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Beyond Digital Access: Generative Artificial Intelligence and Digital Literacy Predict Vocational Students' Academic Writing

[1] Ria Candra Dewi, [2] Aziz Azindani, [3] Lily Budinurani, [4] Novita Wulandari

[1] [2] [3] Department of Mechanical Engineering, Politeknik Baja Tegal, Tegal, Central Java, Indonesia
[4] Department of Information Technology Education, Universitas Pendidikan Muhammadiyah Sorong, Sorong, Southwest Papua, Indonesia

***Correspondence Author:** Ria@pbjt.ac.id

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ABSTRACT

This study examined the partial and simultaneous statistical effects of digital literacy and responsible generative artificial intelligence utilization on vocational students' academic writing skills. A quantitative explanatory-correlational approach with a cross-sectional survey design was employed. The sample comprised 100 students from five vocational study programs selected through proportionate stratified random sampling. Data were collected using two 10-item Likert questionnaires measuring digital literacy and generative artificial intelligence utilization, together with a source-based academic essay performance test assessed using an analytic rubric. Pearson correlation and multiple linear regression were applied. Digital literacy had a positive and significant statistical effect on academic writing skills ($B = 6.413$; $\beta = 0.334$; $p < 0.001$). Generative artificial intelligence utilization also had a positive and significant effect and provided a stronger relative contribution ($B = 9.097$; $\beta = 0.494$; $p < 0.001$). Simultaneously, both predictors produced $F(2,97) = 42.013$; $p < 0.001$ and explained 46.4% of the variance. These findings indicated that vocational students' academic writing development required the integration of digital literacy and critical, ethical, and responsible artificial intelligence practices in writing instruction and institutional policy.

Informasi Artikel

Kata Kunci:
kecerdasan buatan generatif; keterampilan menulis akademik; literasi digital; mahasiswa vokasi; pendidikan vokasi.

ABSTRAK

Penelitian ini menganalisis pengaruh statistik literasi digital dan pemanfaatan kecerdasan buatan generatif yang bertanggung jawab terhadap keterampilan menulis akademik mahasiswa vokasi, baik secara parsial maupun simultan. Penelitian menggunakan pendekatan kuantitatif dengan desain eksplanatori korelasional melalui survei potong lintang. Sampel terdiri atas 100 mahasiswa dari lima program studi vokasi yang dipilih menggunakan proportionate stratified random sampling. Data dikumpulkan melalui dua angket Likert yang masing-masing terdiri atas 10 butir untuk mengukur literasi digital dan pemanfaatan kecerdasan buatan generatif, serta tes kinerja menulis esai akademik berbasis sumber yang dinilai menggunakan rubrik analitik. Data dianalisis dengan korelasi Pearson dan regresi linear berganda. Literasi digital berpengaruh statistik positif dan signifikan terhadap keterampilan menulis akademik ($B = 6,413$; $\beta = 0,334$; $p < 0,001$). Pemanfaatan kecerdasan buatan generatif juga berpengaruh positif dan signifikan dengan kontribusi relatif lebih kuat ($B = 9,097$; $\beta = 0,494$; $p < 0,001$). Secara simultan, kedua prediktor menghasilkan $F(2,97) = 42,013$; $p < 0,001$ dan menjelaskan 46,4% variasi keterampilan menulis akademik. Temuan menunjukkan bahwa pengembangan keterampilan menulis mahasiswa vokasi memerlukan integrasi literasi digital serta penggunaan kecerdasan buatan yang kritis, etis, dan bertanggung jawab dalam pembelajaran dan kebijakan institusi.

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Corresponding Author: (1) Ria Candra Dewi, (2) Department of Mechanical Engineering, (3) Politeknik Baja Tegal, (4) Jl. Raya Barat Dukuhwaru Km 7, Tegal 52451, Indonesia. (5) Email: Ria@pbjt.ac.id

1. Introduction

Digital transformation has changed how students obtain information, construct knowledge, and produce academic work. Academic writing, which previously relied on printed sources, face-to-face consultation, and manual revision, now involves academic search engines, journal databases, reference management applications, similarity-checking software, language correction tools, and generative artificial intelligence. These developments offer opportunities to improve writing efficiency and quality, while also creating new concerns, including technological dependence, the use of non-credible sources, weak information evaluation, violations of academic ethics, and diminished independent thinking. In higher education, students must be able not only to operate digital devices but also to select, evaluate, process, and use information critically, ethically, and responsibly. Digital literacy and the ability to use generative artificial intelligence are therefore two important competencies that may be associated with students' academic writing skills.

The development of generative artificial intelligence in higher education has progressed rapidly and become a global phenomenon. Ravšelj et al. [1], in a study involving 23,218 students from 109 countries and territories, found that students primarily used ChatGPT for brainstorming, summarizing texts, and searching for research articles. Students considered the technology useful for simplifying complex information, although they remained uncertain about its reliability in providing factual information and supporting deep learning. Respondents also believed that ChatGPT use required regulation because of its potential association with cheating, plagiarism, and misuse in completing academic assignments. These findings indicate that extensive use of generative artificial intelligence is not always accompanied by the ability to evaluate the quality, accuracy, and ethical implications of its outputs. Accordingly, the use of artificial intelligence should be examined not only in terms of frequency but also in relation to purpose, strategy, verification skills, and user responsibility.

