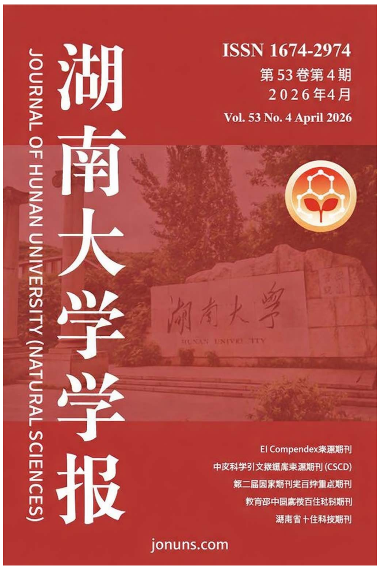

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Bridging Academic Performance and Employability Skills through AI Adoption: Evidence from Vocational Higher Education in Indonesia

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Abstract: The rapid diffusion of artificial intelligence (AI) in higher education has intensified attention on technology-enhanced learning practices, particularly regarding their potential to strengthen employability skills in vocational education. The main challenge lies in understanding how AI-enabled personalized learning contributes to employability development beyond improving academic efficiency alone. This study aims to examine the effect of AI-enabled personalized learning on employability skills among vocational higher education students in Indonesia by integrating Self-Determination Theory and Human Capital Theory. A quantitative causal approach was applied using cross-sectional survey data collected from 260 vocational students at Universitas Padjadjaran and analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results show that employability skills are significantly influenced by relatedness, student engagement, academic performance, and institutional support, while autonomy and competence do not exert direct effects. Furthermore, AI-enabled personalized learning significantly enhances students' autonomy, competence, relatedness, engagement, and academic performance, and has a direct positive effect on employability skills. Mediation analysis indicates that relatedness and academic performance are the primary mechanisms through which AI contributes to employability. These findings highlight that AI most effectively enhances employability when embedded within socially interactive and performance-oriented vocational learning environments.

Keywords: Artificial intelligence; Employability; Vocational education; Motivation; Academic performance.

通过人工智能应用提升学业成绩与就业技能：来自印度尼西亚职业高等教育的证据

摘要：人工智能（AI）在高等教育领域的快速普及，使得人们更加关注技术增强型学习实践，尤其是在职业教育中提升就业技能的潜力。主要挑战在于理解人工智能赋能的个性化学习如何促进就业能力的发展，而不仅仅是提高学业效率。本研究旨在通过整合自我决定理论和人力资本理论，探讨人工智能赋能的个性化学习对印度尼西亚职业高等教育学生就业技能的影响。研究采用定量因果分析方法，收集了来自帕贾贾兰大学260名职业学生的横断面调查数据，并运用偏最小二乘结构方程模型（PLS-SEM）进行分析。结果表明，就业技能显著受到归属感、学生参与度、学业成绩和机构支持的影响，而自主性和胜任力则没有直接影响。此外，人工智能赋能的个性化学习显著提升了学生的自主性、胜任力、归属感、参与度和学业成绩，并对就业技能产生直接的积极影响。中介分析表明，人际关系和学业成绩是人工智能提升就业能力的主要机制。这些发现强调，当人工智能融入社交互动和以绩效为导向的职业学习环境时，它能最有效地提升就业能力。

关键词：人工智能；就业能力；职业教育；动机；学业成绩

1. Introduction

Artificial Intelligence (AI) has rapidly transformed higher education since its widespread adoption in recent years, it is reshaping how students access information, completely academic tasks, brainstorm something new topic, practice question and prepare for professional careers. AI based tools such as ChatGPT, perplexity, Copilot, Grammarly and other generative AI enable students to brainstorm ideas, automate analytical processes, receive instant feedback, and produce creative outputs with unprecedented efficiency. (Truong & Papagiannidis, 2022) said that AI is increasingly positioned as a strategic enabler of teaching and leading innovation in higher education institution (HEIs), particularly in context that demand flexibility, personalization and digital competence. In most of the published thus far, (Adewale et al., 2024; Giannakos et al., 2025) mentioned that AI making a promise and opportunities for higher education by enhancing teaching and learning practices and enabling automated content creation. AI powered tool can support instructors and student through personalized feedback, adaptive learning pathway and efficient academic assistance. Nevertheless, the limitation of AI also existing such as potential disruption, ethical violation, academic integrity issues and other misuse when AI without adequate guidance and regulation.

The integration of AI in HEIs creates heterogeneity learning for students in terms of knowledge, skill development and future career growth. Academic success is often facing an obstacle, such as limited access to high-quality resources, insufficient feedback and lack of personalized instructional support. The study of (Dahri et al., 2024) mentioned that AI from developing country context in Pakistan and Malaysia indicates that can support their academic performance when the accuracy of AI critically evaluated and when students activety engage with these tools. Different study of (Dekker et al., 2020) give any statement that AI not only enhances the learning journey of student, but also can contribute to broader developmental outcomes, including improved self-regulation and well-being.

Beyond academic performance, the role of AI developing employability skills also. Study by Portocarrero Ramos et al., (2025) stated that AI skills play into the workforce, the result indicated that graduates more frequent with AI tools more likely to be employed in areas related to their majors and perceive higher productivity. In the contemporary market now, critical thinking, creativity, communication and collaboration is the good skills should be managed for students. Vocational higher education students, emphazise workplace readiness and applied professional skill can supported by AI facilitate development competencies are problem solving, creative task excecution, collaborative learning and reflective thinking. However, this condition remin mixed, proved that AI skills urgently needed to be factor employability and can into university curricula.

Vocational higher education differs fundamentally from general academic education in its orientation toward practical skills and labor market relevance. In

Indonesia, vocational higher education has become a strategic priority in national education policy, aiming to reduce graduate unemployment and strengthen alignment between education and industry needs. Despite this policy emphasis, the integration of AI into vocational learning practices remains uneven across institutions and study programs. Many vocational students use AI tools primarily to complete assignments efficiently, rather than to enhance engagement, motivation, or employability-oriented competencies. This pragmatic usage pattern raises important questions about whether AI-enabled personalized learning genuinely contributes to meaningful educational outcomes in vocational contexts.

A review of existing studies reveals several critical research gaps. First, much of the empirical evidence on AI in higher education originates from developed countries, leaving emerging economies such as Indonesia underrepresented. Second, vocational higher education has received limited scholarly attention compared to general university settings, despite its distinct mission and learning characteristics. Third, prior research often examines academic performance and employability skills as separate outcomes, without investigating the motivational and engagement mechanisms that connect AI adoption to both domains. Finally, limited research incorporates students' perceptions of challenges, ethical risks, and institutional support related to AI use in learning.

