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Enhancing Deep Learning in Accounting Education through Meaningful, Mindful, and Joyful Learning: The Moderating Role of Technological Self-Efficacy among Vocational Students

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ABSTRACT

This study investigates the effects of meaningful learning, mindful learning, and joyful learning on deep learning, as well as the moderating role of technological self-efficacy in vocational accounting education. Despite increasing attention to deep learning, prior studies have largely examined these pedagogical approaches separately, resulting in limited understanding of their integrated effects, particularly in vocational contexts. A quantitative research design was employed using a survey method involving 339 vocational high school students in the Accounting and Financial Services program. Data were collected through a structured questionnaire consisting of 38 measurement items and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings reveal that meaningful learning ($\beta = 0.260$, $p < 0.001$), mindful learning ($\beta = 0.261$, $p < 0.001$), and joyful learning ($\beta = 0.233$, $p < 0.001$) each have a positive and significant effect on deep learning. In addition, technological self-efficacy significantly moderates these relationships, indicating that the effects of the three learning approaches on deep learning are stronger among students with higher levels of technological confidence. The model demonstrates strong explanatory power ($R^2 = 0.754$), indicating that deep learning is shaped by the integrated influence of cognitive, metacognitive, affective, and technological dimensions. This study contributes to the literature by proposing an integrative framework that combines meaningful, mindful, and joyful learning with technological self-efficacy as a boundary condition. Practically, the findings provide insights for designing technology-enhanced, student-centered instructional strategies to foster deep learning in vocational education.

Keywords: Meaningful Learning, Mindful Learning, Joyful Learning, Deep Learning, Technological Self-Efficacy, Vocational Education, PLS-SEM

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INTRODUCTION

The rapid advancement of the digital era has fundamentally transformed the paradigm of education from a mere process of knowledge transmission into a comprehensive effort to develop complex and adaptive competencies. Contemporary education no longer positions students as passive recipients of information but rather as active learners who construct knowledge through critical, reflective, creative, and collaborative thinking processes (Febriyanti, Suharyati, & Sunaryo, 2025). This transformation aligns with the demands of twenty-first-century skills, which emphasize problem-solving ability, conceptual thinking, effective communication, and the capacity to apply knowledge across diverse real-world contexts (Hirzulloh & Annadhif, 2024). Consequently, educational systems are required to adopt learning approaches that foster meaningful understanding and long-term competence development among students. These transformations are particularly relevant in vocational education, where learning is expected to bridge theoretical understanding with real-world professional applications, especially in accounting education.

Within this context, deep learning, conceptualized as a pedagogical approach, has emerged as a crucial approach in improving the quality of learning processes and outcomes. This approach emphasizes meaningful conceptual understanding, integration of knowledge, and the ability to transfer learning to new situations in a reflective and applicative manner (Doleck et al., 2020; Feriyanto & Anjariyah, 2024; Levin, 2024). Rather than focusing solely on surface-level memorization, deep learning enables students to connect newly acquired knowledge with prior learning experiences, engage in critical reflection, and construct sustainable understanding. In accounting education, deep learning is particularly important, as students are required not only to understand accounting principles but also to interpret financial information, make judgments, and adapt to increasingly digitalized professional environments (Jangid & Kumar, 2025).

Despite its importance, the implementation of learning practices that promote deep learning remains limited, particularly in vocational education settings. Vocational education plays a strategic role in preparing competent and work-ready human resources; however, instructional practices often remain oriented toward procedural knowledge acquisition and rote learning. Several studies suggest that such tendencies may still be found in vocational accounting classrooms, particularly in Accounting and Institutional Finance programs, where teaching practices are often characterized by teacher-centered and conventional instructional approaches (Azzahra & Fauzan, 2023; Efferin & Soeherman, 2024). Such approaches tend to position students as passive learners, resulting in limited engagement in the learning process and insufficient development of critical thinking skills.

This situation has significant implications for students' ability to connect accounting concepts with real-world professional practices. Vocational education requires students not only to understand theoretical concepts but also to apply knowledge contextually and adaptively in professional environments (Efferin & Soeherman, 2024). The mismatch between instructional approaches and workplace competency demands contributes to the limited cognitive readiness and adaptive skills of vocational graduates, particularly in responding to increasingly digitalized work environments. Therefore, innovative and holistic learning strategies are necessary to enhance student engagement and promote learning processes oriented toward deep understanding.

One instructional approach that can support the development of deep learning is meaningful learning. This approach emphasizes the connection between new knowledge and students' existing cognitive structures, enabling learning to become more meaningful and comprehensible (Kostiainen et al., 2018). Through meaningful learning, students actively construct knowledge by linking concepts, contextualizing understanding, and integrating learning experiences. Previous studies have demonstrated that meaningful learning contributes significantly to conceptual understanding and the development of critical thinking skills (Bryce & Blown, 2024; Polman et al., 2021). These findings indicate that meaningful learning has strong potential to improve the quality of learning processes oriented toward deep understanding.

In addition to meaningful learning, mindful learning also plays an important role in enhancing the quality of learning processes. Mindful learning emphasizes awareness, openness to learning experiences, and reflective thinking in understanding subject matter (Santi et al., 2024). This approach encourages students to maintain focus, develop awareness of their learning processes, and regulate attention and emotions during learning activities. Bakosh et al. (2016) found that mindful learning practices positively influence students' academic achievement and learning quality through improved self-regulation and learning awareness. Therefore, mindful learning contributes not only to cognitive learning outcomes but also to the development of affective and metacognitive competencies.

Another approach that contributes to improved learning quality is joyful learning. This approach highlights the importance of creating an enjoyable, interactive, and motivating learning environment in which students feel comfortable and actively engaged in learning activities (Diputera et al., 2024; Yeh et al., 2023). A positive learning environment can enhance intrinsic motivation, engagement, and meaningful learning experiences. Sundaram & Ramesh (2022) demonstrated that game-based learning as a form of joyful learning significantly improves students' learning outcomes and engagement. These findings indicate that emotional aspects of learning play a crucial role in shaping both the learning process and its outcomes. Taken together, these three approaches reflect complementary cognitive, metacognitive, and affective dimensions of learning that may jointly contribute to the development of deep learning.

Although previous research has demonstrated the effectiveness of each of these learning approaches, empirical studies that integrate meaningful learning, mindful learning, and joyful learning into a unified conceptual framework to promote deep learning remain limited. Most existing studies examine these approaches separately, thereby failing to provide a comprehensive understanding of their simultaneous contributions to the development of deep learning (Asmawan & Arianto, 2022; Chirenje & Williams, 2024). This indicates not only a lack of integration but also limited empirical evidence explaining how these approaches interact in shaping deep learning, particularly in vocational education contexts where learning requires the integration of conceptual understanding, practical skills, and technological competencies. However, the effectiveness of these integrated learning approaches may not be uniform across students, as it can be influenced by individual readiness factors.

