Teacher Readiness in STEM–Deep Learning: A Cluster-Based Approach to Tiered Professional Development

Ni Wayan Ekayanti[1]*, I Wayan Suastra [2], Ketut Suma [3]
Ida Bagus Putu Arnyana[4]
[1,2,3,4]Pascasarjana, Universitas Pendidikan Ganesha, Singaraja, Indonesia

Keywords:
Teacher readiness, STEM, Deep Learning, cluster analysis, professional development.

***Correspondence Address:**
ekayanti.2@student.undiksha.ac.id

Abstract: This study examines teacher readiness in implementing STEM (Science, Technology, Engineering, and Mathematics)-oriented Deep Learning, with the aim of designing a phased professional development framework. Using a quantitative approach with a cross-sectional survey design, data were collected from 115 teachers at various levels of education in Bali Province. Teacher readiness was measured through five main dimensions: basic STEM mastery, Deep Learning literacy, technological self-efficacy, application usage skills, and perceived learning difficulties. Data analysis using K-Means Cluster Analysis identified three distinct readiness profiles: High Readiness (high scores across all dimensions, minimal barriers), Medium Readiness (strong on STEM and technology integration, but moderate barriers and lower DL literacy), and Low Readiness (low scores across almost all dimensions, high barriers). Each cluster demonstrates distinct professional development needs, ranging from mentor and innovator roles for high-readiness teachers to foundational strengthening and intensive mentoring for low-readiness teachers. These findings underscore the importance of a data-driven, differentiated training model that integrates the Mindful, Joyful, and Meaningful framework to enhance both technical competency and pedagogical depth. This approach has implications for education policy, teacher training practices, and future research linking teacher readiness profiles to student learning outcomes.

INTRODUCTION

The transformation of 21st-century education in Indonesia is directed toward developing high-quality human resources to realize the vision of Indonesia Emas 2045 (Puspa et al., 2023). This paradigm shift in learning is reflected in curriculum modifications, the utilization of new media, and the integration of technology (Rosyid & Mubin, 2024) with innovations such as the Blended

Learning Model (BLM) deemed relevant for addressing challenges while preparing 21st-century competencies (R. Rahayu et al., 2022). Modern educational management demands comprehensive innovation, cross-stakeholder collaboration, and the optimization of information technology (Missouri et al., 2025), in line with the emphasis on developing the 4C skills: critical thinking, communication, collaboration, and creativity to cultivate an excellent, intelligent, competitive, and character-driven generation (Puspa et al., 2023). This transformation requires a shift from bureaucratic systems toward more innovative, collaborative, and technology-based approaches(Missouri et al., 2025), characterized by the integration of advanced technologies, personalized learning approaches, and a focus on strengthening critical thinking and problem-solving skills (Arsyad et al., 2024);(Dangar, 2025). Such a shift aims to address global challenges, technological advancements, and the evolving demands for competencies (Kurniawan, 2025) through curriculum adjustments, innovative teaching methods, and a redefinition of the educator’s role (Arsyad et al., 2024; Kurniawan, 2025).

Although barriers such as unequal access and resistance to change persist, opportunities emerge through global collaboration and flexible learning approaches (Kurniawan, 2025). Ultimately, this transformation underscores the creation of an inclusive, adaptive, and sustainable education system (Bell, 2016; Kurniawan, 2025), oriented toward sustainability and responsible citizenship to prepare learners for environmental, social, and economic challenges. This requires a transformative educational approach that fosters future-oriented thinking and strategic planning toward a more sustainable world (Bell, 2016). Teachers, therefore, must master skills that go beyond subject matter expertise. The integration of Science, Technology, Engineering, and Mathematics (STEM) with the principles of Deep Learning has been recognized as an effective strategy to equip students with critical, creative, collaborative, and communicative thinking skills. However, the successful implementation of such innovations largely depends on teacher readiness, which encompasses not only mastery of STEM concepts and Deep Learning literacy but also confidence in using technology, proficiency in operating educational application features, and the ability to address challenges that arise in the classroom.

Teacher readiness in mastering STEM (Science, Technology, Engineering, and Mathematics) instruction, Deep Learning literacy, and educational technology varies significantly across individuals and groups. These differences are influenced by educational background, teaching experience, access to professional development, and the availability of technological infrastructure (Kafyulilo et al., 2023; Voogt et al., 2018). This is reinforced by findings showing that contextual, project-based STEM training in Indonesia can significantly enhance teachers' TPACK mastery and confidence in integrating technology particularly when combined with direct mentoring and problem-based tasks grounded in local issues (Rahayu & Widodo, 2021). High-readiness teachers typically possess strong STEM conceptual mastery, can design Deep Learning-based instruction that fosters higher-order thinking skills, and are confident in leveraging digital technologies to support learning (Darling-Hammond et al., 2020). In contrast, low-readiness teachers often face barriers such as limited digital literacy, insufficient experience in technology integration, and resistance to instructional innovation (Bingimlas, 2009; Ertmer & Ottenbreit-Leftwich, 2010). Unfortunately, many existing teacher training programs remain generic and undifferentiated, making them less effective in addressing the specific needs of different teacher groups. Professional development designed without considering variations in initial competence, learning styles, and contextual challenges tends to have limited impact on changing teaching practices (Dixon et al., 2014;Liang et al., 2025). Cluster-based professional development approaches in Java and Bali have proven effective in tailoring content and support to teachers' readiness levels, resulting in increased technological self-efficacy among novice clusters and improved quality of authentic tasks among advanced clusters (Suwarma & Wibowo, 2022). A mismatch between training design and teacher profiles can reduce the effectiveness of knowledge and skill transfer, as well as diminish teachers' motivation to implement new strategies (Opfer & Pedder, 2011). Conversely, training that integrates the principles of differentiated instruction by adapting content, processes, and support to teacher profiles, has been shown to enhance teacher efficacy, job satisfaction, and the sustainability of practice changes. In this study, teacher readiness is mapped into five complementary dimensions: (1) STEM: the level of mastery of core concepts in science, technology, engineering, and mathematics; (2) Deep Learning Literacy: the understanding and application of instructional strategies that promote deep thinking and knowledge transfer; (3) Self-Efficacy in Technology-Enhanced Learning: teachers' confidence in integrating technology into the teaching–learning process; (4) Application Feature Skills: technical proficiency in operating software or applications that support learning; and (5) Learning Challenges: both technical and non-technical barriers encountered in implementing innovative teaching.

