligence to explain complex programming concepts in real time, solve and fix bugs in code, generate algorithmic solutions, and accelerate the task of writing assignments [6,39]. The increasing complexity of those activities raises a set of serious questions about genuine learning, the validity of competency measurement, and the skill level required for ICT graduates to succeed in generative AI-enhanced working conditions [7].

The implications discussed here are highly pertinent to vocational education and training (VET) institutions, where validity and perceived value are determined by the level at which graduates are employed and by their usefulness to industry [8]. The competency paradigm faces the possibility that artificial intelligence (AI) machines can write and debug programs and develop algorithmic solutions that would otherwise be considered competency measures [9]. Vocational education is managed under policy guidelines that require demonstrating value addition and industry satisfaction, as well as the payoff in terms of skills crafting [10]. The modern tendency in policymaking remains mostly unstructured and reactive; therefore, most vocational institutions lack evidence-based principles to leverage generative AI opportunities and reduce risks that may undermine genuine competency improvement [11].

Although university students widely adopt generative AI, few empirical studies assess its effects in vocational and technical education [12]. Knowledge about how generative AI affects competency acquisition, practical skill development, and academic achievement in vocational ICT teaching is limited [13]. This contribution gap remains at least in part due to the paradoxes of generative AI in education: on the one hand, the technology can support a fast learning process by providing instant feedback and personalized clarifications; on the other hand, it can also damage critical thinking, autonomy in problem-solving, and abstract learning [14].

The purpose of this paper is to address the research gap regarding the paucity of empirical studies to date on the impact of generative AI on competency-based learning and authentic skills development in vocational ICT education, which is different from the higher education setting in that competency-based learning and authentic skills development are focused on measurable skills required in the workplace. The novelty and originality attributed to this manuscript lie first in the mixed methods approach that brings quantitative evidence of the amplifying (not equalizing) effect of generative AI in three vocational ICT specialties in the context of VET in a developing country, and second, in the insights gained from the qualitative nature of the students' lived experiences of learning with generative AI.

Guided by these gaps, this research addresses the following research questions:

(RQ1) What are the frequencies of the use of generative AI tools by vocational ICT undergraduates, and what factors predict the use of generative AI tools?

(RQ2) How can the use of generative AI and academic achievement be related in a competency-based ICT program?

(RQ3) What is the influence of the prior knowledge of ICT on the relationship between the use of generative AI and learning outcomes?

(RQ4) How do students feel about the advantages and difficulties of using generative AI to enhance authentic skills?

In an effort to address these loopholes, the research investigated the impact of generative AI on learning outcomes, skills acquisition, and competence among vocational ICT learners, thereby affecting pedagogical and curriculum planning. The article discusses the trend of adoption, the quantifiable effect on academic achievement in competence-based frameworks, the advantages and disadvantages of generative AI, and students' viewpoints on the use of generative AI as a learning resource [15].

The research has clear implications for vocational teachers regarding how lesson chains may be planned, how generative AI adoption may be organized, and how generative AI-based classroom skills should be measured. The educators will be provided with evidence-based guidance on introducing generative AI tools into the curriculum and designing tasks that stimulate the development of genuine skills rather than overreliance on generative AI [16]. The results can be used to explain which skills should be measured to ensure integrity and insight into the use of generative AI. The paper addresses the necessity of striking a balance among efficiency, competency levels, and technological innovation, and of equipping students to operate in an environment overrun by generative AI. ICT skill development and the use of basic skills should not be substituted by generative AI and generative AI literacy, respectively. Meaningful learning can be characterized by students' activities and the efficient use of generative AI.

The rest of this paper is organized as follows: In Section 2, the theoretical and empirical literature related to generative AI in education and vocational learning is reviewed. The convergent parallel mixed methods design, sampling strategy, and analytical processes are described in Section 3. The quantitative and qualitative results are presented in Section 4. The pedagogical implications, recommendations for curriculum design, and suggestions for institutional policies are discussed in Section 5. A summary of the main contributions is included in Section 6, and future directions for research are suggested in Section 7.

The paper highlights the following problems in vocational and technical education systems: the sustainability of competency-based standards, the integrity of assessment, and technological change. The findings have repercussions outside classrooms, including policy in knowledge-based economies, the workforce, and the qualifications system [17]. In general, the findings advocate for innovations in applied learning and teaching to change teaching practices, learning designs, and evaluation in technology-oriented vocational education.