Digital literacy provides the foundation that enables students to use technology productively in academic activities. It extends beyond the technical ability to operate computers or applications and includes the capacity to locate information, evaluate source credibility, think critically, communicate, collaborate, create content, maintain digital security, and understand copyright and ethical information use. The systematic review by Zhao et al. [2] showed that digital competence in higher education encompasses broad dimensions that have not always been defined or measured consistently. In the context of academic writing, Nabhan and Habók [3] developed the Digital Literacy Academic Writing Scale, which includes critical thinking, online safety, digital culture, collaboration and creativity, information searching, communication, and functional skills, including the use of reference management tools. This framework emphasizes that academic writing in digital environments requires an integration of technical, cognitive, social, and ethical competencies.

Academic writing is a complex ability encompassing idea development, argument construction, text organization, use of scholarly evidence, cohesion and coherence, linguistic accuracy, citation, reference-list preparation, and the preservation of originality. Students are expected not only to produce grammatically accurate writing but also to construct arguments supported by relevant and accountable literature. These competencies are essential because students must complete various forms of academic work, including laboratory reports, papers, project proposals, journal articles, research reports, and final projects. Indriyani et al. [4] emphasized that academic writing skills are required not only for coursework but also for competencies needed in professional careers. Inadequate academic writing skills may therefore affect learning achievement, the quality of scholarly work, the ability to communicate ideas, and students' readiness to enter the workplace.

Academic writing is particularly important in vocational education because the learning process emphasizes the application of knowledge, skills mastery, problem solving, and work readiness. Vocational students must be able not only to perform technical tasks but also to document procedures, analyze test results, prepare project reports, write proposals, and communicate solutions to academic and industrial stakeholders. Suharno et al. [5] explained that vocational education in Indonesia continues to face challenges related to quality, relevance, and alignment with labor-market needs. Conceptually, the ability to communicate technical information in systematic written form is a supporting competence that connects academic learning with professional practice. Nevertheless, research on vocational students' academic writing remains more limited than research involving language-education students, EFL students, or students at general universities.

Several studies have reported a positive relationship between digital literacy and academic writing skills. For example, Indriyani et al. [4] investigated 48 students in an Indonesian Language Education program using a quantitative causal-associative design. Regression analysis indicated that digital literacy and collaboration skills had positive and significant effects on academic writing skills. Digital literacy helped students identify credible information sources, apply citation and paraphrasing practices, and use digital media to support the writing process. These findings demonstrate that access to technology must be accompanied by the capacity to process and evaluate information if it is to contribute to writing quality. However, the study used a relatively small sample, involved students from only one language-education program, and examined digital literacy together with collaboration rather than with generative artificial intelligence utilization.

The relationship between digital literacy and academic writing has not produced entirely consistent findings. Salsabila

and Lengkanawati [6] studied 68 undergraduate students who had completed courses in information technology and academic writing. Their findings showed that overall digital literacy scores were not significantly correlated with academic writing performance. However, analyses of individual dimensions identified weak but significant positive correlations for critical thinking, character, and digital citizenship. Students considered digital tools useful for accessing sources and formatting documents, but such tools did not automatically improve the substantive quality of their writing. This suggests that general technological proficiency does not necessarily translate directly into writing ability. Digital literacy dimensions that are closely related to academic work, including information evaluation, ethics, and critical thinking, may contribute more strongly than technical competence alone.

In addition to digital literacy, generative artificial intelligence provides a range of functions that may support different stages of academic writing. It can be used to generate alternative topics, develop outlines, explain concepts, suggest organizational improvements, refine language, provide feedback, assist with paraphrasing, and support revision. Marzuki et al. [7] found that artificial intelligence-based writing tools could improve the content and organization of student writing from the perspective of English as a Foreign Language (EFL) lecturers. Mahapatra [8] similarly reported that the use of ChatGPT as a formative feedback tool had a significant positive effect on the academic writing skills of English as a Second Language (ESL) students. The intervention group achieved better post-test results than the comparison group. These findings indicate that artificial intelligence can function as a pedagogical support tool when it is used to enrich thinking, provide feedback, and facilitate revision rather than simply generate complete texts automatically.

The effectiveness of generative artificial intelligence in academic writing is strongly influenced by the pattern of interaction between users and technology. Nguyen et al. [9] analyzed 626 interactions generated by 10 doctoral students while using artificial intelligence-based writing tools. The study identified varied patterns of human-AI collaboration, indicating that output quality depends not only on technological capability but also on users' strategies for formulating prompts, evaluating responses, refining outputs, and integrating information into their writing. Students who retained control over their objectives, arguments, sources, and revision processes tended to use artificial intelligence as a cognitive partner. In contrast, practices centered on directly accepting generated outputs could reduce students' intellectual engagement. Generative artificial intelligence utilization should therefore be measured as a multidimensional academic practice that includes purpose of use, prompt formulation, information verification, revision, transparency, and compliance with academic ethics.

Despite its benefits, generative artificial intelligence also poses risks to learning quality and academic integrity. Artificial intelligence outputs may contain incorrect information, unverifiable references, excessive generalizations, bias, and apparently persuasive arguments that lack an adequate scholarly basis. In a survey of 399 students, Chan and Hu [10] found generally positive attitudes toward generative artificial intelligence because it supported personalized learning, writing activities, brainstorming, and information searching and analysis. However, students also expressed concerns about accuracy, privacy, ethics, personal development, and the technology's implications for future competencies. These conditions demonstrate that using artificial intelligence does not invariably improve skills. Without strong digital literacy, students may accept technological outputs without critical examination, use invalid sources, or surrender too much of the thinking and writing process to the system.