One of the root causes of the low effectiveness of teacher training is the lack of comprehensive, data-based teacher readiness profiles to serve as a foundation for designing targeted training programs. A data-driven profiling approach enables more accurate mapping of teachers' strengths and weaknesses, whether in content mastery, pedagogical skills, or technology literacy, through surveys, classroom observations, and performance assessments (Hu et al., 2025; Kafyulilo et al., 2023). Such profiles can be used to group teachers into specific categories or clusters, allowing training to be differentiated according to the needs of each group (Meutstege et al., 2023). Without such profiles, training risks being irrelevant, less effective, and failing to produce sustainable changes in teaching practice (Dixon et al., 2014). Therefore, integrating data-driven profiling into teacher professional development planning is a strategic step to ensure that interventions have a tangible impact on improving instructional quality. Studies in Malaysia and Thailand have shown that school-based professional learning communities (PLCs) combining lesson study and coaching can enhance teachers' higher-order questioning skills and collaboration, while also positively influencing students' problem-solving abilities (Phonapichat & Wongwanich, 2021).

Cluster analysis is an effective statistical approach for mapping and grouping teachers based on similarities in their readiness profiles, encompassing pedagogical competence, content mastery, and technological skills. By identifying recurring patterns and shared characteristics, this method enables the development of more accurate readiness profiles, such as high-, medium-, or low-readiness groups ((Howard et al., 2021; Pozas et al., 2022; Doğan et al., 2023). These profiles serve as a critical foundation for designing relevant and targeted professional development interventions. The resulting mapping can be translated into a clear training needs map, allowing development strategies to be structured in a staged or tiered manner according to each teacher group's readiness level. This tiered professional development approach enables the delivery of general training at the initial stage, followed by more specific support for groups requiring intensive mentoring, while high-readiness teachers can be directed toward developing instructional innovations and serving as mentors.

Furthermore, linking the results of cluster analysis with the pillars of mindful, joyful, and meaningful ensures that teacher training is not solely oriented toward enhancing technical skills, but also toward fostering mindfulness, creating joy in teaching, and embedding meaningfulness in the learning process (Feriyanto & Anjariyah, 2024; Subali et al., 2023). Mindful training helps teachers manage stress and improve focus; joyful training fosters an engaging and motivating learning atmosphere; while meaningful training ensures that the content remains relevant to real classroom contexts. Integrating these three pillars into cluster-based training design can enhance teacher engagement, strengthen pedagogical competence, and promote the implementation of learning practices that have a holistic positive impact on students. Thus, the combination of data-driven mapping through cluster analysis, tiered training design, and the integration of mindful, joyful, and meaningful values constitutes a comprehensive strategy that not only improves teachers' technical capacity but also enhances the quality of the teaching–learning experience in a sustainable manner. Cluster analysis offers an evidence-based approach to grouping teachers according to their readiness profiles across the five key dimensions. By identifying groups of teachers with similar characteristics, training designers can develop differentiated and staged professional development schemes. This approach ensures that each teacher receives interventions aligned with their specific needs, while simultaneously integrating the principles of mindful, joyful, and meaningful so that professional development unfolds with full awareness, enjoyment, and relevance.

The objectives of this study are to: (1) map teacher readiness profiles across five key dimensions using cluster analysis; (2) formulate a staged professional development scheme aligned with these profiles; and (3) link the development strategy with the principles of mindful, joyful, and meaningful.

RESEARCH METHODS

This study employed a quantitative approach with a cross-sectional survey design to capture the profile of teacher readiness at a specific point in time. The primary objective was to identify patterns of teacher readiness for STEM instruction oriented toward Deep Learning through cluster analysis, thereby enabling the formulation of a differentiated professional development framework. The participants were teachers from various educational levels in the Province of Bali, selected through purposive sampling based on their involvement in programs or training related to STEM and Deep Learning. A total of 115 teachers participated, representing diverse educational backgrounds, teaching experience, and subject areas. The research instrument was a structured questionnaire developed based on a literature review and teacher readiness indicators across five main dimensions: (1) STEM : measuring mastery of core concepts in science, technology, engineering, and mathematics; (2) Deep Learning Literacy : measuring understanding and application of instructional strategies that promote deep thinking; (3) Self-Efficacy in Technology-Enhanced Learning : measuring teachers' confidence in integrating technology into instruction; (4) Application Feature Skills : measuring technical proficiency in operating learning-support applications; and (5) Learning Difficulties : measuring technical, pedagogical, and contextual barriers faced by teachers. Each item used a 4-point Likert scale (1 = very low, 4 = very high), with items in the Learning Difficulties dimension reverse-coded so that higher scores indicated lower barriers. The questionnaire was distributed both online (via Google Forms/Microsoft Forms) and offline during teacher training activities. Respondents were provided with an explanation of the study's objectives and assurances of data confidentiality. The collected data were exported into Excel format for cleaning and analysis. The procedure for data analysis is presented in the flowchart below.

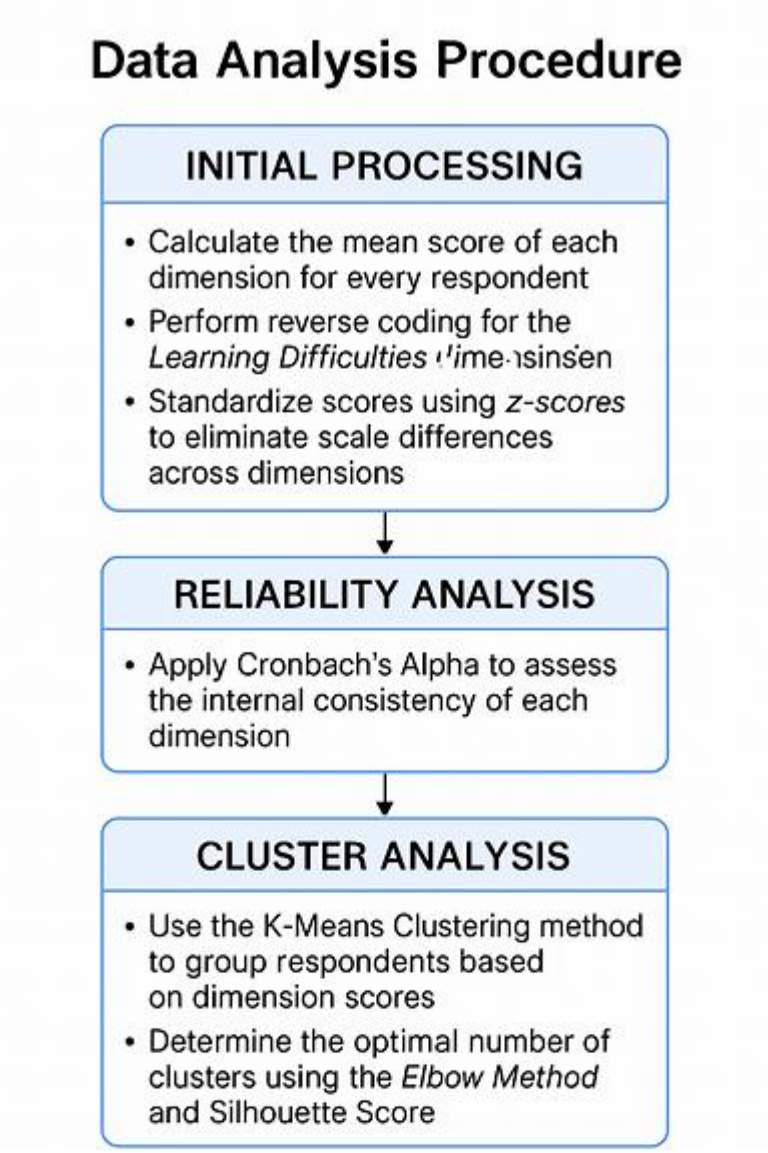

Figure 1. Data Analysis Procedure

The flowchart depicts the sequential stages of data analysis, beginning with initial data processing (mean score calculation, reverse coding, and z-score standardization), followed by reliability testing using Cronbach's Alpha, cluster analysis with the K-Means method (including determination of the optimal number of clusters via the Elbow Method and Silhouette Score), and concluding with cluster profile visualization. This study adhered to the principles of educational research ethics, including informed consent, data confidentiality, and the use of data solely for academic purposes.

