FACULTY INTEGRATION OF GENERATIVE ARTIFICIAL INTELLIGENCE AND TEACHER-PERCEIVED STUDENT LEARNING SUPPORT IN A PHILIPPINE STATE UNIVERSITY

Alfie P. Alga [1,] Jonathan L. Delos Santos [2]
[1,2] Zamboanga Peninsula Polytechnic State University, Philippines
Corresponding email: alumna_rhed@yahoo.com

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ABSTRACT– *This study examined the relationship between faculty integration of Generative Artificial Intelligence (GenAI) and teacher-perceived student learning support at Zamboanga Peninsula Polytechnic State University. A quantitative descriptive-correlational design was employed using total enumeration of the accessible faculty population. All 87 eligible faculty members participated, resulting in a 100% response rate. Data were collected through an expert-validated 30-item questionnaire measuring GenAI integration in instructional planning and content development, teaching efficiency and classroom management, and assessment, feedback, and evaluation. The instrument also assessed faculty perceptions of GenAI-supported student learning in academic learning and research, problem solving and skill development, and assessment and examination preparation. The instrument obtained a Cronbach's alpha coefficient of .94. Means, standard deviations, and Pearson product–moment correlations were used to analyze the data, with a Bonferroni-adjusted significance level of .0056. Results showed high to very high faculty integration of GenAI across the three pedagogical dimensions. Teacher-perceived student learning support was likewise rated high to very high, particularly in problem solving, skill development, and assessment preparation. All nine correlations were positive and statistically significant, ranging from* $r = .681$ *to* $r = .784$*, with* $p < .001$*. These findings indicate that higher faculty-reported GenAI integration was associated with stronger faculty perceptions of student learning support. However, because both constructs were measured through faculty reports in a cross-sectional design, the findings should not be interpreted as evidence of causation or direct student outcomes. Institutional AI policies, sustained faculty development, ethical-use guidelines, and future multi-source research are recommended.*

Keywords: *Academic support, Assessment, Faculty integration, Generative Artificial Intelligence, Higher education, Teacher perception*

1. INTRODUCTION

Generative Artificial Intelligence has moved rapidly from an emerging technology to a practical tool used in lesson planning, content generation, feedback, assessment preparation, and academic support. Higher education faculty increasingly encounter GenAI as both an instructional resource and a governance challenge. Educators report potential gains in efficiency, differentiated explanations, idea generation, and learner support, but they also identify risks involving inaccurate outputs, over-reliance, privacy, bias, and academic integrity [1, 2, 22, 23, 25]. Evidence across academic levels further indicates that students regard ChatGPT as a useful but potentially risky research-writing tool whose ethical use requires output verification, transparent acknowledgment of AI assistance, clearly defined boundaries, and preservation of human authorship and independent thinking [31]. Teacher uptake is also shaped by AI self-efficacy, prior experience, perceived relevance, and access to professional and technical support [21, 22].

Awareness and actual pedagogical use do not always develop at the same pace. Teaching interns may recognize ChatGPT while using GenAI only sparingly for lesson planning, action research, and electronic portfolios [3]. Preservice mathematics teachers have reported positive attitudes and practical learning support, together with concerns about accuracy, depth, and advanced-content reliability [4, 5]. This further indicates that access to faculty development, technology leadership, autonomy, commitment, and institutional support shape educators' capacity to adopt innovative practices [26-28]. Efficiency, positive user experience, administrative support, institutional-value alignment, and responsible use as drivers of GenAI adoption. In contrast, perceived risks, policy gaps, academic-integrity concerns, overdependence, and the time required to learn and verify AI-generated outputs acted as barriers [32]. modular, experiential, and peer-supported professional development can improve teachers' digital competence, practical technology integration, and instructional confidence, although time constraints and inadequate device access may limit sustained implementation [33]. These findings suggest that educational value depends not simply on access to GenAI, but on users' AI literacy, pedagogical judgment, sustained professional learning, and institutional guidance.

