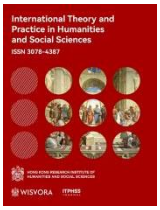
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Generative AI in Professional Learning at a Chinese Private Vocational College: Student Experiences and Teacher Perspectives

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Abstract

GenAI is now part of ordinary study for many students, but frequent use does not automatically mean deeper learning. This mixed-methods study examined professional-course use of GenAI at a private vocational college in Jiangxi Province, China. The evidence came from 431 student questionnaires and written responses from 18 teachers. After response-quality screening, 184 cases were retained for the primary quantitative analyses; 203 moderately screened cases and the full 431 responses were used for sensitivity checks. Meaningful learning engagement (MLE) was measured with two items and is therefore treated as a brief indicator of cognitive engagement rather than a validated multidimensional scale.

Students reported using GenAI most often for knowledge clarification (82.6%) and coursework or exercises (74.5%); practical-training use was lower (20.7%). Perceived professional value (PPV) was associated with MLE (β = .550). When PPV and MLE were entered together, both remained associated with post-adoption learning experience (PAE; β = .339 and β = .364, respectively). The standardized indirect association from PPV to PAE through MLE was .200, with a 95% bootstrap CI of [.109, .307]. These cross-sectional results describe associations rather than causal effects.

Teacher accounts added important context. Teachers valued GenAI for quick explanations but also described answer-oriented use, inaccurate professional content, weak links with practical training, and uncertainty about institutional guidance. They wanted more discipline-specific examples, clearer expectations, and assessment that made student reasoning visible. Across both strands, three tensions stood out: efficiency versus engagement, general usefulness versus professional fit, and rapid student adoption versus slower institutional response. Because the evidence came from one college, the findings should be interpreted as context-specific.

1. Introduction

Generative AI has moved quickly from a new technology to an everyday study aid on many campuses. Students use it for very ordinary tasks: asking for another explanation of a difficult point,

shortening a long reading, testing an idea for an assignment, or getting unstuck on a problem. The attraction is easy to understand. Help is available immediately, particularly when students are studying alone or working under time pressure.

Research findings are not consistently positive. Deng et al. (2025) reported improvements in performance, motivation, and some higher-order thinking outcomes, but they also found a reduction in mental effort. Heung and Chiu (2025) reached a similarly cautious conclusion about engagement. GenAI can encourage participation, yet it can also invite overreliance. Concerns about reliability, dependence, ethics, and human oversight had already been raised by Tlili et al. (2023). The effect of GenAI therefore appears to depend on the learner, the task, and the way the activity is organized. Evidence for better metacognition remains mixed (Deng et al., 2025; Heung & Chiu, 2025).

This creates a simple but important question for teaching: when students finish a task more quickly with GenAI, are they also learning more from it?

A search tool usually points students toward information; GenAI can go much further. It may produce a draft, arrange an argument, compress a reading, or offer a ready-made solution before the student has worked through the problem. In some cases that gives the learner a useful foothold. In others, the polished result can hide how little reasoning the student actually did. Earlier work has described this difference as one between supporting thought and substituting for it (Lim et al., 2023; Tlili et al., 2023).

Technology-adoption research has traditionally asked whether users find a system useful, whether they are satisfied with it, and whether they intend to keep using it (Bhattacherjee, 2001; Davis, 1989). Those questions still help explain why students adopt GenAI. They do not, however, show what happens to the learner's own thinking once the tool is in use. A student can rate a system positively without necessarily engaging in the reasoning through which understanding develops.

For example, a student may be pleased with GenAI because it produces quick, usable answers and may plan to keep using it for that reason. The same student may still rely on those answers with little checking or revision. For this reason, perceived value and the quality of the student's cognitive engagement need to be examined separately rather than treated as the same outcome.

The issue is sharper in vocational and professionally oriented programmes. Students are not only expected to know information; they must use disciplinary knowledge under practical constraints, follow professional standards, complete hands-on tasks, and make judgements that fit real situations. A general-purpose AI tool may therefore be useful in a broad sense without being suitable for a particular professional task. Its output also needs to be accurate, relevant to the course, and workable in the context in which students are expected to apply it.

The present study therefore distinguishes perceived professional value (PPV)—students' appraisal of GenAI as both useful and professionally relevant—from meaningful learning engagement (MLE), which captures students' active evaluation, verification, modification, and extension of AI-generated information.

Self-regulated learning offers a useful way to think about this distinction. Lan and Zhou (2025) note that AI can support feedback, learner autonomy, and self-regulation when it is woven into the learning activity. That benefit is less certain when students use the tool mainly to avoid the work itself. Saving effort on routine steps is not necessarily a problem. What matters is the kind of effort being saved. If students allow the system to compare evidence, check claims, or make professional judgements for them, they may get less practice in the reasoning that the course is meant to strengthen.

Professional learning intensifies this concern. A student may be able to produce a professionally formatted response with AI assistance while lacking the judgement needed to determine whether that response is technically or contextually appropriate.

A tool can perform well in general use and still fit a professional course poorly. It may give a clear explanation while missing a curriculum requirement, a technical standard, or a practical condition that matters in real work. Institutions also move at a different pace from students. Learners may adopt a new tool within days, whereas teacher preparation, assessment redesign, policy development, and resource building take much longer. UNESCO has noted this gap between rapid technological change and slower institutional response (Miao & Holmes, 2023). Higher-education implementation studies make a similar point: strong general performance does not guarantee equal usefulness across subjects or tasks (Chiu, 2024; Guan et al., 2025).

This matters especially in vocational education, where students eventually have to carry what they learn in class into practical situations. Evidence from vocational and broader higher-education research presents a mixed picture. GenAI may support explanation, feedback, and applied learning, yet its benefits depend on pedagogical design and can be accompanied by inaccuracies, overreliance, or reduced independent reasoning (Xu et al., 2023; Farrokhnia et al., 2024; Grassini, 2023; Lo, 2023). Responsible implementation is therefore increasingly discussed in terms of educator involvement, institutional guidance, and deliberate pedagogical integration rather than simple access to the technology (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). Research focused specifically on vocational education adds a further classroom concern: teachers need enough disciplinary, technical, and pedagogical knowledge to judge whether an AI response is actually appropriate for the professional learning expected in the course (Schmitt & Brutzer, 2025).

To examine these issues from more than one angle, this study combines student survey data with written accounts from teachers at a private vocational college in Jiangxi Province, China.

The study addresses four research questions:

RQ1. In what ways do students use generative AI in professional-course learning, and what motivates that use or shapes the support they want?

RQ2. How are perceived professional value, meaningful learning engagement, and post-adoption learning experience related to one another?

RQ3. What benefits, risks, and practical limitations do teachers see when GenAI is used in professional-course learning?

RQ4. Where do student and teacher accounts agree or differ on what is needed for GenAI to support meaningful learning in vocational education?

The quantitative analysis was organized around four hypotheses:

H1. Perceived professional value is positively associated with meaningful learning engagement.

H2. Meaningful learning engagement is positively associated with post-adoption learning experience.

H3. Perceived professional value is positively associated with post-adoption learning experience.

H4. PPV is statistically associated with PAE partially through its association with MLE.

2. Literature Review and Conceptual Framework

2.1 GenAI as Cognitive Support and Cognitive Substitution

Speed is one reason students turn to GenAI. When a concept is difficult, an explanation can

appear almost at once. Reviews have found gains in achievement and engagement in some settings (Deng et al., 2025; Heung & Chiu, 2025), but convenience can also reduce the amount of thinking a learner does independently. This may help explain why results vary across courses and instructional designs, particularly for metacognitive outcomes (Deng et al., 2025; Heung & Chiu, 2025). For that reason, recent higher-education research focuses increasingly on how GenAI is built into teaching, rather than asking only whether it should be permitted or prohibited (Chiu, 2024; Lim et al., 2023).

Students adopted GenAI quickly, but questions about accuracy, dependence, and responsible use appeared just as quickly (Chan & Hu, 2023; Tlili et al., 2023; von Garrel & Mayer, 2023). Assessment shows why this matters. A carefully written assignment may now contain substantial AI-generated material, making it harder for a teacher to see how the student reached the final answer. Several authors therefore argue that assessment should capture at least some of the reasoning, checking, and decision-making that took place before the final submission (Cotton et al., 2024; Eke, 2023; Moorhouse et al., 2023).

This creates a distinction between augmentation-oriented use, in which AI supports learner reasoning, and substitution-oriented use, in which AI replaces reasoning that students are expected to perform themselves. The educational effect of GenAI therefore cannot be inferred from usage frequency or task efficiency alone. The discrepancy between technological efficiency and sustained cognitive participation is described in this study as the efficiency–engagement gap.

2.2 Perceived Professional Value

Perceived usefulness is a long-standing idea in technology-adoption research (Davis, 1989), but usefulness in vocational education has a more specific meaning. A response can be quick and convenient yet still be wrong for the course, inconsistent with a professional standard, or unsuitable for a real task. For vocational learners, usefulness therefore has to be considered together with professional relevance.

In this study, perceived professional value refers to students' overall judgement that GenAI is useful for learning and relevant to the professional content they are studying. The measure therefore brings together instrumental usefulness and professional fit. It is deliberately context-sensitive: a tool may be useful in general but less valuable when a course requires specific standards, cases, or procedures.

2.3 Short-Form Indicator of Cognitive Engagement

In this study, meaningful learning engagement is used in a narrow sense. It concerns whether students continue to think after GenAI gives them something usable. That may involve questioning the response, changing it to fit the task, or using it to pursue the issue further instead of treating the first output as the finished answer.

Self-regulated learning highlights the same issue from another angle. Effective learners notice when they do not understand something and change their approach when needed (Zimmerman, 2002). Research on AI-supported self-regulation also emphasizes reflection and adjustment rather than simple acceptance of system output (Lan & Zhou, 2025). Frequent use of GenAI, then, is not enough by itself to show that meaningful learning has occurred.

Student engagement is not a single behavior. It usually includes behavioral, emotional, and cognitive participation (Fredricks et al., 2004). With GenAI, carefully structured use may strengthen engagement, while overreliance may reduce it (Heung & Chiu, 2025). Our questionnaire does not measure all of these dimensions. Accordingly, MLE is treated only as a two-item indicator of active cognitive participation rather than as a complete engagement scale.

2.4 Cognitive Responsibility

Cognitive offloading helps clarify the boundary. Letting a tool handle routine work can free attention for more demanding parts of a task, so offloading is not inherently undesirable. The problem arises when students also hand over the judgement, interpretation, checking, or problem solving that the lesson is intended to develop. In that case, efficiency may come at the cost of the very cognitive work being taught.

This study uses the concept of cognitive responsibility to describe students' continuing responsibility for judging accuracy, checking evidence, revising generated information, and justifying final decisions. This is particularly important in professional learning, where technically plausible answers may still be professionally inappropriate.