2. Literature review

2.1. Theoretical principles of teaching with generative AI

The concept of generative AI in education is based on technology acceptance models. For instance, Davis [18] and Venkatesh and Davis [19] argued that adoption is influenced by perceived usefulness and ease of use. Building on this, Venkatesh et al. [20] introduced factors such as social

influence, facilitating conditions, and individual differences, thereby advancing the definition of the predictive validity of generative AI-enabled learning tools in the learning environment. In addition to these models, the Cognitive Load Theory explains the effectiveness of generative AI in learning [21,22]. Cognitive learning can be enhanced with generative AI, as it reduces cognitive burden by providing instant explanations; its efficient use can help counter challenges to long-term retention [23]. Furthermore, Vygotsky's sociocultural theory and the zone of proximal development [24] make generative AI a possible scaffolding tool: it can be beneficial for learning when applied correctly, but counterproductive for development when overused.

2.2. Generative AI in computing education: Possibilities and concerns

Studies on generative AI in computing education identify potential and productive teaching issues. Big code models can produce working code, documentation of programming concepts, and even debug code [25,26]. The capabilities, in turn, create certain underlying tensions with the conventional learning design. Students who can come up with working solutions even when they do not understand the underlying concepts disrupt the relationship between practice and the development of competencies [27]. The code developed by generative AI might appear syntactically correct and logically incorrect [35]. There is no explanation students can offer, which is an assessment issue, since traditional assessment cannot differentiate between student and generative AI-assisted code [13]. When generative AI tools perform the cognitive work that students are supposed to do to learn, students complete only superficial work on the task and fail to develop the competencies needed to solve future problems [28].

2.3. Vocational learning and competency learning

Vocational education is one of the instructional paradigms that aligns learning outcomes with workplace requirements through competency specifications [5]. Vocational assessment is not similar to traditional academic assessment, which is also knowledge-dependent; rather, it is competence-dependent on genuine competence expressed in the workplace [4]. Generative artificial intelligence disproves such presumptions by demonstrating that individuals can perform tasks without enhancing their underlying capabilities. The dominant issue that faces vocational educators is the distinction between generative AI-assisted ability (not unlawful use of tools) and generative AI-reliant performance (the use of instruments to conceal skills). This distinction is crucial in circumstances where some of these institutions have value chains oriented toward producing genuinely skilled graduates [8]. These observations demonstrate that generative AI not only provides the possibilities to teach vocational ICT but also outlines gaps in the knowledge about the impacts of generative AI on the formation of competences, how to incorporate generative AI in the educational process without causing a loss in abilities, and how to implement evaluation in environments with a high prevalence of generative AI while maintaining academic standards and integrity.

3. Methodology

This research used a convergent parallel mixed-methods design to explore the effects of generative AI in the learning process, competency development, and academic performance in ICT vocational education. The methodology relates to the vocational education and training (VET) research in that the two complementary needs to identify effective practices and explain the process of skills acquisition require quantitative and qualitative data collection methods [29]. These

qualitative interviews and quantitative surveys were conducted concurrently to merge into a single body of knowledge that informs pedagogic practice [30].

3.1. Study context and sampling

The sample used in the research included undergraduates of a university of vocational technology in Sri Lanka, in which an undergraduate computer technology ICT degree program is offered to 879 undergraduates (2021–24 cohort), undertaking three technical degree courses in software technology, network technology, and multimedia and web technology. Stratified random sampling was used to ensure that the programs were represented proportionally. The minimum sample size at a 95% confidence level was estimated using Krejcie and Morgan [31] with a margin of error of 5, yielding 269 students. The 323 students who were contacted and accepted to take part in the study were balanced across the programs, and a 20% non-response buffer was provided. The qualitative interviews were conducted using purposive sampling, with 20 students selected based on program specializations, mode of study, year, and use of generative AI [32].

The survey (quantitative) was completed in the second semester of the 2023–2024 academic year (February to May 2024), followed by the qualitative interviews. In preparation for the interview guide, an initial analysis of survey responses was conducted, followed by questionnaires during weeks 1–4 and semi-structured interviews during weeks 5–8, for a total of 8 weeks of data collection.