RESULTS AND DISCUSSION

Descriptive analysis of 115 respondents revealed variations in teachers' readiness levels across the five measured dimensions: STEM, Deep Learning Literacy, Self-Efficacy in Technology-Enhanced Learning, Application Feature Skills, and Learning Difficulties. The highest mean scores were observed in the dimensions of Technological Self-Efficacy (M = 3.39; SD = 0.63) and Basic STEM (M = 3.33; SD = 0.54), indicating that teachers generally possess a relatively strong confidence in integrating technology and a solid grasp of fundamental STEM concepts. In contrast, the lowest score was recorded in the Learning Difficulties dimension (M = 2.80; SD = 0.71), suggesting the persistence of significant barriers to implementing innovative teaching practices. Deep Learning Literacy (M = 3.28; SD = 0.63) and Application Feature Skills (M = 3.13; SD = 0.46) fell within the medium category, highlighting the need to strengthen DL-based pedagogical strategies and optimize the use of educational technology features. These findings provide an initial overview of the strengths and challenges that can serve as focal points for targeted teacher professional development interventions. The detailed statistical results are presented in Table 1.

Table 1. Descriptive Statistics by Dimension

Dimension	Min	Maks	Mean	SD
STEM	2,2	4,0	3,33	0,54
Deep Learning Literacy	1,6	4,0	3,28	0,63
Technological Self-Efficacy	1,56	4,0	3,39	0,63
Application Feature Skills	2,0	4,0	3,13	0,46
Learning Difficulties	1,8	4,0	2,80	0,71

Cluster analysis using the K-Means Clustering method with five standardized variables yielded three optimal clusters, as determined by the Elbow

Method and Silhouette Score. Cluster 1 (High) was characterized by high scores across all dimensions of teacher readiness—Basic STEM (M = 3.93), Deep Learning Literacy (M = 4.00), Technological Self-Efficacy (M = 4.00), Application Skills (M = 4.00)—and very low barriers (M = 4.00). Cluster 2 (Medium) demonstrated moderate scores in Basic STEM (M = 3.20) and Technological Self-Efficacy (M = 3.33), with moderate barriers (M = 2.80). In contrast, Cluster 3 (Low) exhibited low scores in nearly all dimensions—Basic STEM (M = 2.73), Deep Learning Literacy (M = 2.40), Technological Self-Efficacy (M = 2.56), Application Skills (M = 2.67)—and high barriers (M = 1.93). These findings indicate substantial differences in teacher readiness profiles, which can serve as a foundation for designing differentiated training strategies tailored to the needs of each cluster. The results of the cluster analysis are presented in Table 2, which displays the mean scores for each dimension across the three clusters.

Table 2. Mean Scores per Dimension by Cluster

Dimension	Klaster 1	Klaster 2	Klaster 3
STEM	3,93	3,20	2,73
Deep Learning Literacy	4,00	3,20	2,40
Technological Self-Efficacy	4,00	3,33	2,56
Application Feature Skills	4,00	3,00	2,67
Learning Difficulties	4,00	2,80	1,93

Table 2 shows that Cluster 1 exhibits an almost symmetrical profile, with scores approaching the maximum across all dimensions. Cluster 2 demonstrates strengths in STEM and technology, but lower performance in the low-barrier dimension. Cluster 3 records low scores across all dimensions, particularly in the low-barrier and Deep Learning Literacy dimensions. The High-Readiness Cluster excels in all dimensions while maintaining low barriers. The Medium-Readiness Cluster is strong in STEM and technology, yet still experiences moderate barriers. The Low-Readiness Cluster is weak across all dimensions, especially in Deep

Learning Literacy and the low-barrier dimension. Individual scores for each dimension are presented in Figure 2.