To address these gaps, this study investigates the role of AI-enabled personalized learning in shaping academic performance and employability skills among vocational higher education students in Indonesia. Drawing on the Self-Determination Theory (SDT), and the Employability Skills (4C) framework, this study proposes an integrated model that explains how AI adoption influences students' autonomy, competence, and relatedness, how these motivational factors affect learning engagement, and how engagement subsequently contributes to academic performance and employability skills. Accordingly, this study seeks to answer the following research questions:

1. To what extent do autonomy, competence, relatedness, student engagement, academic performance, and institutional support influence employability skills among vocational higher education students?
2. Does AI-enabled personalized learning positively influence students' autonomy, competence, relatedness, student engagement, and academic performance in vocational higher education?
3. Do autonomy, competence, relatedness, student engagement, and academic performance mediate the relationship between AI-enabled personalized learning and employability skills among vocational higher education students?

By addressing these questions, this study makes three distinct theoretical and contextual contributions to the AI-in-education literature. First, while prior research has largely examined AI adoption through either motivational lenses (e.g., SDT, TAM; Ellikkal & Rajamohan, 2025; Zhao et al., 2024) or skill-accumulation lenses (e.g., HCT; Yoto et al., 2025) in isolation, this study advances the literature by integrating Self-Determination Theory (SDT) and Human Capital Theory (HCT) into a single explanatory framework. This integration moves beyond incremental theoretical extension by demonstrating that AI's contribution to employability is neither purely motivational nor purely performance-based, but operates through a dual-pathway mechanism—where psychological need satisfaction (SDT) and academic capital accumulation (HCT) function as complementary yet distinct mediators (Wang et al., 2025). This reframes AI-enabled personalized learning not as a technological intervention, but as a socio-cognitive learning mechanism that bridges motivation and measurable human capital outcomes.

Second, this study offers novelty by focusing explicitly on vocational higher education, a context substantially underrepresented in the existing AI-in-education literature, which has predominantly examined general university settings (Daniel et al., 2025; Giannakos et al., 2024). Vocational education differs fundamentally in its applied, outcome-oriented, and industry-aligned pedagogical orientation (Yoto et al., 2025), which means that findings from general higher education cannot be directly transferred. By empirically testing the SDT–HCT integrated model in a vocational setting, this study reveals mechanism-specific insights particularly the dominance of relatedness and academic performance over autonomy and competence as pathways to employability—that are theoretically and practically distinct from general higher education contexts.

Third, this study provides empirical evidence from Indonesia, an emerging economy where vocational higher education has become a national strategic priority (Yoto et al., 2025), thereby extending the geographic and developmental scope of AI-in-education research beyond its dominant focus on developed-country contexts (Ravšelj et al., 2025). The findings offer practical implications for educators, institutions, and policymakers seeking to implement AI-enabled personalized learning in a pedagogically effective and ethically responsible manner.

2. Literature Review and Hypothesis Development

This study is grounded in two major theoretical perspectives that, when integrated, provide a novel explanatory framework for understanding AI's role in vocational learning outcomes. First, Self-Determination Theory (SDT) explains how AI-enabled personalized learning supports students' autonomy, competence, and relatedness, which are essential psychological needs that drive engagement and learning effectiveness (Ryan & Deci, 2020). SDT posits that satisfying these needs fosters autonomous motivation and sustained learning, and recent studies confirm that AI-based tools and chatbots can reinforce these needs by providing adaptive, responsive, and interactive learning experiences (Chiu et al., 2024; Ellikkal & Rajamohan, 2025). Second, Human Capital Theory (HCT) provides a foundation for understanding employability skills as returns on educational investment, where academic performance and transferable competencies represent key outcomes of skill accumulation (Becker, 1993; Jackson & Tomlinson, 2022). Contemporary HCT scholarship has expanded beyond traditional economic framings to include behavioral and capability-based perspectives on learning (Wang et al., 2025; Yoto et al., 2025).

Although SDT and HCT have each been applied to educational technology research, they have rarely been integrated into a unified model that explains AI's impact on employability. SDT alone cannot explain how motivational states translate into labor-market–relevant human capital, while HCT alone cannot account for the psychological and social mechanisms through which AI-supported learning produces measurable outcomes (Wang et al., 2025). By integrating these two perspectives, this study contributes theoretically in three ways: (1) it conceptualizes AI-enabled personalized learning as a dual-pathway mechanism that operates simultaneously through motivational (SDT) and capital-accumulation (HCT) routes; (2) it identifies which specific SDT dimensions function as effective transmitters of AI's benefits to employability, thereby refining rather than merely replicating SDT's application in AI contexts (Ellikkal & Rajamohan, 2025); and (3) it extends HCT into the digital learning era by positioning AI-enabled personalized learning as a new form of educational input that accelerates human capital accumulation (Yoto et al., 2025). This integrated framework is particularly relevant to vocational higher education, where both motivational engagement and demonstrable skill outcomes are central to graduate employability.

Hypothesis Development

RQ1: Determinants of Employability Skills

Employability skills are increasingly recognized as multidimensional outcomes shaped by both individual and institutional factors within higher education. In vocational higher education, employability is not merely reflected in academic credentials, but in students' ability to demonstrate transferable competencies such as critical thinking, creativity, communication, and collaboration (Suleman, 2018; Jackson & Tomlinson, 2022). Drawing on Self-Determination Theory (SDT), students' autonomy, competence, and relatedness are viewed as fundamental psychological resources that foster motivation, persistence, and effective learning behaviors (Deci & Ryan, 2000; Chiu, 2022). Students who feel autonomous tend to take ownership of their learning, those who perceive competence are more confident in problem-solving, and those experiencing relatedness are more actively engaged in collaborative and communicative tasks. These psychological conditions are therefore expected to directly support the development of employability-relevant skills in vocational education contexts.

Beyond psychological needs, student engagement represents the behavioral manifestation of motivation and has been consistently linked to deeper learning and transferable skill acquisition (Bond et al., 2021). Engaged students are more likely to participate in applied learning activities and collaborative projects that directly enhance employability skills. In addition, academic performance reflects the accumulation of cognitive and technical capital which, from a Human Capital Theory perspective, translates into higher employability readiness and labor market value (Becker, 1993). Furthermore, employability skills are not developed solely at the individual level but are strongly shaped by institutional support, including access to digital infrastructure, academic guidance, and supportive learning policies. Such institutional conditions enable students to effectively transform learning experiences into employability-oriented outcomes (Dwivedi & Vig, 2024). In technology-enhanced learning environments, institutional support may also condition how emerging digital tools contribute to employability development (Dwivedi & Vig, 2024). Based on this theoretical and empirical foundation, the following hypotheses are proposed:

- H1a-H1c : Autonomy, Competence, Relatedness positively influences employability skills.
- H2: Engagement positively influences employability skills.
- H3: Academic performance positively influences employability skills.
- H4: Institutional support positively influences employability skills.
- H5: Institutional support moderates the relationship between AI-enabled personalized learning and employability skills.

RQ2: AI-Enabled Personalized Learning as a Learning Mechanism

The rapid diffusion of artificial intelligence in higher education has transformed learning processes by enabling personalization, adaptive feedback, and self-paced study pathways. AI-enabled personalized learning systems allow students to access tailored learning resources, receive immediate feedback, and regulate their learning activities more effectively (Truong & Papagiannidis, 2022). From the perspective of Self-Determination Theory, such AI affordances can enhance students' autonomy by allowing greater control over learning decisions, competence by supporting mastery through adaptive feedback, and relatedness by facilitating interactive and collaborative learning environments (Jeno et al., 2025).

Beyond psychological needs, prior empirical studies indicate that AI-supported learning environments also stimulate student engagement by increasing attention, motivation, and persistence in academic tasks (Aboagye et al., 2020). Engagement, in turn, represents a critical behavioral pathway through which motivational states are translated into meaningful learning experiences. Moreover, AI tools have been shown to support academic performance by improving learning efficiency, conceptual understanding, and self-regulated learning strategies, particularly when students actively and critically engage with these technologies (Dahri et al., 2024). Importantly, while AI-enabled personalized learning has the potential to enhance employability skills, its impact is unlikely to be automatic or direct. Integrating Self-Determination Theory and Human Capital Theory, this study argues that AI influences employability skills indirectly, through intermediate psychological, behavioral, and academic processes. Autonomy, competence, and relatedness shape students' motivation and social learning experiences; engagement reflects sustained learning involvement; and academic performance represents the accumulation of human capital valued in the labor market. These factors therefore function as mediating mechanisms linking AI-enabled personalized learning to employability outcomes in vocational education. However, whether these psychological and academic outcomes fully explain the relationship between AI-enabled personalized learning and employability skills remains unclear, necessitating an examination of their mediating roles. Based on this reasoning, the following hypotheses are proposed:

- H6a-H6e : AI-Enabled Personalized Learning influence Autonomy, Competence, Relatedness, Engagement and Academic Performance.
- H7: AI-Enabled Personalized Learning (X1) influence Employability Skills (Y)

RQ3: Mediating Role of Motivation and Academic Outcomes

While prior studies have examined the direct effects of AI adoption on learning outcomes, limited research has explored the underlying mechanisms through which AI-enabled personalized learning translates into employability skills, particularly in vocational higher education contexts. Integrating SDT and Human Capital Theory, this study argues that AI does not enhance employability skills automatically; rather, its impact operates through intermediate psychological and academic processes. AI-enabled personalized learning first influences students' autonomy, competence, and relatedness, which shape engagement in learning activities. Sustained engagement then contributes to improved academic performance, representing the accumulation of knowledge and skills that are valued in the labor market (Capone & Lepore, 2022; Jackson & Tomlinson, 2022). These motivational and academic factors collectively function as mediators that connect AI adoption to employability readiness. Empirical evidence suggests that without sufficient motivation, engagement, and performance gains, the potential benefits of AI tools for employability remain limited or superficial (Rokkones & Giannakos, 2025). Therefore, understanding these mediating mechanisms is essential for explaining how AI-enabled personalized learning contributes to meaningful educational and career-related outcomes among vocational students. Based on this reasoning, the following hypothesis is proposed:

- H8: Autonomy mediates the relationship between AI-enabled personalized learning and employability skills.
- H9: Competence mediates the relationship between AI-enabled personalized learning and employability skills.
- H10: Relatedness mediates the relationship between AI-enabled personalized learning and employability skills.
- H11: Student engagement mediates the relationship between AI-enabled personalized learning and employability skills.
- H12: Academic performance mediates the relationship between AI-enabled personalized learning and employability skills.

3. Material and Methods

3.1. Research design

This study employs a quantitative approach using a cross-sectional survey design to examine the impact of Artificial Intelligence (AI) adoption on academic performance and employability skills among vocational higher education students at Universitas Padjadjaran. This design was selected because it allows for the collection of measurable empirical evidence regarding trends, perceptions, and students' experiences in using AI as a learning support tool within a single time period. Data were collected through a structured questionnaire developed to reflect the context of AI usage in both academic and professional-related learning activities among vocational students. This approach enables the researcher to capture a comprehensive snapshot of the relationships among variables simultaneously. Data analysis was conducted using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS software. This method was chosen because it is suitable for models involving multiple latent constructs, potential non-normal data distributions, medium sample sizes (n ≈ 200–300), and the need to test mediation, moderation, and multi-group analysis (MGA) (Hair et al., 2021).

3.2. Population and Sample

The population of this study comprises all active students enrolled in the 2022–2025 cohorts at the Vocational School of Universitas Padjadjaran, totaling approximately 1,000 students. A stratified purposive sampling technique was employed to ensure adequate representation across four academic clusters: business and finance, social sciences and humanities, technology and agro-industry, and health sciences. The inclusion criteria required respondents to have prior experience using AI-based applications or tools such as ChatGPT, Copilot, Grammarly, QuillBot, or similar platforms in activities supporting their academic learning or practical coursework. Following data screening and cleaning procedures, 260 valid responses were retained for analysis. This sample size exceeds the minimum requirements recommended for PLS-SEM analysis and ensures sufficient statistical power and reliability (Hair et al., 2021). According to Hair et al., the sample size should be at least 10 times the maximum number of structural paths directed at a latent construct. In addition, recommendations by Kock & Hadaya (2018) suggest that a sample of this size is sufficient to achieve adequate statistical power. Therefore, the sample size used in this study is considered appropriate for the analysis.

3.3. Data Collection

Primary data were collected using an online questionnaire administered via Google Forms, designed according to the context of AI usage in learning activities. The questionnaire consisted of several sections, including: Respondents' demographic information (study program, cohort, and experience with AI); Frequency and purpose of AI use in learning activities; Perceptions of AI-related ease of use, usefulness, and potential risks; and Perceived impacts of AI use on learning motivation and academic outcomes.

3.4. Data Analysis

Data analysis was performed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with SmartPLS 4 to examine both direct and indirect relationships among latent constructs in the research model. This approach is appropriate for complex models involving hierarchical constructs and does not require data normality assumptions (Hair et al., 2021). The analysis followed two main stages: measurement model (outer model) evaluation and structural model (inner model) evaluation. Measurement model assessment included tests of indicator reliability, internal consistency, convergent validity, and discriminant validity using outer loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). Structural model evaluation assessed the strength and direction of relationships among constructs through path coefficient estimation. The analysis was conducted at an aggregate level across all respondents (n = 260), as the distribution of data across semesters and study programs was not sufficiently balanced for subgroup analysis. Mediation effects were also tested to examine the role of intermediary variables linking AI adoption to learning outcomes among vocational students at Universitas Padjadjaran.

4. Result

4.1. Respondent Profile

Based on the distribution of questionnaires via Google Forms, the characteristics of the respondents are summarized as follows:

Demographic variable	Categories	Frequency	Percent
Gender	Male (1.0)	96	36,9
	Female (2.0)	164	63,1
Age	<20 y (1.0)	229	88,1
	21 - 23 y (2.0)	30	11,5
	24 - 26 y (3.0)	1	0,4
Semester	1-2	160	61,5
	3-4	76	29,2
	5-6	12	4,6
	7-8	12	4,6
Academic disciplines	Tax Accounting	97	37,3
	Public Administratio n	55	21,2
	International Business	33	12,7
	Public Sector Accounting	19	7,3
	Chinese Language and Culture	18	6,9
	Marine Tourism	17	6,5

	Digital Marketing	21	8
AI tools Use	ChatGPT	244	93,8
	Gemini	181	69,6
	DeepSeek	60	23,1
	Perplexity	14	5,4
	Blackbox	3	1,2
Frequency of Use	Daily	126	48,5
	Weekly	104	40,0
	Monthly	6	2,3
	Rarely	22	8,5
	Never	2	0,8
Internet Access Quality	Very stable	49	18,8
	Fairly stable	197	75,8
	Unstable	14	5,4
Level of Satisfaction	5	51	19,6
	4	125	48,1
	3	73	28,1
	2	9	3,5
	1	2	0,8

Source: Researcher Data (2025)

Table 1 showed data collected through the online questionnaire administered via Google Forms, the characteristics of the respondents are summarized in the table above. In terms of gender distribution, female students constitute the majority of respondents, with 164 individuals (63.1%), while 96 respondents (36.9%) are male. Regarding age, most respondents are under 20 years old (229 students; 88.1%), followed by those aged 21–23 years (30 students; 11.5%), whereas only one respondent (0.4%) falls within the 24–26 years age group. This distribution indicates that the sample predominantly consists of young vocational students. With respect to academic progression, the majority of respondents are enrolled in semesters 1–2 (160 students; 61.5%), followed by semesters 3–4 (76 students; 29.2%), while students in semesters 5–6 and 7–8 each account for 12 respondents (4.6%).

Based on academic discipline, the largest proportion of respondents comes from the Tax Accounting program (97 students; 37.3%), followed by Public Administration (55 students; 21.2%) and International Business (33 students; 12.7%). Other study programs, including Public Sector Accounting (7.3%), Chinese Language and Culture (6.9%), Marine Tourism (6.5%), and Digital Marketing (8%),

Regarding the use of artificial intelligence (AI) tools, ChatGPT is the most widely used platform, reported by 244 respondents (93.8%), followed by Gemini (69.6%), DeepSeek (23.1%), Perplexity (5.4%), and Blackbox (1.2%). These findings indicate that ChatGPT is the dominant AI tool among vocational students.

In terms of usage frequency, 126 respondents (48.5%) report using AI tools on a daily basis, while 104 respondents (40.0%) use them weekly. A smaller proportion uses AI monthly (2.3%) or rarely (8.5%), and only two respondents (0.8%) report never using AI. This pattern reflects a high level of engagement with AI technologies in both academic and daily activities.

Regarding satisfaction levels, 125 respondents (48.1%) rated their satisfaction at level 4 (satisfied), and 51 respondents (19.6%) rated it at level 5 (very satisfied). Meanwhile, 73 respondents (28.1%) expressed neutral satisfaction, nine respondents (3.5%) reported low satisfaction, and only two respondents (0.8%) reported very low satisfaction. Overall, these results suggest that most students have a positive experience with AI usage.

Finally, in terms of internet access quality, the majority of respondents reported having fairly stable internet access (197 students; 75.8%), followed by those with very stable access (49 students; 18.8%), while only 14 respondents (5.4%) experienced unstable connections. This indicates that most respondents possess adequate internet infrastructure to support AI-based learning activities.

The respondent profile indicates that most participants are early- to mid-semester vocational students who have not yet entered the labor market. Therefore, employability skills in this study are conceptualized as perceived employability readiness, that is, students' self-assessed development of critical thinking, creativity, communication, and collaboration skills acquired during their academic learning process (Jackson & Tomlinson, 2022; Rothwell et al., 2008).

It is important to explicitly distinguish perceived employability from actual employability. Perceived employability refers to students' subjective self-evaluation of their readiness and competencies for the workforce (Rothwell et al., 2008), while actual employability refers to objectively verifiable labor-market outcomes such as job placement rates, employer evaluations, starting salaries, internship performance ratings, or time-to-employment (Wang et al., 2025). These two constructs, though related, are conceptually and empirically distinct: perceived employability captures the developmental dimension of employability cultivated during education, whereas actual employability captures the realized dimension observed in the labor market.

This study deliberately adopts the perceived employability perspective for two reasons. First, the sample consists of students who are still enrolled in vocational education and have not yet entered full-time employment, making objective labor-market indicators inapplicable at this stage (Jackson & Tomlinson, 2022). Second, perceived employability is a well-established construct in educational research and has been shown to be a meaningful predictor of subsequent labor-market outcomes (Rothwell et al., 2008; Wang et al., 2025). Nevertheless, we explicitly acknowledge that perceived employability is not a substitute for objective indicators, and findings should be interpreted as reflecting employability development during education rather than employment outcomes after graduation. This distinction is critical for interpreting the study's contributions and is revisited in the limitations section.

Validity and Reliability Testing

The development and validation of measurement instrument in this study were adapted from the construct of AI-enabled personalized learning such as autonomy, competence and relatedness were defined from the Self determination theory framework (Gao et al., 2023; Mehmood at al., 2024). All items were measured using a five point likert scaling from 1 (disagree) until 5 (strongly disagree). Validity testing in this study was conducted by examining two main aspects: convergent validity and discriminant validity. Convergent validity aims to ensure that each measurement indicator has a strong association with the construct it represents. According to Hair et al. (2010), an indicator is considered acceptable when its factor loading exceeds 0.50, and it is regarded as highly satisfactory when the loading value is above 0.70. The results of the convergent validity assessment are presented in the following table:

Table 2. Convergent Validity

Constructs	Item	Factor Loading
AI-Enabled Personalized	AI_1	0,840
	AI_2	0,717
	AI_3	0,616
	AI_4	0,765
	AI_5	0,821
Autonomy	AUT_1	0,918
	AUT_2	0,922
Competence	COM_1	0,870
	COM_2	0,794
Relatedness	REL_1	0,856
	REL_2	0,905
Engagement	ENG_1	0,771
	ENG_2	0,808
	ENG_3	0,803
	ENG_4	0,783
Academic Performance	ACP_1	0,873
	ACP_2	0,902
	ACP_3	0,813
	ACP_4	0,873
Employability Skills	EPS_1	0,756
	EPS_2	0,775
	EPS_3	0,748
	EPS_4	0,786
	EPS_5	0,806
	EPS_6	0,761
	EPS_7	0,729
	EPS_8	0,792
Institusional Support	INS_1	0,778
	INS_2	0,742
	INS_3	0,842
	INS_4	0,850

Source: Researcher Data, SEM PLS (2025)

Table 2 explained that all measurement indicators exhibit factor loading values above 0.50, with the majority exceeding 0.70. This indicates that each indicator adequately represents its respective construct. Therefore, it can be concluded that all indicators meet the criteria for convergent validity. Subsequently, reliability testing was conducted to evaluate the extent to which the measurement instruments produce consistent, accurate, and stable results in assessing the constructs under study. The results of the reliability analysis are presented in the following table.

Table 3. Construct Reliability

Constructs	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
AI-Enabled Personalized	0,811	0,868	0,572
Autonomy	0,819	0,917	0,847
Competence	0,562	0,819	0,694
Relatedness	0,714	0,874	0,776
Engagement	0,801	0,870	0,626
Academic Performance	0,888	0,923	0,749
Employability Skills	0,901	0,921	0,592
Institusional Support	0,823	0,879	0,647

Source: Researcher Data, SEM PLS (2025)

Based on the table 3, data analysis presented in the table above, all constructs exhibit Average Variance Extracted (AVE) values greater than 0.50, indicating that each construct explains more than 50% of the variance of its indicators. In addition, the Composite Reliability (CR) values for all constructs exceed the recommended threshold of 0.70, demonstrating good internal consistency among the indicators within each construct.

The Cronbach’s Alpha (CA) values for most constructs are also above 0.70, indicating satisfactory reliability. However, the Competence construct shows a Cronbach’s Alpha value of 0.562, which is slightly below the recommended threshold. Nevertheless, this construct can still be considered reliable, as its Composite Reliability (0.819) and AVE (0.694) values meet the acceptable criteria. In the context of PLS-SEM, Composite Reliability is considered a more robust measure of internal consistency than Cronbach’s Alpha (Hair et al., 2021). Therefore, the Competence construct can still be considered reliable and valid for further analysis.

Therefore, it can be concluded that all constructs in this study satisfy the reliability criteria based on CA, CR, and AVE, and the measurement instruments used are reliable and appropriate for assessing the variables in the research model.

Table 4. HTMT ratio

	AI	AUT	COM	REL	ENG	ACP	EPS	INS
AI-Enabled Personalized								
Autonomy	0,801							
Competence	1,041	0,956						
Relatedness	0,809	0,658	1,072					
Engagement	0,796	0,659	0,971	0,904				
Academic Performance	0,811	0,710	1,050	0,719	0,788			
Employability Skills	0,791	0,675	0,884	0,769	0,771	0,827		
Institutional Support	0,684	0,466	0,534	0,501	0,534	0,613	0,613	

Source: Researcher Data, SEM PLS (2025)

Table 5. Fornell-Larcker criterion

	AI	AUT	COM	REL	ENG	ACP	EPS	INS
AI-Enabled Personalized	**0,756**							
Autonomy	0,667	**0,920**						
Competence	0,725	0,661	**0,833**					
Relatedness	0,635	0,512	0,687	**0,881**				
Engagement	0,653	0,535	0,662	0,689	**0,791**			
Academic Performance	0,704	0,604	0,739	0,581	0,666	**0,866**		
Employability Skills	0,688	0,582	0,639	0,622	0,657	0,745	**0,769**	
Institutional Support	0,560	0,399	0,386	0,397	0,447	0,557	0,555	**0,804**

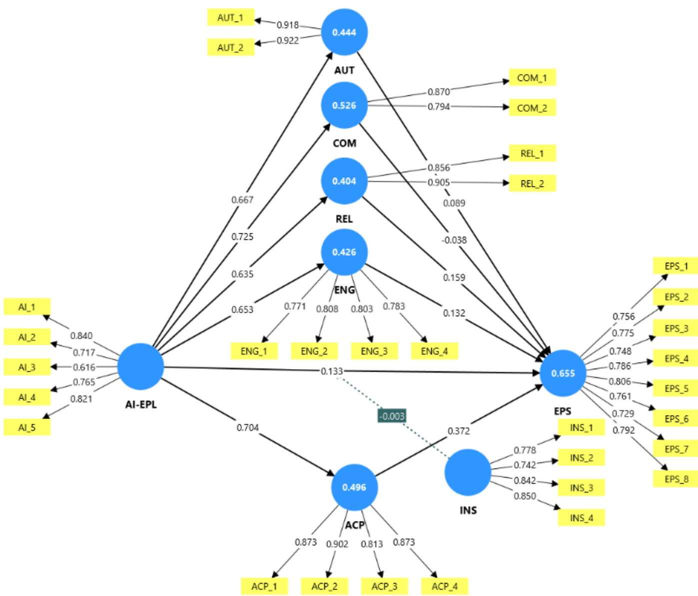
Source: Researcher Data, SEM PLS (2025)

Discriminant validity in this study was assessed using two approaches: the Heterotrait–Monotrait Ratio (HTMT) and the Fornell–Larcker criterion. Based on the results obtained from SmartPLS 4, most HTMT values are below the recommended threshold of 0.90, although a small number of construct pairs exceed this threshold. Meanwhile, the Fornell–Larcker criterion indicates that the square root of the Average Variance Extracted (AVE) for each construct is greater than its correlations with other constructs. Accordingly, discriminant validity is supported based on the Fornell–Larcker approach. The high HTMT values may be attributed to conceptual similarities among the constructs, especially between competence, academic performance, and related psychological factors, which are theoretically interconnected within the Self-Determination Theory framework. Overall, although the HTMT analysis reveals some relatively high correlations among certain constructs, the Fornell–Larcker results confirm that the measurement model demonstrates adequate discriminant validity.

Structural Model (Inner Model)

The structural model is used to examine the causal relationships among variables in a study. This model explains how independent variables influence dependent variables, thereby enabling the testing of hypotheses regarding interactions among constructs. According to Hair et al. (2010), the structural model serves to analyze the relationships between latent variables, which are constructs that cannot be measured directly but are represented by observable indicators. The results of the overall model estimation using SmartPLS 4.1 are presented in the following figure 1.

Figure 1. Structural Model (Inner Model) Research



Coefficient of Determination

The coefficient of determination (R^2) is used to indicate the extent to which exogenous latent variables explain the variance in endogenous latent variables.

Table 6. Determination Coefficient (R^2)

Constructs	R-square	R-square adjusted	Benchmark
Autonomy	0,444	0,442	0.75 => Substantial; 0.50 => Moderate; 0.25 => Weak (Hair et al. 2017)
Competence	0,526	0,524	
Relatedness	0,404	0,402	
Engagement	0,426	0,424	
Academic Performance	0,496	0,494	
Employability Skills	0,655	0,644	

Source: Researcher Data, SEM PLS (2025)

Based on the table 6, the proposed SEM model explains a substantial proportion of variance in the endogenous constructs. According to the criteria suggested by Hair et al. (2017), the R^2 values fall within the moderate to substantial range, indicating that the model demonstrates an adequate level of fit with the empirical data. The highest R^2 value is observed for Employability Skills (0.655), followed by Competence (0.526) and Academic Performance (0.496), while the lowest R^2 value is found for Relatedness (0.404). These findings suggest that the model exhibits a reasonable fit to the data and that the AI-enabled personalized learning approach contributes meaningfully to explaining variations in students' autonomy, competence, relatedness, engagement, academic performance, and employability skills in vocational higher education.

Table 7. Hypothesis Testing

Hypotesis	Interrelationships Among Variables	Path (β)	T statistics	*P* values	Hasil
H1a	Autonomy (M1.1) ➔ Employability Skills (Y)	0,089	1,318	0,094	Rejected
H1b	Competence (M1.2) ➔ Employability Skills (Y)	-0,038	0,544	0,293	Rejected
H1c	Relatedness (M1.3) ➔ Employability Skills (Y)	0,159	2,250	0,012	Accepted
H2	Engagement (M2) ➔ Employability Skills (Y)	0,132	1,682	0,047	Accepted
H3	Academic Performance (M3) ➔ Employability Skills (Y)	0,372	4,933	0,000	Accepted
H4	Institutional Support (Mo) ➔ Employability Skills (Y)	0,131	2,501	0,006	Accepted
H5	Institutional Support × AI-Enabled Personalized Learning ➔ Employability Skills (Y)	-0,003	0,102	0,459	Rejected
H6a	AI-Enabled Personalized Learning (X1) ➔ Autonomy (M1.1)	0,667	17,145	0,000	Accepted
H6b	AI-Enabled Personalized Learning (X1) ➔ Competence (M1.2)	0,725	23,494	0,000	Accepted
H6c	AI-Enabled Personalized Learning (X1) ➔ Relatedness (M1.3)	0,635	16,716	0,000	Accepted
H6d	AI-Enabled Personalized Learning (X1) ➔ Engagement (M2)	0,653	17,084	0,000	Accepted
H6e	AI-Enabled Personalized Learning (X1) ➔ Academic Performance (M3)	0,704	20,67	0,000	Accepted
H7	AI-Enabled Personalized Learning (X1) ➔ Employability Skills (Y)	0,133	1,937	0,027	Accepted

Hypotesis	Interrelationships Among Variables	Path (β)	T statistics	*P* values	Hasil
H8	AI-Enabled Personalized Learning ➔ Autonomy ➔ Employability Skills	0,059	1,300	0,097	Rejected
H9	AI-Enabled Personalized Learning ➔ Competence ➔ Employability Skills	-0,027	0,538	0,295	Rejected
H10	AI-Enabled Personalized Learning ➔ Relatedness ➔ Employability Skills	0,101	2,274	0,012	Accepted
H11	AI-Enabled Personalized Learning ➔ Engagement ➔ Employability Skills	0,086	1,623	0,053	Rejected
H12	AI-Enabled Personalized Learning ➔ Academic Performance ➔ Employability Skills	0,262	4,883	0,000	Accepted

The path analysis in table 7 results indicate that AI-enabled personalized learning has a strong and significant positive effect on autonomy ($\beta = 0.667$; $p < 0.001$), competence ($\beta = 0.725$; $p < 0.001$), and relatedness ($\beta = 0.635$; $p < 0.001$). These findings suggest that AI-based learning environments effectively strengthen the core dimensions of Self-Determination Theory, enhancing students' sense of control over learning, perceived academic capability, and social connectedness. Among these dimensions, relatedness plays a particularly important role, as it shows a significant positive effect on student engagement ($\beta = 0.159$; $p = 0.012$). In contrast, the relationships between autonomy and engagement ($\beta = 0.089$; $p = 0.094$) and between competence and engagement ($\beta = -0.038$; $p = 0.293$) are not statistically significant, indicating that autonomy and competence alone are insufficient to directly stimulate engagement in AI-supported learning contexts without strong social interaction.

Furthermore, student engagement has a significant positive effect on academic performance ($\beta = 0.132$; $p = 0.047$), demonstrating that active involvement in AI-facilitated learning contributes to improved academic outcomes. Academic performance, in turn, shows a strong positive impact on employability skills ($\beta = 0.372$; $p < 0.001$), confirming its central role in developing work-relevant competencies. Institutional support also positively influences employability skills ($\beta = 0.131$; $p = 0.006$), highlighting the importance of supportive policies, infrastructure, and guidance. However, the interaction between institutional support and AI-enabled personalized learning is not significant ($\beta = -0.003$; $p = 0.459$), suggesting that institutional support does not moderate the AI employability relationship. Nevertheless, the direct effect of AI-enabled personalized learning on employability skills remains significant ($\beta = 0.133$; $p = 0.027$), indicating that AI contributes both directly and indirectly through psychological and academic pathways to vocational students' employability readiness.

5. Discussion

5.1. Determinants of Employability Skills

This study examines the determinants of employability skills among vocational higher education students by integrating Self-Determination Theory (SDT) and Human Capital Theory. The findings indicate that employability skills are not shaped uniformly by all motivational components, but rather by selective psychological, behavioral, academic, and institutional factors.

The results on table 7 show that autonomy does not significantly influence employability skills ($\beta = 0.089$; $p = 0.094$), leading to the rejection of H1a. Although SDT conceptualizes autonomy as a core psychological need that enhances intrinsic motivation (Deci & Ryan, 2000), this finding suggests that perceived autonomy alone may not directly translate into employability skills in vocational education contexts. Autonomy may act as a distal motivational factor that requires transformation into observable learning behaviors or performance outcomes before contributing to employability development. Similarly, competence does not have a significant effect on employability skills ($\beta = -0.038$; $p = 0.293$), resulting in the rejection of H1b. While SDT emphasizes competence as a driver of effective functioning, the result indicates that employability in vocational setting is more strongly associated with demonstrable performance and practical achievements rather than self-perceived ability. This suggests that competence may exert its influence indirectly, through engagement or academic performance, rather than as a direct predictor. Therefore, these findings highlight that internal psychological factors alone are insufficient to directly enhance employability skills without being translated into active learning behaviors and measurable outcomes.

In contrast, relatedness has a significant positive effect on employability skills ($\beta = 0.159$; $p = 0.012$), supporting H1c. This finding aligns strongly with SDT, which emphasizes social connectedness as a key condition for sustained motivation and learning effectiveness. Employability skills such as communication, teamwork, and collaboration are inherently social; therefore, students who experience stronger relational ties are better positioned to develop these competencies. Although these relationships are statistically significant, the effect sizes are relatively small, indicating that these factors contribute to employability development but are not the primary drivers. This suggests that employability skills are shaped by a combination of multiple factors rather than a single dominant predictor.

The findings further indicate that student engagement positively influences employability skills (β = 0.132; p = 0.047), supporting H2. From an SDT perspective, engagement represents the behavioral manifestation of motivation. Engaged students invest greater effort and persistence in applied learning activities, facilitating the acquisition of transferable employability skills (Bond et al., 2021). Moreover, academic performance emerges as the strongest determinant of employability skills (β = 0.372; p < 0.001), confirming H3. This result strongly supports Human Capital Theory, which argues that educational achievement reflects accumulated cognitive and technical capital that increases labor market value (Becker, 1993). High academic performance signals mastery, discipline, and problem-solving ability—attributes directly valued by employers.

Finally, institutional support has a significant positive effect on employability skills (β = 0.131; p = 0.006), supporting H4. This highlights the role of institutional environments in enabling students to transform learning experiences into employability outcomes through infrastructure, guidance, and supportive policies. However, institutional support does not moderate the relationship between AI-enabled personalized learning and employability skills (β = −0.003; p = 0.459), leading to the rejection of H5. This suggests that institutional support alone does not strengthen the employability impact of AI unless it is pedagogically embedded and aligned with curriculum design and assessment practices.

However, institutional support does not significantly moderate the relationship between AI-enabled personalized learning and employability skills (β = −0.003; p = 0.459), leading to the rejection of H5. This finding warrants further consideration. One possible explanation is that institutional support functions primarily as a general enabling condition rather than a mechanism that amplifies the effectiveness of specific learning technologies. While institutions may provide access to AI tools, infrastructure, and policy support, these factors alone do not guarantee that students will effectively utilize AI in ways that enhance employability outcomes.

In addition, the impact of AI-enabled personalized learning may depend more on how it is pedagogically integrated into curriculum design, instructional strategies, and assessment practices. Without such alignment, institutional support may remain peripheral and fail to strengthen the relationship between AI use and employability development.

This finding suggests that institutional support plays a facilitative rather than a transformative role, indicating that the effectiveness of AI in enhancing employability is driven more by pedagogical implementation and student engagement than by institutional provision alone.

Overall, the RQ1 findings clearly indicate that employability skills in vocational higher education are shaped primarily by socially embedded learning processes, including social connectedness, active student engagement, and academic achievement, supported by conducive institutional structures. Rather than emerging directly from internal motivational perceptions such as autonomy and competence alone, employability skills appear to develop through sustained participation in collaborative learning environments, consistent academic performance, and institutional conditions that facilitate the translation of learning experiences into labor market–relevant competencies. These results underscore the applied and outcome-oriented nature of vocational education, where employability is constructed through interaction, performance, and structural support rather than through individual motivation in isolation.

5.2. AI-Enabled Personalized Learning as a Learning Mechanism

RQ2 investigates the role of AI-enabled personalized learning as a learning mechanism that shapes students' psychological, behavioral, and academic outcomes. The results on table 7 demonstrate that AI-enabled personalized learning has a strong positive effect on autonomy (β = 0.667; p < 0.001), supporting H6a. This finding aligns with SDT by indicating that AI systems offering flexible learning pathways enhance students' sense of control over learning decisions. Similarly, AI-enabled personalized learning significantly enhances competence (β = 0.725; p < 0.001), supporting H6b, suggesting that adaptive feedback and personalized content strengthen mastery experiences. In addition, AI-enabled personalized learning positively influences relatedness (β = 0.635; p < 0.001), supporting H6c, indicating that AI tools can facilitate interaction and collaborative learning in digital environments. The findings further reveal that AI-enabled personalized learning significantly increases student engagement (β = 0.653; p < 0.001), supporting H6d, consistent with prior research highlighting the motivational benefits of personalized and interactive learning systems. Moreover, AI-enabled personalized learning has a strong positive effect on academic performance (β = 0.704; p < 0.001), supporting H6e. From a Human Capital Theory perspective, this suggests that AI contributes to the accumulation of productive knowledge and skills by improving learning efficiency and self-regulation.

Finally, AI-enabled personalized learning also has a direct positive effect on employability skills (β = 0.133; p = 0.027), supporting H7. This indicates that beyond its indirect effects, AI contributes directly to employability by fostering digital literacy, adaptability, and problem-solving competencies. Although AI-enabled personalized learning shows a significant direct effect on employability skills, the relatively small effect size suggests that its primary contribution may operate indirectly through enhancing engagement and academic performance, rather than exerting a strong direct influence.

Collectively, these findings position AI-enabled personalized learning as an integrated learning mechanism that not only enhances students' psychological needs such as autonomy, competence, and relatedness but also strengthens academic outcomes through improved engagement and performance. Rather than functioning as a standalone technological intervention, AI-enabled personalized learning operates as a multifaceted enabler that supports self-regulated learning, mastery development, and social interaction, thereby contributing directly and indirectly to employability readiness. By simultaneously fostering motivational conditions and the accumulation of human capital, AI-enabled personalized learning plays a strategic role in preparing vocational students for evolving labor market demands.

5.3. Mediating Role of Motivation and Academic Outcomes

RQ3 explores whether motivational and academic factors mediate the relationship between AI-enabled personalized learning and employability skills. The mediation analysis on table 7 shows that autonomy does not significantly mediate this relationship ($\beta = 0.059$; $p = 0.097$), leading to the rejection of H8. This indicates that although AI enhances autonomy, autonomy alone does not transmit employability gains. Similarly, competence does not function as a significant mediator ($\beta = -0.027$; $p = 0.295$), resulting in the rejection of H9, reinforcing the view that perceived competence must be converted into tangible learning outcomes to influence employability. In contrast, relatedness significantly mediates the relationship between AI-enabled personalized learning and employability skills ($\beta = 0.101$; $p = 0.012$), supporting H10. This underscores the importance of social learning mechanisms in translating AI-supported learning into employability-relevant skills. The mediating effect of student engagement is not statistically significant ($\beta = 0.086$; $p = 0.053$), leading to the rejection of H11. Although AI enhances engagement, engagement alone does not sufficiently explain employability gains without corresponding performance improvements. Finally, academic performance significantly mediates the relationship between AI-enabled personalized learning and employability skills ($\beta = 0.262$; $p < 0.001$), supporting H12. This finding strongly supports Human Capital Theory, confirming that AI improves employability primarily by enhancing measurable academic achievement.

Taken together, the RQ3 findings indicate that AI-enabled personalized learning enhances employability skills primarily through socially embedded learning processes, particularly students' sense of relatedness, and through improved academic achievement that reflects accumulated human capital. While AI-enabled learning successfully strengthens motivational conditions such as autonomy, competence, and engagement, these factors alone do not sufficiently translate into employability gains unless they are converted into meaningful social interaction or measurable academic performance. This suggests that the employability value of AI lies not merely in increasing motivation, but in its capacity to facilitate collaborative learning experiences and to improve academic outcomes that signal job readiness. Consequently, AI-enabled personalized learning contributes to employability most effectively when it is embedded within social learning contexts and performance-oriented educational practices rather than being treated as a purely motivational or technological enhancement.

PRACTICAL AND POLICY IMPLICATIONS

The findings of this study offer several important implications for educators, institutions, and policymakers, there are:

1. Vocational higher education institutions should prioritize socially interactive and collaborative learning designs when implementing AI-enabled personalized learning. Since relatedness plays a critical mediating role, AI tools should be integrated into group-based projects, peer feedback systems, and collaborative problem-solving activities rather than being used solely for individual task completion.
2. Institutions should align AI adoption with academic assessment and performance-based outcomes. Given the strong mediating role of academic performance, AI tools should be embedded into curriculum design in ways that support mastery learning, formative feedback, and self-regulated learning strategies that contribute to measurable academic achievement.
3. Institutional support should move beyond infrastructure provision toward pedagogically guided AI implementation. The non-significant moderating effect of institutional support suggests that access to AI alone is insufficient; institutions must provide clear guidelines, ethical frameworks, faculty training, and assessment alignment to ensure that AI use enhances employability rather than merely improving efficiency.
4. From a policy perspective, the results support the inclusion of AI literacy and employability-oriented competencies within vocational

curricula. Policymakers should encourage responsible AI integration that balances innovation with academic integrity, ethical use, and workforce relevance, particularly in emerging economy contexts where AI adoption is accelerating.

6. Conclusion

This study investigates how AI-enabled personalized learning contributes to employability skills among vocational higher education students in Indonesia by integrating Self-Determination Theory (SDT) and Human Capital Theory. The findings demonstrate that employability skills are not driven uniformly by all motivational factors, but instead emerge from a combination of socially embedded learning processes, academic achievement, and supportive institutional conditions.

The results show that autonomy and competence do not directly influence employability skills, whereas relatedness, student engagement, academic performance, and institutional support play significant roles. Among these determinants, academic performance emerges as the strongest predictor of employability skills, underscoring the continued relevance of human capital accumulation in vocational education. These findings highlight that employability in vocational contexts is primarily outcome-oriented and socially constructed rather than solely rooted in internal motivational perceptions.

Furthermore, this study confirms that AI-enabled personalized learning functions as an integrated learning mechanism that enhances students' autonomy, competence, relatedness, engagement, and academic performance. AI also exerts a direct positive effect on employability skills, indicating that exposure to AI-supported learning environments contributes to digital literacy, adaptability, and problem-solving competencies. However, the mediation analysis reveals that AI improves employability skills mainly through relatedness and academic performance, rather than through motivational factors alone. Taken together, the findings suggest that AI adoption enhances employability most effectively when embedded within collaborative learning contexts and performance-oriented educational practices.

Overall, this study contributes empirical evidence from an emerging economy and advances the literature by demonstrating that the employability value of AI in vocational higher education lies not merely in increasing motivation, but in strengthening social interaction and academic outcomes that signal job readiness.

Limitations and Future Research

Despite its contributions, this study has several limitations that should be acknowledged. First, the use of cross-sectional design limits the ability to establish causal relationships among variables, as the data were collected as a single point in time. Future research is encouraged to employ longitudinal or experimental designs to better examine how AI-enabled personalized learning influences employability development over time. Second, this study relies on self-reported measures of employability skills and academic performance, which may introduce response bias, Future studies should incorporate more objective indicators, such as GPA records, performance-based assessments, internship outcomes, or employer evaluations, to enhance measurement validity.

Third, as the sample is drawn from a single vocational higher education institution in Indonesia, the generalizability of the findings is limited; subsequent studies should conduct multi-institutional or cross-country comparisons to explore contextual differences in AI adoption and employability development. Finally, while this study integrates Self-Determination Theory and Human Capital Theory, future research could extend the theoretical framework by incorporating perspectives such as technology ethics, learning analytics, or socio-cultural theory, as well as qualitative methods, to gain deeper insights into students' lived experiences, ethical considerations, and adaptive strategies in AI-supported vocational learning environments.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the arguments developed in this paper.

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