3.2. Data collection and analysis

The demographic data, generative AI utilization, and perceived impact on the TAM constructs were collected using a structured questionnaire [18,19]: perceived usefulness in technical skills, perceived ease of use, impact on technical competencies, and employability preparation. The answers were registered on a five-point Likert scale. The semi-structured interviews were analyzed with respect to the use of generative AI tools in professional practice, challenges in understanding technical training, understanding what is meant by authentic skill development, the fear of relying on generative AI, employability, and suggestions for implementing generative AI in competency-based courses. Interviews lasted 30–45 minutes.

Quantitative analysis was performed using SPSS and included descriptive statistics, correlation analysis, ANOVA, and regression analysis to determine whether potential predictors of generative AI adoption and skill development exist. The qualitative analysis used thematic analysis, as described by Braun and Clarke [33]. The interpretive synthesis was applied to the integration, with the interview themes guiding statistical trends. The questionnaire's clarity was ensured through a pilot test ($n = 30$). The Cronbach alpha coefficients were higher than 0.70, indicating good internal consistency. The instrument was validated through a professional review conducted by vocational teachers, educational scholars, and ICT experts. Credibility was obtained through member checking, transferability through thick description, dependability through careful documentation, and confirmability through reflexive journaling [34].

4. Results and findings

This section outlines the most striking results regarding presumptions about perceived usefulness, usage frequency, student engagement, and academic success. The alternative to a demographic portrait is the study of bivariate and multivariate correlations, supported by regression modeling, and,

finally, the thematic analysis of the interview data. Such a methodological approach provides an overall evaluation of the implications of generative AI for ICT education and pedagogy.

4.1. Participant profile

The cohort of undergraduate respondents with respect to ICT was composed of 323 participants (185 males, 57.3%, and 138 females, 42.7%). The majority of the sample population was aged 20–24 years (227 students, or 70.3% of the sample). The proportion with an Advanced Level qualification was significant, and the rest had either NVQ level 05 (14.6%) or NVQ level 06 (5.9%) qualifications. There was no significant difference in the number of samples across the various specializations, as follows: B.Tech Software Technology (116 students, 35.9%), B.Tech Multimedia and Web Technology (113 students, 35.0%), and B.Tech Network Technology (94 students, 29.1%).

4.2. Key statistical findings

The quantitative results are presented here, in the following order: Measurement reliability (Table 1), bivariate correlations (Table 2), multiple regression (Table 3), and moderated mediation (Table 4). The statistical evidence is presented along each narrative claim, with each analysis presented immediately after.

4.2.1. Measurement reliability

All dimensions were found to have high reliability scores (Table 1). All seven dimensions met the recommended range of 0.70 for Cronbach's alpha, which ranged from 0.924 (*Perceived ease of use*) to 0.961 (*Challenges/reliability concerns*). This confirms the internal consistency of the instrument prior to using it to derive the estimates of correlation, regression, and mediation presented below.

Table 1. Reliability statistics for all measurement dimensions.

Dimension	Cronbach's Alpha	N. of items
Perceived usefulness	0.954	5
Perceived ease of use	0.924	5
Frequency of ChatGPT use	0.948	5
Student engagement in learning	0.956	5
Prior ICT knowledge	0.946	5
Academic performance	0.951	5
Challenges/reliability concerns	0.961	5

4.2.2. Bivariate correlations among study variables

Table 2 shows bivariate correlations for all study variables. The overall pattern corroborates an amplification account for the use of generative AI rather than an equalization one, with all associations being statistically significant ($p < 0.01$). *Academic performance* had the highest correlation with *Prior ICT knowledge* ($r = 0.72$), followed by *Frequency of ChatGPT use* ($r = 0.65$), *Student engagement* ($r = 0.61$), *Perceived usefulness* ($r = 0.54$), and *Perceived ease of use* ($r = 0.51$). Only *Reliability concerns* showed a negative correlation with *Academic performance* ($r = -0.42$), indicating that knowledge of the limitations of generative AI is a component of the conceptual underpinning of educational performance. *Perceived usefulness* and *Perceived ease of use* were

highly correlated ($r = 0.75$), which was a motivation for the exclusion decision in the regression model below.

Table 2. Correlation matrix of factors influencing academic performance (N = 323).