Instructors often show moderate familiarity but uneven direct use, and their trust and distrust can coexist [6]. GenAI can support learning design, feedback, and learner autonomy when activities are aligned with clear outcomes and human oversight [7]. GenAI literacy includes technical understanding, pedagogical application, and critical-ethical judgment rather than tool use alone [8]. Teacher AI self-efficacy and readiness are not uniform, which strengthens the case for differentiated training and continuing support [21, 22]. Teachers' AI competence and pedagogical knowledge are connected to teaching performance [9], while institutional adoption studies emphasize explicit roles, authentic assessment, AI literacy, and coordinated governance [23, 25]. GenAI use should therefore be interpreted within a pedagogical and institutional framework rather than as a purely technological behavior.

The second construct as student academic engagement. However, the survey items asked faculty whether GenAI helps students understand concepts, formulate research titles, develop solutions, prepare for assessments, and improve academic work. Student engagement is commonly treated as a multidimensional construct involving behavioral, cognitive, and emotional participation and is most defensibly measured from students or observable learning data [24]. The present indicators more directly represent teacher-perceived student learning support and perceived learning benefits. The revision therefore uses the more defensible construct label teacher-perceived student learning support, aligning the title, research questions, analysis, results, and conclusions with the actual respondents and instrument.

Varied student and teacher perceptions of ChatGPT [10], while global institutional reviews emphasize cautious adoption, clear policies, discipline-specific guidance, authentic assessment, training, equitable access, and protection of sensitive information [11, 23]. Academic-integrity concerns remain especially important because student use of chatbots for assessment assistance is already widespread and requires coordinated policy, assessment, literacy, and support measures [12, 25]. At the same time, technology-supported learning can promote participation, motivation, and performance when learners receive appropriate pedagogical structure, stable access, and technical support [13-19], [29, 30]. Technology-mediated TLE learning was shaped by learners' access to resources, teacher and family support, socioeconomic conditions, and the authenticity of performance tasks, indicating that digital tools alone cannot ensure meaningful learning without adequate instructional and institutional support [35]. The present study therefore examines how faculty-reported GenAI integration is associated with faculty perceptions of student learning support in one Philippine state university, without treating the association as proof of causal impact.

Research Questions

The study addressed the following questions:

1. To what extent did faculty integrate GenAI in (a) instructional planning and content development, (b) teaching efficiency and classroom management, and (c) assessment, feedback, and evaluation?
2. To what extent did faculty perceive GenAI to support students in (a) academic learning and research, (b) problem solving and skill development, and (c) assessment and examination preparation?
3. What relationships existed between the three faculty GenAI-integration dimensions and the three teacher-perceived student-learning-support dimensions?

The null hypothesis stated that no statistically significant relationships existed between faculty GenAI integration and teacher-perceived student learning support. The alternative hypothesis stated that at least one positive relationship existed between the measured dimensions.

Conceptual Scope

The conceptual scope distinguishes faculty GenAI integration from teacher-perceived student learning support. It is informed by AI-TPACK scholarship, but the questionnaire does not directly measure the seven original TPACK knowledge domains. Instead, the faculty-integration dimensions operationalize where GenAI is applied in pedagogical work, while the outcome dimensions represent teachers' perceptions of how GenAI supports students. Because authentic engagement includes behavioral, cognitive, and emotional dimensions [24], the outcome should not be interpreted as a complete engagement measure. The arrow in Figure 1 represents statistical association only.

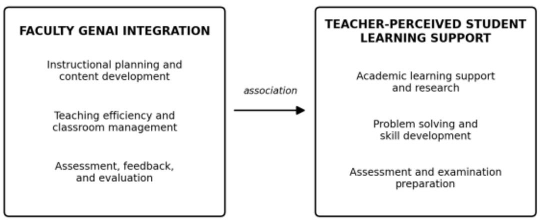

Figure 1. Conceptual scope of faculty GenAI integration and teacher-perceived student learning support.

2. MATERIALS AND METHODS

Research Design

A quantitative descriptive-correlational design was employed. The descriptive component summarized faculty GenAI integration and teacher-perceived student learning support. The correlational component examined the direction and magnitude of associations among the six composite dimensions. No variable was manipulated, no comparison group was used, and no temporal ordering was established. Accordingly, the design supports description and association, not prediction in the causal sense or proof that faculty GenAI use produced student outcomes.

