



Integrating AI-Driven Adaptive Learning and Self-Determination Theory to Enhance Employability Skills: Evidence from Vocational Higher Education

Muhammad Hasim^{1*}, Ahmad Ardillah Rahman², Iris Sumariyanto³, Samnur¹, Misita Anwar⁴, Aminuddin¹

¹Mechanical Engineering Education, Faculty of Engineering, Universitas Negeri Makassar, Makassar, Indonesia

²Department of Culture, Communication & Media, IOE (Institute of Education), University College London, London, United Kingdom

³Electrical Engineering Education, Faculty of Engineering, Universitas Negeri Makassar, Makassar, Indonesia

⁴School of Business, Law and Entrepreneurship, Swinburne University of Technology, Melbourne, Australia

ARTICLE INFO

Article History

Received: December 02, 2025

1st Revision: March 10, 2026

Accepted: April 22, 2026

Available Online: April 30, 2026

Keywords:

Artificial Intelligence; Employability Skills; Vocational Education; Self-Determination Theory; Structural Equation Modeling;

*Corresponding Author

Email address:

hasimapache@unm.ac.id

ABSTRACT

This study tests an integrated structural model linking Artificial Intelligence (AI) use in learning, psychological factors derived from Self-Determination Theory (SDT), and employability skills among vocational education students. Specifically, AI is positioned as a contextual support associated with the fulfillment of competence, autonomy, and relatedness. A quantitative, cross-sectional design was employed using self-reported data from 263 vocational students in Indonesia, which were analyzed through Structural Equation Modeling (SEM). The results show that competence, autonomy, and relatedness are significantly associated with employability skills, with competence emerging as the strongest predictor. AI use demonstrates a significant indirect effect on employability skills, primarily through competence. In contrast, burnout, learning anxiety, and learning motivation do not show significant direct associations with employability skills, suggesting that psychological need fulfillment plays a more central role in the model. This study contributes to the literature by situating AI within the SDT framework as a contextual enabler of psychological need fulfillment in vocational education. The findings indicate that AI-supported learning environments are associated with stronger fulfillment of competence, autonomy, and relatedness, which in turn are linked to employability development. Practically, the results highlight the importance of designing AI-assisted learning environments that support competence, autonomy, and relatedness.

How to cite: Hasim, M., Rahman, A. A., Sumariyanto, I. Samnur, Anwar, M., & Aminuddin. (2026). Integrating AI-Driven Adaptive Learning and Self-Determination Theory to Enhance Employability Skills: Evidence from Vocational Higher Education. *International Journal of Pedagogy and Teacher Education*, 10(1), 169–182. <https://doi.org/10.20961/ijpte.v10i1.111742>

1. INTRODUCTION

Employability skills are a critical requirement for graduates of vocational and technical education to remain competitive in an increasingly dynamic labor market (Haron et al., 2019; Romanova, 2022). These skills encompass both technical and non-technical competencies, including communication, collaboration, and critical thinking (Ardiansyah, 2023; Haron et al., 2019; Jackson, 2015). Relevance to vocational education is especially strong because graduates are expected not only to master occupation-specific competencies but also to demonstrate transferable capabilities that support adaptation, problem solving, and sustainable career development in rapidly changing work environments (Haron et al., 2019; Romanova, 2022). Persistent concern remains, however, regarding the mismatch between graduates' skills and industry needs across multiple sectors (Abbasi et al., 2018; Radermacher et al., 2014). Recent evidence further highlights the urgency of this issue, indicating that automation, digitalisation, demographic change, and the green transition are substantially reshaping skill needs in the labour market. These conditions underscore the need for more adaptive and responsive vocational education approaches that are aligned with labour market demands and capable of supporting students' employability development (OECD, 2023).

Artificial Intelligence (AI) has been increasingly integrated into educational contexts to support personalized learning, adaptive feedback, and simulation-based instruction (Ouyang & Jiao, 2021; Asad & Ajaz, 2024). Vocational education settings have increasingly used AI to approximate real-world work environments and to enhance problem-solving skills (Ciolacu et al., 2018; Qawqzeh, 2024). Existing studies, however, still tend to examine AI primarily as an instructional tool in terms of efficiency, personalization, and feedback delivery,

with less explicit attention to the psychological processes through which AI-supported learning may contribute to skill development (Ouyang & Jiao, 2021; Chen et al., 2020; Asad & Ajaz, 2024). Self-Determination Theory (SDT) provides a relevant framework for understanding these processes by emphasizing the importance of autonomy, competence, and relatedness in fostering motivation and learning outcomes (Ryan & Deci, 2000; Van den Broeck et al., 2016). Burnout and learning anxiety have also been identified as potential challenges in technology-mediated learning environments (Salmela-Aro et al., 2021; Huang et al., 2024). Taken together, these perspectives suggest that AI-supported learning may influence employability development not only through instructional affordances, but also through need-supportive and strain-related psychological mechanisms.

Several important gaps nevertheless remain. First, much of the current literature still positions AI as a technological or instructional aid, while evidence explaining how AI is associated with deeper psychological processes relevant to vocational skill development remains limited (Ouyang & Jiao, 2021; Chen et al., 2020; Asad & Ajaz, 2024). Second, studies grounded in SDT have established the importance of autonomy, competence, and relatedness for learning, yet empirical work that explicitly models AI in relation to these psychological needs in vocational education remains insufficiently developed (Ryan & Deci, 2000; Van den Broeck et al., 2016). Third, the literature on vocational employability has largely emphasized skill readiness and labor-market outcomes, but has not adequately clarified whether AI-supported learning environments are associated with employability through need fulfillment, motivational processes, or strain-related experiences such as burnout and learning anxiety (Abbasi et al., 2018; Radermacher et al., 2014; Salmela-Aro et al., 2021; Huang et al., 2024). Fourth, prior studies have rarely integrated these strands into a single explanatory model within vocational higher education, even though this setting is precisely where employability development is a central educational objective.