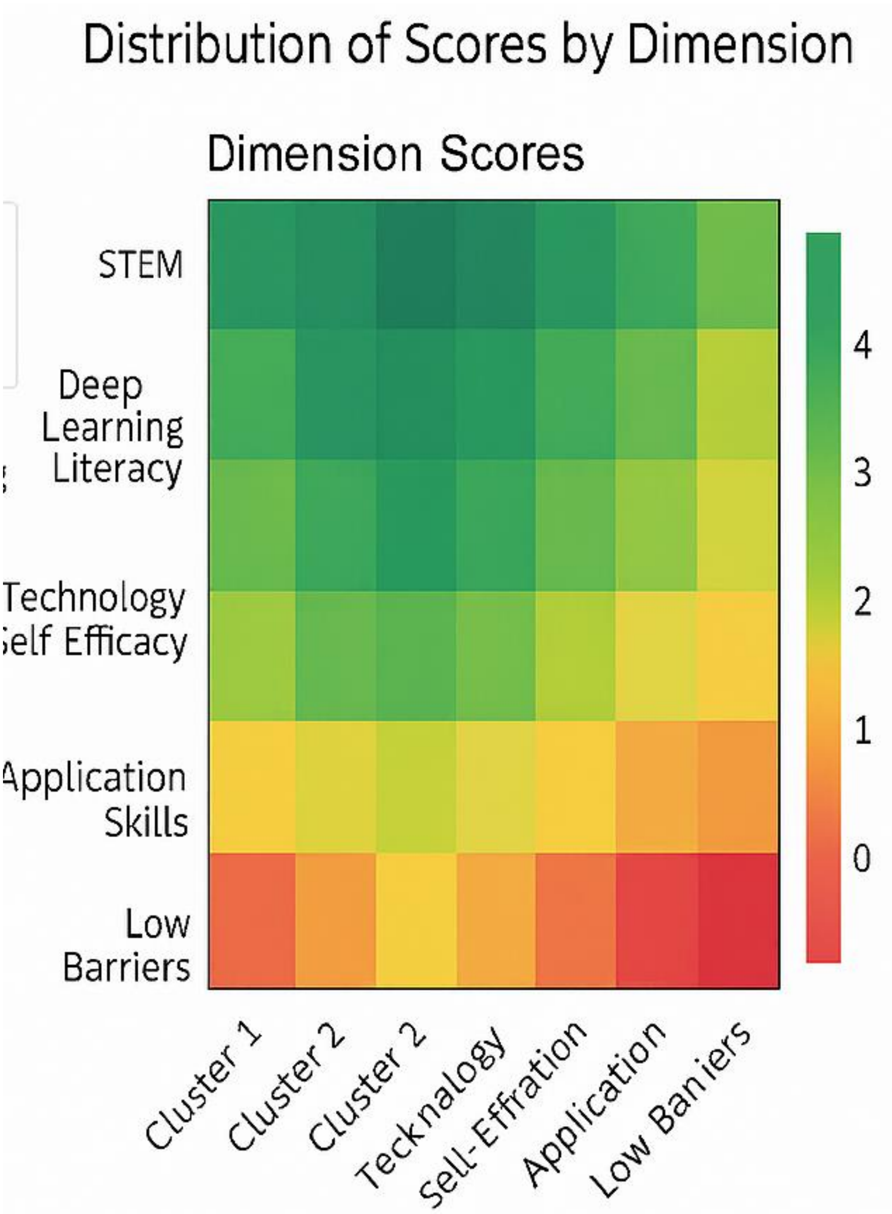

Figure 2. Distribution of Individual Scores Across Five Readiness Dimensions

Figure 2 reveals a clear color gradient pattern across clusters. Cluster 1 is predominantly represented in green (high scores), Cluster 2 displays a mix of green and yellow (moderate scores), and Cluster 3 tends toward yellow and red (low scores). Cluster 2 demonstrates strengths in STEM and technology, yet still exhibits moderate barriers. The color pattern accentuates the distinctions among clusters: the High-Readiness Cluster consistently scores high across all dimensions, the Low-Readiness Cluster consistently scores low, and the Medium-Readiness Cluster shows more variation. Figure 3 presents a comparison of dimensions by cluster.

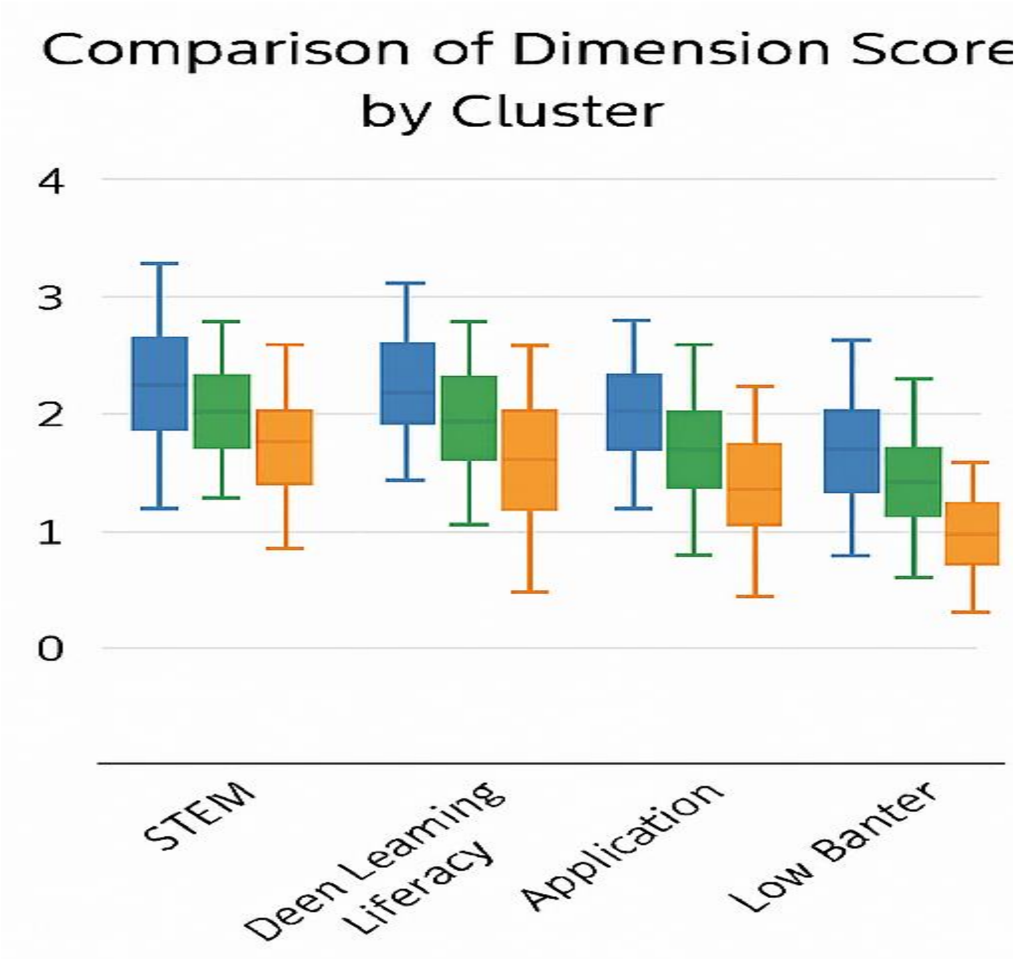

Figure 3. Comparison of Score Distributions by Cluster

Figure 3 illustrates significant median differences among clusters across all dimensions. The greatest score variation is observed in the Learning Difficulties dimension, indicating substantial differences in teachers' perceptions and experiences regarding instructional barriers. Median differences and score ranges between clusters are particularly pronounced in the low-barrier dimension, which exhibits the largest variation.

It can thus be interpreted that samples in the High-Readiness Cluster have strong potential to serve as mentors or training facilitators. Samples in the Medium-Readiness Cluster require reinforcement in Deep Learning literacy and strategies to reduce barriers. Meanwhile, samples in the Low-Readiness Cluster need gradual interventions focusing on foundational mastery and contextual support. These findings reinforce the urgency of differentiated teacher training based on readiness profiles, aligned with the pillars of mindful (full awareness), joyful (enjoyable learning), and meaningful (meaningful learning). The implementation of Teachable Machine in a high school biology image classification project has been shown to enhance students' computational literacy and stimulate critical discussions on data bias (Wang & Zhang, 2022). A staged deep learning workshop utilizing Teachable Machine for STEM project design has also been found to enhance teachers' self-efficacy in using lightweight AI and to produce authentic, data-driven instructional units (Hsu & Ching, 2024). Figure 4 presents the results and implications of this study.