In the Indonesian context, research on the use of artificial intelligence for writing has largely involved students in English language education and has more frequently examined perceptions, experiences, or the types of tools used. Marzuki et al. [7] noted that research on the effects of artificial intelligence-based writing tools on content and organization in Indonesian settings remained limited. Subsequent studies have shown that students use tools such as ChatGPT, QuillBot, Grammarly, and similar applications to generate ideas, improve language, organize texts, and paraphrase. Nevertheless, the dominant approaches remain qualitative studies, perception studies, or investigations with limited numbers of participants. Recent evidence also suggests that general digital literacy may not be significantly associated with writing performance unless dimensions relevant to academic processes are specifically examined. These conditions strengthen the need for quantitative research that tests digital literacy, generative artificial intelligence utilization, and academic writing skills within a single empirical model.

Several research gaps can be identified. First, previous studies have primarily focused on EFL students, language-education students, postgraduate students, or students in general academic disciplines, whereas vocational students remain underrepresented. Second, digital literacy and generative artificial intelligence utilization have often been analyzed separately, and relatively few studies have examined their partial and simultaneous contributions to academic writing skills. Third, several studies have measured perceived technological benefits rather than writing skills based on indicators of academic text quality. Fourth, findings concerning the relationship between digital literacy and writing have been inconsistent, ranging from strong effects to nonsignificant overall relationships. Fifth, some studies have used small samples and qualitative designs, limiting the generalizability of their findings. These gaps demonstrate the need for explanatory quantitative research with an adequate sample in the context of vocational education.

Theoretically, this study was grounded in a multidimensional digital literacy framework and the concept of human-artificial intelligence collaboration in academic writing. Digital literacy

was positioned as a foundational competence that enables students to locate, evaluate, process, create, and use digital information responsibly. Generative artificial intelligence utilization was conceptualized as the use of technology to support idea development, text organization, the exploration of alternative explanations, feedback, editing, and revision. Academic writing skills constituted the learning outcome and were reflected in the quality of ideas, argumentation, organization, coherence, evidence use, linguistic accuracy, citation, and originality. Consistent with the presage-process-product model, students' initial competencies and perceptions of the technological environment may influence how they engage in learning processes, which are subsequently associated with learning outcomes. Digital literacy was therefore expected to strengthen students' ability to use artificial intelligence critically rather than merely technically.

This study contributes novelty by integrating digital literacy and generative artificial intelligence utilization as two predictors of vocational students' academic writing skills. It was conducted during the second semester of the 2025/2026 academic year and involved 100 vocational students. Vocational students were selected because their learning context requires them to connect theory, practice, documentation, data analysis, and professional communication. The study did not conceptualize artificial intelligence use solely in terms of intensity or frequency; it also examined its use for idea generation, outlining, revision, feedback, output verification, and compliance with academic ethics. The findings were expected to contribute theoretically by clarifying the relationships among digital competence, the use of generative technologies, and writing ability. Practically, they may provide a basis for digital literacy instruction, guidelines for artificial intelligence use, and the design of writing assignments suited to vocational education.

Based on this background, the primary objective of this study was to analyze the partial and simultaneous statistical effects of digital literacy and generative artificial intelligence utilization on vocational students' academic writing skills. The research questions were as follows: (1) Does digital literacy affect vocational students' academic writing skills? (2) Does generative artificial intelligence utilization affect vocational students' academic writing skills? and (3) Do digital literacy and generative artificial intelligence utilization simultaneously affect vocational students' academic writing skills? The hypotheses were formulated as follows: H1, digital literacy has a positive and significant effect on vocational students' academic writing skills; H2, generative artificial intelligence utilization has a positive and significant effect on vocational students' academic writing skills; and H3, digital literacy and generative artificial intelligence utilization simultaneously have positive and significant effects on vocational students' academic writing skills.

2. Research Method

This study employed a quantitative approach with an explanatory-correlational design implemented through a cross-sectional survey. The design was selected because the study sought to explain the statistical effects of digital literacy as the first independent variable (X_1) and generative artificial intelligence utilization as the second independent variable (X_2) on vocational students' academic writing skills as the dependent variable (Y). No experimental manipulation or treatment was administered; instead, each variable was measured during a single observation period, after which patterns of association and predictive contributions were analyzed. The research model was expressed as $Y = a + b_1X_1 + b_2X_2 + e$, where a represents the constant, b_1 and b_2 are regression coefficients, and e is the error term. This design was consistent with the objective of not only describing the level of each variable but also testing the partial and simultaneous statistical effects of digital competence and generative technology use on academic writing outcomes.

The study was conducted at Politeknik Baja Tegal, Tegal Regency, Central Java Province, during the second semester of the 2025/2026 academic year. Data were collected from April to June 2026. Primary data were obtained directly from students through closed-ended questionnaires and an academic writing performance test. Data collection comprised three stages: providing research information and obtaining participant consent, administering the digital literacy and generative artificial intelligence utilization questionnaires, and conducting the academic writing task. Participants were informed that participation was voluntary, their identities would remain confidential, and their responses would not affect their academic grades. Each participant was assigned an anonymous code, ranging from MV001 to MV100, to link questionnaire data with writing scores without recording names or student identification numbers in the analytical database.

The population comprised all active students in vocational programs who were enrolled in Semesters 2, 4, and 6 at the institution where the study was conducted. The sample was set at 100 students. This number was determined through an a priori power analysis for multiple linear regression with two predictors. Assuming a medium effect size ($f^2 = 0.15$), a significance level of 0.05, and statistical power of 0.80, the minimum required sample was approximately 68 respondents. The sample was increased to 100 to improve estimation precision, account for incomplete data, and provide stronger representation across study programs and semester levels. Sample size justification should be stated explicitly in terms of effect size, error rate, statistical power, or the expected precision of estimation. The determination of the sample size followed principles of power-based sample size justification [11].