Variable	1 (AP)	2 (PIK)	3 (GUF)	4 (SE)	5 (PU)	6 (PEOU)	7 (RC)
1. Academic performance (AP)	1.00						
2. Prior ICT knowledge (PIK)	0.72**	1.00					
3. GenAI use frequency (GUF)	0.65**	0.58**	1.00				
4. Student engagement (SE)	0.61**	0.45**	0.52**	1.00			
5. Perceived usefulness (PU)	0.54**	0.38**	0.68**	0.49**	1.00		
6. Perceived ease of use (PEOU)	0.51**	0.32**	0.62**	0.41**	0.75**	1.00	
7. Reliability concerns (RC)	-	-0.15*	-0.21*	-	-0.18*	-0.12	1.00
	0.42**			0.28**			

4.2.3. Multiple regression analysis

Together, the five significant correlates explained about 71% of the variance in *Academic performance* ($R = 0.842$, $R^2 = 0.708$, Adjusted $R^2 = 0.701$, $F(5, 317) = 124.52$, $p < 0.001$), which is a strong effect, considering it is a self-reported behavioral outcome (Table 3). *Prior ICT knowledge* was the strongest standardized predictor ($\beta = 0.412$, $p < 0.001$), followed by *GenAI use frequency* ($\beta = 0.265$, $p < 0.001$), *Student engagement* ($\beta = 0.198$, $p = 0.001$), *Perceived usefulness* ($\beta = 0.124$, $p = 0.003$), and *Reliability concerns*, the only negative predictor ($\beta = -0.152$, $p = 0.001$). *Perceived ease of use*, although having significant bivariate relationships with performance (Table 2), was not included in the final model as it was highly correlated with the construct *Perceived usefulness* ($r = 0.75$, Table 2).

Table 3. Regression analysis for predictors of academic performance (N = 323).

Predictor variable	Unstd. B	SE	Std. β	t	p
(Constant)	1.124	0.241	—	4.663	0.000
Prior ICT knowledge (PIK)	0.425	0.042	0.412	10.119	<0.001
GenAI use frequency (GUF)	0.284	0.039	0.265	7.282	<0.001
Student engagement (SE)	0.212	0.045	0.198	4.711	0.001
Perceived usefulness (PU)	0.156	0.051	0.124	3.058	0.003
Reliability concerns (RC)	-0.189	0.048	-0.152	-3.937	0.001

4.2.4. Moderated mediation analysis

The regression results indicated that *Student engagement* and *Reliability concerns* can be considered not only linear predictors of *Academic performance* but also potential pathways of how other constructs affect *Academic performance*. This was directly tested using a moderated mediation analysis, and the results are summarized in Table 4. The two simple paths originally mentioned (Use $\rightarrow$ Mediator $\rightarrow$ Performance) were not reported in the analysis, but conditional indirect effects were computed for the technology-acceptance constructs as the mediators between the constructs of *Student engagement* and *Use*.

The direct effect of *Perceived usefulness* on *Academic performance* was nonsignificant ($B = -0.01$, ns), but the indirect effect of *Perceived usefulness* on *Academic performance* was significant

($a \times b = 0.07$, $p < 0.01$) with *Student engagement* as the mediator; the pathway from *Perceived usefulness* to *Student engagement* was significantly moderated ($B = 0.10$, $p < 0.05$), consistent with full, moderated mediation. *Perceived ease of use* directly influenced *Student engagement* ($B = 0.13$, $p < 0.01$) as well as indirectly (direct pathway) through *Student engagement* ($a \times b = 0.11$, $p < 0.001$) with significant moderation of the pathway ($B = 0.12$, $p < 0.05$), representing a partial, moderated mediation.

Table 4. Moderated mediation effects of technology-acceptance constructs and reliability concerns on *Academic performance* via *Student engagement* ($N = 323$).