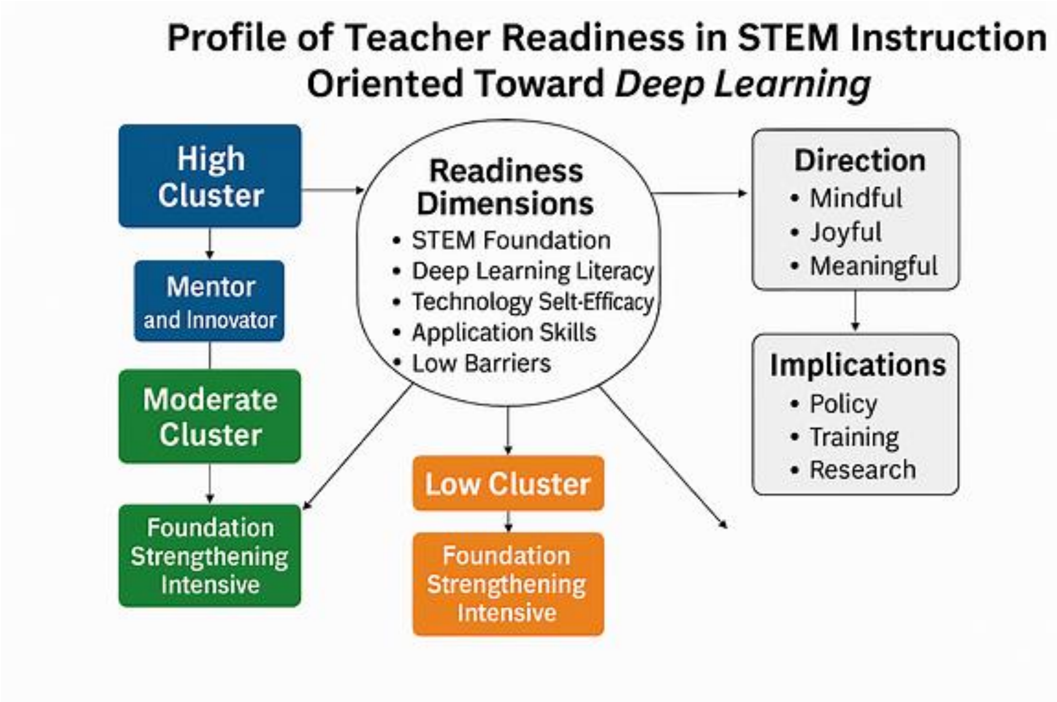

Figure 4. Profile of Teacher Readiness in Deep Learning-Oriented STEM Education

This figure presents the profile of teacher readiness in Deep Learning-oriented STEM education, categorized into three clusters: high, medium, and low. Each cluster exhibits unique characteristics across five readiness dimensions STEM, Deep Learning Literacy, Technological Self-Efficacy, Application Feature Skills, and Low Barriers—along with developmental directions integrated with the pillars of mindful, joyful, and meaningful. The visualization also highlights strategic implications for policy, training, and research, serving as a reference for designing targeted teacher professional development interventions.

The findings of this study reveal three distinct teacher readiness profiles that differ significantly across five key dimensions: Basic STEM, Deep Learning Literacy, Technological Self-Efficacy, Application Feature Skills, and Low Barriers. This pattern reinforces previous evidence that teacher readiness is multidimensional and cannot be measured solely through a single aspect of competence (Fullan et al., 2018; Voogt et al., 2018). The high-readiness cluster, with consistently high scores across all constructs, reflects the condition described by Darling-Hammond (2017) as high-capacity educator teachers who demonstrate mindfulness toward learning objectives, possess strong technological skills, and have high confidence in integrating meaningful learning strategies. Such readiness enables them to manage classrooms with reflective, adaptive approaches oriented toward developing 21st-century competencies. Recent meta-analyses have identified that adequate duration, discipline-specific content focus, active learning, collaboration, and coaching are core features of STEM professional development (PD) that consistently improve teaching practices and student learning outcomes, particularly when aligned with the local curriculum.

The High-Readiness Cluster records scores approaching the maximum across all dimensions, reflecting capacities aligned with the concept of high-agency educators (Darling-Hammond et al., 2020). Teachers in this cluster possess strong STEM mastery, deep pedagogical literacy, high confidence in using technology, and minimal barriers. These conditions enable them to integrate mindful learning (full awareness of goals and processes), joyful learning (creating enjoyable learning experiences), and meaningful learning (connecting instruction to real-world contexts and local culture). Recent literature affirms that teachers with such profiles play a strategic role as peer mentors and drivers of innovation in schools (Kafyulilo et al., 2023). (Kafyulilo et al., 2023). A meta-analysis of science/mathematics teacher coaching indicates that coaching significantly enhances the effects of deep learning on classroom practice and student outcomes, with feedback frequency identified as a key factor (Kraft et al., 2021).

The Medium-Readiness Cluster demonstrates strengths in STEM and technology integration but records moderate scores in Deep Learning literacy and low-barrier dimensions. This aligns with the findings of Howard et al. (2021), which highlight that technological proficiency does not automatically translate into the ability to design meaningful learning experiences. Effective interventions for this group involve training that links technical skills with Deep Learning-based pedagogical strategies, ensuring that technology is used not merely as a tool but as a lever for transformative learning. A systematic review of TPACK research from 2010–2020 emphasizes that authentic task design, simple simulations, and reflective practice are the most effective strategies for enhancing teachers' TPACK (Willermark, 2022). Similarly, a systematic review of deeper learning interventions in STEM reports moderate effects on students' cognitive achievement and motivation, with the sustainability of practice highly dependent on sustained, tiered deep learning support (Hiebert & Morris, 2020).

The Low-Readiness Cluster shows low scores across nearly all dimensions, particularly in Deep Learning literacy and low-barrier dimensions. This profile is consistent with studies by Bingimlas (2009) and Ertmer & Ottenbreit-Leftwich (2010), which highlight that high technical and pedagogical barriers can hinder innovation adoption. A culturally responsive pedagogy approach (Gay, 2018) is recommended for this cluster, focusing on strengthening foundational skills, enhancing technological self-efficacy, and reducing barriers through contextual support relevant to local culture.

Overall, these findings underscore the importance of differentiated teacher training based on readiness profiles. The tiered professional development model derived from this cluster analysis aligns with theOECD (2023) recommendations on personalized professional learning, which emphasize that training should be tailored to teachers' needs, capacities, and contexts. Integrating the pillars of mindful, joyful, and meaningful at every level of training ensures that professional development not only enhances technical competencies but also fosters intrinsic motivation and the relevance of learning.

STEM (Science, Technology, Engineering, and Mathematics) is an integrative instructional approach that combines these four disciplines within interconnected contexts to address real-world problems. Rather than teaching content in isolation, this approach integrates cross-disciplinary concepts and practices to create authentic and meaningful learning experiences (Bybee, 2010; Kelley & Knowles, 2016)). STEM integration encourages students to understand the relationships among science, technology, engineering, and mathematics, and how such knowledge can be applied in everyday life and the workplace (Wells & Ernst, 2015). STEM is an instructional approach that emphasizes active learning strategies, focusing on the resolution of authentic, real-world problems through the integration of technology. This approach is designed to foster heightened engagement across behavioral, empathetic, emotional, and cognitive domains (Santana et al., 2020). In the context of 21st-century education, STEM directly contributes to the development of higher-order thinking skills (HOTS) such as critical thinking, creativity, collaboration, and communication (Baharin et al., 2018; Dare et al., 2021), while also preparing students to address global challenges such as climate change, food security, and digital transformation (Bybee, 2013; Thomas & Watters, 2015).