2.5 Professional Fit and Vocational Learning

Vocational education requires students to integrate conceptual knowledge with procedures, authentic tasks, professional standards, and workplace judgement. General-purpose AI may not consistently satisfy these requirements. Meaningful professional integration may therefore require curriculum-aligned resources, discipline-specific cases, practical simulations, current industry information, and teacher mediation.

Recent scholarship on vocational education reaches a similar conclusion. Xu et al. (2023) describe how ChatGPT/AIGC may reshape occupations, vocational competence, talent cultivation, and research in vocational colleges. Broader GenAI research likewise identifies educational opportunities alongside risks related to inaccurate output, superficial use, overreliance, and reduced higher-order engagement (Farrokhnia et al., 2024; Grassini, 2023; Lo, 2023). Taken together with the vocational evidence, this literature makes professional fit a central issue rather than a secondary one.

The discrepancy between generic utility and professional applicability is referred to as the general–professional fit gap.

2.6 Institutional Support and Teacher Mediation

Students often begin using GenAI before a course has clear rules for it. In practice, this means that everyday expectations may be shaped by individual teachers. Assignment wording, examples, boundaries for acceptable use, and assessment design can all influence what students do with the tool. Students themselves have asked for clearer guidance on useful and appropriate AI use (Chan, 2023; Chan & Hu, 2023; Miao & Holmes, 2023). Mixed-methods research also suggests that teacher involvement remains important. AI use appears more productive when teachers help students frame questions, challenge an answer, and judge whether the result fits the task (Guan et al., 2025).

Publishing an AI policy does not, by itself, make a college ready for GenAI. Teachers still need practical guidance, opportunities to develop their own skills, and procedures that work in everyday teaching (Chan, 2023; Miao & Holmes, 2023). Reviews of AI in higher education similarly emphasize educator involvement, pedagogical design, and institutional capacity rather than technology deployment alone (Crompton & Burke, 2023; Zawacki-Richter et al., 2019). In class, the issue is even more concrete. Students and teachers need opportunities to question AI-generated material and to show how decisions were made. One way to do this is to assess part of the learning process rather than relying only on the final product (Foung et al., 2024; Tzirides et al., 2024; Xia et al., 2024).

For vocational teachers, this often appears as a very practical problem. An answer can sound

persuasive yet still be wrong for a particular procedure, occupation, or workplace setting (Schmitt & Brutzer, 2025; Xu et al., 2023). The situation is harder when students are already using AI regularly but course rules are still evolving. We use the term adoption–governance gap for this difference in timing. Research in vocational education also points to teacher capability and subject-specific conditions as important parts of responsible implementation (Schmitt & Brutzer, 2025; Xu et al., 2023).

2.7 Post-Adoption Learning Experience

Post-adoption learning experience (PAE) refers here to how students evaluate GenAI after they have actually used it. The composite brings together expectation confirmation, satisfaction, and willingness to continue using the tool. It should not be read as a measure of achievement. Rather, it summarizes students' own evaluation of their experience with GenAI-supported learning.

2.8 Conceptual Model

The quantitative component examines the pathway Perceived Professional Value → short-form MLE indicator → Post-Adoption Learning Experience. A direct pathway from perceived professional value to post-adoption experience is also retained. The broader mixed-methods interpretation subsequently examines how this process relates to professional fit and institutional conditions.

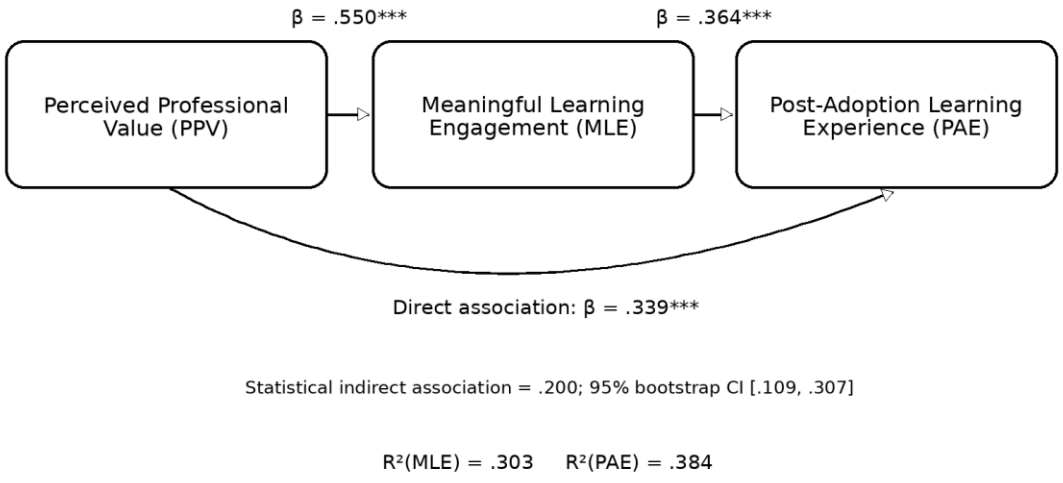


Figure 1. Relationships Examined among Professional Value, Cognitive Engagement, and Post-Adoption Experience

Note. Standardized coefficients are shown. MLE denotes a two-item short-form indicator of cognitive engagement rather than a validated multidimensional engagement scale. R^2(MLE) = .303; R^2(PAE) = .384. The standardized statistical indirect association of PPV with PAE through MLE was .200, 95% bootstrap CI [.109, .307]. ***p < .001.

3. Methodology and Procedures

3.1 Research Design

We used a convergent mixed-methods design (Fetters et al., 2013). The survey and

teacher-response datasets were analysed independently before we compared the two sets of findings. The quantitative analysis described students' patterns of GenAI use and tested associations among PPV, the short-form MLE measure, and PAE. The qualitative analysis asked a different question: what did teachers notice about how students were using AI, particularly when professional relevance, student thinking, and institutional support were at stake?

3.2 Research Context and Participants

The study was conducted at a private vocational college in Jiangxi Province, China. A total of 431 student questionnaires were collected. Qualitative data were obtained from 18 professional-course teachers at the same institution.

3.3 Questionnaire

The student questionnaire combined background and behavioral questions with 15 focal Likert-type items. Those items were initially organized around perceived usefulness, professional content fit, learning engagement, institutional support, expectation confirmation, satisfaction, and continuance intention. Separate questions asked where students used GenAI, why they used it, what professional functions they wanted, what support they expected from the institution, and which learning resources they felt needed improvement.

3.4 Response-Quality Screening

Response quality was examined before the main analyses using three predefined risk indicators. First, 207 cases showed invariant responding across all 15 focal Likert-type items. Second, 62 questionnaires were completed in fewer than 60 seconds. These two indicators overlapped in 41 cases. Excluding responses meeting either of these two criteria yielded a moderately screened sample of N = 203 (47.1% of all collected questionnaires).

A third quality indicator concerned logically inconsistent responses to mutually exclusive multiple-response options. This indicator was assessed across four question groups: professional-learning scenarios, desired GenAI functions, institutional support needs, and resource-improvement needs. Among the moderately screened cases, 19 respondents showed at least one such inconsistency. Excluding these cases yielded the primary strict analytical sample of N = 184 (42.7%).

The N = 184 sample was used for the primary quantitative analyses, while the N = 203 moderately screened sample and the full N = 431 dataset were retained for sensitivity analyses. These criteria are treated as response-quality risk indicators rather than definitive proof that excluded questionnaires were globally invalid.

3.5 Measurement Examination and Composite Construction

The primary strict sample was suitable for exploratory factor analysis (KMO = .886; Bartlett's $\chi^2(105) = 1256.84$, $p < .001$). The original questionnaire was researcher-developed and contained seven theoretically informed dimensions; it was not a set of previously validated independent scales. Exploratory analysis showed substantial overlap among several dimensions, so the final composites were treated as provisional, data-informed analytical indicators rather than validated latent constructs. PPV combined five perceived-usefulness/professional-fit items (M = 3.81, SD = .54, $\alpha = .808$); MLE retained two engagement items (M = 3.66, SD = .66, $\alpha = .701$) and is treated only as a short-form indicator of cognitive engagement; PAE combined six expectation-confirmation, satisfaction, and continuance-orientation items (M = 3.67, SD = .54, $\alpha = .839$). The complete exploratory loading matrix for the strict sample is reported in Supplementary Table S2. Future work should undertake dedicated scale development and independent validation.

Three theoretically interpretable, provisional analytical composites were used. Perceived Professional Value (PPV) combined five items measuring perceived usefulness and professional content fit (M = 3.81, SD = .54, α = .808). PPV is used as a broad exploratory composite; its construction does not imply that general usefulness and specific professional fit form a fully homogeneous or validated latent scale. The two-item MLE composite (M = 3.66, SD = .66, α = .701) was used only as a short-form indicator of active cognitive engagement with AI-generated content; it should not be interpreted as a complete multidimensional measure of meaningful learning engagement. Post-Adoption Learning Experience (PAE) combined six items representing expectation confirmation, satisfaction, and continuance orientation (M = 3.67, SD = .54, α = .839). All three composites were treated as data-informed analytical indicators rather than previously validated independent scales.

3.6 Quantitative Analysis

Descriptive statistics, Pearson correlations, and standardized regression analyses were conducted. A statistical indirect-association analysis examined whether PPV was associated with PAE partially through its association with MLE. The indirect association was evaluated using 10,000 bootstrap resamples and a 95% confidence interval. Because the design was cross-sectional and observational, all H4 results are described as statistical indirect associations; causal mediation is not inferred.

3.7 Qualitative Analysis

The qualitative strand used seven open-ended questions. Teachers were asked how students used AI, what benefits they had seen, which problems had appeared, and what made AI difficult to integrate into professional courses. Other questions covered college rules and resources, differences across subjects or grade levels, and suggested changes. Completion times ranged from 2.2 to 41.6 minutes, with a median of 7.6 minutes. We analysed the responses using reflexive thematic analysis (Braun & Clarke, 2006, 2021). This involved reading the full set several times, comparing responses, revising codes, and adjusting themes when their boundaries were unclear. Because interpretation is central to reflexive thematic analysis, Cohen's kappa was not used as a universal quality criterion (Braun & Clarke, 2021). Instead, proposed themes were checked repeatedly against the full response set, and the reasons for grouping extracts were documented. The final four responses added detail but did not generate a new higher-order theme. We retained three themes: Efficiency-Oriented Adoption and the Engagement Gap; Limits of General-Purpose GenAI for Professional Learning; and Institutional Conditions for Meaningful AI Integration.

3.8 Mixed-Methods Integration

The two strands were analysed separately first and then brought together during interpretation. A joint display was used to place the student results beside the teacher accounts, allowing us to compare patterns of use, the relationships among PPV, MLE, and PAE, and the institutional conditions described by teachers.

Table 1. Student Sample and Response-Quality Screening

Stage	Criterion	N	% of collected
Questionnaires collected	All submitted questionnaires	431	100.0
Invariant-response cases	Same response across all 15 focal Likert items	207	48.0
Rapid-response cases	Completion time < 60 seconds	62	14.4

Stage	Criterion	N	% of collected
Moderately screened sample	Excluded invariant or <60-second responses	203	47.1
Logical inconsistency within moderate sample	Mutually exclusive multiple-response options selected simultaneously	19	4.4
Primary strict analytical sample	Moderate sample with inconsistent cases additionally excluded	184	42.7

4. Results

4.1 Student Use Patterns, Motivations, and Support Needs

Patterns of use varied sharply across tasks. GenAI was most common for difficult course content (82.6%) and coursework or exercises (74.5%), while only 20.7% reported using it for practical training. Efficiency was the leading motivation, selected by 75.5% of students. Resolving difficult knowledge points was selected by 72.3%, and 61.4% used GenAI to supplement learning resources. The support items add an important detail: students were not simply asking for more AI access. They wanted examples, resources, and guidance that were better matched to their own courses and practical learning needs.

Table 2. How Students Reported Using GenAI and the Support They Wanted

Category	Item	n	%
Learning scenario	Knowledge clarification and difficult concepts	152	82.6
Learning scenario	Coursework and exercises	137	74.5
Learning scenario	Course papers and reports	76	41.3
Learning scenario	Professional cases and industry materials	76	41.3
Learning scenario	Knowledge framework and exam preparation	67	36.4
Learning scenario	Professional practical training	38	20.7
Learning scenario	Graduation projects/theses	19	10.3
Learning scenario	Almost never used for professional learning	2	1.1
Motivation	Improve efficiency and save time	139	75.5
Motivation	Resolve difficult knowledge points	133	72.3
Motivation	Supplement learning resources	113	61.4
Motivation	Organize knowledge and prepare for exams	100	54.3
Motivation	Complete course assessments	47	25.5
Motivation	Follow classmates/passive use	9	4.9
Professional function	Layered explanation and error diagnosis	151	82.1
Professional function	Training simulation and procedural guidance	96	52.2
Professional function	Workplace cases and industry-practice materials	92	50.0
Professional function	Personalized revision and knowledge frameworks	89	48.4
Institutional support	Specialized AI training	124	67.4
Institutional support	Discipline-specific AI teaching cases	120	65.2
Institutional support	School-based professional AI resource library	85	46.2
Institutional support	AI-use and academic-integrity guidance	81	44.0

Category	Item	n	%
Resource improvement	Alignment with curricula, textbooks and training standards	134	72.8
Resource improvement	More workplace/practical cases	115	62.5
Resource improvement	Updated industry data and professional practice	108	58.7

4.2 Relationships among the Focal Constructs

PPV, the short-form MLE indicator, and PAE were moderately and positively correlated. PPV was statistically associated with MLE ($\beta = .550$, $p < .001$), explaining 30.3% of the observed variance in the short-form MLE composite ($R^2 = .303$). Within this exploratory model, this represents a practically meaningful, moderate level of explanatory power rather than a trivial statistically significant association. H1 was supported.

Table 3. Descriptive Statistics, Reliability, and Correlations among the Focal Constructs

Construct	Items	M	SD	Cronbach's α	1	2	3
1. Perceived Professional Value	5	3.81	0.54	.808	—		
2. Meaningful Learning Engagement	2	3.66	0.66	.701	.550***	—	
3. Post-Adoption Learning Experience	6	3.67	0.54	.839	.540***	.551***	—

Note. N = 184. ***p < .001.

4.3 Associations with Post-Adoption Learning Experience

When PPV and the short-form MLE indicator were entered simultaneously, both were statistically associated with PAE: PPV → PAE, $\beta = .339$, $p < .001$; MLE → PAE, $\beta = .364$, $p < .001$. The model accounted for 38.4% of the observed variance in PAE ($R^2 = .384$), indicating moderate-to-substantial explanatory value within this sample. H2 and H3 were supported.

The total standardized association between PPV and PAE was $\beta = .540$, $p < .001$. PPV was statistically associated with PAE partially through its association with MLE: the standardized indirect association was .200, with a 95% bootstrap confidence interval of [.109, .307]. The interval excluded zero, supporting H4. The indirect component represented approximately 37% of the total standardized association (.200/.540), indicating a substantively meaningful indirect association. The direct association remained statistically significant. These results do not establish temporal or causal mediation.

Table 4. Regression and Statistical Indirect-Association Results

Relationship	β	p / 95% CI	Result
H1: PPV → MLE	.550	< .001	Supported
H2: MLE → PAE	.364	< .001	Supported
H3: PPV → PAE, direct	.339	< .001	Supported
PPV → PAE, total	.540	< .001	—

Relationship	β	p / 95% CI	Result
H4: PPV associated with PAE partially through MLE	.200	95% CI [.109, .307]	Supported

Note. R^2(MLE) = .303; R^2(PAE) = .384. "Indirect association" is used throughout because the data are cross-sectional. The moderately screened N = 203 sensitivity sample produced nearly identical coefficients (PPV → MLE = .550; PPV → PAE = .349; MLE → PAE = .360; R^2(PAE) = .390).

4.4 Teacher Perspectives

Thematic analysis of the 18 teacher responses produced three higher-order themes. Teachers generally recognized GenAI's efficiency, accessibility, and individualized support, while also describing answer-oriented use, direct copying, dependence, reduced independent reasoning, professional inaccuracies, weak practical alignment, uneven teacher readiness, and unclear institutional rules. Because the responses were not independently double-coded by two human coders, these themes should be interpreted as analytically coherent patterns rather than as categories supported by an intercoder-kappa statistic.

Table 5. Thematic Structure of Teacher Interviews

Higher-order theme	Subtheme	Representative meaning
Efficiency-Oriented Adoption and the Engagement Gap	Efficiency and accessibility	Faster access, immediate assistance, reduced learning barriers
	Shallow or answer-oriented use	Direct answers, assignment completion, fragmented learning
	Cognitive offloading	Dependence, reduced independent reasoning, cognitive outsourcing
Limits of General-Purpose GenAI	Professional reliability	Hallucinations, errors, outdated or unverifiable content
	Discipline and curriculum fit	Weak alignment with professional courses and standards
	Practice gap	Limited integration into authentic tasks and practical training
Institutional Conditions for Meaningful AI Integration	Governance	Unclear boundaries and academic-integrity expectations
	Teacher capability	Uneven AI knowledge and pedagogical competence
	Professional resources	Insufficient discipline-specific and industry-linked resources
	Assessment redesign	Greater emphasis on process, reasoning, and practical demonstration

4.5 Mixed-Methods Integration

Bringing the two strands together showed several points of agreement. Students described frequent, efficiency-oriented use, while teachers said that much of this use remained concentrated in relatively straightforward academic tasks. Students also asked for resources tied more closely to curricula and practice; teachers, from another angle, questioned how well general-purpose AI fitted

professional learning. A similar pattern appeared around support: students wanted training and clearer rules, and teachers described gaps in both institutional guidance and pedagogy.

Table 6. Joint Display of Quantitative and Qualitative Findings

Student evidence	Teacher evidence	Integrated inference
82.6% used GenAI for knowledge clarification; 74.5% for coursework	Teachers described widespread use, mainly in relatively simple academic tasks	High adoption was concentrated in knowledge- and task-oriented activities
75.5% identified efficiency as a major motivation	Teachers consistently recognized time saving and rapid support	Efficiency was a major driver of student adoption
Only 20.7% used GenAI for professional practical training	Teachers reported limited integration into authentic practice and workplace tasks	A practice-oriented integration gap remained
PPV was associated with the short-form MLE indicator (β = .550)	Teachers reported deeper benefits when students evaluated and modified AI outputs	Perceived professional value was associated with more active cognitive engagement
Short-form MLE was associated with PAE (β = .364)	Teachers emphasized verification, reflection, and revision	Active cognitive engagement was associated with more positive learning experience
Statistical indirect association through MLE = .200	Teachers warned that copying and cognitive outsourcing limit learning	Part of the PPV–PAE association was linked to the narrow cognitive-engagement indicator
72.8% requested curriculum- and training-aligned AI resources	Teachers questioned the professional fit of general-purpose AI	Generic usefulness did not ensure professional relevance
67.4% requested AI training; 65.2% requested professional use cases	Teachers identified uneven pedagogical competence and resource shortages	Meaningful integration required formal pedagogical support
44.0% requested explicit AI-use and integrity guidance	Teachers reported unclear or inconsistent institutional boundaries	Student adoption had developed faster than governance

4.6 Direct Responses to the Research Questions

RQ1: GenAI was used mainly for routine academic needs, especially explanation and coursework support. Efficiency also mattered to many students. At the same time, their responses showed that general access was not enough; they wanted training, examples, and resources that reflected the content and expectations of their own disciplines.

RQ2: PPV was statistically associated with the two-item short-form MLE indicator and with PAE, and PPV was statistically associated with PAE partially through its association with this narrow cognitive-engagement indicator. The result should not be interpreted as evidence about the full

multidimensional construct of meaningful learning engagement, and the cross-sectional design does not establish temporal or causal ordering.

RQ3: Teachers perceived clear benefits in efficiency and accessibility but emphasized dependence, cognitive offloading, professional inaccuracies, limited authentic practice, and uneven institutional readiness.

RQ4: The two strands converged on three conditions for meaningful integration: maintaining cognitive engagement, improving professional fit, and strengthening institutional governance. Their integration is summarized in Table 6 and elaborated through the three-gap framework in the Discussion.

5. Discussion

The central challenge identified by this study is not whether students adopt GenAI. It is whether technological efficiency can be translated into cognitively meaningful, professionally relevant, and institutionally supported learning. Table 6 shows that this conclusion is supported by convergence across the student and teacher strands rather than by either data source alone.

The results first point to a strong concern with efficiency. Students most often said that GenAI helped them save time, and their most common uses were clarifying course content and completing coursework. That pattern is understandable: immediate explanations can make independent study easier and lower the barrier to getting started. The teacher accounts, however, add an important qualification. Several teachers described students who stopped at the answer rather than working through the reasoning behind it. In those cases, faster task completion did not necessarily mean deeper learning. We describe this mismatch as the efficiency–engagement gap.

The quantitative results reinforce this distinction. PPV was positively associated with MLE, but the two constructs were not equivalent. The short-form MLE indicator remained statistically associated with PAE after PPV was taken into account. The indirect association through this narrow cognitive-engagement indicator suggests that part of students' positive experience with GenAI is linked to active evaluation, revision, and extension of AI-generated content; it should not be generalized to the full multidimensional construct of meaningful learning engagement. This distinction clarifies the difference between using AI successfully and learning successfully with AI.