Proportionate stratified random sampling was used. The population was first stratified by study program and semester, after which the sample from each stratum was allocated

proportionally using $n_h = (N_h/N) \times n$, where n_h is the sample size for a stratum, N_h is the population size of the stratum, N is the total population, and n is the overall sample size. The resulting sample consisted of 25 students from Informatics Engineering, 20 from Mechanical Engineering, 20 from Retail Business and Management, 20 from Mechatronics Engineering Technology, and 15 from Automotive Engineering. By semester, the sample comprised 35 second-semester students, 35 fourth-semester students, and 30 sixth-semester students. Individuals within each stratum were selected randomly using active-student lists and computer-generated random numbers. The inclusion criteria were active enrollment, placement in one of the designated semesters, willingness to participate, completion of the questionnaire, and participation in the academic writing test. Respondents who left more than 10% of the instrument items unanswered or did not submit the writing task were excluded from the analysis.

The digital literacy instrument consisted of 10 statements developed by adapting the Digital Literacy Academic Writing Scale and studies of digital competence in higher education. The indicators covered the ability to access digital information, evaluate source credibility, use academic keywords, search journal databases, use reference management applications, maintain data security and privacy, communicate and collaborate digitally, understand copyright and digital ethics, manage academic files or data, and create digital academic content. Each statement was rated on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Total scores ranged from 10 to 50, and mean scores ranged from 1 to 5. Higher scores indicated stronger digital literacy in the context of academic activities and scholarly writing.

The generative artificial intelligence utilization instrument also consisted of 10 statements rated on a five-point Likert scale. The indicators addressed the use of generative artificial intelligence to generate initial ideas, develop outlines, improve sentence clarity, support revision, explore concepts or keywords, formulate specific prompts, verify outputs, check reference validity, use technology ethically and transparently, and integrate artificial intelligence suggestions without compromising authorial originality. The measurement focused not only on frequency of use but also on behavioral practices, critical evaluation, user competence, and ethics. The indicators were developed from research on artificial intelligence literacy, students' perceptions of generative artificial intelligence, and the use of artificial intelligence tools for ideation, organization, feedback, editing, and revision. Total scores ranged from 10 to 50, with higher scores indicating increasingly productive, critical, and responsible generative artificial intelligence utilization. The behavioral, cognitive, affective, and ethical dimensions of artificial intelligence literacy were also informed by a validated instrument framework [12].

Academic writing skills were measured through a performance test requiring a 750-1,000-word source-based academic essay. Students received topics aligned with their respective fields of study and several initial scholarly sources that could be used to develop their arguments. The task was completed under controlled conditions, with the same time allocation for all participants and without direct use of generative artificial intelligence during the test, so that the scores reflected students' existing writing skills. The essays were evaluated using an analytic rubric containing 10 indicators: clarity of topic and problem formulation, structural accuracy, coherence of argumentation, use of evidence, accuracy of citations and references, use of academic language, spelling and grammatical accuracy, cohesion across sections, originality, and strength of conclusion. Each indicator was scored from 1 to 5. Raw scores ranging from 10 to 50 were converted to a 20-100 scale using (raw score/50) × 100. A performance task was used to ensure that the academic writing variable was not based solely on students' self-perceptions.

Instrument validity was established through content validity, face validity, and empirical testing. Content validity involved at least three experts with expertise in research methodology, digital literacy or educational technology, and language instruction and academic writing. The experts evaluated indicator appropriateness, item relevance, linguistic clarity, and construct representation using a four-point scale [13]. Aiken's V was calculated; items with values of at least 0.80 were retained, whereas items below the criterion were revised or removed. Face validity was assessed with 10 students outside the primary sample to ensure that the instructions and statements were comprehensible. The instruments were then piloted with at least 30 students who were not included in the main sample. Empirical validity was examined through corrected item-total correlations, using a criterion above 0.30. Internal consistency was assessed using Cronbach's alpha and McDonald's omega, with coefficients of at least 0.70 considered acceptable [14]. The writing rubric was applied independently by two raters who had completed a calibration process, and inter-rater consistency was assessed using the intraclass correlation coefficient. These procedures followed the principle that instrument validation should encompass construct definition, appropriate operationalization, and empirical evidence of measurement quality.

Data were analyzed using IBM SPSS Statistics version 29. Initial screening included examinations of data completeness, coding errors, outliers, and patterns of missing data. Descriptive statistics were used to summarize participant characteristics and variable distributions through frequencies, percentages, means, standard deviations, minimum scores, and maximum scores. Preliminary relationships among variables were examined using Pearson correlation. Before regression analysis, the assumptions of linearity, residual normality, homoscedasticity, error independence, and absence of multicollinearity were evaluated. Residual normality was examined using the Shapiro-Wilk test and Q-Q plots; linearity and homoscedasticity were assessed through residual plots; and multicollinearity was evaluated using

tolerance values above 0.10 and variance inflation factor (VIF) values below 5. Observations with standardized residuals outside ±3 or high Cook's Distance values were re-examined before decisions were made to retain or remove them. All data cleaning, transformation, exclusion, and variable-selection procedures were to be reported transparently.

Hypotheses were tested using multiple linear regression with the enter method, in which digital literacy and generative artificial intelligence utilization were entered into the model simultaneously. The first hypothesis was supported when the digital literacy regression coefficient (b_1) was positive and $p < 0.05$. The second hypothesis was supported when the generative artificial intelligence utilization coefficient (b_2) was positive and $p < 0.05$. The third hypothesis was tested using the F test; the two predictors were considered to have a significant simultaneous effect when the F-test significance value was below 0.05. All tests used a 5% significance level and two-tailed testing. Regression results were reported using unstandardized coefficients (B), standard errors, standardized beta coefficients, t values, p values, 95% confidence intervals, F values, R^2, and adjusted R^2. R^2 indicated the proportion of variance in academic writing skills jointly explained by the predictors, whereas adjusted R^2 provided an estimate that accounted for the number of predictors and the sample size. Reporting of the regression model followed recommendations for transparent presentation of multivariable models [15].