In parallel, Deep Learning (DL) in education emphasizes meaningful learning, conceptual connections, and the transfer of knowledge across contexts (Mystakidis, 2021). DL focuses on developing complex competencies such as critical thinking, problem-solving, creativity, and metacognitive skills (Osika et al., 2022). Teachers' DL literacy is reflected in their ability to design learning experiences that promote analysis, synthesis, and evaluation (Anderson & Krathwohl, 2001), facilitate reflective discussions, and integrate strategies such as project-based learning, case studies, or simulations (Levin, 2024; Polman et al., 2021).

Research indicates that teachers' DL literacy is positively correlated with student engagement and learning outcomes (Hussain et al., 2021; Kikas et al., 2024). However, its development remains constrained by the limited availability of training focused on DL strategies rather than solely on content mastery (Mehta & Fine, 2019; Tucker, 2023).

In addition to STEM mastery and Deep Learning literacy, technological self-efficacy is a critical factor in teacher readiness. Technological self-efficacy refers to teachers' belief in their ability to integrate technology into instruction (Bandura, 1997), which is positively correlated with the frequency and quality of ICT use in the classroom (Ertmer & Ottenbreit-Leftwich, 2010). Factors such as prior experience, institutional support, and the availability of infrastructure also influence this level of confidence (Tschannen-Moran & Hoy, 2001). Teachers with low self-efficacy tend to avoid using technology or limit its use to basic functions (Inan & Lowther, 2010).

Conversely, application feature skills, the technical ability to operate educational software or applications such as learning management systems (LMS), interactive quiz tools, or online collaboration platforms (Redecker, 2017), enable teachers to facilitate interaction, assessment, and personalized learning (Breiner et al., 2012), and contribute significantly to the effectiveness of both online and face-to-face instruction (Trust et al., 2016). However, skill gaps persist, particularly in the use of advanced features that require specialized training (Howard et al., 2021).

Teachers also face learning difficulties that encompass technical, pedagogical, and contextual barriers (Ertmer & Ottenbreit-Leftwich, 2010), such as limited infrastructure, resistance to change, heavy workloads, and insufficient support from school leadership (Hew & Brush, 2007). Unaddressed barriers can diminish teachers' motivation to innovate (Bingimlas, 2009), underscoring the need for strategies such as contextualized training, mentoring, and consistent policy support (Kafyulilo et al., 2023).

To design targeted interventions, cluster analysis can be employed to group teachers based on shared characteristics (Hair et al., 2010). In education, this method is valuable for mapping teacher readiness profiles so that training can be tailored to the specific needs of each group (Liu, 2009). Research has shown that cluster-based differentiated training can enhance the effectiveness of professional development and accelerate the adoption of instructional innovations (Guskey, 2002)

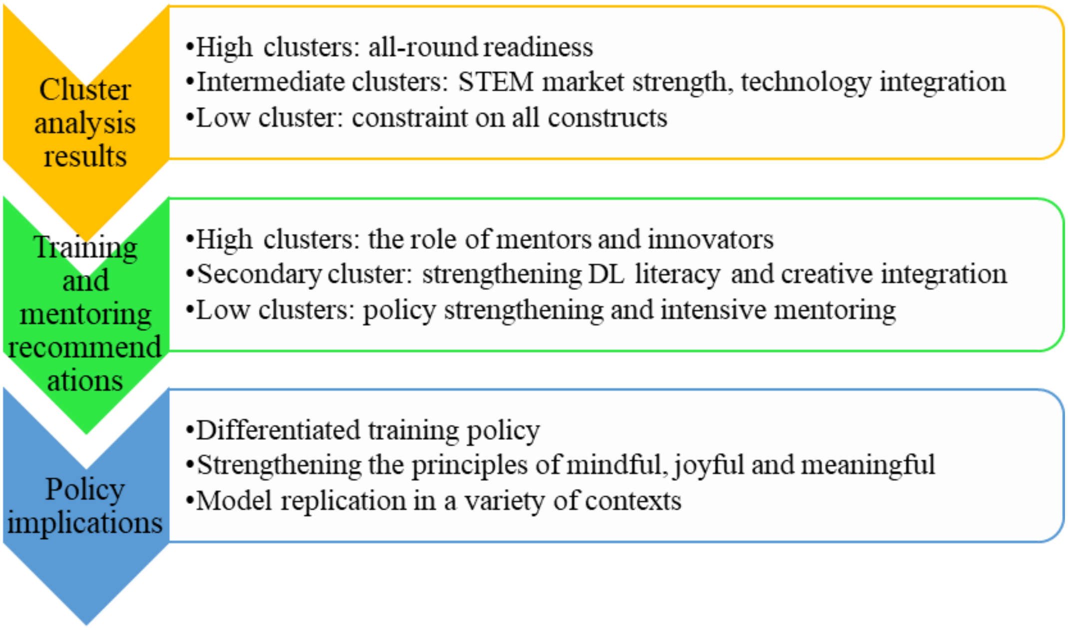

Figure 5. Cluster Analysis Results, Training Recommendations, and Policy Implications

Figure 5 summarizes the outcomes of the cluster analysis, associated training and mentoring recommendations, and resulting policy implications. The **cluster analysis results** indicate three distinct readiness profiles: the *High-Readiness Cluster* (all-round readiness), the *Medium-Readiness Cluster* (strengths in STEM and technology integration), and the *Low-Readiness Cluster* (constraints across all constructs). The training and mentoring recommendations highlight differentiated strategies: high-readiness teachers as mentors and innovators, medium-readiness teachers requiring reinforcement in Deep Learning literacy and creative integration, and low-readiness teachers needing foundational strengthening and intensive mentoring. The policy implications emphasize the need for differentiated training policies, the integration of *mindful*, *joyful*, and *meaningful* principles, and the potential for replicating the model across diverse educational contexts.

The findings of this study carry strategic implications for education policy, teacher training practices, and future research. At the policy level, teacher readiness cluster profiles can serve as a foundation for formulating more targeted training policies, enabling more efficient allocation of resources—time, budget, and facilitators. Integrating the pillars of mindful, joyful, and meaningful into professional development policies has the potential to strengthen commitment and ensure the sustainability of STEM–DL implementation in schools. Cluster data can also be utilized as performance indicators for regions or schools in adopting instructional innovations, thereby enabling evidence-based monitoring and evaluation processes.

In practice, cluster-based differentiated training allows teachers to receive content aligned with their readiness level, reducing cognitive overload for low-readiness clusters while maximizing the potential of high-readiness clusters. A peer mentoring approach, in which high-readiness teachers support medium- and low-readiness peers, can accelerate skill transfer and foster collaborative professional networks. Integrating local wisdom into training modules can further enhance relevance and teacher engagement, particularly in regions with strong cultural contexts such as Bali.