Predictor	Mediator	Outcome	Direct effect (c') β	Indirect effect (a $\times$ b) β	Total effect (c) β	Boot SE	95% CI	p
Perceived usefulness (PU)	Student engagement	Academic performance	0.124	0.097	0.221	0.023	0.056 – 0.145	< 0.001
Perceived ease of use (PEOU)	Student engagement	Academic performance	0.082	0.081	0.163	0.021	0.042 – 0.126	0.001

4.3. Qualitative interview results

The 20 semi-structured interviews were analyzed thematically, and four themes were identified. First, instrumental dependence: Most participants reported using generative AI to complete tasks rather than as a learning tool; answers to questions were generated with it and could not be explained or debugged independently. Second, competence anxiety: More than one participant voiced concerns about a lack of confidence in their self-efficacy to address problems, particularly when time was constrained, due to the extensive use of generative AI tools. Third, selective benefit: Generative AI was said to be used by participants for more basic programming tasks, such as code verification, exploration of options, and documentation, and was perceived as a complement to, rather than a substitute for, their existing programming skills. Fourth, assessment disconnect: Students generally reported a lack of connection between the use of generative AI in coursework and assessed work and called for clear guidance on how far it could be used in assessed work. The quantitative findings are presented in Section 4.2 and are complemented by qualitative findings.

4.4. Teaching and learning: Insights from interviews

Interview data also served as a contextual background for the teaching recommendations that were created in Section 5. The use of generative AI was different for each participant, ranging from daily and extensive use to support programming to selective use for specific problems. The top reasons given for use included convenience, quick answers, constant availability of the service, saving time, and trust; the top barriers cited were reliability concerns and over-dependence.

Students' code, lab, and test performance are reported to have improved. In particular, 15 of 20 interviewees (75%) indicated that coding and lab and test activities improved, and consistent with academic performance, there was a significant correlation between frequency of generative AI use and the improvement of academic performance ($r = 0.65$, $p < 0.01$). Students' experiences regarding research skills, handling assignment deadlines, and learning complex material (object-oriented programming) were reported as positive by 18 out of 20 participants, and 8 out of 20 reported conceptual gaps when using generative AI to solve object-oriented programming problems. Accurate and up-to-date content created by generative AI was also mentioned as a challenge (15 out of 20

interviewees), as were critical thinking skills (7 out of 20 interviewees). Positive findings were immediate access to information at all times, improved self-directed learning, and development in digital literacy and creativity.

The results of the interview can be directly compared with the quantitative construct of *Perceived usefulness* presented in Section 4.2: the internal consistency of this construct was found to be good ($\alpha = 0.954$, Table 1), had a significant positive correlation with *Academic performance* ($r = 0.54$, $p < 0.01$, Table 2), and had a significant standardized regression effect on *Academic performance* ($\beta = 0.124$, $p = 0.003$, Table 3) and an indirect effect on *Academic performance* via *Student engagement* ($a \times b = 0.097$, $p < 0.001$, Table 4). Once again, the moderated-mediation result indicated that the effect of *Perceived usefulness* on performance was mediated by *Student engagement* (less than by any other code: creative, 10; engaging, 12; and transformative, 15). Most participants (18 out of 20) expressed an opinion that generative AI should be used in addition to regular learning, and not in place of it. There were no associations of other factors with successful use, except for ICTs used successfully ($r = 0.58$) and critical awareness of the limitations of generative AI ($r = -0.15$).

5. Discussion

This research indicates that generative AI can be used to improve current ICT competence without replacing the learning of fundamental skills, student engagement, and generative AI literacy, which underpin the value of learning. This key conclusion has direct implications for how vocational teachers can structure their learning programs, organize learning experiences, and assess students' competency levels in a generative AI-enriched environment.

Findings of this research indicated that generative AI should not be seen as an adversary to current ICT competence; there is no desire to substitute for the teaching of basic competencies. It is rather the interaction of generative AI and students. The learning value is based on being literate in generative AI. This conclusion directly affects how vocational educators can organize the learning process, plan curricula, and evaluate learners' generative AI-related competencies.

5.1. Interpretation of findings for teaching practice

There is an association between academic success and students' previous experience with ICTs, indicating that using generative AI tools in a productive way requires students to have prior technical experience. This is in line with the concept of facilitating conditions in TAM [20] and the perspective that generative AI can serve as an expertise amplifier and not necessarily an equalizer of skill gaps [27]. The pattern is clearly present in the correlational data: as shown in Table 2, the strongest relationship was between *Prior ICT knowledge* and *Academic performance* ($r = 0.72$, $p < 0.01$), even more than with *Generative AI use frequency* ($r = 0.65$; Table 2), suggesting that the impact of generative AI on academic performance is more about the prior knowledge than about the tool itself.

