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Adaptive Cognitive Learning in Vocational Education: Integrating Deep Learning for Fiber optic Network Competencies

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Abstract

The rapid advancement of digital technologies, particularly Deep Learning, presents opportunities to enhance adaptive cognitive learning in vocational education. This study investigates the integration of Deep Learning into the teaching of fiber optic network competencies in the Computer and Network Engineering (TJKT) program at vocational schools. Using a Systematic Literature Review (SLR) based on the PRISMA protocol, relevant studies published between 2020 and 2025 were retrieved from Scopus, IEEE Xplore, and Google Scholar. Findings reveal that Deep Learning enables real-time modeling of student learning patterns, supports personalized content delivery via learning management systems, and facilitates simulation and troubleshooting in fiber optic training. However, challenges include limited training data, inadequate computing infrastructure, and insufficient teacher readiness. The study concludes that implementing Deep Learning can significantly improve practical learning effectiveness, provided that infrastructure and educator competencies are strengthened.

Keywords: adaptive learning, deep learning, digital transformation, fiber optic, vocational education.

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INTRODUCTION

The development of digital technology has brought significant changes to several sectors, including vocational education. Vocational education is required to produce graduates who possess technical skills in line with industry needs. Currently, the area that is most urgent is Information and Communication Technology (ICT), as one of the competencies that is highly in demand across many sectors is networking. In particular, fiber optic networks, because they are a crucial part of the global communications infrastructure that underpins high-speed Internet services, 5G networks, and cloud computing systems (Cruzes, 2024). Consequently, fiber optic networking is highly sought after by students in Technical and Vocational High Schools (TVET) (Sa'adah, 2025). However, traditional methods sometimes remain an alternative for VHS's teachers to present theory related to the complexity of installation, maintenance, and troubleshooting of fiber optics. Based on the study conducted by Sa'adah (2025) at VHS across East Java, this is due to several factors: (1) limited laboratory facilities, (2) high costs of tools and materials, and (3) limited governance of VHS's industry collaborations in the fiber optic sector.

Conventional learning responses to the limitations the concept of cognitive-based adaptive learning has emerged. This approach emphasizes the design of strategies, content, and learning pace that align with learners' cognitive abilities. A cognitive-based adaptive system is characterized by the personalization of materials through real-time cognitive monitoring, the provision of tailored feedback, and the reinforcement of metacognitive aspects to foster learner autonomy. While this approach is rooted in cognitivist theory, its development has been greatly supported by digital technologies particularly learning analytics and artificial intelligence making the learning process more responsive and better aligned with individual needs (Orji & Vassileva, 2022; Zhao et al., 2024).

Alongside this development, the emergence of Artificial Intelligence (AI) particularly the increasingly prominent Deep Learning (DL) offers new opportunities for advancing cognitive-based adaptive learning. Deep Learning enables real-time analysis of learners' learning patterns, the personalization of instructional materials, and the provision of interactive simulations that can approximate hands-on laboratory experiences, even when physical facilities are limited (Aljaloud et al., 2022; Lin et al., 2025). A growing body of research has demonstrated that the integration of DL into e-learning and learning management systems (LMS) can enhance learner motivation, efficiency, and learning outcomes (Brunotte et al., 2025; Xie et al., 2025).

However, most studies on the application of Deep Learning in education remain focused on general academic areas such as language learning, academic performance prediction, or educational pattern recognition. In contrast, within technical domains, several studies have highlighted the use of Deep Learning for detecting fiber optic network disruptions and maintaining communication systems. Research on AR/VR-based media for fiber optic installation training has also begun to emerge (Sa'adah, 2025). Nevertheless, these initiatives have not yet fully incorporated Deep Learning. Furthermore, recent reviews on DL in vocational education reveal persistent challenges related to digital infrastructure and educators' capacity (Zhao et al., 2024).

Given these conditions, the present study aims to systematically examine the integration of Deep Learning in adaptive learning for fiber optic networks through a Systematic Literature Review (SLR) using the PRISMA framework (Page et al., 2021). The focus of this research is to analyze the role of Deep Learning in modeling student learning patterns, supporting instructional personalization, and providing troubleshooting simulation facilities in fiber optic network learning.