Teachers often came back to the same practical question: who makes the final judgement? A GenAI answer may read smoothly and still contain errors, omit key details, or offer advice that does not suit the professional situation. Students therefore have to decide what needs checking, what should be revised, and when an answer should be rejected. From this perspective, AI literacy is not just technical skill. It also involves responsibility for the accuracy and professional suitability of work produced with AI support.

Another issue is professional fit. Students asked for resources that were more closely tied to their curriculum, practical work, and industry context. This suggests that finding GenAI useful in general is not the same as finding it suitable for professional learning. Teachers made a similar point from their own experience, noting inaccurate content and weak links with authentic practice. Taken together, the two strands support a distinction between general usefulness and professional fit.

Students' use of GenAI for practical training remained substantially lower than their use for knowledge clarification and coursework. Current integration therefore appears more developed in

text-centered academic activities than in authentic professional practice. Vocational institutions may need to move toward simulated professional scenarios, authentic workplace cases, project-based learning, practical problem solving, and industry-linked AI resources.

The third issue concerns institutional readiness. Students and teachers both identified unmet needs for AI training, professional resources, clearer governance, teacher capability, and redesigned assessment. This convergence suggests an adoption–governance gap in which student adoption develops faster than institutional capacity to guide it. Meaningful AI integration should therefore be treated as an institutional learning-design issue rather than solely an individual technology-use issue.

The three gaps are closely connected in practice. Where institutional guidance is weak, students and teachers tend to fall back on familiar routines and general-purpose tools. That is also where problems of professional fit become easier to see. If AI output does not match course standards or workplace conditions, students may keep it for lower-risk activities such as explanation, summarizing, or assignment support. Tasks may be completed faster without becoming more intellectually demanding. Stronger institutional support could shift this pattern by providing clearer expectations and resources that fit the discipline. Subject-specific materials, teacher development, and assignments that require students to explain their reasoning may make professional use more credible while keeping students involved in the thinking. This interpretation is consistent with vocational and higher-education research emphasizing professional alignment, teacher capability, pedagogical design, and institutional support (Xu et al., 2023; Schmitt & Brutzer, 2025; Crompton & Burke, 2023).

6. Theoretical Implications

The first theoretical implication is that positive evaluation and active thinking should not be treated as the same thing. Students may regard GenAI as useful and relevant to their course while still engaging with it only superficially.

Second, it extends conventional perceived usefulness by incorporating professional fit, including disciplinary relevance, curriculum alignment, and practical applicability.

Third, integration of student and teacher evidence supports a three-gap framework for meaningful GenAI integration: the efficiency–engagement gap, the general–professional fit gap, and the adoption–governance gap. Together, these gaps locate GenAI integration at three levels: learner cognition, professional context, and institutional design.

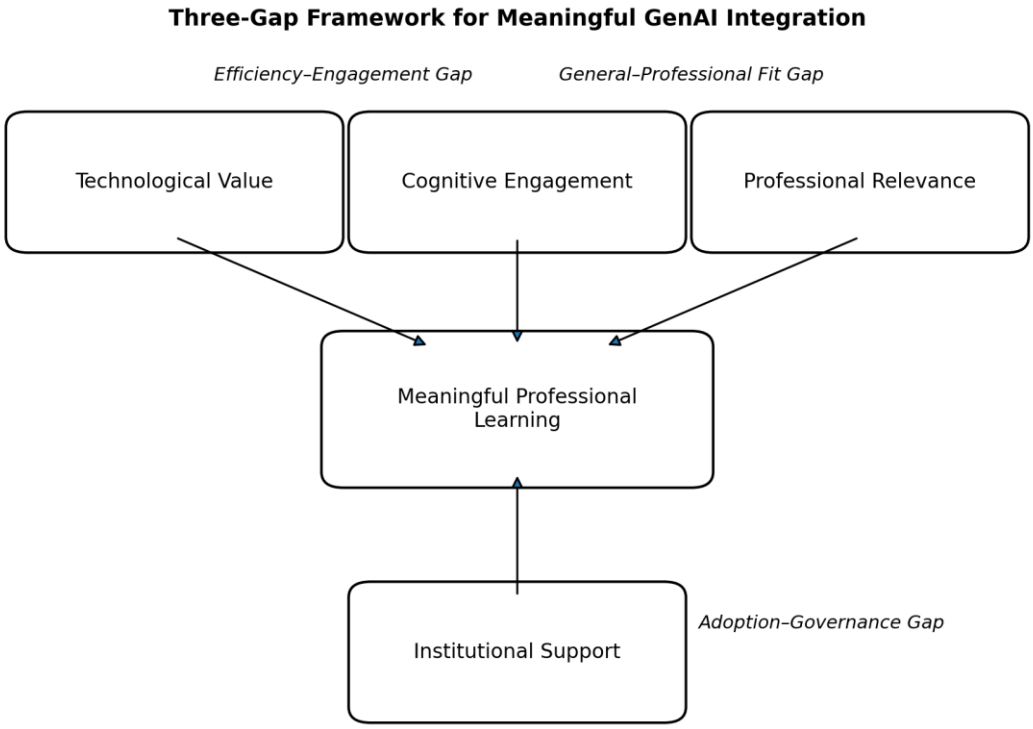


Figure 2. Three Interacting Gaps in Meaningful GenAI Integration

7. Practical Implications

Vocational institutions should prioritize four areas. First, they should develop discipline-embedded AI resources aligned with curricula, practical standards, professional cases, and current industry information.