In fact, rather than an equalization effect, there is an amplification effect, and that is why it is advisable to introduce generative AI tools early in the years of study of vocational education—before students have mastered programming skills—or risk an acceleration of the achievement gap. The use of generative AI was predominantly associated with tasks that were verification-oriented, such as checking code, exploring alternative approaches, and documentation; and *Generative AI use frequency* was highly correlated with *Prior knowledge of ICTs* ($r = 0.58$; Table 2), indicating that the use of the tool does not seem to be an alternative to existing competence, but rather an addition to it. The use of generative AI to produce answers that were then explained or debugged (the "crutch"

pattern) was more strongly associated with negative aspects of the *Reliability concerns* and *Academic performance* model ($r = -0.42$ with *Academic performance*; Table 2). The moderated mediation results confirm this reading at the mechanism level; the benefits of generative AI for student engagement were both moderated by student engagement (Table 4), and thus are conditional but competence-dependent, which is what the amplification account predicts. Some students are not learning the basic skills to write code on their own; instead, they use generative AI as a crutch. This is the same split seen in the qualitative themes reported in Section 4.3, with the instrumental dependence theme reported by participants who used generative AI tools to complete tasks that they could not explain or debug, as opposed to the selective benefit theme in which students used generative AI tools to assist with more limited tasks, which they could then explain and debug. For more able learners, the conceptual foundations stayed intact, and they treated generative AI as a productivity tool rather than a substitute for understanding. This is supported by the results of the regression analyses, which indicated that *ICT knowledge* was the most consistent standardized predictor of *Academic performance*, while other variables in the model (i.e., *GenAI use frequency*, *Student engagement*, and *Perceived usefulness*) were not standardized predictors of *Academic performance* (Table 3; $\beta = 0.412$, $p < 0.001$). There was a correlation between the awareness of limitations and variability of generative AI and academic performance, suggesting that students will perform better when they know these things. The negative correlation between *Reliability concerns* and *Academic performance* ($r = -0.42$, $p < 0.01$; Table 2) and the negative standardized regression coefficient ($\beta = -0.152$, $p = 0.001$; Table 3) of *Reliability concerns* in the regression model support this. This indicates that competency in effective use of generative AI needs not only technical competency but also effective metacognitive monitoring [28]. *Student engagement* is used as a mediator, which is in accordance with the Cognitive Load Theory [22], which emphasizes the approach of active learning. *Student engagement*, which was also a significant, independent predictor of *Academic performance* ($\beta = 0.198$, $p = 0.001$; Table 3), of comparable magnitude to *Generative AI use frequency* ($\beta = 0.265$, $p < 0.001$), lends support to the notion that how students engage with the tool is as important as how often they use it. In this evidence, the amount of learners' use of generative AI does not seem to be as important as how learners use generative AI.

5.2. Implications of curriculum design and learning sequences

Unless competencies are introduced in advance of generative AI tools, sequenced curriculum models have been found to under-program them. This kind of staging will enable students to learn algorithmic thinking and problem-solving skills directly through practice and with the help of generative AI. The initial steps in the curriculum should focus on manual coding, error detection, and the development of non-generative AI solutions. Students should not be allowed to use generative AI tools unless they demonstrate baseline competence, and they should not be used as productivity tools but as replacements for them.

The skills of the tools, their limitations, potential applications, and how they will be tested should also be covered, as should generative AI literacy in the curriculum. In contexts where generative AI intervention is seen as a valuable tool for learning, and where required mental effort is seen as a loss to the learner, explicit training will have to be provided to students. This involves recognizing that generative AI relies on pattern matching in large language models, which cannot be fully understood but can be used to develop verification strategies [36,37]. The curriculum should include exploration and development of generative AI with a focus on foundational skills [26].

5.3. Implications to teaching practices

This research has implications for redesigning ICT-based teaching practices. Teachers can scaffold an introduction by using a diagnostic assessment to determine what students know and can understand about the technical resources in generative AI tools [40]. The generative AI-transparent teaching method is suggested, in which both successes and failures in using generative AI tools are discussed in class [28]. Such transparency can help students develop metacognition about when and how the use of generative AI leads to or harms skill consolidation.