Research Locale and Respondents

The study was conducted at Zamboanga Peninsula Polytechnic State University, a public higher education institution in the Zamboanga Peninsula, Philippines. The accessible population comprised 87 faculty members from different colleges who were involved in instructional planning, classroom teaching, assessment, and academic support. Total enumeration was employed: all 87 eligible faculty members participated and completed the questionnaire, resulting in a 100% response rate. The findings therefore represent the complete accessible faculty population during the study period, but they remain specific to one institution and should not be generalized automatically to other higher education institutions. Prior AI experience, self-efficacy, and access to professional development may influence reported integration [21, 26].

Research Instrument and Operational Definitions

A modified survey questionnaire contained 30 substantive Likert-type items. Fifteen items measured faculty GenAI integration across three five-item dimensions: instructional planning and content development; teaching efficiency and classroom management; and assessment, feedback, and evaluation. Fifteen items measured teacher-perceived student learning support across academic learning and research; problem solving and skill development; and assessment and examination preparation. Dimension scores were computed as the mean of their five items.

Responses used a five-point scale. To align the interpretation with the research question on extent of use, mean scores were classified as very low (1.00-1.80), low (1.81-2.60), moderate (2.61-3.40), high (3.41-4.20), and very high (4.21-5.00). This replaces the original use of agreement labels, which was inconsistent with the stated construct of extent.

Instrument Review and Pilot Testing

The modified questionnaire underwent expert validation for clarity, relevance, appropriateness, and alignment with the study objectives, and the instruments were reported by the authors as validated before administration. A pilot test was conducted with respondents who had characteristics similar to those of the target population. Based on the authors' confirmed research information, the instrument obtained a Cronbach's alpha coefficient of .94, indicating excellent internal consistency.

Data Collection

Administrative permission was sought from the University President, College Deans, program heads, and other authorized officials. Questionnaires were distributed personally or through appropriate online platforms, depending on respondent availability. Completed responses were checked for completeness, coded, tabulated, and prepared for analysis. The

Data Analysis

Means and standard deviations summarized each item and dimension. Nine pre-specified Pearson product-moment correlations were used to examine the three-by-three set of relationships between faculty GenAI integration and teacher-perceived student learning support. To control familywise error across nine tests, the decision threshold was Bonferroni-adjusted to alpha = .05/9 = .0056. All reported p-values were below .001 and therefore remained statistically significant after adjustment. Ninety-five percent confidence intervals for r were calculated using Fisher's z transformation with n = 87. Correlations were interpreted as associations only.

3. RESULTS

Dimension-Level Results

Table 1: Summary of Faculty GenAI Integration and Teacher-Perceived Student Learning Support

Dimension	M	SD	Extent
Faculty integration: instructional planning and content development	4.04	0.72	High
Faculty integration: teaching efficiency and classroom management	4.26	0.70	Very high
Faculty integration: assessment, feedback, and evaluation	4.19	0.70	High
Perceived support: academic learning and research	4.19	0.70	High
Perceived support: problem solving and skill development	4.28	0.69	Very high
Perceived support: assessment and examination preparation	4.25	0.70	Very high

Note. N = 87. M = mean; SD = standard deviation. Extent: 3.41-4.20 = high; 4.21-5.00 = very high.

Faculty reported the highest GenAI integration in teaching efficiency and classroom management (M = 4.26, SD = 0.70), followed by assessment, feedback, and evaluation (M = 4.19, SD = 0.70) and instructional planning and content development (M = 4.04, SD = 0.72). The first dimension was classified as very high, whereas the latter two were high. Faculty also perceived very high student learning support in problem solving and skill development (M = 4.28, SD = 0.69) and assessment and examination preparation (M = 4.25, SD = 0.70), and high support in academic learning and research (M = 4.19, SD = 0.70).