Second, writing a good prompt is only one part of using AI well. In professional-course work, students still have to judge whether a response is dependable, decide which claims need checking, and revise material before they use it. Source checking and professional judgement are therefore essential. This view is consistent with research that describes AI literacy as the ability to understand, question, and responsibly combine human and artificial intelligence (Tzirides et al., 2024). Student-focused studies make a similar point by placing evaluation, ethical judgement, and awareness of system limitations alongside access and prompting skills (Chan & Hu, 2023; Tzirides et al., 2024).

Third, teacher development should involve more than basic tool training. Teachers also need time to rethink learning activities, discuss risks that arise in their own disciplines, and develop assessment methods that still reveal what students understand.

Fourth, the final submission may no longer provide enough evidence of learning on its own. Because GenAI can help produce a fluent answer, teachers may need some record of the thinking that led to the final version. That evidence need not look the same in every course. One subject may use an oral defence, while another may prefer a practical demonstration, a brief AI-use record, or a short explanation of a professional decision. Foung et al. (2024) make a similar point: purposeful AI use can be permitted while students are still asked to account for the choices they made. Reviews of GenAI assessment likewise give greater weight to authentic tasks, self-regulation,

responsible learning, and academic integrity than to polished outputs that reveal little about the reasoning behind them (Moorhouse et al., 2023; Xia et al., 2024).

8. Limitations and Future Research

The first limitation is the setting. All data came from one private vocational college in Jiangxi Province. Conditions in private colleges can differ from those in public institutions, including student preparation, staffing, resources, governance, and digital infrastructure. The results should therefore be read as evidence from this institutional context rather than as a description of Chinese vocational education as a whole. Future studies could test the same questions across public and private institutions, different regions, and different disciplinary clusters.

Second, the quantitative data were cross-sectional. The statistical indirect association among PPV, MLE, and PAE does not establish temporal ordering or causality. Longitudinal and experimental designs are needed to test whether changes in perceived professional value precede changes in engagement and subsequent learning experience.

Third, the original dataset contained a substantial proportion of invariant response patterns. Transparent screening and sensitivity analyses reduced this threat, but future studies should use stronger quality controls, including attention checks, planned minimum response-time criteria, variation-sensitive items, and behavioral indicators.

Fourth, measurement is an important limitation. PPV and PAE were data-informed researcher-constructed composites rather than scales developed through a full validation process, and MLE was represented by only two items ($\alpha = .701$). The MLE indicator should therefore be interpreted as a short-form composite, not as a mature scale. The current two-item MLE indicator primarily captures judgment/modification and deeper inquiry rather than a complete set of verification and metacognitive behaviors. Future instrument development should include at least four to five engagement items covering verification of AI outputs, correction of AI content, reflection on AI limitations, metacognitive monitoring, and transfer of AI-supported knowledge to practical training tasks, followed by independent EFA/CFA validation.

Fifth, PAE captures subjective experience rather than objective learning performance, and the teacher responses were structured open-ended interviews rather than observed classroom behavior. The qualitative dataset was not independently double-coded by two human coders, so intercoder reliability (e.g., Cohen's kappa) was unavailable. Future research should combine richer interviews with classroom observation, student AI interaction logs, objective practical-training scores, examination performance, transfer tasks, and discipline-specific comparisons.

9. Conclusion and Suggestion

Within this single private vocational-college context, GenAI had already become part of students' everyday professional learning. The key educational question was therefore not simply whether students used AI, but under what conditions that use was associated with more meaningful professional learning.

The findings indicate that students value GenAI for efficiency, accessibility, and professional-learning support, but current use remains substantially more concentrated in knowledge clarification and coursework than in authentic professional practice.

PPV was statistically associated with the two-item short-form MLE indicator and with PAE, and PPV was statistically associated with PAE partially through its association with this narrow cognitive-engagement indicator. Teacher perspectives added complementary evidence about cognitive offloading, professional inaccuracies, practical integration, teacher preparedness, and governance. These findings are suggestive for comparable vocational settings but should not be read as representative of all Chinese private or public vocational institutions.

Together, the findings identify three challenges: the efficiency–engagement gap, the general–professional fit gap, and the adoption–governance gap. Meaningful GenAI integration in vocational education therefore requires the alignment of technological value, cognitive engagement, professional relevance, and institutional support.

The educational value of GenAI should ultimately be judged not by how much work it can perform for students, but by how effectively it helps students understand, evaluate, apply, and justify professional knowledge.

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Supplementary Materials

Supplementary Table S2. Exploratory three-factor loading matrix for the 13 items used in the focal composites

Item	Factor 1: PPV-oriented	Factor 2: MLE/applied	Factor 3: PAE-oriented
PU1	0.581	0.291	0.191
PU2	0.825	0.110	0.145
PCF1	0.682	0.221	0.202
PCF2	0.459	0.413	0.256
PCF3	0.273	0.717	0.162
SLE1	0.152	0.584	0.265
SLE2	0.166	0.650	0.359
EC1	0.173	0.164	0.486
EC2	0.124	0.156	0.608
SAT1	0.204	0.183	0.725
SAT2	0.140	0.351	0.631
CI1	0.272	0.210	0.644
CI2	0.201	0.265	0.619

Note. Loadings are reported for transparency only. The solution does not establish validated three-factor scales. PPV items show partial differentiation between general utility and applied professional fit, and the two-item MLE composite represents only a narrow cognitive-engagement indicator. These patterns support treating PPV, MLE, and PAE as provisional analytical composites rather than mature latent measures.