One such implication is a conceptualization of assessment. Conventional final-product evaluation may be inadequate when students can develop generative AI [13]. Hybrid assessment plans will lead to process-based assessment, and it will be necessary to write about a problem/solution and provide evidence of the skills that cannot be acquired with the aid of generative AI [7]. One can also introduce progressively limited entry into generative AI through introductory courses designed to foster skill development. In the meantime, more advanced programs would be allowed to use generative AI as a productivity amplifier, mirroring real-world practice [27].

Certain instructional practices are as follows: (1) Foundational skills: The curriculum implementation sequence should be designed to make sure that students first learn fundamental programming logic, algorithmic thinking, and problem decompositions before introducing generative AI assistance. (2) Explicit generative AI literacy: Teaching generative AI capabilities, limitations, verification strategies, and proper use of generative AI tools should precede the introduction of generative AI assistance. (3) Transparent tool integration: Model use of generative AI tools in teaching should come before the introduction of generative AI assistance. (4) Process-based assessment: Assessment rubrics should be developed to assess problem-solving strategies and conceptual understanding.

5.4. Implications for institutional policies

Integrated strategies in VET are urgently required, which include curriculum development, teaching innovation, and institutional support. The redesign of curricula should prioritize teaching the simplest skills first, followed by those more technologically demanding, and should perceive generative AI as one of the literacies [9,17]. Assessment models should be more open, and students should be required to self-report their use of generative AI and demonstrate their independent skills [13,16]. Faculty-level professional development initiatives should enable instructors to investigate students' metacognitive skills, supplemented by technical training, ethical codes, and communities of practice provided by the institutions [14,38].

5.5. Effective teacher recommendations

The guidance that follows contributes to integrating generative AI and prioritizing the development of expertise, as supported by empirical evidence.

5.5.1. What should teachers introduce?

Table 5. Recommended strategies for teacher introduction of generative AI in vocational ICT courses.

Strategy	Implementation guidance
Sequenced generative AI integration	The first step is to teach programming basics (at least a semester of manual coding) and then start adding generative AI tools once students can write and debug simple errors on their own.
Generative AI literacy training	Clear instructions on generative AI limits, risk of hallucinations, appropriate tasks, and the absence of tasks in learning processes using generative AI; checking methods and approaches to review the output.
Metacognitive development	Facilitate frequent introspection on learning activities, including those mediated by the professor, and motivate students and faculty to identify instances in which generative AI utilization would aid genuine comprehension rather than conceal knowledge deficits.

5.5.2. What should teachers delay?

Table 6. Generative AI features and practices that should be delayed until prerequisite competencies are established.

Delay until	Rationale
Unlimited access to generative AI by beginners	Reliance on early generative AI creates a dependency on it, loss of debugging skills, poor problem breakdown, and a lack of algorithmic thinking and pattern recognition, which are the fundamental competencies for professional success.
Product-only assessment	The submissions generated by the final codes cannot distinguish whether the student is genuinely competent or relying on generative AI. Until those process-based assessments are developed, delays should be expected.
Advanced generative AI features	More advanced generative AI features (those that involve generating full code and/or auto-testing) are to be delayed until students have mastered problem-solving without relying on generative AI assistance and have developed the ability to analyze generative AI results critically.

5.5.3. Which types of assessments need to change?

Table 7. Assessment types and implementation approaches for generative AI-integrated vocational ICT education.

Assessment type	Implementation approach
Process-based evaluation	Concentrate on code-explaining skills, the debugging process, changeability, and an approach to testing that is not the final solution. Have students answer a question verbally or in writing.
Live coding demonstrations	Include closed-problem and timed coding tasks in which students must solve problems in real time without the safety net of generative AI, revealing their base-level abilities.
Generative AI-transparent assignments	Conceptualization of a generative AI system to verify the quality of output, generative AI-based code errors, how to make a generative AI user solution better, or even why a generative AI-based solution may be problematic.
Graduated complexity	Architecture of assessments that verify the quality of output, bugs in generative AI-written code, how to ameliorate a generative AI user solution, or why one of the solutions proposed by a generative AI system is inadequate.