Faculty GenAI Integration by Item

Table 2:Faculty-Reported GenAI Integration in Pedagogical Practices

Indicator	M	SD	Extent
Instructional planning: prepare lesson plans	4.28	0.66	Very high
Instructional planning: create instructional materials	4.19	0.71	High
Instructional planning: generate quizzes, tests, or assessment tasks	3.62	0.83	High
Instructional planning: simplify difficult lessons	4.35	0.63	Very high
Instructional planning: provide examples and classroom activities	3.78	0.79	High
Teaching efficiency: improve classroom discussions and engagement	4.35	0.65	Very high
Teaching efficiency: generate real-life analytical scenarios	4.30	0.68	Very high
Teaching efficiency: prepare examples and illustrations	4.27	0.70	Very high
Teaching efficiency: create critical-thinking activities	4.22	0.73	Very high
Teaching efficiency: require reasons for answers	4.18	0.76	High
Assessment: create quizzes, tests, and written examinations	4.32	0.63	Very high
Assessment: create rubrics, scoring guides, and criteria	4.28	0.66	Very high
Assessment: prepare formative assessment activities	4.16	0.71	High
Assessment: align activities with learning outcomes	4.12	0.74	High
Assessment: provide timely feedback	4.04	0.77	High

Note. Item wording was shortened for table presentation without changing the substantive meaning of the original items.

The highest item means occurred for simplifying difficult lessons and improving classroom discussions and engagement (both M = 4.35). Faculty also reported very high use for creating tests (M = 4.32), generating real-life scenarios (M = 4.30), creating rubrics (M = 4.28), preparing lesson plans (M = 4.28), and preparing examples (M = 4.27). The lowest item mean was for generating quizzes, tests, or assessment tasks within the instructional-planning dimension (M = 3.62), although this still represented high use.

Teacher-Perceived Student Learning Support by Item

Table 3: Faculty Perceptions of GenAI-Supported Student Learning

Indicator	M	SD	Extent
Academic learning: understand research-related concepts	4.32	0.63	Very high
Academic learning: formulate clear research titles	4.28	0.66	Very high
Academic learning: develop outlines for papers and research	4.16	0.71	High
Academic learning: improve writing clarity, grammar, and organization	4.12	0.74	High
Academic learning: analyze and interpret research data	4.04	0.77	High
Problem solving: understand and solve difficult problems	4.18	0.75	High
Problem solving: analyze problems before selecting solutions	4.38	0.62	Very high
Problem solving: develop critical-thinking skills	4.28	0.69	Very high
Problem solving: develop step-by-step solutions	4.23	0.72	Very high
Problem solving: develop creative solutions	4.34	0.65	Very high
Assessment preparation: understand difficult course topics	4.12	0.76	High
Assessment preparation: identify areas needing improvement	4.31	0.67	Very high
Assessment preparation: prepare for assessment activities	4.26	0.70	Very high

Indicator	M	SD	Extent
Assessment preparation: improve quiz and examination scores	4.17	0.73	High
Assessment preparation: prepare for oral recitations and presentations	4.36	0.64	Very high

Note. These are faculty perceptions of student support and should not be described as student-reported engagement or verified learning outcomes.

The highest perceived-support item was analyzing problems before selecting a solution (M = 4.38), followed by preparing for oral recitations and presentations (M = 4.36), developing creative solutions (M = 4.34), understanding research concepts (M = 4.32), and identifying areas needing improvement before examinations (M = 4.31). The lowest perceived-support values were for research-data analysis (M = 4.04), writing improvement (M = 4.12), understanding difficult course topics (M = 4.12), and improving examination scores (M = 4.17). These ratings represent faculty judgments and cannot confirm students' actual performance, engagement, or independent use of GenAI.

Relationships Between the Study Dimensions

Table 4: Pearson Correlations Between Faculty GenAI Integration and Teacher-Perceived Student Learning Support

Faculty integration dimension	Perceived student-support dimension	r	95% CI
Planning and content development	Academic learning and research	.782	[.684, .852]
Planning and content development	Problem solving and skill development	.782	[.684, .852]
Planning and content development	Assessment preparation	.780	[.681, .851]
Teaching efficiency and management	Academic learning and research	.682	[.550, .781]
Teaching efficiency and management	Problem solving and skill development	.781	[.683, .852]
Teaching efficiency and management	Assessment preparation	.681	[.549, .780]
Assessment, feedback, and evaluation	Academic learning and research	.751	[.642, .830]
Assessment, feedback, and evaluation	Problem solving and skill development	.784	[.687, .854]
Assessment, feedback, and evaluation	Assessment preparation	.748	[.638, .828]

Note. N = 87. Shortened dimension labels are used for table presentation. All $p < .001$ and remained significant at the Bonferroni-adjusted alpha of .0056. Confidence intervals were calculated using Fisher's z transformation.