3. Results and Discussion

3.1. Results

3.1.1. Participant Characteristics

The study analyzed data from 100 vocational students during the second semester of the 2025/2026 academic year. The participants comprised 55 women and 45 men. Their ages ranged from 18 to 22 years, with a mean age of 19.90 years and a standard deviation of 1.04. By semester level, 35 students were enrolled in Semester 2, 35 in Semester 4, and 30 in Semester 6. This distribution ensured representation from the early, middle, and later stages of vocational education.

Table 1. Participant Characteristics

Characteristic	Category	Frequency	Percentage
Gender	Female	55	55.0%
	Male	45	45.0%
Study program	Informatics Engineering	25	25.0%
	Mechanical Engineering	20	20.0%
	Retail Business and Management	20	20.0%
	Mechatronics Engineering Technology	20	20.0%
	Automotive Engineering	15	15.0%
Semester	Semester 2	35	35.0%
	Semester 4	35	35.0%
	Semester 6	30	30.0%
Age	Mean ± SD	19.90 ± 1.04	-
	Range	18-22 years	-

The distribution by study program showed that the largest group comprised 25 students (25%) from Informatics Engineering. Mechanical Engineering, Retail Business and Management, and Mechatronics Engineering Technology each contributed 20 students, whereas 15 students were enrolled in Automotive Engineering. The inclusion of students from several study programs provided a more diverse representation of digital literacy, generative artificial intelligence utilization, and academic writing skills within vocational education.

3.1.2. Instrument Validity and Reliability

Instrument quality testing showed that all items for the three variables met the empirical validity criterion. Corrected item-total correlations ranged from 0.697 to 0.784 for the digital literacy instrument, from 0.674 to 0.800 for the generative artificial intelligence utilization instrument, and from 0.649 to 0.797 for the academic writing skills instrument. All coefficients exceeded the minimum criterion of 0.30; therefore, all items were considered valid and retained for analysis.

Table 2. Instrument Validity and Reliability

Variable	Number of items	Corrected item-total correlation	Cronbach's alpha	Interpretation
Digital literacy (X_1)	10	0.697-0.784	0.937	Highly reliable

Variable	Number of items	Corrected item-total correlation	Cronbach's alpha	Interpretation
Generative artificial intelligence utilization (X_2)	10	0.674-0.800	0.941	Highly reliable
Academic writing skills (Y)	10	0.649-0.797	0.932	Highly reliable

3.1.3. Descriptive Statistical Results

Descriptive analysis showed that the mean digital literacy score was 3.173 (SD = 1.067) on a 1-5 scale, indicating a moderate level. The mean generative artificial intelligence utilization score was 3.140 (SD = 1.112), which was also classified as moderate. The mean academic writing score was 63.06 (SD = 20.48) on a 20-100 scale.

Cronbach's alpha was 0.937 for digital literacy, 0.941 for generative artificial intelligence utilization, and 0.932 for academic writing skills. All coefficients exceeded the reliability threshold of 0.70. The three instruments therefore demonstrated very high internal consistency, indicating that each item set measured its respective construct consistently.

Table 3. Descriptive Statistics of the Research Variables

Variable	N	Mean	Standard deviation	Minimum	Maximum	Category
Digital literacy (X_1)	100	3.173	1.067	1.10	5.00	Moderate
Generative artificial intelligence utilization (X_2)	100	3.140	1.112	1.10	5.00	Moderate
Academic writing skills (Y)	100	63.06	20.48	20.00	100.00	Moderate

Based on the academic writing skill categories, 12 students were classified as very low, 19 as low, 28 as moderate, 29 as high, and 12 as very high. The high category contained the largest proportion of students; however, 31% remained in the low or very low categories. This finding indicates a substantial disparity in academic writing ability among the students.

Table 4. Distribution of Academic Writing Skill Categories

Category	Frequency	Percentage
Very low	12	12.0%
Low	19	19.0%
Moderate	28	28.0%
High	29	29.0%
Very high	12	12.0%
Total	100	100.0%

The standard deviation of 20.48 for academic writing skills indicates considerable heterogeneity in student performance. Some students were able to produce systematic and well-argued academic texts, whereas others continued to experience difficulties with text organization, the use of scholarly evidence, citation accuracy, argumentative coherence, and academic language.

3.1.4. Correlation Analysis

Pearson correlation analysis was conducted to examine the direction and strength of the relationships among the constructs before regression analysis. Digital literacy was positively and significantly correlated with academic writing skills ($r = 0.497$, $p < 0.001$), representing a moderate relationship. Students with stronger digital literacy therefore tended to demonstrate higher academic writing skills.

Generative artificial intelligence utilization was also positively and significantly correlated with academic writing skills ($r = 0.604$, $p < 0.001$). This relationship was stronger than the association between digital literacy and writing skills. The correlation between digital literacy and generative artificial intelligence utilization was $r = 0.329$ ($p = 0.001$), indicating a positive relationship of low-to-moderate strength.

Table 5. Intervariable Correlation Matrix

Variable	Digital literacy (X_1)	Generative artificial intelligence utilization (X_2)	Academic writing skills (Y)
Digital literacy (X_1)	1	0.329**	0.497**
Generative artificial intelligence utilization (X_2)	0.329**	1	0.604**
Academic writing skills (Y)	0.497**	0.604**	1

*Note: **p < 0.01, two-tailed.*

The correlation of 0.329 between the two independent variables indicates that digital literacy and generative artificial intelligence utilization are related but distinct constructs. Students with high digital literacy did not necessarily report high levels of generative artificial intelligence utilization. Conversely, frequent use of generative artificial intelligence did not necessarily reflect an ability to evaluate digital information critically.

3.1.5. Regression Assumption Tests

Before multiple linear regression was performed, the data were examined to ensure that the assumptions of residual normality, homoscedasticity, error independence, and absence of multicollinearity were satisfied. The Shapiro-Wilk test produced W = 0.993 with p = 0.892. Because the significance value exceeded 0.05, the model residuals were considered normally distributed.

Table 6. Regression Assumption Test Results

Assumption	Statistical indicator	Result	Decision
Residual normality	Shapiro-Wilk	W = 0.993; p = 0.892	Normality assumption satisfied
Homoscedasticity	Breusch-Pagan	LM = 1.426; p = 0.490	No heteroscedasticity
Residual independence	Durbin-Watson	2.152	Independence assumption satisfied
Multicollinearity X_1	VIF; tolerance	1.122; 0.892	No multicollinearity
Multicollinearity X_2	VIF; tolerance	1.122; 0.892	No multicollinearity

The Breusch-Pagan test yielded p = 0.490, indicating no evidence of heteroscedasticity. The Durbin-Watson statistic was 2.152, which was close to 2 and indicated that the residuals were relatively independent. Both predictors had VIF values of 1.122 and tolerance values of 0.892. Multicollinearity was therefore not a concern because the VIF values were well below 5 and the tolerance values exceeded 0.10. These results confirmed that the model met the requirements for multiple linear regression.

3.1.6. Multiple Linear Regression Results

Multiple linear regression was used to test the statistical effects of digital literacy and generative artificial intelligence utilization on academic writing skills. The analysis produced a multiple correlation coefficient of R = 0.681, a coefficient of determination of R^2 = 0.464, and an adjusted R^2 of 0.453.

Table 7. Regression Model Summary

R	R^2	Adjusted R^2	Standard error of estimate
0.681	0.464	0.453	15.145

The R^2 value of 0.464 indicates that digital literacy and generative artificial intelligence utilization jointly explained 46.4% of the variance in vocational students' academic writing skills. The remaining 53.6% was attributable to factors not included in the model, such as academic reading ability, language proficiency, disciplinary knowledge, writing motivation, self-efficacy, writing experience, the quality of lecturer feedback, and habits of using scholarly sources.

Table 8. Analysis of Variance for the Regression Model

Source	Sum of squares	df	Mean square	F	p
Regression	19,273.926	2	9,636.963	42.013	<0.001
Residual	22,249.714	97	229.378	-	-
Total	41,523.640	99	-	-	-

The simultaneous test yielded F(2, 97) = 42.013, p < 0.001. This result indicates that the model containing digital literacy and generative artificial intelligence utilization was statistically superior to a model without predictors. The two variables

therefore had a significant simultaneous statistical effect on vocational students' academic writing skills.

The resulting regression equation was as follows:

$$Y = 14.145 + 6.413X_1 + 9.097X_2$$

The equation indicates that a one-point increase in digital literacy predicted a 6.413-point increase in the academic writing score when generative artificial intelligence utilization was held constant. A one-point increase in generative artificial intelligence utilization predicted a 9.097-point increase in the academic writing score when digital literacy was held constant.

Table 9. Multiple Linear Regression Coefficients

Predictor	B	Standard error	β	t	p	95% CI for B
Constant	14.145	5.624	-	2.515	0.014	2.983-25.307
Digital literacy (X_1)	6.413	1.510	0.334	4.246	<0.001	3.416-9.411
Generative artificial intelligence utilization (X_2)	9.097	1.450	0.494	6.273	<0.001	6.219-11.975

The digital literacy coefficient was positive (B = 6.413, t = 4.246, p < 0.001), indicating a positive and significant statistical effect on academic writing skills. The generative artificial intelligence utilization coefficient was also positive (B = 9.097, t = 6.273, p < 0.001), indicating a positive and significant statistical effect on academic writing skills.

The standardized beta coefficients showed that generative artificial intelligence utilization made a stronger relative contribution (β = 0.494) than digital literacy (β = 0.334). This result does not imply that generative artificial intelligence can replace digital literacy. Productive artificial intelligence use still requires the ability to select sources, verify output accuracy, understand ethical considerations, and preserve the originality of the text.

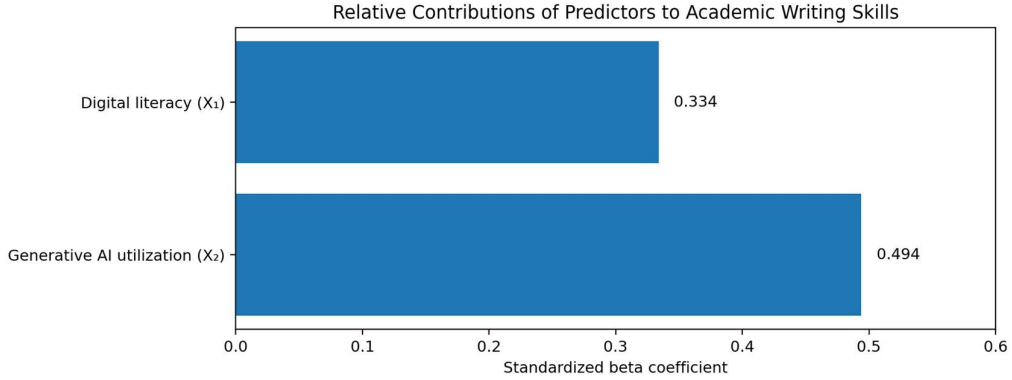

Figure 1. Relative Contributions of the Predictor Variables to Academic Writing Skills

3.1.7. Hypothesis Testing

Based on the regression results, all three research hypotheses were supported. The hypothesis-testing results are presented in Table 10.

Table 10. Summary of Hypothesis Testing

Hypothesis	Statistical result	Decision
H_1: Digital literacy has a positive effect on vocational students' academic writing skills	B = 6.413; β = 0.334; t = 4.246; p < 0.001	Supported
H_2: Generative artificial intelligence utilization has a positive effect on vocational students' academic writing skills	B = 9.097; β = 0.494; t = 6.273; p < 0.001	Supported
H_3: Digital literacy and generative artificial intelligence utilization simultaneously affect vocational students' academic writing skills	F(2, 97) = 42.013; p < 0.001; R^2 = 0.464	Supported

3.2. Discussion

3.2.1. Effect of Digital Literacy on Academic Writing Skills

The findings showed that digital literacy had a positive and significant statistical effect on vocational students' academic writing skills. The ability to use digital technology critically and responsibly not only assisted students in obtaining information but also enabled them to transform information into academic arguments. Students who could use effective search terms, access scholarly journals, evaluate source credibility, manage references, and understand digital ethics tended to produce more structured and accountable writing.

This finding supports the digital literacy framework for academic writing, which positions critical thinking, information searching, digital culture, communication, creativity, online safety, and functional skills as components of writing competence in digital environments. Digital literacy should therefore not be reduced to the ability to operate technological devices. Rather, it is an epistemic competence that helps students determine which information is valid, relevant, and appropriate as a basis for argumentation.

The result is consistent with Indriyani et al. [4], who found a positive and significant relationship between digital literacy and academic writing skills. Digital literacy enables students to identify credible sources, develop arguments, apply citation practices, and produce evidence-based texts. However, that study involved a smaller sample of Indonesian Language Education students, whereas the present study examined vocational students from several study programs.

The present findings differ in part from those of Salsabila and Lengkanawati [6], who reported that overall digital literacy was not significantly correlated with academic writing performance. Their study identified relationships only for particular dimensions, including critical thinking, character, and digital citizenship. Differences in operational definitions, participant characteristics, sample size, disciplinary context, and writing-assessment methods may account for the contrasting results.

In the present study, digital literacy indicators were directly linked to academic writing activities, including article searching, source-credibility evaluation, reference management, citation, and information organization. This contextualized measurement may have produced a clearer relationship with writing skills than a more general digital literacy instrument. In addition, writing skills were measured through performance indicators rather than solely through students' self-perceptions.

3.2.2. Effect of Generative Artificial Intelligence Utilization on Academic Writing Skills

Generative artificial intelligence utilization had a positive and significant statistical effect on academic writing skills. Its higher standardized beta coefficient indicates that it was a relatively stronger predictor than digital literacy. This finding may be explained by the capacity of generative artificial intelligence to support multiple stages of writing, including brainstorming, outlining, generating alternative sentence formulations, checking readability, and providing feedback for revision.

This result is consistent with Mahapatra [8], who showed that ChatGPT-based formative feedback positively affected the academic writing skills of ESL students. Generative artificial intelligence enables students to obtain rapid responses, identify weaknesses in their writing, and revise repeatedly. These benefits are most apparent when artificial intelligence is used as a feedback mechanism and learning support rather than as a replacement for the writer.

The findings also support Marzuki et al. [7], who reported that artificial intelligence-based writing tools can improve the content and organization of student writing. From the perspective of EFL lecturers, these tools supported idea development, paragraph structure, connections among information, and text organization. Although Marzuki et al. [7] used a qualitative approach, their findings clarify mechanisms that may underlie the positive relationship between artificial intelligence utilization and writing quality.

The stronger contribution of generative artificial intelligence utilization may reflect the direct interaction of artificial intelligence support with the written product. Digital literacy provides foundational capabilities for obtaining and evaluating information, whereas generative artificial intelligence can provide immediate assistance through structural examples, language feedback, alternative arguments, and revision recommendations. Its statistical effect may therefore be more readily observed in final academic writing scores.

The positive relationship should not, however, be interpreted to mean that more frequent artificial intelligence use automatically produces better writing. The instrument measured productive, critical, and ethical utilization, including prompt formulation, output evaluation, source verification, response revision, and preservation of authorial originality. Passive practices, such as copying artificial intelligence outputs without evaluation, may instead weaken thinking processes and increase the risks of misinformation, academic integrity violations, and loss of ownership over the text.

Chan and Hu [10] found that students generally regarded generative artificial intelligence as beneficial for ideation, writing, information searching, and personalized learning. At the same time, they expressed concerns about information accuracy, privacy, ethics, and effects on competence development. These findings reinforce the argument that the impact of artificial intelligence depends on the quality of its use rather than merely on its availability or frequency.

3.2.3. Simultaneous Effects of Digital Literacy and Generative Artificial Intelligence Utilization

Digital literacy and generative artificial intelligence utilization jointly explained 46.4% of the variance in academic writing skills, indicating a substantial combined contribution.

Digital literacy provides a foundation for accessing, evaluating, managing, and using information, whereas generative artificial intelligence supports the development, editing, and revision of written work.

The simultaneous relationship also demonstrates that generative artificial intelligence utilization does not operate independently. Students require digital literacy to evaluate the accuracy of artificial intelligence outputs, verify the existence of references, compare information with scholarly sources, protect personal data, and understand ethical boundaries. Without digital literacy, students may be technically capable of using artificial intelligence but unable to account for the quality and originality of their writing.

The model did not explain 53.6% of the variance in academic writing skills, indicating that academic writing is multidimensional. Other potentially relevant factors include critical reading ability, vocabulary and grammar proficiency, knowledge of vocational subject matter, motivation, self-efficacy, writing habits, participation in training, the quality of lecturer guidance, and access to scholarly sources.

3.2.4. Theoretical and Practical Implications

Theoretically, this study extends research on digital literacy and generative artificial intelligence by integrating the two constructs within a single predictive model. Previous research has generally examined digital literacy or generative artificial intelligence separately. The findings indicate that they are distinct constructs that both contribute to academic writing skills.

A further contribution lies in the vocational education context. Vocational students are expected to produce laboratory reports, project reports, technical proposals, procedural documentation, articles, and final projects. Academic writing skills are therefore not only learning requirements but also components of professional communication competence.

Practically, vocational higher education institutions should integrate digital literacy and artificial intelligence literacy into academic writing instruction. Course content should address techniques for searching for articles, evaluating journals, managing references, paraphrasing, maintaining academic integrity, formulating prompts, verifying artificial intelligence outputs, identifying fabricated references, and disclosing artificial intelligence use.

Lecturers should also implement process-oriented writing instruction. Students may be required to submit evidence of each stage of writing, including idea maps, search terms, source lists, draft versions, feedback notes, revision histories, and reflections on artificial intelligence use. This approach is more effective than simply prohibiting artificial intelligence because it enables lecturers to evaluate the development of students' thinking processes.

Vocational institutions also require clear policies on generative artificial intelligence use. Such policies should distinguish between permitted, restricted, and prohibited uses. Using artificial intelligence to obtain language feedback may be treated differently from using it to generate the entire content of an assignment. Transparency of artificial intelligence use, source verification, data protection, and authorial responsibility should be central components of institutional policy.

3.2.5. Limitations and Recommendations for Future Research

This study has several limitations. First, its cross-sectional and correlational design means that the term effect should be interpreted as a statistical or predictive effect rather than as a causal relationship established through experimentation. Future research should use experimental or quasi-experimental designs to compare academic writing instruction supported by generative artificial intelligence with instruction conducted without artificial intelligence.

Second, the sample was limited to 100 vocational students. Generalization to the broader population of vocational students should therefore be undertaken cautiously because student characteristics, digital facilities, artificial intelligence policies, and instructional practices may vary across institutions. Future studies should involve multiple polytechnics or vocational higher education institutions from different regions and use larger samples.

Third, generative artificial intelligence utilization was measured through a questionnaire and may therefore have been affected by perceptual bias and socially desirable responding. Future studies should incorporate additional data, including artificial intelligence activity logs, prompt analyses, revision histories, interviews, observations of the writing process, or task-based experiments.

Fourth, the model included only two predictors and left 53.6% of the variance in academic writing skills unexplained. Further research should examine critical reading ability, writing self-efficacy, motivation, language proficiency, writing habits, academic integrity, quality of lecturer feedback, and artificial intelligence literacy as predictors, mediators, or moderators.

Fifth, the statistical values reported in this section were derived from a synthetic dataset created to simulate 100 students. The results can therefore be used only as an example of analysis and report preparation. Before the article is submitted to a journal, all tables, statistical tests, interpretations, and conclusions must be recalculated using authentic field data collected through appropriate research procedures and with participant consent.

4. Conclusion

The study showed that digital literacy and generative artificial intelligence utilization had positive and significant statistical effects on vocational students' academic writing skills. Digital literacy made a positive contribution ($B = 6.413$, $\beta = 0.334$, $p < 0.001$), whereas generative artificial intelligence utilization made a stronger contribution ($B = 9.097$, $\beta = 0.494$, p

< 0.001). Simultaneously, the two variables produced $F(2, 97) = 42.013$, $p < 0.001$, and explained 46.4% of the variance in academic writing skills. H1, H2, and H3 were therefore supported. These findings emphasize that vocational students' academic writing skills are associated not only with access to technology but also with the ability to evaluate information, verify artificial intelligence outputs, preserve originality, and use technology ethically.

Practically, vocational higher education institutions should integrate digital literacy and artificial intelligence literacy into academic writing instruction. Implementation may include training in searching for and evaluating scholarly sources, using reference management applications, formulating effective prompts, verifying artificial intelligence-generated information and references, and adopting process-oriented writing instruction that documents the development of ideas, drafts, feedback, and revisions. Institutions should also establish generative artificial intelligence policies that differentiate permitted, restricted, and prohibited uses while emphasizing transparency, data protection, academic integrity, and authorial responsibility.

This study was limited by its cross-sectional correlational design, a sample of 100 students from one vocational higher education institution, questionnaire-based measurement of generative artificial intelligence utilization, and a model containing only two predictors. The findings therefore demonstrate statistical predictive capacity and should not be interpreted as causal evidence. Future studies should use experimental, quasi-experimental, or longitudinal designs; involve samples from multiple institutions and regions; and incorporate process data such as revision histories, prompt analyses, observations, and artificial intelligence usage records. Additional variables, including critical reading ability, writing self-efficacy, motivation, language proficiency, academic integrity, the quality of lecturer feedback, and artificial intelligence literacy, should also be tested as predictors, mediators, or moderators.

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