Beyond the integration of learning approaches, the effectiveness of learning implementation in the digital era is also influenced by students' technological readiness. The rapid development of digital technology has transformed how students access information and interact within learning environments (Fiandra et al., 2022; Syah et al., 2023). The effective use of technology in education requires not only adequate infrastructure but also individual readiness and competence in utilizing digital tools. One key factor determining the success of technology integration in learning is technological self-efficacy (TSE), defined as individuals' beliefs in their ability to use technology to support learning activities (Klusmann et al., 2023; Weng et al., 2022), which is conceptually grounded in Social Cognitive Theory emphasizing the role of self-belief in shaping behavior and learning outcomes.

Technological self-efficacy influences students' confidence in using digital devices, accessing online learning resources, and participating in technology-based learning environments (Sutama & Fajriani, 2022). Students with high levels of technological self-efficacy tend to utilize technology more actively as a learning tool, demonstrate higher motivation, and optimize their digital learning experiences. Previous studies have shown that confidence in technology use significantly affects the utilization of digital learning resources and the effectiveness of technology-enhanced learning (Dewi Kunthi & Az-Zahra, 2025). Furthermore, Purwandari & Khoirunnisa (2023) reported that technological self-efficacy strengthens the relationship between learning strategies and technology-based learning outcomes. These findings suggest that psychological factors related to technological confidence play a critical role in determining learning effectiveness.

However, research examining technological self-efficacy as a moderating variable in the relationship between learning approaches and deep learning remains relatively scarce. Existing studies primarily position technological self-efficacy as an independent or mediating variable in technology-enhanced learning contexts, while its role as a factor that strengthens the relationship between instructional strategies and deep learning outcomes has received limited attention, particularly within vocational education settings. This limitation presents an opportunity to investigate the moderating role of technological self-efficacy in enhancing the effectiveness of learning strategies aimed at promoting deep learning. This suggests that technological self-efficacy may function as a boundary condition that explains when and for whom learning approaches are more effective in promoting deep learning.

Based on these considerations, this study proposes an integrative approach by combining meaningful learning, mindful learning, and joyful learning into a single conceptual model to explain the development of deep learning. In addition, this study examines the role of technological self-efficacy as a moderating variable that strengthens the relationship between these learning approaches and deep learning. This integrative framework is expected to provide a more comprehensive understanding of the factors influencing deep learning within technology-supported vocational education contexts.

This research focuses on vocational high school students enrolled in Accounting and Institutional Finance programs in Kota Surakarta, a context highly relevant to the development of vocational competencies in the digital era. Vocational education in accounting requires the integration of conceptual understanding, technical skills, and technological literacy. Therefore, the development of learning models that promote deep understanding and technological readiness is essential for improving the quality of vocational education and preparing students for technology-driven work environments.

Theoretically, this study is expected to contribute to the development of technology-based learning models by integrating multiple learning approaches oriented toward deep learning. It also enriches the literature on technological self-efficacy in digital learning contexts, particularly by positioning it as a moderating variable in the relationship between learning strategies and learning outcomes. Practically, the findings are expected to provide implications for designing innovative instructional strategies that enhance the quality of vocational learning in accounting educational contexts and improve students' readiness to meet the demands of technology-based professional environments.

Specifically, this study aims to examine the effects of meaningful learning, mindful learning, and joyful learning on students' deep learning and to investigate the moderating role of technological self-efficacy in these relationships among vocational high school students in Accounting and Institutional Finance programs. The findings are expected to contribute to the development of more adaptive, meaningful, and competency-oriented learning practices in the digital era.

METHOD

This study employed a quantitative research approach to obtain empirical evidence regarding the influence of meaningful learning, mindful learning, and joyful learning on students' deep learning, with technological self-efficacy acting as a moderating variable. The quantitative approach was selected because it enables systematic measurement of variables, hypothesis testing, statistical analysis, and objective interpretation of relationships among constructs through numerical data. This approach allows researchers to examine predictive and associative relationships and generalize findings within a defined population through structured data collection procedures and statistical inference.

The research design used in this study was explanatory research with a survey method. The explanatory design aims to explain the predictive relationships among variables and test the moderating effect of technological self-efficacy on the relationship between independent and dependent variables. The survey method was implemented through structured questionnaires distributed to respondents using an online platform. This design was considered appropriate to examine behavioral and psychological constructs related to learning processes in educational settings.

Data collection was conducted through a structured questionnaire consisting of 38 items distributed via Google Forms. The questionnaire was designed to measure four main constructs, namely meaningful learning, mindful learning, joyful learning, and deep learning, as well as technological self-efficacy as a moderating variable. Each construct was operationalized into measurable indicators based on established theoretical frameworks, adapted from prior validated studies in educational psychology and learning research. The instrument was reviewed by experts to ensure content validity and clarity, and a pilot test was conducted prior to full data collection. The instrument employed a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to capture respondents' perceptions and experiences related to learning practices and technology use in the classroom.

The population of this study consisted of students enrolled in the Accounting and Institutional Finance (Akuntansi dan Keuangan Lembaga) program at vocational high schools in Surakarta, Indonesia. The selection of vocational school students was based on the consideration that vocational education emphasizes practical competence, applied knowledge, and technological adaptation, which are relevant to the development of deep learning and technological self-efficacy. The sampling technique applied in this study was proportional sampling, based on the number of students in each participating school, with the total population obtained from school administrative records. The selection of schools was based on accessibility and willingness to participate, which reflects a combination of proportional and convenience sampling approaches. The sample size of 339 respondents is considered adequate for PLS-SEM analysis, as it exceeds the minimum sample size requirement based on the rule of ten times the maximum number of structural paths directed at a latent construct.

Prior to data collection, permission was obtained from the respective schools. Participation was voluntary, and respondents were informed about the purpose of the study. Informed consent was obtained, and data confidentiality and anonymity were ensured throughout the research process. The characteristics of respondents based on school distribution and gender composition are presented in Table 1.

The research sample involved students from three vocational schools in Surakarta. A total of 43 students were selected from SMK Batik 1 Surakarta, 201 students from SMK Negeri 3 Surakarta, and 95 students from SMK Negeri 6 Surakarta. These schools were selected because they offer Accounting and Institutional Finance programs and implement technology-supported learning environments relevant to the research variables. The total number of respondents involved in this study was 339 students, consisting of 313 female students and 26 male students. The distribution of respondents across grade levels shows that 30.4% of students were in Grade X, 32.4% were in Grade XI, and 37.2% were in Grade XII. The demographic composition reflects the characteristics of the Accounting and Institutional Finance program, which is generally dominated by female students, which is consistent with the typical demographic composition of the program, although this imbalance may influence affective and perceptual variables.

Table 1. Table Sampling Characteristic

Respondent	Frequency	%
School		
SMK Batik 1 Surakarta	43	12.68%
SMK N 3 Surakarta	201	59.29%
SMK N 6 Surakarta	95	28.03%
Total	339	100%
Gender		
Female	313	92.3%
Male	26	7.7%
Total	339	100%
Grade Level		
X	103	30.4%
XI	110	32.4%
XII	126	37.2%
Total	339	100%
N = 339		

Prior to analysis, data were screened to identify missing values, duplicate responses, and response inconsistencies. Incomplete responses were removed to ensure data quality. The collected data were analyzed using quantitative statistical techniques to examine the relationships among variables and test research hypotheses. The analysis included descriptive statistics to describe respondent characteristics and variable distribution, as well as inferential statistical analysis to test the direct effects of meaningful learning, mindful learning, and joyful learning on deep learning and the moderating role of technological self-efficacy. Statistical analysis was conducted to ensure the validity and reliability of the measurement model and to evaluate the structural relationships among constructs. The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), including evaluation of the measurement model (outer model) and structural model (inner model). To reduce the potential for common method bias, respondents were assured of anonymity and instructed to answer honestly. All constructs in this study were treated as reflective constructs, as the indicators were assumed to represent manifestations of the underlying latent variables.

RESULTS & DISCUSSION

Result

Descriptive Statistic

Descriptive statistics were calculated to provide an overview of respondents' perceptions regarding each research construct. The analysis includes the minimum value, maximum value, mean score, and standard deviation for each indicator. Given that all items were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), the mean values indicate the general tendency of students' responses, while the standard deviation reflects the variability of responses. The results of the descriptive statistical analysis are presented in Table 2.

Table 2. Descriptive Statistic

Construct	Indicator	N	Min	Max	Mean	Std. Deviation
Meaningful Learning	ML1 - Learning relevance	339	1	5	4.425	0.781
	ML2 - Connectedness of experience	339	1	5	4.056	0.752
	ML3 - Meaningful learning activities	339	1	5	4.242	0.761
	ML4 - Application of knowledge	339	1	5	3.855	0.802
	ML5 - Knowledge organization	339	1	5	4.189	0.772
	ML6 - Conceptual understanding	339	2	5	4.130	0.780
	ML7 - Discussion and collaboration	339	1	5	4.351	0.808
	ML8 - Learning reflection	339	1	5	4.165	0.796
Mindful Learning	MFL1 - Awareness during learning	339	1	5	4.516	0.680
	MFL2 - Awareness of learning strategies	339	1	5	3.938	0.801
	MFL3 - Emotional regulation	339	1	5	3.643	0.959
	MFL4 - Reflection on errors	339	1	5	4.348	0.718
	MFL5 - Openness to perspectives	339	1	5	3.997	0.836
	MFL6 - Attention regulation	339	1	5	3.696	0.855
Joyful Learning	JL1 - Enjoyment in learning	339	1	5	3.973	0.811

Construct	Indicator	N	Min	Max	Mean	Std. Deviation
	JL2 - Learning enthusiasm	339	1	5	3.746	0.849
	JL3 - Creative activities	339	1	5	4.168	0.801
	JL4 - Pleasant learning experience	339	1	5	4.245	0.913
	JL5 - Positive collaboration	339	1	5	4.245	0.874
	JL6 - Learning autonomy	339	1	5	4.124	0.839
	JL7 - Curiosity	339	1	5	4.077	0.802
	JL8 - Learning comfort	339	1	5	3.891	0.822
Deep Learning	DL1 - Conceptual understanding	339	2	5	4.251	0.724
	DL2 - Elaboration	339	1	5	3.985	0.85
	DL3 - Problem-solving	339	1	5	4.018	0.783
	DL4 - Knowledge transfer	339	1	5	3.788	0.821
	DL5 - Motivation to understand	339	1	5	4.162	0.845
	DL6 - Critical thinking	339	1	5	4.068	0.778
	DL7 - Learning organization	339	1	5	4.068	0.812
	DL8 - Reflection	339	1	5	4.106	0.78
Technological Self-Efficacy	TSE1 - Device operation	339	1	5	4.319	0.801
	TSE2 - Use of learning applications	339	1	5	4.15	0.83
	TSE3 - Technical problem-solving	339	1	5	3.835	0.829
	TSE4 - General digital literacy	339	1	5	4.109	0.833
	TSE5 - Evaluation of digital resources	339	1	5	4.115	0.817
	TSE6 - Adaptation to new technologies	339	1	5	4.13	0.802
	TSE7 - Use of technology for complex tasks	339	1	5	4.127	0.851

Construct	Indicator	N	Min	Max	Mean	Std. Deviation
	TSE8 - Technological independence	339	1	5	3.678	0.95

The descriptive results indicate that, overall, students demonstrate relatively high perceptions across all constructs, as reflected by mean scores predominantly above 3.80 on a five-point scale. This suggests that respondents generally agree with statements related to meaningful learning, mindful learning, joyful learning, deep learning, and technological self-efficacy.

For the Meaningful Learning construct, the mean values range from 3.855 to 4.425. The highest mean is observed for Learning relevance (M = 4.425), indicating that students strongly perceive their learning activities as relevant to their needs and future professional contexts. Similarly, Discussion and collaboration (M = 4.351) shows a high level of agreement, suggesting that collaborative engagement is well-integrated into classroom learning. The relatively lower mean for Application of knowledge (M = 3.855) may indicate that although students understand concepts, applying them in practical contexts remains moderately challenging.

In the Mindful Learning construct, mean scores range from 3.643 to 4.516. The highest score is found in Awareness during learning (M = 4.516), reflecting strong student awareness in learning activities. Meanwhile, Emotional regulation (M = 3.643) and Attention regulation (M = 3.696) show comparatively lower means and higher standard deviations, suggesting variability in students' ability to manage emotions and maintain focus. This indicates that while reflective awareness is present, emotional and attentional control may still require development among vocational students.

For Joyful Learning, the mean values range from 3.746 to 4.245. Indicators such as Pleasant learning experience (M = 4.245) and Positive collaboration (M = 4.245) demonstrate that students generally perceive the classroom environment as supportive and enjoyable. However, learning enthusiasm (M = 3.746) shows a slightly lower mean, suggesting that while students experience positive classroom interactions, intrinsic enthusiasm may vary across individuals.

Regarding Deep Learning, mean values range between 3.788 and 4.251. The highest mean is found in Conceptual understanding (M = 4.251), indicating that students perceive themselves as having a solid grasp of core concepts. Conversely, Knowledge transfer (M = 3.788) shows a relatively lower mean, suggesting that applying knowledge across different contexts may be more demanding. The standard deviations across deep learning indicators are moderate, reflecting reasonable consistency in responses.

Finally, the Technological Self-Efficacy construct demonstrates generally high mean values, ranging from 3.678 to 4.319. The highest mean is observed in Device operation (M = 4.319), indicating strong confidence in basic technological usage. In contrast, Technological independence (M = 3.678) shows the lowest mean and the highest standard deviation (SD = 0.95), suggesting variability in students' ability to independently manage technological tasks without assistance. This finding implies that while students are comfortable using technology, full autonomy in technological engagement may still be developing.

Overall, the descriptive statistics reveal that students exhibit positive perceptions across all constructs, particularly in learning relevance, awareness during learning, conceptual understanding, and basic technological skills. However, relatively lower mean scores in knowledge application, emotional regulation, knowledge transfer, and technological independence suggest potential areas for pedagogical improvement. These descriptive findings provide an important contextual foundation for interpreting the subsequent structural model analysis.

Measurement Model Evaluation

Before examining the structural relationships among constructs, it is essential to assess the measurement model to ensure that the indicators reliably and validly represent their respective latent variables. Convergent validity was evaluated by examining the outer loading values of each indicator using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. According to established guidelines, indicator loadings of 0.70 or higher are considered ideal, while loadings between 0.60 and 0.70 are still acceptable in exploratory and social science research, provided that the construct demonstrates adequate composite reliability and average variance extracted (AVE). Table 3 presents the validity test results for each indicator.

Table 3. Validity Test Results for Each Indicator

Construct	Indicator	Loading Factor	Result
Meaningful Learning	ML1 - Learning relevance	0.709	Valid
	ML2 - Connectedness of experience	0.737	Valid
	ML3 - Meaningful learning activities	0.799	Valid
	ML4 - Application of knowledge	0.737	Valid
	ML5 - Knowledge organization	0.766	Valid
	ML6 - Conceptual understanding	0.704	Valid
	ML7 - Discussion and collaboration	0.642	Valid
	ML8 - Learning reflection	0.724	Valid
Mindful Learning	MFL1 - Awareness during learning	0.693	Valid
	MFL2 - Awareness of learning strategies	0.794	Valid
	MFL3 - Emotional regulation	0.666	Valid
	MFL4 - Reflection on errors	0.752	Valid
	MFL5 - Openness to perspectives	0.750	Valid
	MFL6 - Attention regulation	0.651	Valid
Joyful Learning	JL1 - Enjoyment in learning	0.795	Valid

Construct	Indicator	Loading Factor	Result
	JL2 - Learning enthusiasm	0.788	Valid
	JL3 - Creative activities	0.718	Valid
	JL4 - Pleasant learning experience	0.658	Valid
	JL5 - Positive collaboration	0.661	Valid
	JL6 - Learning autonomy	0.707	Valid
	JL7 - Curiosity	0.742	Valid
	JL8 - Learning comfort	0.766	Valid
Deep Learning	DL1 - Conceptual understanding	0.727	Valid
	DL2 - Elaboration	0.683	Valid
	DL3 - Problem-solving	0.772	Valid
	DL4 - Knowledge transfer	0.714	Valid
	DL5 - Motivation to understand	0.701	Valid
	DL6 - Critical thinking	0.784	Valid
	DL7 - Learning organization	0.796	Valid
	DL8 - Reflection	0.829	Valid
Technological Self-Efficacy	TSE1 - Device operation	0.774	Valid
	TSE2 - Use of learning applications	0.807	Valid
	TSE3 - Technical problem-solving	0.787	Valid
	TSE4 - General digital literacy	0.78	Valid
	TSE5 - Evaluation of digital resources	0.739	Valid
	TSE6 - Adaptation to new technologies	0.817	Valid
	TSE7 - Use of technology for complex tasks	0.846	Valid
	TSE8 - Technological independence	0.677	Valid

The discussion is written to interpret and describe the significance of your findings in light of what was already known about the issues being investigated, and to explain any new understanding or insight into the problem after you have considered the findings. It should connect to the introduction by way of the research questions or hypotheses you posed and the literature you reviewed, but it does not simply repeat or rearrange the introduction; this section should always explain how your study has moved the reader's understanding of the research problem forward from where you left them at the end of the introduction.

The results presented in Table 3 indicate that all measurement indicators demonstrate acceptable convergent validity. The outer loading values range from 0.642 to 0.846, exceeding the minimum threshold of 0.60 commonly accepted in educational research using PLS-SEM. This finding suggests that each indicator sufficiently reflects its corresponding latent construct. For the Meaningful Learning construct, the loading factors range from 0.642 to 0.799. Most indicators exceed the recommended threshold of 0.70, indicating strong representation of the construct. Although the indicator "Discussion and collaboration" (0.642) falls slightly below 0.70, it remains within the acceptable range and therefore was retained, as it contributes conceptually to the multidimensional nature of meaningful learning.

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Similarly, the Mindful Learning construct demonstrates satisfactory indicator reliability, with loading values ranging from 0.651 to 0.794. Indicators such as "Awareness of learning strategies" (0.794) and "Reflection on errors" (0.752) show strong associations with the construct, reinforcing the theoretical assumption that reflective awareness and strategic regulation are central components of mindful learning.

The Joyful Learning construct also exhibits adequate convergent validity, with loading values between 0.658 and 0.795. Indicators related to emotional engagement, such as "Enjoyment in learning" (0.795) and "Learning enthusiasm" (0.788), show particularly strong loadings, supporting the theoretical framework that positive affect enhances learning engagement.

For the Deep Learning construct, all indicators exceed 0.68, with the highest loading observed for "Reflection" (0.829). This indicates that reflective processes, critical thinking, and conceptual organization strongly represent deep learning among vocational students. The relatively high loading values across indicators confirm that the construct is well-defined and internally consistent.

Lastly, the Technological Self-Efficacy construct demonstrates strong convergent validity, with loadings ranging from 0.677 to 0.846. Indicators such as "Use of technology for complex tasks" (0.846) and "Adaptation to new technologies" (0.817) show particularly strong associations, suggesting that students' confidence in handling advanced technological tasks is a central component of technological self-efficacy.

Overall, the measurement model demonstrates satisfactory convergent validity across all constructs. None of the indicators fall below the minimum acceptable threshold, and the majority exceed the recommended 0.70 level. These findings indicate that the instrument is statistically valid for measuring meaningful learning, mindful learning, joyful learning, deep learning, and technological self-efficacy among vocational high school students. Consequently, the structural model analysis can be conducted with confidence that the constructs are adequately represented by their respective indicators.

Following the assessment of indicator validity, the next step in evaluating the measurement model involves examining construct reliability and convergent validity at the latent variable level. Reliability was assessed using Cronbach's Alpha, rho_A, and Composite Reliability (CR), while convergent validity was further evaluated using the Average Variance Extracted (AVE). In PLS-SEM, Cronbach's Alpha and rho_A values above 0.70 indicate satisfactory internal consistency, whereas Composite Reliability values between 0.70 and 0.95 suggest adequate construct reliability. Additionally, AVE values above 0.50 indicate that a construct explains more than half of the variance of its indicators. The reliability test results are presented in Table 4.

Table 4. Reliability Test Results

Variable	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Meaningful Learning	0.873	0.878	0.900	0.531
Mindful Learning	0.813	0.822	0.865	0.518
Joyful Learning	0.876	0.884	0.901	0.534
Deep Learning	0.890	0.892	0.912	0.566
Technological Self-Efficacy	0.907	0.912	0.925	0.608

The results in Table 4 indicate that all constructs demonstrate satisfactory levels of internal consistency and convergent validity. The Cronbach's Alpha values range from 0.813 to 0.907, exceeding the recommended threshold of 0.70. This finding suggests that the indicators within each construct consistently measure the same underlying concept. Similarly, the rho_A values, which are considered a more precise reliability estimator in PLS-SEM, range between 0.822 and 0.912. All values surpass the minimum acceptable level of 0.70, reinforcing the internal consistency of the measurement model.

Composite Reliability (CR) values for all constructs range from 0.865 to 0.925, indicating strong construct reliability. None of the CR values exceed 0.95, which suggests that there is no issue of redundancy among the indicators. In particular, Technological Self-Efficacy (CR = 0.925) and Deep Learning (CR = 0.912) demonstrate very strong reliability, reflecting well-structured measurement scales.

Regarding convergent validity, the AVE values range from 0.518 to 0.608. All constructs exceed the recommended threshold of 0.50, meaning that more than 50% of the variance in the indicators is explained by their respective latent variables. Technological Self-Efficacy shows the highest AVE (0.608), indicating that its indicators strongly represent the construct. Meanwhile, Mindful Learning (AVE = 0.518) and Meaningful Learning (AVE = 0.531) also meet the acceptable criteria, confirming adequate convergent validity.

Overall, these findings demonstrate that the measurement model possesses strong internal consistency and satisfactory convergent validity. The reliability indices (Cronbach's Alpha, rho_A, and Composite Reliability) consistently exceed recommended thresholds, and all AVE values meet the minimum requirement. Therefore, the constructs of Meaningful Learning, Mindful Learning, Joyful Learning, Deep Learning, and Technological Self-Efficacy are reliably and validly measured, supporting the appropriateness of proceeding to the structural model analysis.

In addition to convergent validity and reliability, discriminant validity was assessed to ensure that each construct is empirically distinct from others. In this study, discriminant validity was evaluated using the Heterotrait-Monotrait ratio (HTMT).

Table 5. Discriminant Validity Using HTMT

Construct	Deep Learning	Joyful Learning	Meaningful Learning	Mindful Learning
Joyful Learning	0.851			
Meaningful Learning	0.862	0.821		
Mindful Learning	0.842	0.884	0.854	
Technological Self-Efficacy	0.825	0.718	0.799	0.800

The HTMT results presented in Table 5 indicate that all values are below the recommended threshold of 0.90, suggesting that discriminant validity is established among the constructs. These findings confirm that each construct measures distinct conceptual dimensions, supporting the adequacy of the measurement model.

Structural Model Evaluation

After confirming the adequacy of the measurement model, the next step involves evaluating the structural model to assess its explanatory power, predictive relevance, effect sizes, and collinearity before proceeding to hypothesis testing. The results indicate that the model has strong explanatory capability, with an R^2 value of 0.754 (adjusted $R^2 = 0.749$) for Deep Learning, suggesting that 75.4% of the variance is explained by meaningful learning, mindful learning, joyful learning, and their interactions with technological self-efficacy. In addition, the Q^2 value of 0.417 indicates strong predictive relevance, demonstrating that the model has substantial capability in predicting the endogenous construct.

Furthermore, the effect size (f^2) analysis shows that meaningful learning (0.083), mindful learning (0.091), joyful learning (0.078), and technological self-efficacy (0.109) exert small effects on deep learning. Nevertheless, the overall model exhibits strong explanatory and predictive power, as reflected by the high R^2 and Q^2 values, indicating that the combined influence of the predictors is substantial. Collinearity diagnostics also confirm that all VIF values range between 1.439 and 2.683, well below the recommended thresholds, indicating no multicollinearity issues and stable model estimation. Given these results, the structural model is considered robust and suitable for hypothesis testing.

The structural relationships were examined using the bootstrapping procedure in PLS-SEM to assess the significance of path coefficients. The decision criteria were based on a t-statistic greater than 1.96 and a p-value below 0.05 at the 5% significance level. Table 5 presents the summary of the hypothesis testing results, including path coefficients (β), t-statistics, p-values, and hypothesis decisions.

Table 6. Summary of Hypothesis Testing Results

Hypothesis	Relationship	β	T Statistics	P Values	Result
H1	Meaningful Learning → Deep Learning	0.260	4.494	0.000	Supported
H2	Mindful Learning → Deep Learning	0.261	3.897	0.000	Supported
H3	Joyful Learning → Deep Learning	0.233	3.765	0.000	Supported
H4	Technological Self-Efficacy × Meaningful Learning → Deep Learning	0.148	3.020	0.003	Supported
H5	Technological Self-Efficacy × Mindful Learning → Deep Learning	0.121	2.327	0.020	Supported
H6	Technological Self-Efficacy × Joyful Learning → Deep Learning	0.136	2.473	0.014	Supported

The results presented in Table 6 indicate that all proposed hypotheses are supported. The findings demonstrate that meaningful learning, mindful learning, and joyful learning significantly influence deep learning among vocational high school students.

First, Meaningful Learning has a significant positive effect on Deep Learning ($\beta = 0.260$, $t = 4.494$, $p < 0.001$). This result suggests that when students perceive learning activities as relevant, connected to prior experiences, and conceptually organized, they are more likely to engage in deeper cognitive processing. The relatively strong coefficient indicates that meaningful learning plays a substantial role in enhancing students' conceptual understanding, knowledge integration, and reflective thinking. This finding supports constructivist learning theory, which emphasizes the importance of linking new information to existing cognitive structures.

Second, Mindful Learning also shows a significant positive effect on Deep Learning ($\beta = 0.261$, $t = 3.897$, $p < 0.001$). This implies that students who demonstrate awareness during learning, emotional regulation, and reflective practices tend to achieve higher levels of deep learning. The comparable magnitude of this coefficient to meaningful learning indicates that cognitive awareness and reflective engagement are equally important in fostering deep learning outcomes. Mindful learning enables students to regulate attention and critically evaluate their understanding, thereby strengthening conceptual mastery.

Third, Joyful Learning significantly influences Deep Learning ($\beta = 0.233$, $t = 3.765$, $p < 0.001$). Although slightly lower in magnitude compared to meaningful and mindful learning, the coefficient remains statistically significant and practically meaningful. This finding suggests that positive emotional experiences, enthusiasm, and supportive collaboration contribute to students' motivation to engage deeply with learning materials. A pleasant learning environment appears to facilitate cognitive engagement and sustained effort.

Beyond the direct effects, the moderating role of Technological Self-Efficacy (TSE) is also supported. The interaction between TSE and Meaningful Learning significantly affects Deep Learning ($\beta = 0.148$, $t = 3.020$, $p = 0.003$), indicating that students with higher technological confidence benefit more from meaningful learning strategies. Similarly, TSE significantly moderates the relationship between Mindful Learning and Deep Learning ($\beta = 0.121$, $t = 2.327$, $p = 0.020$), as well as between Joyful Learning and Deep Learning ($\beta = 0.136$, $t = 2.473$, $p = 0.014$).

These findings indicate a pattern of partial moderation, where learning approaches directly influence deep learning while their effects are further strengthened by students' technological self-efficacy. In other words, technological confidence enhances the effectiveness of meaningful, mindful, and joyful learning strategies. Students who are more confident in using digital tools are better able to leverage learning activities, access digital resources, and engage in reflective and collaborative processes, thereby deepening their understanding.

Overall, the structural model confirms that meaningful learning, mindful learning, and joyful learning significantly contribute to deep learning, while technological self-efficacy functions as a reinforcing factor. However, it is important to note that although the relationships are statistically significant, the effect size (f^2) values indicate that these contributions are relatively small, and the moderating effects are negligible. This suggests that each predictor individually exerts a modest influence on deep learning, despite their statistical significance, which may be influenced by the relatively large sample size ($N = 339$). Nevertheless, the overall model demonstrates strong explanatory and predictive power, as reflected by the high R^2 and Q^2 values, indicating that the combined influence of meaningful, mindful, and joyful learning remains substantial. These findings highlight the importance of integrating pedagogical innovation with technological competence to foster deep learning in vocational education contexts.

Discussion

The present study provides robust empirical evidence that meaningful learning, mindful learning, and joyful learning significantly contribute to deep learning among vocational high school students in accounting and financial studies. Furthermore, technological self-efficacy (TSE) significantly moderates these relationships, reinforcing the argument that pedagogical effectiveness in the digital era depends not only on instructional design but also on students' technological confidence. These findings collectively advance the theoretical and empirical understanding of deep learning within vocational education contexts.

Deep learning, in educational discourse, refers to the learner's capacity to understand concepts at a structural level, integrate knowledge across domains, and apply understanding to novel situations. Unlike surface learning, which emphasizes memorization, deep learning is characterized by conceptual elaboration, reflection, and transferability. The significant influence of meaningful learning ($\beta = 0.260$) confirms that contextual relevance and cognitive integration are central drivers of deep learning processes. This result aligns with the constructivist perspective articulated by Feriyanto & Anjariyah (2024) and Kostiainen et al. (2018), who argue that meaningful learning emerges when students actively connect new information to prior knowledge frameworks. Similarly, Narimo et al. (2022), Polman et al. (2021), and Shi et al. (2025) emphasize that meaningful learning in mathematics enhances conceptual coherence through contextual engagement. Extending these findings to vocational accounting education, the present study demonstrates that when students perceive accounting materials as relevant to professional practice, they are more likely to engage in higher-order cognitive processing. Importantly, vocational education presents a unique context where theoretical abstraction must be directly linked to occupational application. The positive effect observed in this study suggests that meaningful learning bridges the gap between academic knowledge and workplace readiness. Thus, deep learning in vocational settings cannot be achieved through content delivery alone; it requires deliberate contextualization and cognitive scaffolding.

The equally strong effect of mindful learning ($\beta = 0.261$) highlights the importance of metacognitive awareness in fostering deep learning. Mindful learning emphasizes attention regulation, emotional control, and reflective awarenes components that directly influence cognitive engagement. The findings are consistent with Cochran & Parker Peters (2023), Feriyanto & Anjariyah (2024), and Gu et al. (2024), who found that mindfulness interventions significantly improve students' academic outcomes. More recently, Chirenje & Williams (2024) and Gan et al. (2015) demonstrated that mindfulness practices enhance the quality of classroom learning by strengthening attentional stability and reflective depth. The present research extends these insights by empirically confirming that mindful engagement in vocational classrooms enhances students' ability to organize knowledge, reflect on mistakes, and critically analyze financial information. From a theoretical standpoint, mindful learning functions as a regulatory mechanism that transforms meaningful experiences into deeper cognitive integration. Without metacognitive awareness, contextual relevance alone may not guarantee deep processing. Therefore, this study suggests that meaningful and mindful learning operate synergistically one provides conceptual structure, while the other ensures reflective consolidation.

The significant influence of joyful learning ($\beta = 0.233$) further underscores the role of affective engagement in deep learning. Although often considered secondary to cognitive factors, emotional climate significantly shapes motivation and sustained attention. Joyful learning creates a psychologically safe environment that encourages curiosity, collaboration, and creative exploration. This finding resonates with Bhakti et al. (2018) and Feriyanto & Anjariyah (2024), who conceptualized joyful learning as a strategy to enhance student happiness and academic engagement. Similarly, Sundaram & Ramesh (2022) and Yeh et al. (2023) demonstrated that game-based joyful learning improves learning outcomes in blended contexts. The present study confirms that positive emotional experiences are not merely peripheral outcomes but integral components of deep cognitive engagement. In vocational accounting education, where content may be perceived as technical or abstract, joyful learning reduces cognitive resistance and enhances intrinsic motivation. Emotional positivity thus acts as a catalyst that sustains deep exploration and knowledge transfer.

One of the most theoretically significant contributions of this study lies in demonstrating the moderating role of technological self-efficacy. TSE significantly strengthens the relationships between meaningful, mindful, joyful learning and deep learning. This finding reflects a partial moderation pattern, indicating that while pedagogical strategies directly influence deep learning, their effectiveness is amplified by students' technological confidence. The result aligns with Masry & Makaldy (2025) and Trinovita et al. (2025), who identify technological self-efficacy as a critical determinant of digital adoption and pedagogical transformation. Similarly, Downes et al. (2020), Kim & Park (2018) and Masry & Haim (2022) demonstrate that technology-enabled learning environments enhance self-efficacy and psychological well-being. The present study advances this literature by positioning technological self-efficacy not merely as an outcome of digital exposure but as an interactive enhancer of learning depth.

In the digital era, vocational education increasingly integrates financial software, online simulations, and digital accounting tools. Students with higher technological self-efficacy are better equipped to navigate complex tasks, evaluate digital resources, and independently solve technical problems. Consequently, they are able to extract deeper meaning from meaningful, mindful, and joyful learning experiences. This perspective also resonates with Choli et al. (2024) and Downes et al. (2020), who argue that beliefs about technology significantly influence learning engagement, and with Rahman Hakim et al. (2023) and Tondeur et al. (2018), who highlight that adaptive digital tools enhance higher-order thinking skills. Therefore, technological self-efficacy functions as a psychological bridge between pedagogical design and digital implementation.

CONCLUSION

This study demonstrates that meaningful, mindful, and joyful learning significantly enhance deep learning among vocational accounting students. Additionally, technological self-efficacy positively moderates these relationships, amplifying the impact of these pedagogical strategies. Theoretically and practically, these findings suggest educators should design reflective, emotionally engaging environments while actively building students' technological confidence. However, limitations include a cross-sectional design, reliance on self-reported perceptual data, and a narrow, predominantly female sample. Future research should employ longitudinal or experimental designs, incorporate objective learning outcomes, and explore broader demographics to validate this model.

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REFERENCES

Asmawan, M. C., & Arianto, B. (2022). Pembelajaran Daring pada Masa Covid 19: Studi Kasus pada Sekolah Menengah Kejuruan. Jurnal Pendidikan Ilmu Sosial, 32(1). https://doi.org/10.23917/jpis.v32i1.17197

Azzahra, S., & Fauzan, S. (2023). Computational Thinking of Accounting Students in Terms of Critical Thinking and Problem-Solving Skills. Jurnal Pendidikan Ilmu Sosial, 33(1). https://doi.org/10.23917/jpis.v33i1.22689

Bakosh, L. S., Snow, R. M., Tobias, J. M., Houlihan, J. L., & Barbosa-Leiker, C. (2016). Maximizing Mindful Learning: Mindful Awareness Intervention Improves Elementary School Students' Quarterly Grades. Mindfulness, 7(1), 59–67. https://doi.org/10.1007/s12671-015-0387-6

Bhakti, C. P., Alfarizqi, M., Ghiffari, N., & Salsabila, K. (2018). Joyful Learning: Alternative Learning Models to Improving Student Happiness. Varidika Pendidikan, 30(2), 30–35. https://doi.org/10.23917/varidika.v30i2.7572

Bryce, T. G. K., & Blown, E. J. (2024). Ausubel's meaningful learning re-visited. Current Psychology, 43(5), 4579–4598. https://doi.org/10.1007/s12144-023-04440-4

Chirenje, L. I., & Williams, J. B. (2024). Learning design for impact: a transformative education model for sustainability. Society and Business Review, 20(3), 623–646. https://doi.org/https://doi.org/10.1108/SBR-12-2024-0414

Choli, I., Mujib, A., Saputra, E., Rahmawan, F., & Oktapiani, M. (2024). 21st Century Learning and Smartphone Preference as a Learning Media. Jurnal Iqra': Kajian Ilmu Pendidikan, 9(2). http://journal.iaimnumetrolampung.ac.id/index.php/ji/

Cochran, L. M., & Parker Peters, M. (2023). Mindful preparation: An exploration of the effects of mindfulness and SEL training on pre-service teacher efficacy and empathy. Teaching and Teacher Education, 123. https://doi.org/10.1016/j.tate.2022.103986

Dewi Kunthi, Y., & Az-Zahra, K. (2025). Development of the Behaviorism Learning Model in Fiqh Subjects in the Digital Era. Jurnal Iqra': Kajian Ilmu Pendidikan, 10(3). https://journal.iaimnumetrolampung.ac.id/index.php/ji/index

Diputera, M. A., Zulpan, & Eza, G. N. (2024). Memahami Konsep Pendekatan Deep Learning dalam Pembelajaran Anak Usia Dini Yang Meaningful, Mindful dan Joyful: Kajian Melalui Filsafat Pendidikan. Jurnal Bunga Rampai Usia Emas, 10(2). https://doi.org/10.24114/jbrue.v10i2.65978

Doleck, T., Lemay, D. J., Basnet, R. B., & Bazelais, P. (2020). Predictive analytics in education: a comparison of deep learning frameworks. Education and Information Technologies, 25(3), 1951–1963. https://doi.org/10.1007/s10639-019-10068-4

Downes, T., Di Cesare, D. M., Gallagher, T. L., & Rowsell, J. (2020). Parents' beliefs about and associations to their elementary children's home technology usage. Education and Information Technologies, 25(5), 4557–4574. https://doi.org/10.1007/s10639-020-10188-2

Efferin, S., & Soeherman, B. (2024). Mindfulness for sustainable development: a case of accounting education in Indonesia. Accounting Education. https://doi.org/10.1080/09639284.2024.2303730

Febriyanti, C., Suharyati, H., & Sunaryo, W. (2025). Strategies to Increase Teacher Innovativeness through Strengthening Learning Organisation, Creativity, Self-Efficacy and Job Satisfaction. Jurnal Iqra': Kajian Ilmu Pendidikan, 10(1). https://journal.iaimnumetrolampung.ac.id/index.php/ji/index

Feriyanto, F., & Anjariyah, D. (2024). Deep Learning Approach Through Meaningful, Mindful, and Joyful Learning: A Library Research. Electronic Journal of Education, Social Economics and Technology, 5(2), 208–212. https://doi.org/10.33122/ejeset.v5i2.321

Fiandra, Y. A., Jalinus, N., Ridwan, R., & Abdullah, R. (2022). The Effect of Prior Knowledge and ASSURE Model on Simulation and Digital Communication Learning Outcomes in Vocational High School. Jurnal VARIDIKA, 1(1), 53–62. https://doi.org/10.23917/varidika.v1i1.18283

Gan, B., Menkhoff, T., & Smith, R. (2015). Enhancing students' learning process through interactive digital media: New opportunities for collaborative learning. Computers in Human Behavior, 51, 652–663. https://doi.org/10.1016/j.chb.2014.12.048