All nine correlations were positive and statistically significant. The largest association was between assessment, feedback, and evaluation and problem solving and skill development (r = .784, 95% CI [.687, .854]). Instructional planning was similarly associated with academic learning and research (r = .782) and problem solving and skill development (r = .782). The smallest correlations involved teaching efficiency and classroom management with assessment preparation (r = .681) and academic learning and research (r = .682), although both remained substantial. These results indicate co-variation among faculty ratings; they do not demonstrate that faculty GenAI integration caused changes in students.

4. DISCUSSION

Faculty Integration Patterns

Faculty reported their greatest GenAI integration in teaching efficiency and classroom management. This pattern is consistent with educators' tendency to adopt GenAI first for practical tasks such as simplifying explanations, generating examples, creating scenarios, and organizing classroom activities [1]. Teachers' AI self-efficacy, prior experience, perceived benefits, and access to training can shape whether such use becomes routine [21, 22]. The application of GenAI can remain uneven even when awareness is high [3], while studies of faculty development, technology leadership, and innovative work behavior point to the importance of institutional support, professional learning, autonomy, and commitment [26-28]. The high ratings in the present study may reflect a sample intentionally composed of faculty with relevant GenAI exposure, which limits generalization to faculty who do not use such tools.

Assessment-related use was also high, especially for creating tests and rubrics. GenAI can reduce preparation time, but assessment is an area where accuracy, fairness, validity, transparency, and academic integrity require strong human oversight [2, 11, 12]. Cross-institutional policy analysis recommends authentic assessment, clear responsibility, and systematic AI-literacy development [23], while academic-integrity frameworks call for coordinated action across policy, pedagogy, student preparation, and institutional culture [25]. The lower ratings for formative assessment, outcome alignment, and timely feedback suggest that faculty may use GenAI more readily to generate products than to support continuous, context-sensitive assessment decisions. This distinction is important because pedagogical quality depends on alignment and professional judgment rather than volume of generated content.

Teacher-Perceived Student Learning Support

Faculty perceived the strongest student support in problem analysis, creative solution development, oral-presentation preparation, and examination readiness. These results resemble reports that GenAI can provide step-by-step explanations and support independent learning, while still producing limitations in accuracy and depth [5]. Senior high school, undergraduate, and graduate levels similarly found that ChatGPT can scaffold research tasks from conceptualization to manuscript preparation; however, its use should strengthen rather than replace human scholarly competence [34]. This indicates that ChatGPT may affect behavioral, cognitive, and emotional engagement, but the magnitude and direction depend on learning design, teacher support, and the manner of use [24]. Local technology studies likewise show that perceived benefits can coexist with connectivity, access, and implementation challenges [29, 30]. However, the current study did not collect responses from students or observe their learning behavior; therefore, the findings should be interpreted as faculty perceptions of support, not verified engagement or achievement.

Technology-supported learning indicate that structured digital environments can promote independent learning, satisfaction, motivation, participation, and academic performance [14-19, 29, 30]. These studies support the plausibility of technology-assisted learning benefits but do not validate the present study's specific causal claims. Differences in intervention design, learner population, subject area, access conditions, and measurement mean that the current findings should be viewed as a context-specific description of faculty perceptions.

Interpretation of the Correlations

The strong positive correlations indicate that faculty who rated their own GenAI integration more highly also tended to rate student learning support more highly. One interpretation is that pedagogically active faculty use GenAI across connected stages of planning, teaching, assessment, and learner support. This interpretation is consistent with AI-TPACK research linking AI competence, pedagogical knowledge, and teaching performance [8], [9]. Institutional reviews also show that successful implementation combines professional development, policy, learning design, assessment adaptation, clear stakeholder roles, and AI-literacy initiatives rather than isolated tool adoption [7], [11], [22], [23].