For future research, expanding the study to other regions is necessary to test the consistency of cluster patterns and identify contextual factors influencing teacher readiness. Developing more sensitive instruments to detect short-term changes is also important to enable real-time measurement of intervention effectiveness. Furthermore, exploring the relationship between teacher readiness profiles and student learning outcomes is crucial to ensure that improvements in teacher competence translate directly into enhanced instructional quality.

This study has several limitations that should be considered when interpreting the findings and formulating follow-up actions. First, the sample was limited to teachers in a specific region, meaning the resulting cluster profiles may not fully represent the diversity of contexts in other areas. Second, the use of selfreport instruments through perception-based questionnaires may be influenced by social desirability bias or differences in respondents' interpretation of the items. Third, the cross-sectional design captures conditions at a single point in time and therefore cannot record longitudinal changes in teacher readiness. Fourth, contextual variables such as school policy support, technology access, and organizational culture were not analyzed in depth, even though these factors may influence readiness levels. Finally, the limited generalizability of the results means that the findings and recommendations are most relevant to contexts with similar characteristics, and their application in different settings will require careful adaptation.

CONCLUSIONS AND RECOMMENDATIONS

This study maps teacher readiness for Deep Learning-oriented STEM instruction into three distinct clusters. The High-Readiness Cluster demonstrates comprehensive readiness, with consistently high scores across all constructs, reflecting the capacity to integrate instructional innovations in a mindful, joyful, and meaningful manner. The Medium-Readiness Cluster shows strengths in STEM and technology integration but requires reinforcement in Deep Learning literacy and application skills. The Low-Readiness Cluster faces significant barriers across all constructs, indicating the need for gradual interventions that are contextually and culturally relevant. These findings affirm that differentiated teacher training based on readiness profiles is an effective strategy to maximize the potential of each group while reducing competency gaps in implementing innovative teaching practices.

Based on these findings, the following recommendations are proposed. In a cluster-based professional development strategy, high-readiness teachers should serve as mentors and innovators, be engaged as facilitators or peer mentors in internal training, and be encouraged to develop locally informed DL–STEM projects and disseminate their innovations. Medium-readiness teachers should focus on strengthening Deep Learning literacy and creative integration through staged training that links technological proficiency with DL-based pedagogical strategies, as well as the use of local case studies to enhance relevance and engagement. Low-readiness teachers should prioritize strengthening foundational STEM concepts and digital literacy, accompanied by intensive mentoring using a culturally responsive approach that connects content to local wisdom, thereby making learning more meaningful. Across all clusters, a cross-cutting strategy should be applied by integrating the mindful, joyful, and meaningful pillars into every training module, alongside regular evaluations to monitor progress and adjust interventions as needed.

REFERENCES

Anderson, L. W., & Krathwohl, D. R. (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives* Longman.

Arsyad, M., Fitroh, I., & Arifin, M. S. (2024). Transforming 21st Century Education: Analysing the Implementation of Technology in Teaching and Learning. *Jurnal Ilmiah Edukatif*, *10*(2), 332–341. https://doi.org/10.37567/jie.v10i2.3423

Baharin, N., Kamarudin, N., & Manaf, U. K. A. (2018). Integrating STEM Education Approach in Enhancing Higher Order Thinking Skills. *International Journal of Academic Research in Business and Social Sciences*, *8*(7). https://doi.org/10.6007/IJARBSS/v8-i7/4421

Bell, D. V. J. (2016). Twenty-first Century Education: Transformative Education for Sustainability and Responsible Citizenship. *Journal of Teacher Education for Sustainability*, *18*(1), 48–56. https://doi.org/10.1515/jtes-2016-0004

Bingimlas, K. A. (2009). Barriers to the Successful Integration of ICT in Teaching and Learning Environments: A Review of the Literature. *EURASIA Journal of Mathematics, Science and Technology Education*, *5*(3). https://doi.org/10.12973/ejmste/75275

Breiner, J. M., Harkness, S. S., Johnson, C. C., & Koehler, C. M. (2012). *What Is STEM? A Discussion About Conceptions of STEM in Education and Partnerships*. https://sci-hub.soik.top/10.1111/j.1949-8594.2011.00109.x

Bybee, R. W. (2010). Advancing STEM education: A 2020 vision. . *Technology and Engineering Teacher, 70*(1), 30–35.

Bybee, R. W. (2013). *The case for STEM education: Challenges and opportunities.*

Dangar, H. N. (2025). Transforming Learning Spaces: Key Demands for 21st Century Classrooms. *Edumania-An International Multidisciplinary Journal*, *03*(01), 30–33. https://doi.org/10.59231/edumania/9095

Dare, E. A., Keratithamkul, K., Hiwatig, B. M., & Li, F. (2021). Beyond Content: The Role of STEM Disciplines, Real-World Problems, 21st Century Skills, and STEM Careers within Science Teachers' Conceptions of Integrated STEM Education. *Education Sciences*, *11*(11), 737. https://doi.org/10.3390/educsci11110737

Darling-Hammond, L., Flook, L., Cook-Harvey, C., Barron, B., & Osher, D. (2020). Implications for educational practice of the science of learning and development. *Applied Developmental Science*, *24*(2), 97–140. https://doi.org/10.1080/10888691.2018.1537791

Dixon, F. A., Yssel, N., McConnell, J. M., & Hardin, T. (2014). Differentiated Instruction, Professional Development, and Teacher Efficacy. *Journal for the Education of the Gifted*, *37*(2), 111–127. https://doi.org/10.1177/0162353214529042

Ertmer, P. A., & Ottenbreit-Leftwich, A. T. (2010). Teacher Technology Change. *Journal of Research on Technology in Education*, *42*(3), 255–284. https://doi.org/10.1080/15391523.2010.10782551

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

Fullan, M., Quinn, J., & McEachen, J. (2018). *Deep learning: Engage the world change the world*. Corwin.

Guskey, T. R. (2002). Professional Development and Teacher Change. *Teachers and Teaching*, *8*(3), 381–391. https://doi.org/10.1080/135406002100000512

Hew, K. F., & Brush, T. (2007). Integrating technology into K-12 teaching and learning: current knowledge gaps and recommendations for future research. *Educational Technology Research and Development*, *55*(3), 223–252. https://doi.org/10.1007/s11423-006-9022-5

Howard, S. K., Tondeur, J., Siddiq, F., & Scherer, R. (2021). Ready, set, go! Profiling teachers' readiness for online teaching in secondary education. *Technology, Pedagogy and Education*, *30*(1), 141–158. https://doi.org/10.1080/1475939X.2020.1839543

Hsu, T.-C., & Ching, Y.-H. (2024). Tiered professional development for integrating AI tools in STEM classrooms: The case of Teachable Machine. . *Computers & Education*. https://doi.org/10.1016/j.caeo.2024.100157

Hu, Y., Pan, J., & Liu, J. (2025). *Data-Driven Teachers' Professional Development* (pp. 485–497). https://doi.org/10.1007/978-981-97-8148-5_52

Hussain, S., Gaftandzhieva, S., Maniruzzaman, Md., Doneva, R., & Muhsin, Z. F. (2021). Regression analysis of student academic performance using deep learning. *Education and Information Technologies*, *26*(1), 783–798. https://doi.org/10.1007/s10639-020-10241-0

Inan, F. A., & Lowther, D. L. (2010). Factors affecting technology integration in K-12 classrooms: a path model. *Educational Technology Research and Development*, *58*(2), 137–154. https://doi.org/10.1007/s11423-009-9132-y

Kafyulilo, A., Fisser, P., & Voogt, J. (2023). Teacher design teams for technology integration: Sustainability and professional growth. *Education and Information Technologies*, *28*(5), 5671–5692.