This study addresses these gaps by examining AI not merely as a technological tool, but as a contextual enabler associated with the fulfillment of psychological needs within the SDT framework. Specifically, this study investigates whether AI use in learning is associated with autonomy, competence, relatedness, burnout, and learning anxiety, and whether these factors, together with learning motivation, are related to employability skills among vocational students (Huang et al., 2021; Chen et al., 2020; Chiu et al., 2024; Romanova, 2022; Rosli & Saleh, 2023; Martin et al., 2018). Novelty of this study lies in the integration of AI-supported learning, SDT-based need fulfillment, strain-related variables, and employability skills within one empirical framework focused on vocational higher education. This study contributes to the literature by empirically positioning AI within an SDT-based model as a contextual enabler of psychological need fulfillment linked to employability outcomes in vocational education. The inclusion of burnout, learning anxiety, and learning motivation also allows the model to distinguish the relative roles of need-supportive and strain-related factors in explaining employability skills. This positioning offers a more specific understanding of how AI-supported learning environments are associated with workforce-relevant skill development in vocational higher education.

2. MATERIAL AND METHOD

Research Design

This study employed a quantitative research design using a Structural Equation Modeling (SEM) framework to examine the relationships among Artificial Intelligence (AI) use in learning, psychological factors derived from Self-Determination Theory (SDT), and employability skills among vocational students. The model included autonomy, competence, and relatedness as core SDT constructs, together with burnout, learning anxiety, and learning motivation, in relation to employability skills. This study adopted a non-experimental, cross-sectional design and relied on self-reported questionnaire responses collected at a single point in time. Accordingly, the findings should be interpreted as indicating associations among variables rather than causal relationships. The proposed conceptual model is presented in Figure 1. All measurement instruments were adapted from established studies and were reviewed prior to data collection to ensure conceptual relevance, clarity, and contextual suitability for vocational higher education. The measurement model was evaluated through convergent validity, discriminant validity, and internal consistency reliability, while the structural model was assessed through path coefficients, coefficients of determination, model fit indicators relevant to PLS-SEM, and indirect effects

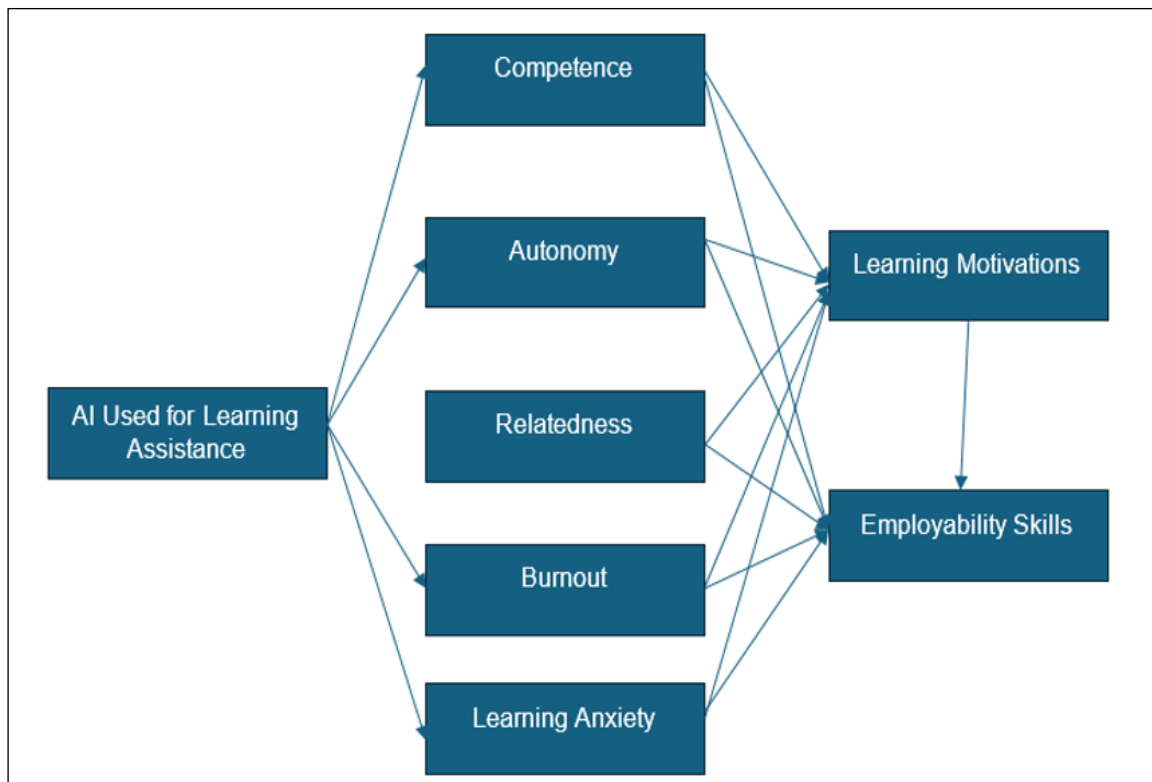


Figure 1. The proposed conceptual model

Participants and Sampling

The target population of this study consisted of vocational and technical education students at Universitas Negeri Makassar. Accordingly, the findings of this study are intended to be generalized only to this specific institutional population. A purposive sampling approach was employed to recruit participants who had prior experience using AI-based learning tools in their learning activities. This selection criterion was applied to ensure that respondents possessed sufficient familiarity with AI-supported learning environments relevant to the variables examined in the study. Data were collected through an online questionnaire distributed via institutional communication channels, including email and WhatsApp. The use of online distribution enabled efficient data collection and broader reach among the target participants. A total of 263 valid responses were retained for analysis after screening for completeness and consistency. The sample consisted of 158 male students (60.1%) and 105 female students (39.9%), reflecting a relatively balanced gender distribution. The final sample size was considered adequate for PLS-SEM analysis, as it exceeded the minimum requirement based on the structural complexity of the model and was sufficient to ensure stable and reliable parameter estimation.

Instruments and Measures

Data were collected using a structured questionnaire comprising adapted measurement scales from prior studies. The instrument covered AI in Learning, Self-Determination Theory (SDT) constructs, burnout, learning anxiety, learning motivation, and employability skills, as summarized in Table 1. Each construct was operationalized using indicators adapted to the context of vocational higher education to ensure conceptual relevance to the target respondents. All items were measured on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Following data collection, the measurement model was evaluated using standard procedures for convergent validity, discriminant validity, and internal consistency reliability. Discriminant validity was assessed using the Heterotrait–Monotrait Ratio (HTMT), while internal consistency reliability was evaluated using Cronbach’s alpha and composite reliability. (Pavlov et al., 2021; Hair & Alamer, 2022).

Table 1. Summary of Instruments and Measures

Construct	Measurement Focus
AI in Learning	Measured students' perceptions of AI use in learning activities, particularly AI-based assistance that supported learning processes and students' perceived engagement with AI-supported learning. The items were adapted from prior studies on artificial intelligence in education (Zawacki-Richter et al., 2019; Chen et al., 2020).
Autonomy	Measured students' perceived sense of agency, choice, and self-direction in learning activities. The items were aligned with the basic psychological needs framework proposed by Ryan and Deci (2000) and Deci et al. (2017).
Competence	Measured students' confidence in handling learning tasks and their perceived capability in AI-supported learning contexts. The items were aligned with the basic psychological needs framework proposed by Ryan and Deci (2000) and Deci et al. (2017).
Relatedness	Measured students' perceived sense of connection, support, and belonging within the learning environment. The items were aligned with the basic psychological needs framework proposed by Ryan and Deci (2000) and Deci et al. (2017).
Burnout	Measured strain-related experiences associated with academic exhaustion in technology-mediated learning. The items were adapted from academic burnout studies (Salmela-Aro et al., 2021).
Learning Anxiety	Measured students' anxiety and tension related to learning experiences in higher education contexts. The items were adapted from higher education learning experience studies (Jie & Kamrozzaman, 2024).
Learning Motivation	Measured students' motivation to engage in learning activities within AI-supported environments, covering intrinsic and extrinsic dimensions. The items were adapted from studies on motivation within the SDT framework (Deci et al., 2017; Xu et al., 2025).
Employability Skills	Measured workforce-relevant competencies, including communication, critical thinking, teamwork, and time management. The items were adapted from studies on employability skills in education (Jackson, 2015).

Data Collection and Analysis

Data were collected through an online survey administered via Google Forms over a four-week period. The questionnaire link was distributed through institutional communication channels, including email and WhatsApp, to vocational and technical education students who met the inclusion criteria established for this study. Before accessing the questionnaire, respondents were informed about the objectives of the study, the voluntary nature of participation, and their right to withdraw at any stage without any consequence. Electronic informed consent was obtained before respondents proceeded to complete the survey. Anonymous administration was applied to minimize the possibility of socially desirable responses and to encourage more accurate self-reporting. Confidentiality of all responses was maintained throughout the research process, and the collected data were used exclusively for academic purposes. Following the completion of the data collection period, all responses were screened to ensure completeness, consistency, and conformity with the study criteria, and only valid responses were retained for subsequent analysis.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software in two stages. The first stage involved evaluation of the measurement model. Convergent

validity was assessed using factor loadings (> 0.70), Average Variance Extracted (AVE > 0.50), and Composite Reliability (CR > 0.70), while internal consistency reliability was evaluated using Cronbach's alpha and composite reliability. Discriminant validity was examined using the Heterotrait–Monotrait Ratio (HTMT), and the HTMT values for all construct pairs are presented in Table 2 in the Results section. The second stage involved evaluation of the structural model using bootstrapping with 5,000 resamples to estimate path coefficients (β), t -statistics, and p -values. The coefficient of determination (R^2) was used to assess the explanatory power of the endogenous constructs. Model fit indices, including SRMR and NFI, were also examined as supplementary indicators of model adequacy in the PLS-SEM context. Mediation effects were tested using bootstrapping procedures, and the significance of indirect effects was determined based on the bootstrapped estimates (Pavlov et al., 2021; Hair & Alamer, 2022).

Hypothesis Testing

The structural model positioned AI in Learning as the primary exogenous construct and Employability Skills as the main endogenous outcome variable. Autonomy, competence, and relatedness were specified as SDT-based mediating constructs, while burnout and learning anxiety were included as strain-related variables. Learning motivation was also modeled as an endogenous mediator linking the psychological variables to employability skills. This model was intended to examine whether AI-supported learning was associated with employability skills through both need-supportive and strain-related psychological pathways. Hypothesis testing focused on both direct and indirect effects among the modeled constructs. Direct effects were examined for the paths from AI in Learning to autonomy, competence, relatedness, burnout, and learning anxiety, as well as for the paths from these psychological variables to learning motivation and employability skills. Indirect effects were tested to determine whether AI in Learning was associated with employability skills through the proposed mediating variables. The significance of the hypothesized relationships was assessed using bootstrapping procedures with 5,000 resamples, based on path coefficients (β), t -statistics, and p -values. Statistically significant paths were interpreted as empirical support for the proposed hypotheses, whereas non-significant paths indicated insufficient evidence for the hypothesized associations.

3. RESULTS

Evaluation of Global Model Fit in PLS-SEM

The model fit results presented in Table 2 reveal a clear distinction between the saturated model and the estimated model. The saturated model produced an SRMR value of 0.061, which falls below the recommended threshold of 0.08, indicating an acceptable level of fit (Pavlov et al., 2021). In contrast, the estimated model yielded an SRMR value of 0.159, which exceeds the recommended threshold and suggests that the full structural specification did not achieve strong global fit. A similar pattern can be observed for the NFI values. The saturated model obtained an NFI of 0.755, whereas the estimated model showed a lower NFI of 0.721, and both values remained below the recommended threshold of 0.90. These results indicate that the estimated model demonstrated only limited fit when evaluated against conventional reference criteria (Hair & Alamer, 2022). Table 2 also shows that the discrepancy measures d_{ULS} and d_G were notably higher in the estimated model ($d_{ULS} = 33.478$; $d_G = 4.632$) than in the saturated model ($d_{ULS} = 5.008$; $d_G = 3.515$), which further suggests greater divergence between the empirical covariance structure and the model-implied structure after the hypothesized relationships were imposed (Pavlov et al., 2021). A similar tendency is reflected in the chi-square values, which increased from 4468.314 in the saturated model to 5085.581 in the estimated model. Overall, the pattern in Table 2 suggests that the structural model should not be interpreted as having strong global fit. Nevertheless, because global fit indices in PLS-SEM are treated as supplementary rather than definitive, the model was evaluated further on the basis of measurement quality, path significance, and explanatory relationships among constructs. Accordingly, the structural results should be interpreted with caution at the level of overall model fit, while greater emphasis is placed on the predictive and relational evidence produced by the measurement and structural model assessment (Pavlov et al., 2021)

Table 2. Model Fit Indices

Fit Index	Saturated Model	Estimated Model	Recommended Threshold	Interpretation
SRMR	0.061	0.159	< 0.08	Good (Saturated), Marginal (Estimated)
d_ULS	5.008	33.478	—	—
d_G	3.515	4.632	—	—
Chi-square	4468.314	5085.581	—	—
NFI	0.755	0.721	> 0.90	Moderate Fit

Evaluation of Discriminant Validity Using HTMT

Table 3. HTMT Ratios for Discriminant Validity Assessment

Construct Pair	HTMT
Autonomy ↔ AI Used for Learning Assistance	0.774
Burnout ↔ AI Used for Learning Assistance	0.135
Burnout ↔ Autonomy	0.085
Competence ↔ AI Used for Learning Assistance	0.725
Competence ↔ Autonomy	0.887
Competence ↔ Burnout	0.070
Employability Skills ↔ AI Used for Learning Assistance	0.852
Employability Skills ↔ Autonomy	0.894
Employability Skills ↔ Burnout	0.085
Employability Skills ↔ Competence	0.898
Learning Anxiety ↔ AI Used for Learning Assistance	0.160
Learning Anxiety ↔ Autonomy	0.108
Learning Anxiety ↔ Burnout	0.897
Learning Anxiety ↔ Competence	0.117
Learning Anxiety ↔ Employability Skills	0.111
Learning Motivation ↔ AI Used for Learning Assistance	0.592
Learning Motivation ↔ Autonomy	0.608
Learning Motivation ↔ Burnout	0.407
Learning Motivation ↔ Competence	0.569
Learning Motivation ↔ Employability Skills	0.626
Learning Motivation ↔ Learning Anxiety	0.381
Relatedness ↔ AI Used for Learning Assistance	0.761
Relatedness ↔ Autonomy	0.739
Relatedness ↔ Burnout	0.137
Relatedness ↔ Competence	0.728
Relatedness ↔ Employability Skills	0.786
Relatedness ↔ Learning Anxiety	0.130
Relatedness ↔ Learning Motivation	0.685

The HTMT values used to assess discriminant validity among the latent constructs are presented in Table 3. The results indicate that all HTMT ratios were below the recommended threshold of 0.90, suggesting that the constructs are empirically distinct and that acceptable discriminant validity was established across the measurement model. However, several construct pairs were relatively close to the threshold, including Employability Skills–Competence (0.898), Learning Anxiety–Burnout (0.897), Employability Skills–Autonomy

(0.894), and Competence–Autonomy (0.887).. These values suggest that the paired constructs share a relatively strong conceptual association, although they still remain within the acceptable range for discriminant validity assessment (Cheung et al., 2023). The pattern shown in Table 3 is also theoretically meaningful. The relatively high HTMT values between Employability Skills and Competence, as well as between Employability Skills and Autonomy, indicate that employability is closely related to students' perceptions of capability and self-direction, which is consistent with the conceptual model of the study. Similarly, the high HTMT value between Learning Anxiety and Burnout suggests that both constructs reflect closely related strain-related experiences in AI-supported learning contexts. At the same time, several other construct pairs showed substantially lower HTMT values, such as Competence–Burnout (0.070), Burnout–Autonomy (0.085), and Relatedness–Learning Anxiety (0.130), which indicates clearer empirical separation between those constructs. Overall, the results reported in Table 3 support the conclusion that the measurement model demonstrated adequate discriminant validity, although a few construct pairs should be interpreted with some caution because of their relatively high conceptual proximity (Cheung et al., 2023).

Hypothesis Testing Results

Table 4. Path Coefficients and Hypothesis Testing Results

Path	Original Sample (O)	STDEV	T Statistics	P Values	Result
AI → Autonomy	0.731	0.033	22.367	p < 0.001	Supported
AI → Burnout	-0.136	0.062	2.209	0.027	Supported
AI → Competence	0.682	0.039	17.356	p < 0.001	Supported
AI → Learning Anxiety	-0.157	0.064	2.463	0.014	Supported
Autonomy → Employability Skills	0.373	0.058	6.396	p < 0.001	Supported
Autonomy → Learning Motivation	0.244	0.086	2.849	0.004	Supported
Burnout → Employability Skills	-0.071	0.050	1.418	0.156	Not Supported
Burnout → Learning Motivation	-0.367	0.115	3.197	0.001	Supported
Competence → Employability Skills	0.404	0.062	6.511	p < 0.001	Supported
Competence → Learning Motivation	0.059	0.093	0.638	0.523	Not Supported
Learning Anxiety → Employability Skills	0.068	0.055	1.238	0.216	Not Supported
Learning Anxiety → Learning Motivation	0.014	0.113	0.121	0.904	Not Supported
Learning Motivation → Employability Skills	0.060	0.040	1.486	0.137	Not Supported
Relatedness → Employability Skills	0.166	0.048	3.446	0.001	Supported
Relatedness → Learning Motivation	0.400	0.053	7.597	p < 0.001	Supported

Table 4 presents the path coefficients and bootstrapping results of the structural model. The findings show that AI use in learning had significant associations with four psychological variables. Positive and relatively strong effects were found on autonomy ($\beta = 0.731$, $t = 22.367$, $p < 0.001$) and competence ($\beta = 0.682$, $t = 17.356$, $p < 0.001$), indicating that greater AI-supported learning was associated with stronger perceptions of agency and capability among students. Negative and statistically significant effects were also found on burnout ($\beta = -0.136$, $t = 2.209$, $p = 0.027$) and learning anxiety ($\beta = -0.157$, $t = 2.463$, $p = 0.014$), suggesting that AI use was associated with lower strain-related experiences, although the magnitudes of these effects were notably smaller than those observed for autonomy and competence. With regard to employability skills, three predictors showed significant positive relationships, namely competence ($\beta = 0.404$, $t = 6.511$, $p < 0.001$), autonomy ($\beta = 0.373$, $t = 6.396$, $p < 0.001$), and relatedness ($\beta = 0.166$, $t = 3.446$, $p = 0.001$). Among these, competence emerged as the strongest predictor of employability skills, followed by autonomy and relatedness, indicating that students' perceived capability and self-directed engagement were more strongly associated with workforce-relevant skills than the other variables included in the model (Eimer & Bohndick, 2023).

The results indicate that several hypothesized paths were not supported. Burnout did not significantly predict employability skills ($\beta = -0.071$, $p = 0.156$), and learning anxiety likewise showed no significant relationship with employability skills ($\beta = 0.068$, $p = 0.216$). Learning motivation also did not significantly predict employability skills ($\beta = 0.060$, $p = 0.137$), suggesting that motivation alone was not a direct explanatory factor of employability skills in the presence of the other psychological constructs. In the prediction of learning motivation, autonomy ($\beta = 0.244$, $t = 2.849$, $p = 0.004$) and relatedness ($\beta = 0.400$, $t = 7.597$, $p < 0.001$) showed significant positive effects, whereas burnout showed a significant negative effect ($\beta = -0.367$, $t = 3.197$, $p = 0.001$). Competence ($\beta = 0.059$, $p = 0.523$) and learning anxiety ($\beta = 0.014$, $p = 0.904$), however, were not significant predictors of learning motivation. Overall, the pattern reported in Table 4 indicates that the model is primarily driven by need-supportive pathways, particularly autonomy, competence, and relatedness, whereas strain-related variables and learning motivation played a more limited or indirect role in explaining employability skills (Eimer & Bohndick, 2023).

Indirect Effects

The results presented in Table 5 summarize the direct, indirect, and total effects of the modeled constructs on employability skills. The findings indicate that AI exerted a significant indirect effect on employability skills ($\beta = 0.563$, $p < 0.001$), suggesting that its influence primarily operated through mediating psychological variables rather than through a direct path. This finding suggests that AI-supported learning was associated with employability skills mainly through its relationships with need-supportive and motivational processes captured in the model. Among the direct predictors, competence showed the strongest total effect on employability skills (total $\beta = 0.408$, $p < 0.001$), consisting of a substantial direct effect ($\beta = 0.404$) and a very small indirect effect ($\beta = 0.004$). Autonomy also demonstrated a strong total effect (total $\beta = 0.387$, $p < 0.001$), with most of the effect arising from its direct contribution ($\beta = 0.373$) and a smaller indirect component ($\beta = 0.015$). Relatedness showed a weaker but still significant total effect on employability skills (total $\beta = 0.190$, $p < 0.001$), indicating that social connectedness contributed positively to employability, although its magnitude was notably lower than that of competence and autonomy (Ergün & Şeşen, 2021).

Table 5. Direct, Indirect, and Total Effect on Employability Skills

Hypothesis	Path	Direct (β)	Indirect (β)	Total (β)	p-value
H1	AI \rightarrow Employability Skills	–	0.563	0.563	$p < 0.001$
H2	Competence \rightarrow Employability Skills	0.404	0.004	0.408	$p < 0.001$
H3	Autonomy \rightarrow Employability Skills	0.373	0.015	0.387	$p < 0.001$
H4	Relatedness \rightarrow Employability Skills	0.166	0.024	0.190	$p < 0.001$
H5	Burnout \rightarrow Employability Skills	-0.071	-0.022	-0.093	0.071
H6	Learning Anxiety \rightarrow Employability Skills	0.068	0.001	0.069	0.218
H7	Learning Motivation \rightarrow Employability Skills	0.060	–	0.060	0.137

Based on the results presented in Table 5, burnout, learning anxiety, and learning motivation did not have significant total effects on employability skills. Burnout showed a negative total effect ($\beta = -0.093$, $p = 0.071$), but this relationship did not reach statistical significance. Learning anxiety also showed a very small and non-significant total effect ($\beta = 0.069$, $p = 0.218$), indicating that anxiety was not a meaningful predictor of employability skills in this model. Learning motivation likewise did not significantly predict employability skills ($\beta = 0.060$, $p = 0.137$), suggesting that its explanatory role was limited when considered alongside the other psychological constructs. Overall, the pattern indicates that employability skills were more strongly associated with competence, autonomy, and relatedness than with burnout, learning anxiety, or learning motivation. The indirect effect of AI on employability therefore appears to be mainly channeled through need-supportive mechanisms rather than through strain-related variables (Sumra et al., 2026; Ergün & Şeşen, 2021).

Bootstrapping Results

The bootstrapping results of the SEM model are presented in Figure 2, visually summarizing the magnitude and significance of the hypothesized structural relationships. The figure confirms that AI Used for Learning Assistance had strong positive effects on competence ($\beta = 0.682$, $p < 0.001$) and autonomy ($\beta = 0.731$,

$p < 0.001$), while showing smaller but significant negative effects on burnout ($\beta = -0.136, p = 0.027$) and learning anxiety ($\beta = -0.157, p = 0.014$). Competence, autonomy, and relatedness were positively associated with employability skills, with competence emerging as the strongest predictor ($\beta = 0.404, p < 0.001$), followed by autonomy ($\beta = 0.373, p < 0.001$) and relatedness ($\beta = 0.166, p = 0.001$). Learning motivation, burnout, and learning anxiety did not show significant direct effects on employability skills, as indicated by their non-significant path coefficients. Figure 2 also shows that autonomy ($\beta = 0.244, p = 0.004$), relatedness ($\beta = 0.400, p < 0.001$), and burnout ($\beta = -0.367, p = 0.001$) significantly predicted learning motivation, whereas competence and learning anxiety did not. In terms of explanatory power, the model accounted for 46.6% of the variance in competence, 53.4% in autonomy, 57.3% in learning motivation, and 81.8% in employability skills, while the explained variance for burnout (1.9%) and learning anxiety (2.5%) was comparatively low. Overall, the pattern displayed in Figure 2 indicates that the model was primarily driven by need-supportive pathways, with AI-related learning support contributing most strongly to employability skills through competence, autonomy, and relatedness (Meng et al., 2025).

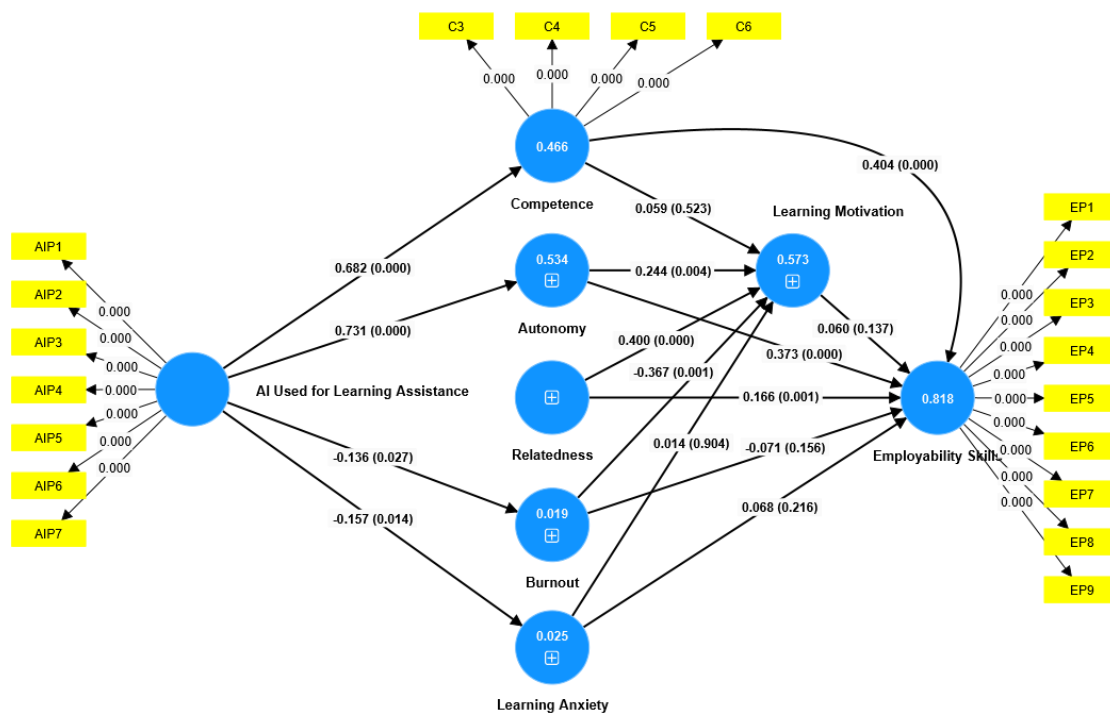


Figure 2. Bootstrapping Results of the SEM Model

4. DISCUSSION

Main Findings and SDT Interpretation

The findings indicate that competence, autonomy, and relatedness were significant positive predictors of employability skills, with competence emerging as the strongest predictor, followed by autonomy and relatedness. Statistical evidence for this pattern is presented in Table 4, where competence showed the largest direct effect on employability skills ($\beta = 0.404, p < 0.001$), followed by autonomy ($\beta = 0.373, p < 0.001$) and relatedness ($\beta = 0.166, p = 0.001$). Figure 2 further reinforces this interpretation by showing that the model explained a substantial proportion of variance in employability skills ($R^2 = 0.818$), indicating that the included psychological constructs contributed meaningfully to the outcome. This pattern suggests that employability development in vocational higher education is more closely associated with students' perceived capability, self-direction, and social connectedness than with the other psychological variables included in the model (Ergün & Şeşen, 2021). From the perspective of Self-Determination Theory, these findings are theoretically plausible because competence, autonomy, and relatedness represent core psychological needs that support effective

functioning, motivation, and adaptive performance in learning environments (Ryan & Deci, 2000; Van den Broeck et al., 2016). Relevance to employability is particularly strong in vocational contexts, where students' perceptions of being capable of performing tasks, solving problems, and responding effectively to practical demands are closely linked to workforce readiness and competence development (Abelha et al., 2020).

A significant indirect effect of AI on employability skills also emerged, indicating that AI is more meaningfully understood as a contextual support linked to psychological processes than as a direct determinant of employability outcomes (Arly et al., 2023). Table 5 shows that AI had a significant indirect effect on employability skills ($\beta = 0.563, p < 0.001$), while Table 4 indicates that AI was strongly associated with autonomy ($\beta = 0.731, p < 0.001$) and competence ($\beta = 0.682, p < 0.001$), and more modestly but significantly associated with lower burnout ($\beta = -0.136, p = 0.027$) and lower learning anxiety ($\beta = -0.157, p = 0.014$). Figure 2 visualizes this mediated pattern and suggests that AI-supported learning becomes educationally meaningful when it strengthens students' perceptions of capability and self-direction rather than merely increasing technological exposure (Sumra et al., 2026). This interpretation is consistent with recent evidence showing that AI-supported learning environments can enhance self-regulated and self-directed learning when they are designed to support learner autonomy and competence (Achuthan, 2025). Taken together, the present findings support an SDT-based interpretation in which AI contributes to employability not because technology itself directly produces workforce readiness, but because it helps create need-supportive learning conditions through which employability-relevant skills can develop (Sumra et al., 2026; Achuthan, 2025).

AI as a Contextual Support for Employability Development

The present findings suggest that AI should be understood not as an autonomous driver of employability outcomes, but as a contextual support that shapes the psychological conditions through which employability-relevant skills develop. This interpretation is supported by the structural results, which showed that AI had no direct path to employability skills, yet demonstrated a substantial indirect effect through mediating psychological variables ($\beta = 0.563, p < 0.001$). The path coefficients reported in Table 4 further indicate that AI was strongly associated with autonomy ($\beta = 0.731, p < 0.001$) and competence ($\beta = 0.682, p < 0.001$), while Figure 2 shows that these variables contributed meaningfully to the explanatory power of the model. Such a pattern suggests that the value of AI in vocational higher education lies less in technological exposure itself and more in its ability to create learning conditions in which students feel capable, supported, and able to regulate their own learning (Meng et al., 2025). This interpretation is consistent with the view that AI in education functions most effectively when it supports adaptive learning, personalized feedback, and self-regulated learning processes rather than merely automating instruction (Ouyang & Jiao, 2021; Achuthan, 2025).

The mediated role of AI is particularly important in vocational higher education, where employability depends not only on knowledge acquisition but also on the development of applied competence, problem solving, and adaptive performance (Meng et al., 2025). In this context, AI-supported learning environments may strengthen employability development when they provide structured guidance, practice-oriented feedback, and opportunities for students to engage more actively with task demands (Meng et al., 2025). This interpretation is consistent with evidence showing that AI-based tools can enhance critical thinking, problem solving, and creativity in educational settings when they are integrated into meaningful learning processes (Qawqzeh, 2024). It is also compatible with broader employability research emphasizing that graduate readiness is closely linked to the development of transferable competencies, especially those associated with confidence, capability, and adaptive performance in authentic learning contexts (Abelha et al., 2020). Taken together, the present findings support the argument that AI contributes to employability development not because technology directly produces workforce readiness, but because it strengthens the need-supportive and competence-building conditions through which employability skills are more likely to emerge.

Non-Significant Paths: Burnout, Learning Anxiety, and Learning Motivation

A different pattern emerged for burnout, learning anxiety, and learning motivation, all of which failed to show significant direct effects on employability skills. Table 4 indicates that burnout had a negative but non-significant relationship with employability skills ($\beta = -0.071, p = 0.156$), while learning anxiety showed a small and non-significant positive coefficient ($\beta = 0.068, p = 0.216$). Learning motivation also did not significantly predict

employability skills ($\beta = 0.060$, $p = 0.137$). These findings suggest that, within the present model, employability skills were more strongly associated with need-supportive psychological conditions than with strain-related experiences or motivation alone. From an SDT perspective, this pattern is theoretically plausible because competence, autonomy, and relatedness are more proximal indicators of adaptive functioning and effective performance, whereas burnout and anxiety are more likely to operate as contextual constraints whose effects may be indirect, conditional, or cumulative rather than immediately reflected in employability judgments (Ryan & Deci, 2000; Van den Broeck et al., 2016). Relevance of this interpretation is also supported by prior work showing that burnout and anxiety in technology-mediated learning environments are important challenges, but their impact often depends on broader contextual and motivational processes rather than appearing as simple direct predictors of educational outcomes (Salmela-Aro et al., 2021; Huang et al., 2024; Jie & Kamrozzaman, 2024).

The indirect pattern reported in Table 4 further strengthens this interpretation. Burnout showed a significant negative effect on learning motivation ($\beta = -0.367$, $p = 0.001$), indicating that higher levels of burnout were associated with lower motivation to engage in AI-supported learning. In contrast, learning anxiety did not significantly predict motivation ($\beta = 0.014$, $p = 0.904$), and competence also showed no significant effect on motivation ($\beta = 0.059$, $p = 0.523$). This pattern suggests that not all psychological variables contributed to motivation in the same way, and that the motivational pathway itself was not sufficient to explain employability once competence, autonomy, and relatedness were simultaneously included in the model. One possible interpretation is that employability in vocational higher education is evaluated more in terms of capability, task-readiness, and perceived performance than in terms of general motivational state alone. Another possibility is that motivation functions as a more distal mechanism in this context, whereas competence and autonomy operate as more immediate explanatory pathways linking AI-supported learning to employability development. Such an interpretation is consistent with research showing that technology-supported learning is more educationally meaningful when it strengthens students' capacity for self-direction, competence development, and sustained engagement, rather than simply increasing exposure to digital tools or elevating motivation at a general level (Van den Broeck et al., 2016; Huang et al., 2024; Jie & Kamrozzaman, 2024).

Limitations

Several limitations should be acknowledged in interpreting the findings of this study. Cross-sectional data limit the ability to draw causal inferences among the variables. Self-reported questionnaire responses may also introduce bias, including self-perception bias, social desirability bias, and potential common method variance. These limitations require the findings to be interpreted as associations rather than causal effects. Sample characteristics also limit the generalizability of the results. Participants were drawn from vocational and technical education students at Universitas Negeri Makassar, Indonesia. Generalization of the findings should therefore be restricted to similar institutional and educational contexts. Future research may strengthen this line of inquiry by testing the model across multiple institutions, using behavioral or performance-based indicators of employability skills, and applying longitudinal or mixed-method approaches. Greater attention to specific types of AI-supported learning may also help clarify which forms of AI use are most closely associated with psychological need fulfillment and employability development.

5. CONCLUSION

Competence, autonomy, and relatedness were significantly associated with employability skills among vocational students, with competence emerging as the strongest predictor. AI use in learning also showed a significant indirect effect on employability skills, primarily through psychological pathways related to competence, autonomy, and relatedness. These findings suggest that AI is more meaningfully understood as a contextual support linked to psychological need fulfillment than as a direct determinant of employability outcomes. This study contributes to the literature by empirically positioning AI within an SDT-based framework in vocational higher education. AI-supported learning was associated with competence, autonomy, and relatedness, and these need-supportive factors were in turn associated with employability skills. This pattern offers a more integrated understanding of the linkage between AI-supported learning, psychological need

fulfillment, and workforce-relevant skill development in vocational education. Burnout, learning anxiety, and learning motivation did not show significant direct associations with employability skills in the present model. This result suggests that these variables may operate in a more context-dependent or indirect manner and may be less proximal to employability than competence-related and autonomy-related processes in this dataset. Future research may build on these findings by using longitudinal designs, multi-source assessments of employability skills, and broader institutional samples. Further studies may also examine specific forms of AI use in vocational learning and explore more closely how AI-supported environments are associated with competence, autonomy, and relatedness across different educational contexts.

6. REFERENCES

- Abbasi, F. K., Ali, A., & Bibi, N. (2018). Analysis of skill gap for business graduates: Managerial perspective from banking industry. *Education + Training*, 60(4), 354–367. <https://doi.org/10.1108/ET-08-2017-0111>
- Abelha, M., Fernandes, S., Mesquita, D., Seabra, F., & Ferreira-Oliveira, A. T. (2020). Graduate employability and competence development in higher education—A systematic literature review using PRISMA. *Sustainability*, 12(15), Article 5900. <https://doi.org/10.3390/su12155900>
- Achuthan, K. (2025). Artificial intelligence and learner autonomy: A meta-analysis of self-regulated and self-directed learning. *Frontiers in Education*, 10, 1738751. <https://doi.org/10.3389/educ.2025.1738751>
- Ardiansyah, W. M. (2023). Peran teknologi dalam transformasi ekonomi dan bisnis di era digital. *JMEB Jurnal Manajemen Ekonomi & Bisnis*, 1(1), 12–16.
- Arly, A., Dwi, N., & Andini, R. (2023). Implementasi penggunaan artificial intelligence dalam proses pembelajaran mahasiswa ilmu komunikasi di kelas A. *Prosiding Seminar Nasional Ilmu Ilmu Sosial (SNIIS)*, 2, 362–374.
- Asad, M. M., & Ajaz, A. (2024). Impact of ChatGPT and generative AI on lifelong learning and upskilling learners in higher education: Unveiling the challenges and opportunities globally. *The International Journal of Information and Learning Technology*, 41(5), 507–523. <https://doi.org/10.1108/IJILT-03-2023-0059>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264–75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., Wang, L.C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41, 745–783. <https://doi.org/10.1007/s10490-023-09871-y>
- Chiu, T. K. F., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2024). Teacher support and student motivation to learn with Artificial Intelligence (AI) based chatbot. *Interactive Learning Environments*, 32(7), 3240–3256. <https://doi.org/10.1080/10494820.2023.2172044>
- Ciolacu, M., Tehrani, A. F., Binder, L., & Svasta, P. M. (2018). Education 4.0—Artificial intelligence assisted higher education: Early recognition system with machine learning to support students’ success. 2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME), 23–30. <https://doi.org/10.1109/SIITME.2018.8599203>
- Deci, E. L., Olafsen, A. H., & Ryan, R. M. (2017). Self-determination theory in work organizations: The state of a science. *Annual Review of Organizational Psychology and Organizational Behavior*, 4(1), 19–43. <https://doi.org/10.1146/annurev-orgpsych-032516-113108>
- Eimer, A., & Bohndick, C. (2023). Employability models for higher education: A systematic literature review and analysis. *Social Sciences & Humanities Open*, 8(1), Article 100588. <https://doi.org/10.1016/j.ssaho.2023.100588>
- Ergün, M., & Şeşen, H. (2021). A comprehensive study on university students’ perceived employability: Comparative effects of personal and contextual factors. *SAGE Open*, 11(3). <https://doi.org/10.1177/21582440211036105>

- Hair, J., & Alamer, A. (2022). Partial least squares structural equation modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, 1(3), Article 100027. <https://doi.org/10.1016/j.rmal.2022.100027>
- Haron, M. A., Hussain, M. A. M., Zulkifli, R. M., Nashir, I. M., & Ma'arof, N. N. I. (2019). Employability skills needed by vocational college graduates: Feedback from the industry. *Journal of Technical Education and Training*, 11(4), 13–23. <https://doi.org/10.30880/jtet.2019.11.04.002>
- Huang, C., Tu, Y., He, T., Han, Z., & Wu, X. (2024). Longitudinal exploration of online learning burnout: The role of social support and cognitive engagement. *European Journal of Psychology of Education*, 39(1), 361–388. <https://doi.org/10.1007/s10212-023-00744-y>
- Huang, J., Saleh, S., & Liu, Y. (2021). A review on artificial intelligence in education. *Academic Journal of Interdisciplinary Studies*, 10(3). doi: <https://doi.org/10.36941/ajis-2021-0077>
- Jackson, D. (2015). Employability skill development in work-integrated learning: Barriers and best practice. *Studies in Higher Education*, 40(2), 350–367. <https://doi.org/10.1080/03075079.2013.842221>
- Jie, A. L. X., & Kamrozzaman, N. A. (2024). The challenges higher education students face in using artificial intelligence (AI) against their learning experiences. *Open Journal of Social Sciences*, 12(10), 362–387. <https://doi.org/10.4236/jss.2024.1210025>
- Martin, N., Kelly, N., & Terry, P. (2018). A framework for self-determination in massive open online courses: Design for autonomy, competence, and relatedness. *Australasian Journal of Educational Technology*, 34(2). <https://doi.org/10.14742/ajet.3722>
- Meng, N., Mat Deli, M., & Abdul Rauf, U. A. (2025). Educational technology and AI: Bridging cognitive load and learner engagement for effective learning. *SAGE Open*, 15(4). <https://doi.org/10.1177/21582440251395930>
- OECD (2023), *Building Future-Ready Vocational Education and Training Systems*, OECD Reviews of Vocational Education and Training, OECD Publishing, Paris, <https://doi.org/10.1787/28551a79-en>
- Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence*, 2, 100020. <https://doi.org/10.1016/j.caeai.2021.100020>
- Pavlov, G., Maydeu-Olivares, A., & Shi, D. (2021). Using the standardized root mean squared residual (SRMR) to assess exact fit in structural equation models. *Educational and Psychological Measurement*, 81(1), 110–130. <https://doi.org/10.1177/0013164420926231>
- Qawqzeh, Y. (2024). Exploring the influence of student interaction with ChatGPT on critical thinking, problem solving, and creativity. *International Journal of Information and Education Technology*, 14(4), 596–601. <https://doi.org/10.18178/ijiet.2024.14.4.1975>
- Radermacher, A., Walia, G., & Knudson, D. (2014). Investigating the skill gap between graduating students and industry expectations. *Companion Proceedings of the 36th International Conference on Software Engineering*, 291–300. <https://doi.org/10.1145/2591062.2591169>
- Romanova, O. (2022). Embedding employability skills in vocational education and training: What works best for students' self-evaluation and aspirations?. *Journal of Teaching and Learning for Graduate Employability*, 13(1), 20-36. <https://doi.org/10.21153/jtlge2022vol13no1art1488>
- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68–78. <https://doi.org/10.1037/0003-066X.55.1.68>
- Rosli, M. S., & Saleh, N. S. (2023). Technology enhanced learning acceptance among university students during Covid-19: Integrating the full spectrum of Self-Determination Theory and self-efficacy into the Technology Acceptance Model. *Current Psychology*, 42(21), 18212–18231. <https://doi.org/10.1007/s12144-022-02996-1>

- Salmela-Aro, K., Upadyaya, K., Vinni-Laakso, J., & Hietajärvi, L. (2021). Adolescents' longitudinal school engagement and burnout before and during COVID-19—The role of socio-emotional skills. *Journal of Research on Adolescence*, 31(3), 796–807. <https://doi.org/10.1111/jora.12654>
- Sumra, B., Sultana, A., Elbashir, A. M., et al. (2026). Institutional support and students' interest in AI: The mediating role of learning aspirations and the moderating effect of gender. *TechTrends*. <https://doi.org/10.1007/s11528-026-01184-3>
- Van den Broeck, A., Ferris, D. L., Chang, C.-H., & Rosen, C. C. (2016). A review of self-determination theory's basic psychological needs at work. *Journal of Management*, 42(5), 1195–1229. <https://doi.org/10.1177/0149206316632058>
- Xu, Q., Liu, Y., & Li, X. (2025). Unlocking student potential: How AI-driven personalized feedback shapes goal achievement, self-efficacy, and learning engagement through a self-determination lens. *Learning and Motivation*, 91, 102138. <https://doi.org/10.1016/j.lmot.2025.102138>
- Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education*, 16(1), 1–27. <https://doi.org/10.1186/s41239-019-0171-0>