A competing explanation is common-method bias. The same faculty respondents completed both the integration and student-support sections in the same questionnaire. A generally favorable attitude toward GenAI, confidence in digital teaching, or desire to present current practice positively could increase both sets of scores. The cross-sectional design also cannot establish whether faculty integration preceded perceived student support. Adoption research indicates that perceived usefulness, social influence, control, risk, institutional context, and AI self-efficacy shape GenAI behavior [20, 21]. Because student engagement is multidimensional and ordinarily requires direct evidence from learners or learning behavior [24], the correlations should not be presented as evidence that GenAI integration predicts or improves student engagement.

Institutional and Pedagogical Implications

The findings support a structured institutional response. First, faculty development should move beyond prompt writing to include output verification, discipline-specific use cases, learning-outcome alignment, assessment validity, data privacy, bias awareness, and documentation of AI-assisted work [21, 22, 26-28]. Second, institutional policies should clarify acceptable use for lesson planning, feedback, research assistance, and assessment, while avoiding exclusive reliance on AI detectors [11], [12], [23], [25]. Third, departments should review high-stakes AI-generated assessments and rubrics before use. Fourth, student AI literacy should emphasize source verification, independent reasoning, transparent disclosure, and protection of personal or institutional data. These measures reflect the need to coordinate leadership, training, technical support, assessment redesign, and academic-integrity education rather than treating responsible GenAI use as an individual responsibility alone [22], [23], [25], [27].

A stronger evidence system should separate data sources. Faculty can report integration practices, while students report behavioral, cognitive, and emotional engagement using a validated engagement scale [24]. Course records or performance tasks can provide objective outcomes. Local research that gathers both teacher and student perspectives illustrates the value of comparing stakeholder accounts and documenting access or technical constraints [29]. Matching these data at the course or class level would reduce common-source bias and permit multilevel or longitudinal analysis. Such a design would test whether pedagogically guided GenAI integration is related to measurable student outcomes rather than relying solely on faculty impressions.

5. LIMITATIONS

The study has six principal limitations. First, although all 87 members of the accessible faculty population participated and the response rate was 100%, the study was conducted in only one university; external generalizability is therefore limited. Second, the source records did not include a detailed respondent profile by discipline, years of teaching, prior AI training, frequency of use, or specific GenAI tools. Third, the same faculty respondents rated both their own GenAI integration and student learning support, creating common-source and common-method bias. Fourth, the outcome was a validated faculty-rated measure of perceived student learning support rather than a student self-report or an objective measure of engagement and achievement; no student survey, course grades, attendance, completion, or assessment records were supplied for matched analysis. Fifth, the cross-sectional correlational design cannot establish temporal order or causation. Sixth, the full instrument showed excellent overall internal consistency (Cronbach's alpha = .94), but the source records did not provide validator profiles, content-validity indices, pilot-sample size, subscale alpha coefficients, item-total statistics, or raw data for independent assumption checks and reanalysis. These limitations require cautious interpretation and should be explicitly acknowledged in any submitted version.

6. CONCLUSION

Faculty members who reported greater integration of Generative Artificial Intelligence in instructional planning, teaching, and assessment also tended to perceive stronger GenAI-supported student learning in academic work, problem solving, skill development, and assessment preparation. The nine associations were positive and remained statistically significant after Bonferroni adjustment. However, the findings demonstrate substantial co-variation between faculty ratings rather than causal effects, verified student engagement, or actual academic performance. Student-level, objective, multi-institutional, and longitudinal evidence is required before claims about the educational effectiveness of GenAI integration can be established.

7. RECOMMENDATIONS

1. Develop clear institutional policies for the ethical, transparent, and responsible use of Generative AI in teaching, assessment, research, and academic writing.
2. Provide continuous faculty training on AI literacy, instructional design, output verification, data privacy, and discipline-specific applications.
3. Redesign assessments to emphasize authentic performance, critical thinking, oral defense, reflection, and documentation of AI-assisted processes.
4. Integrate student AI literacy into the curriculum, focusing on source verification, academic integrity, responsible disclosure, and independent learning.
5. Conduct longitudinal and multi-source studies using faculty reports, student responses, and objective academic outcomes to evaluate the actual effects of Generative AI integration.

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