METHOD

This study employs a Systematic Literature Review (SLR) approach, following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). SLR was chosen as the research method because it allows for a comprehensive, transparent, and structured synthesis of

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various studies related to the integration of Deep Learning in fiber optic network learning. The review process involved the following stages:

a. Identification: Articles were identified through a systematic search in reputable international databases, namely Scopus, IEEE Xplore, Web of Science (WoS), and Google Scholar using the Publish or Perish application. The search was restricted to publications from 2020-2025 to ensure alignment with the most recent developments in Deep Learning technology. The keywords used included Deep Learning, Artificial Intelligence, Adaptive Learning, Cognitive Learning, Vocational Education, Fiber Optic, Optical Network. The initial search yielded 420 articles.
b. Screening: At this stage, a peer review of article titles and abstracts was conducted to assess their relevance to the research topic. After this process, 110 relevant articles remained and were taken to the next stage.
c. Eligibility: A full-text review was carried out. Articles that did not meet the criteria, such as editorial reviews or those not focused on the integration of Deep Learning in vocational learning, were excluded. After this stage, 50 articles were deemed eligible for further analysis.
d. Inclusion: Articles that fulfilled all criteria were included in the synthesis stage. The 50 eligible articles were analyzed both narratively and thematically in order to answer the research questions and draw conclusions.

The final outcomes of these four stages are as follows: (1) The integration of Deep Learning in vocational education, (2) Its implementation in fiber optic network learning at vocational high schools (VHS), and (3) The strengthening of digital infrastructure and the enhancement of teacher competence in implementing adaptive learning using Deep Learning.

RESULTS AND DISCUSSION

3.1 Result

Based on the Systematic Literature Review (SLR) using the PRISMA protocol of articles published between 2020 and 2025, three main findings were identified that illustrate the direction and challenges of integrating Deep Learning (DL) in vocational education, particularly in fiber optic network learning at vocational high schools (VHS). These findings include: (1) the integration of DL in vocational education to promote cognitive-based adaptive learning, (2) the implementation of DL in fiber optic learning with an emphasis on intelligent simulation and troubleshooting, and (3) the importance of strengthening infrastructure and teacher competence as key factors for successful implementation. The first finding is elaborated as follows:

3.1.1 Integration of Deep Learning in Vocational Education

The integration of Deep Learning (DL) in vocational education not only introduces technological innovation but also transforms the learning paradigm from teacher-centered to learner-centered adaptive learning. DL functions by modeling students' cognitive representations through rich data sources such as learning activity logs, response times, error trajectories, and knowledge tracing. Theoretically, the integration of DL can be understood through several frameworks:

a) Cognitive Load Theory (Sweller, 2011): DL can regulate students' cognitive load by adjusting the level of material difficulty to match individual capacity.
b) Personalized Learning Paradigm: Through student modeling, DL creates dynamic and contextual learning profiles rather than static ones.
c) Self-Regulated Learning (Zimmerman, 2002): DL supports the development of metacognitive skills, such as awareness of repeated mistakes or delays in task completion.

LSTM (Long Short-Term Memory) models have proven effective for sequential prediction of

student performance, while Transformer-based architectures (e.g., BERT and GPT derivatives) are capable of understanding complex relationships between learning activities (Alnasyan et al., 2024). Recent meta-analyses indicate that DL-based student performance prediction improves content recommendation accuracy by up to 35% higher compared to traditional rule-based methods.

DL implementation requires a teacher-in-the-loop system importantly, where teachers are not replaced but rather empowered. Teachers act as curators and validators, ensuring that algorithmic recommendations remain aligned with students' social and psychological contexts. This aligns with the framework of Augmented Pedagogy, which positions technology as a supportive agent, while teachers remain the primary drivers of the learning process (Sperling et al., 2024). The implication is that integrating DL into vocational education paves the way for an adaptive learning ecosystem that accommodates differences in learning styles, learning pace, and student readiness levels, while simultaneously maintaining relevance to industry needs.

3.1.2 Implementation in Fiber Optic Network Learning at Vocational High Schools

At the implementation level, particularly in fiber optic network programs at vocational high schools (VHS), