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Factors Influencing Vocational Students' Perceived Learning Effectiveness When Using Generative Artificial Intelligence in Vocational Education

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ARTICLE INFO **ABSTRACT**

Generative artificial intelligence (GenAI) is increasingly being integrated into vocational education, yet the factors shaping students' perceived learning effectiveness remain unclear. This study examines the effects of perceived usefulness, ease of use, AI literacy and self-efficacy, and perceived ethical and learning risk on vocational students' perceived learning effectiveness. A quantitative cross-sectional survey framework was used, with a self-administered online questionnaire and five-point Likert-scale measures; statistical procedures were demonstrated on a synthetic dataset comprising 270 valid cases using descriptive statistics, Cronbach's alpha, and multiple linear regression. The regression model explained 57.4% of the variance in perceived learning effectiveness ($R^2 = 0.574$, $p < .001$). Perceived usefulness ($\beta = 0.389$), ease of use ($\beta = 0.173$), and AI literacy and self-efficacy ($\beta = 0.311$) showed significant positive effects, whereas perceived ethical and learning risk had a significant negative effect ($\beta = -0.279$); all four hypotheses were supported. The findings indicate that effective GenAI integration in vocational education depends not only on tool availability and usability, but also on students' AI capabilities and appropriate risk governance. As the analysis is based on synthetic data, the findings require validation using real respondents.

1. Introduction

1.1 Overarching Research Question

Generative artificial intelligence (GenAI) refers to artificial intelligence systems that can produce new text, explanations, images, code, learning resources, and other content in response to user prompts. In education, GenAI has moved from a peripheral digital tool to a direct learning support mechanism. UNESCO's global guidance states that GenAI requires immediate policy action, long-term planning, human capacity development, and a human-centred approach to use in education and research. For vocational education, the issue is particularly important because vocational learning depends not only on theoretical understanding, but also on practical

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problem-solving, technical reasoning, workplace-oriented knowledge, and students' ability to transfer learning into employable skills.

The problem examined in this study is that vocational education institutions increasingly face pressure to integrate GenAI into teaching and learning, but it remains unclear which factors determine whether students perceive GenAI as improving their learning effectiveness. The problem is not simply whether GenAI is available. The more important managerial and educational question is whether students use it productively, understand how to evaluate AI-generated answers, and avoid overdependence, plagiarism, misinformation, and privacy risks. If this problem is not addressed, vocational institutions may invest in AI-enabled teaching without achieving better learning outcomes. Students may also use GenAI superficially, replacing independent learning with automated answers rather than strengthening technical understanding.

Several underlying causes explain this problem. First, students differ in their perceptions of GenAI's usefulness and ease of use. Second, students vary in AI literacy and self-efficacy, especially in prompt writing, answer verification, and responsible use. Third, GenAI creates learning and ethical risks that may weaken independent thinking and academic integrity. Therefore, this research focuses on vocational students' perceived learning effectiveness as the dependent variable and investigates four independent variables: Perceived Usefulness of GenAI, GenAI Ease of Use, AI Literacy and Self-Efficacy, and Perceived Ethical and Learning Risk.

Overarching Research Question:

What are the factors that determine vocational students' perceived learning effectiveness when using generative artificial intelligence in vocational education?

This research can help address the business problem by identifying the factors that shape students' perceived learning effectiveness. The findings can guide vocational institutions, programme managers, and teachers in making better decisions about GenAI tool adoption, AI literacy development, classroom guidance, and ethical governance.

1.2 Research Objectives

The aim of this research is to examine the factors influencing vocational students' perceived learning effectiveness when using generative artificial intelligence in vocational education. To achieve this aim, the study has four research objectives:

- To examine the effect of Perceived Usefulness of GenAI on Vocational Students' Perceived Learning Effectiveness.
- To examine the effect of GenAI Ease of Use on Vocational Students' Perceived Learning Effectiveness.
- To examine the effect of AI Literacy and Self-Efficacy on Vocational Students' Perceived Learning Effectiveness.
- To examine the effect of Perceived Ethical and Learning Risk on Vocational Students' Perceived Learning Effectiveness.

1.3 Conceptual Model

This study proposes Vocational Students' Perceived Learning Effectiveness as the dependent variable and four independent variables: Perceived Usefulness of GenAI, GenAI Ease of Use, AI Literacy and Self-Efficacy, and Perceived Ethical and Learning Risk. The conceptual model assumes that each independent variable has a direct effect on perceived learning effectiveness.

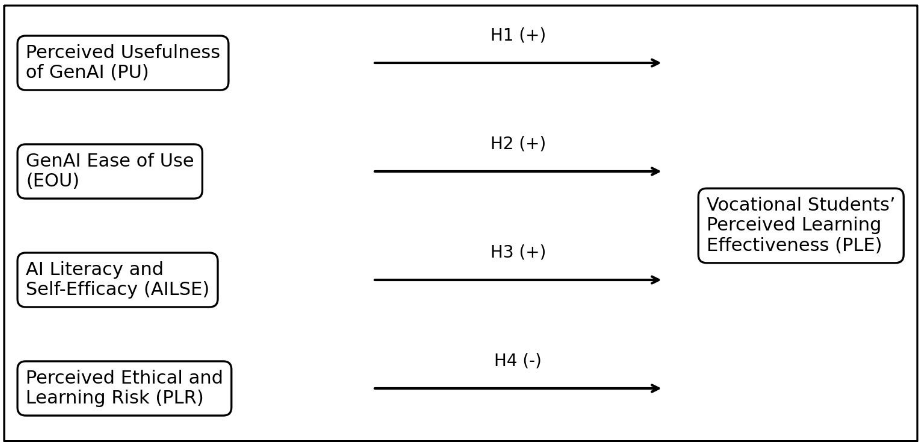

Figure 1. Conceptual Model

Proposed hypotheses:

H1: Perceived Usefulness of GenAI positively influences Vocational Students' Perceived Learning Effectiveness.

H2: GenAI Ease of Use positively influences Vocational Students' Perceived Learning Effectiveness.

H3: AI Literacy and Self-Efficacy positively influences Vocational Students' Perceived Learning Effectiveness.

H4: Perceived Ethical and Learning Risk negatively influences Vocational Students' Perceived Learning Effectiveness.

2. Literature Review

2.1 Dependent Variable: Vocational Students' Perceived Learning Effectiveness

Perceived learning effectiveness refers to students' subjective judgement of whether a learning activity, learning environment, or learning tool helps them understand knowledge, complete tasks, and achieve better learning outcomes. In online learning research, perceived learning is often treated as a learner-reported outcome that reflects the extent to which students believe they have gained knowledge and competence through a learning experience (Alqurashi, 2019). This differs from objective academic achievement, such as examination scores, because it focuses on students' own evaluation of learning gains. However, it is still important because students' perceived learning can influence motivation, confidence, continued engagement, and acceptance of digital learning tools.

In vocational education, perceived learning effectiveness is particularly relevant because students are expected to acquire applied knowledge and practice-oriented skills. GenAI may support this process by explaining technical concepts, generating examples, offering immediate feedback, and helping students solve learning problems. At the same time, perceived effectiveness may be weakened if students cannot judge the accuracy of AI-generated content or if AI use replaces independent thinking. For this reason, Vocational Students' Perceived Learning Effectiveness is selected as the dependent variable in this study.

2.2 Independent Variable 1: Perceived Usefulness of GenAI

Perceived Usefulness is rooted in the Technology Acceptance Model. Davis (1989) defines perceived usefulness as the degree to which a person believes that using a particular system would enhance performance. In the present study, Perceived Usefulness of GenAI refers to the extent to which vocational students believe that GenAI improves their learning efficiency, problem-solving ability, assignment quality, and understanding of vocational course content. Compared with general attitudes toward AI, perceived usefulness is more outcome-oriented because it focuses on whether students believe GenAI adds practical learning value.

Previous literature generally supports a positive relationship between perceived usefulness and technology-related learning outcomes. In educational technology contexts, students are more likely to accept and continue using a system when they believe that it improves task performance. GenAI can provide instant explanations, examples, summaries, and learning support. These functions are closely related to vocational education because students often need to connect theory with practical application. However, usefulness may vary depending on course type and students' ability to evaluate AI-generated answers. Some studies on GenAI also warn that students may overestimate the usefulness of AI when they do not recognise errors, hallucinations, or limitations. Therefore, usefulness should be treated as a perceived benefit rather than an automatic guarantee of learning improvement.

Accordingly, this study proposes that students who perceive GenAI as more useful are more likely to report higher perceived learning effectiveness in vocational education. This leads to the following hypothesis: H1: Perceived Usefulness of GenAI positively influences Vocational Students' Perceived Learning Effectiveness.

2.3 Independent Variable 2: GenAI Ease of Use

GenAI Ease of Use is also derived from the Technology Acceptance Model. Davis (1989) defines perceived ease of use as the degree to which a person believes that using a system would be free of effort. In this research, GenAI Ease of Use refers to the extent to which vocational students perceive GenAI tools as easy to learn, easy to operate, clear to interact with, and usable without substantial technical assistance. This construct is distinct from usefulness because a tool can be useful in principle but still difficult to use in practice.

Prior technology acceptance research suggests that ease of use can influence users' satisfaction, perceived usefulness, and continued use. In vocational learning, ease of use may be especially important for students who have uneven levels of digital competence. If GenAI tools are easy to access and interact with, students may experience less cognitive burden and may be more willing to use them for learning tasks. Conversely, if students struggle with prompt formulation, interface navigation, or interpreting responses, GenAI may become a source of confusion rather than support. Some literature also suggests that ease of use may become less important once a technology becomes familiar, because users then focus more on usefulness and outcomes. Nevertheless, in an emerging GenAI learning context, ease of use remains a relevant factor.

Accordingly, this study proposes that students who perceive GenAI tools as easier to use will report higher perceived learning effectiveness. Therefore, the following hypothesis is proposed: H2: GenAI Ease of Use positively influences Vocational Students' Perceived Learning Effectiveness.

2.4 Independent Variable 3: AI Literacy and Self-Efficacy

AI Literacy and Self-Efficacy refers to students' knowledge, skills, judgement, and confidence in using AI tools effectively and responsibly. AI literacy includes understanding what AI can and cannot do, evaluating AI-generated content, recognising errors or bias, and using AI ethically. Self-efficacy refers to students' belief in their ability to perform a task successfully. In this study, the construct combines AI literacy and self-efficacy because vocational students need both technical awareness and confidence to use GenAI productively.

The relevance of this construct is reinforced by current international guidance. UNESCO's AI Competency Framework for Students emphasises critical judgement, responsible AI use, foundational AI knowledge, and safe engagement with AI. The UNESCO teacher framework similarly highlights ethics, AI foundations, AI pedagogy, and human agency. These frameworks imply that GenAI does not improve learning automatically; learning benefits depend on users' competencies. For vocational students, AI literacy may help them write clearer prompts, check whether generated content is correct, and apply AI outputs to technical learning tasks. Without such literacy, students may copy inaccurate answers or fail to transfer AI-supported explanations into genuine competence.

Previous research on AI literacy also suggests that users with stronger AI-related competence and self-efficacy are better positioned to use AI systems critically and effectively. Therefore, this study proposes that higher AI Literacy and Self-Efficacy will be associated with stronger perceived learning effectiveness. This leads to the following hypothesis: H3: AI Literacy and Self-Efficacy positively influences Vocational Students' Perceived Learning Effectiveness.

2.5 Independent Variable 4: Perceived Ethical and Learning Risk

Perceived Ethical and Learning Risk refers to students' concerns that GenAI may create negative consequences for learning quality, academic integrity, independent thinking, privacy, and data security. Unlike the first three independent variables, this construct represents a negative mechanism. In this study, it includes concerns about overdependence, inaccurate or misleading AI-generated content, plagiarism, inappropriate assistance, and privacy risks.

Prior literature and policy guidance consistently identify these issues as core concerns in GenAI adoption. UNESCO's guidance on GenAI in education highlights data privacy, ethical validation, pedagogical design, and safe use as necessary conditions for meaningful implementation. In education, GenAI can generate fluent but inaccurate content, which may mislead students if they lack evaluation skills. It may also blur the boundary between legitimate learning support and academic misconduct. In vocational education, the risk is not only academic. If students rely on incorrect AI-generated explanations for technical procedures or workplace-related knowledge, this may weaken competence development and practical readiness.

The literature is therefore mixed in the sense that GenAI is viewed as both an opportunity and a risk. Its benefits depend on how it is governed and used. Accordingly, this study proposes that higher perceived ethical and learning risk will reduce students' perceived learning effectiveness. Therefore, the following hypothesis is proposed: H4: Perceived Ethical and Learning Risk negatively influences Vocational Students' Perceived Learning Effectiveness.

3. Methodology

3.1 Proposed Research Approach

This study adopts a causal research approach. A causal study is appropriate when the purpose of the research is to examine whether one or more independent variables influence a dependent variable. In the present study, the dependent variable is Vocational Students' Perceived Learning Effectiveness, while the independent variables are Perceived Usefulness of GenAI, GenAI Ease of Use, AI Literacy and Self-Efficacy, and Perceived Ethical and Learning Risk. The study does not merely aim to describe students' general opinions about AI. Instead, it seeks to test whether these four factors significantly influence perceived learning effectiveness when vocational students use GenAI.

A causal approach is justified for three reasons. First, the study is guided by a theory-based conceptual model developed from prior literature, and each independent variable is linked to the dependent variable through a proposed hypothesis. Second, the study aims to measure the direction and strength of the effect of each predictor. Third, the study applies multiple linear regression, which is appropriate for assessing the influence of several independent variables on one dependent variable. Although the design uses cross-sectional survey data rather than an experiment, it still fits an explanatory business research design because the objective is to test hypothesised relationships among measurable constructs.

3.2 Data Type

Based on the causal research approach, this study uses quantitative data. Quantitative research is suitable because the purpose of the study is to test predefined hypotheses and examine statistical relationships between measurable variables. Each construct in this study can be operationalised into a set of questionnaire items and converted into numerical data through five-point Likert-scale responses.

The use of quantitative data is appropriate for three reasons. First, the study seeks to determine whether significant relationships exist between the independent variables and perceived learning effectiveness. Second, it aims to compare the relative strength of four predictors, which requires numerical analysis. Third, quantitative data allow respondents' perceptions to be collected in a structured and standardised form. The data can then be analysed using descriptive statistics, reliability analysis, and multiple regression.

3.3 Proposed Data Collection Method(s)

The proposed data collection method is a self-administered online questionnaire survey. This method is appropriate because the target respondents are vocational students who have used GenAI tools for learning-related tasks. Since the research focuses on students' perceptions, evaluations, and self-reported learning outcomes, a questionnaire is an efficient way to collect standardised responses from a relatively large number of respondents.

The questionnaire contains screening questions, demographic questions, and main measurement items. The screening questions confirm that respondents are vocational education students, are aged 18 or above, and have used GenAI tools for learning in the past six months. The demographic questions collect information on gender, age group, institution type, and frequency of GenAI use. The main measurement section measures the five constructs using five-point Likert-scale items from 1 = strongly disagree to 5 = strongly agree. This format is simple for respondents and produces numerical data suitable for SPSS analysis.

3.4 Sampling

3.4.1 Target population

The target population consists of vocational education students who are aged 18 or above and have used GenAI tools for learning or study-related tasks within the past six months. This population is appropriate because the study focuses on students who have direct and recent experience with GenAI in a vocational learning context. Respondents without such experience would not be able to evaluate the usefulness, ease of use, AI literacy requirements, risks, or learning effectiveness of GenAI meaningfully.

The inclusion criteria are: (1) the respondent must currently be a vocational education student; (2) the respondent must be 18 years old or above; and (3) the respondent must have used GenAI tools for learning or study-related tasks within the past six months. The exclusion criteria are the reverse of these conditions. These criteria are directly linked to the questionnaire's screening questions, which are placed at the beginning of the survey to ensure that only eligible respondents proceed to the main questionnaire.

3.4.2 Sampling Plan

3.4.2.1 Sampling frame

A complete sampling frame is unlikely to be obtainable for this study. A sampling frame would require a comprehensive list of all eligible vocational education students who have recently used GenAI for learning. Such a list is not publicly accessible, and access to student records would normally be restricted by privacy and institutional policies. For this reason, a full probability-based sampling frame is not realistic for the present study.

3.4.2.2 Sampling technique

This study uses non-probability sampling rather than probability sampling. The specific technique is purposive sampling implemented through online convenience recruitment. Purposive sampling is suitable because respondents must meet specific eligibility criteria. Online convenience recruitment is practical because GenAI users in vocational education are digitally reachable through class groups, student networks, learning platforms, and social media channels. However, this approach limits generalisability because the achieved sample may not fully represent all vocational students.

3.5 Research Instrument

The research instrument is a structured self-administered online questionnaire. It is designed to collect standardised responses for statistical analysis and is consistent with the study's quantitative causal design. The questionnaire contains four sections. The first section includes screening questions. The second section gathers demographic information. The third section measures the four independent variables: Perceived Usefulness of GenAI, GenAI Ease of Use, AI Literacy and Self-Efficacy, and Perceived Ethical and Learning Risk. The fourth section measures the dependent variable: Vocational Students' Perceived Learning Effectiveness.

The measurement items are adapted from established scales and prior literature rather than created entirely from scratch. Perceived Usefulness and Ease of Use are adapted from the Technology Acceptance Model. AI Literacy and Self-Efficacy items are informed by AI literacy and AI competency literature. Ethical and learning risk items are adapted from GenAI education guidance and student perception studies. Perceived Learning Effectiveness items are adapted from perceived learning research in online learning environments. This adaptation improves content validity because the items are aligned with recognised constructs while being rewritten for the vocational GenAI learning context.

A five-point Likert scale is used for all main measurement items, ranging from 1 = strongly disagree to 5 = strongly agree. This scale is appropriate because the constructs are perceptual and evaluative in nature. Before full data collection, the questionnaire should be pre-tested with a small group of peers, academic reviewers, and target-like respondents to identify ambiguous wording, technical issues, excessive length, or item overlap. Ethical considerations include voluntary participation, informed consent, anonymity, confidentiality, and the right to withdraw before submission. No unnecessary personal identifiers are collected.

4. Results and Analysis

A total of 300 questionnaire responses are included in the synthetic dataset. After applying the screening criteria and attention-check rule, 270 valid responses were retained for analysis, while 30 responses were excluded. The invalid responses consisted of: no GenAI use in the past six months (8), not being a vocational student (6), being under 18 (6), no consent (5), and failed attention check (5). The valid sample was then used for descriptive analysis, reliability testing, and hypothesis testing. Descriptive statistics were applied to profile the respondents, Cronbach's alpha was used to assess internal consistency, and multiple regression analysis was employed to test the hypothesised relationships between the four independent variables and perceived learning effectiveness.

4.1 Profile of Respondents

4.1.1 Demographic Question 1: Gender

Table 1. Gender distribution (n = 270)

Gender	Frequency	Percentage
Male	115	42.6%
Female	144	53.3%
Prefer not to say	8	3.0%
Other	3	1.1%

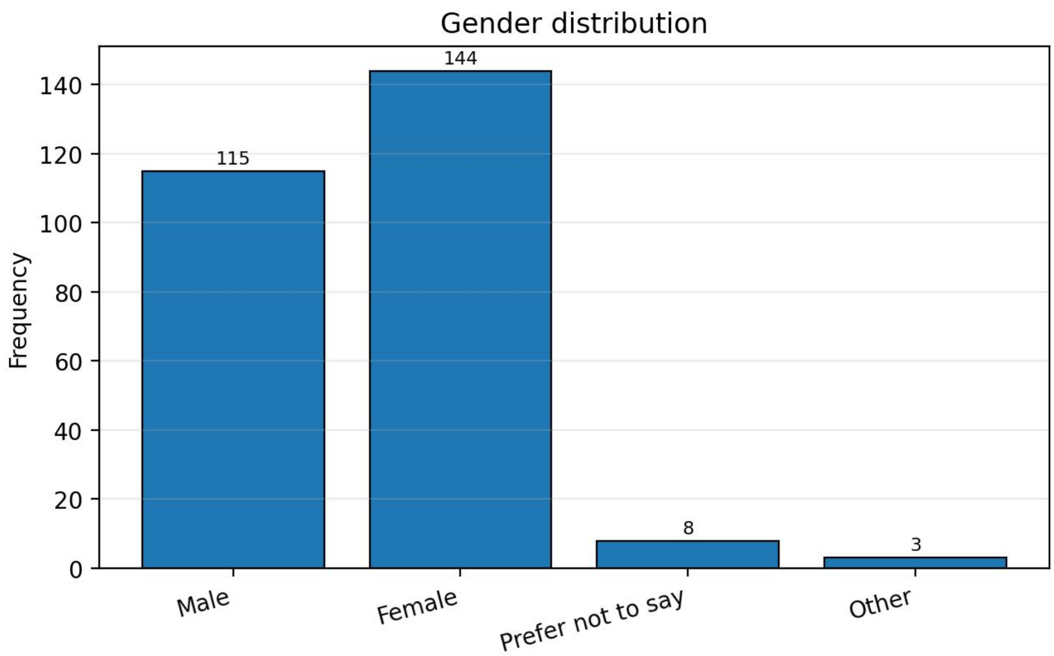

Figure 2. Gender distribution

The gender distribution shows that female respondents formed the largest group, accounting for 53.3% of the valid sample, while male respondents accounted for 42.6%. A smaller proportion selected prefer not to say (3.0%) or other (1.1%). Although the sample contains slightly more female than male respondents, the distribution is not extremely skewed. Therefore, the data provide a reasonable basis for examining perceived learning effectiveness without a severe gender concentration effect.

4.1.2 Demographic Question 2: Age Group

Table 2. Age-group distribution (n = 270)

Age group	Frequency	Percentage
18-20 years	81	30.0%
21-23 years	96	35.6%
24-26 years	62	23.0%
27 years and above	31	11.5%

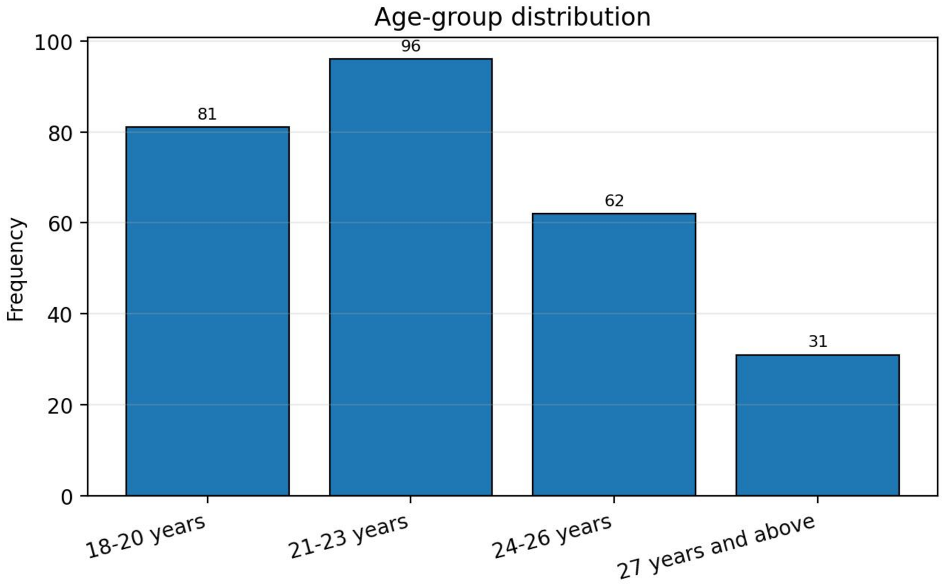

Figure 3. Age-group distribution

The largest age segment was 21-23 years, representing 35.6% of respondents. This was followed by the 18-20 years group (30.0%) and the 24-26 years group (23.0%), while respondents aged 27 years and above accounted for 11.5%. This indicates that the sample was dominated by young adult vocational students, which is consistent with the expected profile of full-time vocational education learners and digitally active GenAI users.

4.1.3 Demographic Question 3: Institution Type

Table 3. Institution type distribution (n = 270)

Institution type	Frequency	Percentage
Secondary vocational school	57	21.1%
Higher vocational college	108	40.0%
Technical college	60	22.2%
Applied undergraduate institution	27	10.0%
Other	18	6.7%

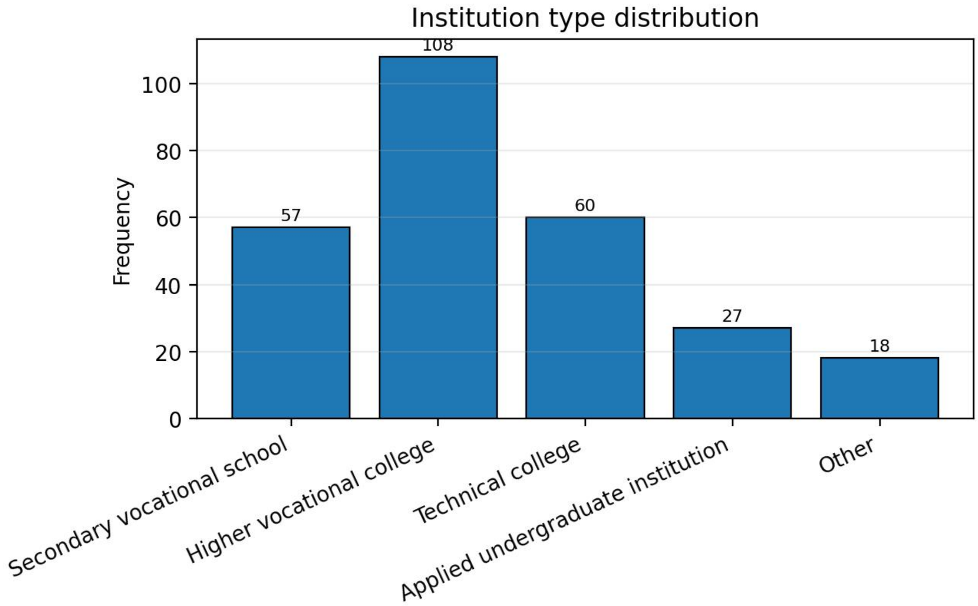

Figure 4. Institution type distribution

Higher vocational college students made up the largest share of the sample, accounting for 40.0% of respondents. Technical college students accounted for 22.2%, secondary vocational school students accounted for 21.1%, applied undergraduate institution students accounted for 10.0%, and other institution types accounted for 6.7%. This distribution suggests that the dataset covers several vocational education settings rather than being restricted to one institutional category.

4.1.4 Demographic Question 4: GenAI Use Frequency

Table 4. GenAI use frequency (n = 270)

Frequency of GenAI use	Frequency	Percentage
Less than once a month	25	9.3%
1-2 times per month	38	14.1%
1-2 times per week	91	33.7%
3-4 times per week	83	30.7%
Almost every day	33	12.2%

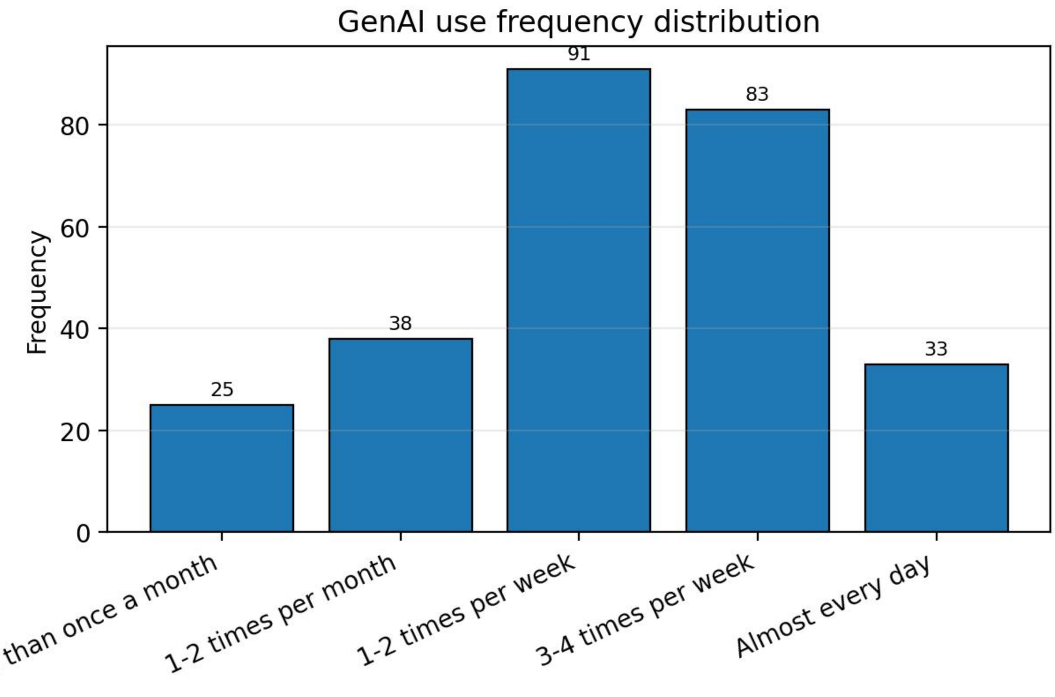

Figure 5. GenAI use frequency distribution

In terms of GenAI use frequency, the largest group of respondents used GenAI 1-2 times per week (33.7%), followed by those using it 3-4 times per week (30.7%). Respondents using GenAI almost every day accounted for 12.2%, while less frequent users accounted for smaller proportions. This suggests that most respondents had regular exposure to GenAI tools and were therefore able to evaluate their learning value and risks meaningfully.

4.2 Reliability Analysis using Cronbach Alpha

Before hypothesis testing, reliability analysis was conducted for all five constructs using Cronbach's alpha. A Cronbach's alpha value of 0.70 or above is commonly treated as acceptable for internal consistency. In this study, all constructs exceeded the 0.70 threshold. Therefore, no questionnaire items were removed and the original scales were retained in full for subsequent analysis.

Table 5. Reliability analysis results

Construct	Number of items	Cronbach's alpha	Reliability assessment
Perceived Usefulness of GenAI	5	0.866	Good
GenAI Ease of Use	5	0.846	Good
AI Literacy and Self-Efficacy	5	0.879	Good
Perceived Ethical and Learning Risk	5	0.852	Good
Vocational Students' Perceived Learning Effectiveness	5	0.889	Good

As shown in Table 4.5, all constructs achieved good internal consistency, with Cronbach's alpha values ranging from 0.846 to 0.889. More specifically, Perceived Usefulness of GenAI (α = 0.866), GenAI Ease of Use (α = 0.846), AI Literacy and Self-Efficacy (α = 0.879), Perceived Ethical and Learning Risk (α = 0.852), and Vocational Students' Perceived Learning Effectiveness (α = 0.889) all exceeded the accepted threshold. This indicates that the items within each construct measured the same underlying concept consistently.

The construct scores were calculated by averaging the five items belonging to each construct. Accordingly, PU_mean was computed from PU1-PU5, EOU_mean from EOU1-EOU5, AILSE_mean from AILSE1-AILSE5, PLR_mean from PLR1-PLR5, and PLE_mean from PLE1-PLE5. These summated variables were then used in the multiple regression analysis.

4.3 Hypotheses Testing

4.3.1 Statistics Test

To test the four hypotheses, this study used multiple linear regression analysis. Multiple regression is appropriate because the research model contains four independent variables and one dependent variable. It allows the researcher to examine the unique effect of each predictor while controlling for the other predictors in the model. Before running the regression, summated construct variables were created from the Likert-scale items. The dependent variable was PLE_mean, while the independent variables were PU_mean, EOU_mean, AILSE_mean, and PLR_mean.

Table 6. Model summary for multiple regression

R^2	Adjusted R^2	F	Sig.
0.574	0.567	89.095	< .001

Table 4.6 shows that the regression model explained 57.4% of the variance in Vocational Students' Perceived Learning Effectiveness ($R^2 = 0.574$), with an adjusted R^2 of 0.567. The overall model was statistically significant, $F = 89.095$, $p < .001$. This means that the four independent variables jointly explained a significant proportion of the variance in perceived learning effectiveness.

4.3.2 Hypotheses

H1: Perceived Usefulness of GenAI positively influences Vocational Students' Perceived Learning Effectiveness.

Table 7. Regression result for H1

Predictor	B	Standardised β	t	p	Decision
Perceived Usefulness of GenAI	0.425	0.389	9.230	< .001	Supported

The regression coefficient for Perceived Usefulness of GenAI was positive and statistically significant ($B = 0.425$, $\beta = 0.389$, $t = 9.230$, $p < .001$). Therefore, H1 is supported. This indicates that students who perceive GenAI as more useful tend to report higher perceived learning effectiveness. This result is consistent with the Technology Acceptance Model because perceived usefulness reflects whether a technology improves task performance. In the vocational education context, students may feel that GenAI improves learning effectiveness because it helps them understand course content, solve learning problems, and complete learning tasks more efficiently.

H2: GenAI Ease of Use positively influences Vocational Students' Perceived Learning Effectiveness.

Table 8. Regression result for H2

Predictor	B	Standardised β	t	p	Decision
GenAI Ease of Use	0.196	0.173	4.088	< .001	Supported

The regression coefficient for GenAI Ease of Use was positive and statistically significant ($B = 0.196$, $\beta = 0.173$, $t = 4.088$, $p < .001$). Therefore, H2 is supported. The result suggests that students who find GenAI tools easier to use are more likely to perceive them as improving learning effectiveness. This finding is consistent with technology acceptance literature, which argues that lower effort and clearer interaction processes can increase favourable evaluations of digital systems. In vocational learning, easy-to-use GenAI tools may reduce operational barriers and allow students to focus more on understanding technical content.

H3: AI Literacy and Self-Efficacy positively influences Vocational Students' Perceived Learning Effectiveness.

Table 9. Regression result for H3

Predictor	B	Standardised β	t	p	Decision
AI Literacy and Self-Efficacy	0.328	0.311	7.233	< .001	Supported

The regression coefficient for AI Literacy and Self-Efficacy was positive and statistically significant ($B = 0.328$, $\beta = 0.311$, $t = 7.233$, $p < .001$). Therefore, H3 is supported. This means that students with stronger AI-related literacy and confidence tend to report higher perceived learning effectiveness. This result is theoretically reasonable because GenAI learning benefits depend on students' ability to ask clear questions, evaluate generated answers, recognise errors, and use AI responsibly. Among the predictors, AI Literacy and Self-Efficacy showed the second strongest standardised effect, indicating that competence in using AI is a substantial condition for learning value.

H4: Perceived Ethical and Learning Risk negatively influences Vocational Students' Perceived Learning Effectiveness.

Table 10. Regression result for H4

Predictor	B	Standardised β	t	p	Decision
Perceived Ethical and Learning Risk	-0.297	-0.279	-6.579	< .001	Supported

The regression coefficient for Perceived Ethical and Learning Risk was negative and statistically significant ($B = -0.297$, $\beta = -0.279$, $t = -6.579$, $p < .001$). Therefore, H4 is supported. This indicates that students who perceive greater ethical and learning risks tend to report lower perceived learning effectiveness. The result is consistent with GenAI education guidance, which warns that inaccurate AI output, overdependence, plagiarism, privacy risks, and weak academic integrity controls may reduce the educational value of GenAI. In vocational education, these risks are especially important because learning quality is closely related to practical competence and workplace readiness.

4.3.3 Overall Discussion of Hypotheses Testing

Overall, all four hypotheses were supported at the 0.05 significance level in the simulated dataset. Three predictors had significant positive effects on perceived learning effectiveness: Perceived Usefulness of GenAI, GenAI Ease of Use, and AI Literacy and Self-Efficacy. One predictor had a significant negative effect: Perceived Ethical and Learning Risk. Among the positive predictors, Perceived Usefulness of GenAI had the strongest standardised coefficient, followed by AI Literacy and Self-Efficacy and GenAI Ease of Use. This suggests that students' perceived learning effectiveness depends most strongly on whether they see GenAI as practically beneficial for learning tasks, but this benefit is also shaped by their ability to use AI critically and confidently.

The negative effect of perceived risk is also important. It shows that GenAI adoption in vocational education should not be evaluated only through convenience and usefulness. If students are concerned about overdependence, misinformation, academic integrity, or privacy, they may be less likely to view GenAI as improving learning. Therefore, the results support a balanced interpretation: GenAI can enhance vocational learning, but its effectiveness depends on usefulness, usability, student capability, and risk governance.

5. Conclusion

This study examined the factors that determine vocational students' perceived learning effectiveness when using generative artificial intelligence in vocational education. Specifically, it investigated the effects of Perceived Usefulness of GenAI, GenAI Ease of Use, AI Literacy and Self-Efficacy, and Perceived Ethical and Learning Risk. Based on the simulated dataset of 270 valid responses, all four hypotheses were supported. Perceived Usefulness of GenAI, GenAI Ease of Use, and AI Literacy and Self-Efficacy had significant positive effects on perceived learning effectiveness, while Perceived Ethical and Learning Risk had a significant negative effect.

The findings indicate that GenAI's impact on vocational education is not one-dimensional. Students do not perceive GenAI as effective simply because the technology exists. Instead, perceived learning effectiveness is shaped by whether GenAI is seen as useful, whether it is easy to use, whether students have the literacy and confidence to use it properly, and whether learning risks are controlled. This supports the broader view that GenAI integration should be understood as a pedagogical and governance issue rather than only a technological upgrade.

In relation to the business problem described in Section 1, the study helps clarify why vocational institutions cannot rely only on tool availability. If institutions introduce GenAI without AI literacy training and ethical guidance, students may use it mechanically or inappropriately. Conversely, if institutions combine GenAI access with clear learning tasks, responsible-use policies, prompt training, verification skills, and assessment redesign, GenAI is more likely to support learning effectiveness. Therefore, the results provide a practical basis for vocational education managers and teachers to design more effective GenAI integration strategies.

5.1 Implications

The first implication is that vocational education managers should prioritise learning usefulness when introducing GenAI. Since Perceived Usefulness of GenAI showed the strongest positive standardised coefficient, students are more likely to value GenAI when it helps them understand course content, solve learning problems, and complete applied learning tasks. Therefore, institutions should embed GenAI into specific vocational learning scenarios rather than treating it as a general-purpose add-on. For example, teachers can design guided activities where students use GenAI to compare technical explanations, generate practice cases, revise project drafts, or simulate workplace problem-solving.

The second implication is that ease of use still matters. Institutions should not assume that students automatically know how to use GenAI effectively. Training should include basic tool access, prompt writing, iterative questioning, source checking, and output refinement. If GenAI is difficult to use or students do not understand how to interact with it, its learning benefit will be reduced.

The third implication is that AI literacy and self-efficacy should be treated as core vocational competencies. The findings show that students' confidence and ability to evaluate AI outputs significantly influence perceived learning effectiveness. Therefore, AI literacy should be incorporated into vocational curricula. Students should be trained to identify hallucinations, check factual accuracy, recognise bias, protect privacy, and distinguish appropriate learning support from academic misconduct.

The fourth implication is that risk governance is necessary. Since Perceived Ethical and Learning Risk had a significant negative effect, institutions should develop clear rules for acceptable AI use, assessment boundaries, citation requirements, and data protection. Teachers should also redesign assessments to test practical reasoning, demonstrations, reflections, and process evidence, rather than relying only on final written outputs that can be generated by AI.

5.2 Limitations and Recommendations

This draft has several limitations. First, the empirical results are based on a synthetic dataset created for SPSS practice and report drafting. Therefore, the numerical findings should not be treated as evidence from real respondents. Before formal academic submission, real questionnaire data must be collected and re-analysed. Second, even with real data, a cross-sectional survey design would limit causal inference because it measures perceptions at one point in time rather than tracking learning development over time. Third, the use of non-probability purposive sampling may limit generalisability beyond the achieved sample.

There are also measurement limitations. Although Cronbach's alpha values indicate internal consistency, reliability alone does not prove construct validity. Some constructs may overlap conceptually. For example, students who perceive GenAI as useful may also perceive it as easy to use, and students with stronger AI literacy may be more likely to recognise both benefits and risks. Future research should consider confirmatory factor analysis or structural equation modelling to test construct validity more rigorously.

Future research should address these limitations in several ways. First, researchers should collect a larger and genuine sample from vocational students across different institution types and subject areas. Second, future studies could compare different vocational disciplines, such as business, engineering, health care, hospitality, and information technology. Third, future research could use longitudinal data to examine whether GenAI use improves actual learning performance over time. Fourth, qualitative interviews could be added to explore how students use GenAI in real learning tasks and how teachers manage academic integrity. Finally, future studies should compare perceived learning effectiveness with objective performance indicators such as grades, skills assessments, project quality, or workplace simulation outcomes.

Appendix

Questionnaire Item Comparison Table

The table lists the original questionnaire item or original source wording used as the adaptation basis, the modified item used in this study, and the corresponding literature source. The items were adapted to fit the context of vocational education and generative AI-supported learning. Some risk-related items were adapted by reversing or broadening the meaning of ethical-risk items so that they align with the construct of perceived ethical and learning risk.

Table A1. Perceived Usefulness of GenAI (PU)

Code	Original item	Modified item	Source
PU1	Using [system] in my job would enable me to accomplish tasks more quickly.	Generative AI helps me understand vocational course content more effectively.	Davis (1989), perceived usefulness scale, TAM.
PU2	Using [system] would improve my job performance.	Generative AI improves the efficiency of my learning.	Davis (1989), perceived usefulness scale, TAM.
PU3	Using [system] in my job would increase my productivity.	Generative AI helps me solve study-related problems more quickly.	Davis (1989), perceived usefulness scale, TAM.
PU4	Using [system] would enhance my effectiveness on the job.	Generative AI improves the quality of my assignments or learning outputs.	Davis (1989), perceived usefulness scale, TAM.
PU5	I would find [system] useful in my job.	Overall, generative AI is useful for my vocational learning.	Davis (1989), perceived usefulness scale, TAM.

Table A2. GenAI Ease of Use (EOU)

Code	Original item	Modified item	Source
EOU1	Learning to operate [system] would be easy for me.	Learning how to use generative AI tools is easy for me.	Davis (1989), perceived ease of use scale, TAM.
EOU2	I would find it easy to get [system] to do what I want it to do.	It is easy for me to use generative AI tools to obtain learning support.	Davis (1989), perceived ease of use scale, TAM.
EOU3	It would be easy for me to become skillful at using [system].	I can use generative AI tools without needing much technical assistance.	Davis (1989), perceived ease of use scale, TAM.
EOU4	My interaction with [system] would be clear and understandable.	The interaction process with generative AI tools is clear and understandable.	Davis (1989), perceived ease of use scale, TAM.
EOU5	I would find [system] easy to use.	Overall, generative AI tools are easy to use for my vocational learning.	Davis (1989), perceived ease of use scale, TAM.

Table A3. AI Literacy and Self-Efficacy (AILSE)

Code	Original item	Modified item	Source
AILSE1	I have the ability to write prompts to get sufficient results.	I know how to write clear prompts or questions when using generative AI tools.	Eisenbardt et al. (2025), GenAI readiness item A.7.
AILSE2	I can assess what the limitations and opportunities of using an AI are.	I can judge whether AI-generated answers are accurate and reliable.	Carolus et al. (2023), MAILS, Understand AI item.
AILSE3	I understand generative AI technologies like ChatGPT can generate output that is factually inaccurate / can exhibit biases and unfairness in their output.	I understand that AI-generated content may contain errors or biased information.	Chan and Zhou (2023), GenAI knowledge items Q3 and Q5.
AILSE4	I can incorporate ethical considerations when deciding whether to use data provided by an AI.	I know how to use generative AI tools	Carolus et al. (2023), MAILS, AI Ethics

Code	Original item	Modified item	Source
		responsibly in my learning.	item.
AILSE5	I can rely on my skills in difficult situations when using AI.	I feel confident in using generative AI tools to support my vocational learning.	Carolus et al. (2023), MAILS, AI self-efficacy item.

Table A4. Perceived Ethical and Learning Risk (PLR)

Code	Original item	Modified item	Source
PLR1	Generative AI technologies such as ChatGPT will hinder my development of generic or transferable skills such as teamwork, problem-solving, and leadership skills.	Using generative AI may reduce students' independent thinking ability.	Chan and Zhou (2023), student-perceived cost item Q20.
PLR2	I can become over-reliant on generative AI technologies.	Using generative AI may make students overly dependent on AI-generated answers.	Chan and Zhou (2023), student-perceived cost item Q21.
PLR3	I understand generative AI technologies like ChatGPT can generate output that is factually inaccurate.	AI-generated content may lead to inaccurate or misleading learning outcomes.	Chan and Zhou (2023), GenAI knowledge item Q3.
PLR4	"Cut & Paste" from a GenAI answer is ethical. / Submitting an exercise created by GenAI is ethical.	Using generative AI may create academic integrity problems, such as plagiarism or inappropriate assistance.	Eisenbardt et al. (2025), ethical consideration items B.7 and B.8.
PLR5	The use of GenAI applications can violate the user's privacy.	I am concerned about the privacy or data security risks of using generative AI tools for learning.	Eisenbardt et al. (2025), ethical consideration item B.2.

Table A5. Vocational Students' Perceived Learning Effectiveness (PLE)

Code	Original item	Modified item	Source
PLE1	I am pleased with what I learned in the course.	Generative AI helps me achieve better learning outcomes in vocational courses.	Gray and DiLoreto (2016), SLS-OLE perceived learning item.
PLE2	The learning tasks enhanced my understanding of the content.	Generative AI helps me improve my understanding of practical or technical knowledge.	Gray and DiLoreto (2016), SLS-OLE perceived learning item.
PLE3	The learning activities promoted the achievement of student learning outcomes.	Generative AI helps me complete learning tasks more effectively.	Gray and DiLoreto (2016), SLS-OLE perceived learning item.
PLE4	I learned skills that will help me in the future.	Generative AI increases my confidence in learning vocational subjects.	Gray and DiLoreto (2016), SLS-OLE perceived learning item.
PLE5	The course contributed to my professional development.	Overall, using generative AI improves my learning effectiveness in vocational education.	Gray and DiLoreto (2016), SLS-OLE perceived learning item.

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