Kelley, T. R., & Knowles, J. G. (2016). A conceptual framework for integrated STEM education. In *International Journal of STEM Education* (Vol. 3, Issue 1). Springer. https://doi.org/10.1186/s40594-016-0046-z

Kikas, E., Silinskas, G., & Härma, E. (2024). Topic- and learning-related predictors of deep-level learning strategies. *European Journal of Psychology of Education*, *39*(3), 2129–2153. https://doi.org/10.1007/s10212-023-00766-6

Kraft, M. A., Blazar, D., & Hogan, D. (2021). The effect of teacher coaching on instruction and achievement: A meta-analysis of the causal evidence. *Journal* *of Teacher Education*, *72*(4), 394–417. https://doi.org/10.1177/002248712100005

Kurniawan, S. (2025). Transformation Education System and Challenges and Opportunities in the 21st Century. *Nuris Journal of Education and Islamic Studies*, *5*(2), 139–150. https://doi.org/10.52620/jeis.v5i2.121

Levin, O. (2024). Simulation as a pedagogical model for deep learning in teacher education. *Teaching and Teacher Education*, *143*, 104571. https://doi.org/10.1016/j.tate.2024.104571

Liu, X. (2009). *Science and the Public Beyond Science Literacy: Science and the Public*. http://www.ijese.com/

Mehta, J., & Fine, S. (2019). *In search of deeper learning: The quest to remake the American high school*. Harvard University Press.

Missouri, R., Jamilah, S., Masita, Sahid, A., & Safira, D. P. (2025). Tinjauan Sistematis terhadap Inovasi, Kolaborasi, dan Teknologi dalam Manajemen Pendidikan Abad 21. *Pendiri: Jurnal Riset Pendidikan*, *2*(2), 65–73. https://doi.org/10.63866/pendiri.v2i2.88

Mystakidis, S. (2021). Deep Meaningful Learning. *Encyclopedia*, *1*(3), 988–997. https://doi.org/10.3390/encyclopedia1030075

OECD. (2023). *PISA 2022 Assessment and Analytical Framework*. https://doi.org/10.1787/1330e9b6-en

Opfer, V. D., & Pedder, D. (2011). Conceptualizing Teacher Professional Learning. *Review of Educational Research*, *81*(3), 376–407. https://doi.org/10.3102/0034654311413609

Osika, A., MacMahon, S., Lodge, J. M., & Carroll, A. (2022). *Deep and meaningful learning: Taking learning to the next level.* . Times Higher Education.

Phonapichat, P., & Wongwanich, S. (2021). Professional learning communities for STEM pedagogy in ASEAN secondary schools. *Asia-Pacific Education Researcher*, *30*(5), 451–463. https://doi.org/10.1007/s40299-020-00542-3

Polman, J. L., Kyza, E. A., & O'Neill, D. K. (2021). *Learning and becoming in practice: The role of professional learning communities in education.* . Routledge.

Puspa, C. I. S., Rahayu, D. N. O., & Parhan, M. (2023). Transformasi Pendidikan Abad 21 dalam Merealisasikan Sumber Daya Manusia Unggul Menuju Indonesia Emas 2045. *Jurnal Basicedu*, *7*(5), 3309–3321. https://doi.org/10.31004/basicedu.v7i5.5030

Rahayu, R., Iskandar, S., & Abidin, Y. (2022). Inovasi Pembelajaran Abad 21 dan Penerapannya di Indonesia. *Jurnal Basicedu*, *6*(2), 2099–2104. https://doi.org/10.31004/basicedu.v6i2.2082

Rahayu, S., & Widodo, A. (2021). Enhancing Indonesian science teachers' technological pedagogical content knowledge through project-based STEM training. *Jurnal Pendidikan IPA Indonesia*, *10*(3), 355–366. https://doi.org/10.15294/jpii.v10i3.31584

Redecker, C. (2017). European framework for the digital competence of educators: DigCompEdu. *Publications Office of the European* .

Rosyid, A., & Mubin, F. (2024). PEMBELAJARAN ABAD 21: MELIHAT LEBIH DEKAT INOVASI DAN IMPLEMENTASINYA DALAM KONTEKS PENDIDIKAN INDONESIA. *Tarbawi : Jurnal Pemikiran Dan Pendidikan Islam*, *7*(1), 1–12. https://doi.org/10.51476/tarbawi.v7i1.586

Santana, O. A., Sousa, B. A. de, Monte, S. R. S. do, Lima, M. L. de F., & Silva, C. F. e. (2020). Deep learning practice for high school student engagement in STEM careers. *2020 IEEE Global Engineering Education Conference (EDUCON)*, 164–169. https://doi.org/10.1109/EDUCON45650.2020.9125281

Subali, B., Ellianawati, Faizah, Z., & Sidiq, M. (2023). Indonesian national assessment support: Can RE-STEM Android app improve students' scientific literacy skills? *International Journal of Evaluation and Research in Education*, *12*(3), 1399–1407. https://doi.org/10.11591/ijere.v12i3.24794

Suwarma, I. R., & Wibowo, F. C. (2022). Cluster-based professional development to differentiate STEM teacher learning needs in Indonesia. *Cakrawala Pendidikan*, 319–331. https://doi.org/10.21831/cp.v41i2.41239

Trust, T., Krutka, D. G., & Carpenter, J. P. (2016). "Together we are better": Professional learning networks for teachers. *Computers & Education*, *102*, 15–34. https://doi.org/10.1016/j.compedu.2016.06.007

Tschannen-Moran, M., & Hoy, A. W. (2001). Teacher efficacy: capturing an elusive construct. *Teaching and Teacher Education*, *17*(7), 783–805. https://doi.org/10.1016/S0742-051X(01)00036-1

Voogt, J., Fisser, P., Good, J., Mishra, P., & Yadav, A. (2018). Computational thinking in compulsory education: Towards an agenda for research and practice. *Education and Information Technologies*, *23*(3), 1–17.

Wang, F., & Zhang, J. (2022). Bringing machine learning to the biology classroom with Teachable Machine: A case study. *International Journal of STEM Education*, *9*(1), 45. https://doi.org/10.1186/s40594-022-00357-4

Wells, J. G., & Ernst, J. V. (2015). Integrative STEM education. . *Technology and Engineering Teacher*, *74*(4), 8–13.