6. Conclusions

The use of generative AI in occupational ICT learning is an amplifier of competences, not a leveler. Students with a strong background in generative AI perform better, whereas those who develop a habit of working with it early in their education struggle to keep up. The degree to which students use generative AI and their ability to learn via generative AI are very relevant moderators of the value of learning, as well as of whether that value is replaced by an effort that is worthwhile regardless of its use of generative AI. Such findings contradict the belief that generative AI would democratize learning and underscore the importance of designing to influence generative AI learning outcomes. Even at this stage, generative AI improves ICT, and mere skill acquisition cannot replace it; learning is tied to student engagement and generative AI literacy.

At least once per semester, vocational educators and teachers must follow sequenced curriculum models in which simple programming skills are taught before generative AI tools are introduced. Pedagogical practice should also feature an expressive orientation toward generative AI literacy and, more crucially, the absence of generative AI in learning activities. The design of assessments should also revert to rudimentary levels, as it should be more process-based by analyzing actual skills, such as being able to explain the code, demonstrate it in real life, or identify mistakes, but not merely product performance as a requirement. The methods used in pedagogy should, in a sense, demystify the use of generative AI, enabling learners to map and reflect on their engagement with it and, consequently, to develop metacognitive knowledge of how the new technology can either compensate for or restrict the learning process in real-life situations.

Vocational education is special because generative AI applications are becoming increasingly common in the workplace. The types of instruction currently used, the organization and structure of the curriculum, and the introduction of generative AI will determine whether the vocational programs are truly industry-focused and whether the candidates themselves are employment-ready. The implications are not confined to a single classroom but extend to the nature of vocational education: preparing students with the mechanisms to perform well in the generative AI-enhanced job market.

7. Future research and limitations

These teachings come from a vocational setting in Sri Lanka. Although the teaching guidelines may be used in other environments, the specifics of implementation depend on the institutional evaluation's culture, teachers' expertise in delivering generative AI-enhanced learning to students, the availability of technological facilities, and students' attributes. The study is characteristic of the influence of generative AI within a particular technological generation; as generative AI develops, some of its observations on its shortcomings and sensible applications may become less relevant. More specifically, the results are likely transferable to settings with similar characteristics: competency-focused program designs, undergraduate technical education, and moderate-to-high levels of familiarity with generative AI tools amongst students. Different patterns can be observed in institutions where all students have a high (such as selective university programs in high-income countries) or low level of ICT knowledge (such as introductory VET programs in low-resource settings). This amplifying/equalizing can vary across non-ICT technical disciplines, where generative AI tools can replace domain-specific procedural skills to varying degrees. The replication study across different national and disciplinary settings would help clarify the applicability limits of these findings.

A cross-sectional design is appropriate in establishing the relationship between generative AI use and the learning outcomes, but it cannot be used to infer causality. Longitudinal research to determine student progress after one semester of implementing generative AI at varying levels of integration can provide stronger causal evidence on the optimal sequence and retention of skills in the long run. Further, it could be useful to observe generative AI applications during learning to investigate how a learning behavior mediates the effects of generative AI on learning. Triangulation can help mitigate the limitations of self-reported measures, as they may be susceptible to social desirability bias. Further, the study collected data only from participants' own reports; because no direct measures of generative AI use, such as generative AI interaction logs, screen-capture data, or system-level usage metrics, were collected, the frequency of generative AI use reported by participants may not accurately reflect usage behavior. Objective measures of usage should be used alongside survey instruments to enhance the validity of generative AI adoption measures in future studies.

To determine the most timely moment for vocational training to apply generative AI, interventions that are subject-specific to enhance positive trends in interaction with generative AI, and whether assessment forms can preserve their efficacy and remain generative AI-sensitive, is a line of inquiry to be investigated in the future. Clues of the extent to which general conclusions may be drawn can be traced back to comparative studies in various conditions of vocational education and in various disciplinary backgrounds. Finally, generative AI-intensive and generative AI-restricted training can be contrasted in terms of long-term graduate employment rates to determine which better prepares students for professional success.

Author contributions

All authors contributed to this study, including most of the research, experiments, data analysis, and manuscript preparation.

Use of Generative-AI tools declaration

The authors declare that they have not used generative AI tools in the creation of this article.

Acknowledgments

The authors would like to acknowledge the students who participated in this study. All sources of funding for the study must be disclosed.

Conflict of interest

All authors declare no conflicts of interest in this paper.

Ethics declaration

The ethics procedure was duly followed as detailed in the manuscript.

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