Gu, Y., Sun, B., He, J., & Huang, W. (2024). Sustainability Education as a Predictor of Student Well-Being Through Mindfulness and Social Support: A Mediated Moderation Model. Sustainability (Switzerland), 16(23). https://doi.org/10.3390/su162310508

Hirzulloh, M. F., & Annadhif, T. A. (2024). Islamic Education in the Era of Industrial Revolution 4.0 and the Utilization of Digital Technology in the Teaching and Learning Process. Jurnal Iqra' : Kajian Ilmu Pendidikan, 9(2), 409–437. https://journal.iaimnumetrolampung.ac.id/index.php/ji/

Jangid, M., & Kumar, R. (2025). Deep learning approaches to address cold start and long tail challenges in recommendation systems: a systematic review. Multimedia Tools and Applications, 84(5), 2293–2325. https://doi.org/10.1007/s11042-024-20262-3

Kim, B., & Park, M. J. (2018). Effect of personal factors to use ICTs on e-learning adoption: comparison between learner and instructor in developing countries. Information Technology for Development, 24(4), 706–732. https://doi.org/10.1080/02681102.2017.1312244

Klusmann, B., Sanderman, R., & Schroevers, M. J. (2023). Delivering mindfulness in the classroom via a technology-enabled approach: Feasibility and the potential impact on teachers' psychological well-being, self-efficacy, and mindfulness. Teaching and Teacher Education, 122. https://doi.org/10.1016/j.tate.2022.103950

Kostiainen, E., Ukskoski, T., Ruohotie-Lyhty, M., Kauppinen, M., Kainulainen, J., & Mäkinen, T. (2018). Meaningful learning in teacher education. Teaching and Teacher Education, 71, 66–77. https://doi.org/10.1016/j.tate.2017.12.009

Levin, O. (2024). Simulation as a pedagogical model for deep learning in teacher education. Teaching and Teacher Education, 143. https://doi.org/10.1016/j.tate.2024.104571

Masry, A. H., & Haim. (2022). Teachers' technological competence and success in online teaching during the COVID-19 crisis: the moderating role of resistance to change. International Journal of Educational Management, 36(1), 1–13. https://doi.org/10.1108/IJEM-03-2021-0086

Masry, A. H., & Makaldy, R. (2025). Technological self-efficacy and sense of coherence: Key drivers in teachers' AI acceptance and adoption. Computers and Education: Artificial Intelligence, 8, 100377. https://doi.org/https://doi.org/10.1016/j.caeai.2025.100377

Narimo, S., Anggraini, S., Efita Sari, D., & Mustapha, R. (2022). Analysis of Effectiveness of Economics Subject Tutoring After School. Jurnal Pendidikan Ilmu Sosial, 32(1). https://journals.ums.ac.id/index.php/jpis/article/view/18844/7710

Polman, J., Hornstra, L., & Volman, M. (2021). The meaning of meaningful learning in mathematics in upper-primary education. Learning Environments Research, 24(3), 469–486. https://doi.org/10.1007/s10984-020-09337-8

Purwandari, E., & Khoirunnisa. (2023). Student Engagement Models: Parental Support, Academic Self-Efficacy, and the Teacher-Student Relationship. Jurnal Iqra': Kajian Ilmu Pendidikan, 8(2), 481–494. http://journal.iaimnumetrolampung.ac.id/index.php/ji/

Rahman Hakim, A., Widayati, A., Ary Wibawa, E., & Septiana, Y. (2023). The Effectiveness of Digital Literature-Based Learning Video on Improving Student's Digital Literature Skill. Jurnal Pendidikan Ilmu Sosial, 33(1). https://doi.org/10.23917/jpis.v33i1.21782

Santi, S., Andriyaningsih, A., Seneru, W., Burmansah, B., Luwiha, L., Pratama, A. S., & Suryanadi, J. (2024). Mindful Learning: Mindfulness Practice Matters for Students on the Quality of Learning in the Classroom. International Journal of Science and Applied Science: Conference Series, 8(2), 53. https://doi.org/10.20961/ijsascs.v8i2.95098

Shi, Y. R., Sin, K. F. K., & Wang, Y. Q. (2025). Teacher professional development of digital pedagogy for inclusive education in post-pandemic era: Effects on teacher competence, self-efficacy, and work well-being. Teaching and Teacher Education, 168. https://doi.org/10.1016/j.tate.2025.105230

Sundaram, S., & Ramesh, R. (2022). Effectiveness of joyful game-based blended learning method in learning chemistry during COVID-19. International Journal of Evaluation and Research in Education, 11(4), 2140–2146. https://doi.org/10.11591/ijere.v11i4.22427

Sutama, S., & Fajriani, I. N. (2022). Media Pembelajaran E-Learning Berbasis WEB di Tingkat Sekolah Menengah Kejuruan. Jurnal VARIDIKA, 33(2), 129–140. https://doi.org/10.23917/varidika.v33i2.15330

Syah, M. F. J., Janudin, S. E., Mansor, M., Fuadi, D., Suranto, S., Romadhoni, D. N., & Hafidah, A. S. N. (2023). Pre-Service Teacher Professional Identity Formation: Narrative study on Indonesian Accounting Teacher Candidate. Jurnal VARIDIKA, 35(2), 80–93. https://doi.org/10.23917/varidika.v1i2.23190

Tondeur, J., Aesaert, K., Prestridge, S., & Consuegra, E. (2018). Computers & Education A multilevel analysis of what matters in the training of pre-service teacher's ICT competencies. Education, Computer Science. https://doi.org/https://doi.org/10.1016/J.COMPEDU.2018.03.002

Trinovita, D., Nurchurifiani, E., Hastomo, T., Andewi, W., & Hasbi, M. (2025). Exploring the Influence of Generative AI on Self-Regulated Learning: A Mixed-Methods Study in the EFL Context. Jurnal Iqra': Kajian Ilmu Pendidikan, 10(2). https://journal.iaimnumetrolampung.ac.id/index.php/ji/index

Weng, Xiaojing, Ng, Oi-Lam, Cui, Zhihao, & Leung, Suzannie. (2022). Creativity Development with Problem-Based Digital Making and Block-Based Programming for Science, Technology, Engineering, Arts, and Mathematics Learning in Middle School Contexts. Journal of Educational Computing Research, 61(2), 304–328. https://doi.org/10.1177/07356331221115661

Yeh, Y., Jui-Yen, C., & and Ting, Y.-S. (2023). Engaging Elementary School Children in Mindful Learning Through Story-Based Creativity Games Facilitates Their Growth Mindset. International

Journal of Human–Computer Interaction, 39(3), 519–528. https://doi.org/10.1080/10447318.2022.2041901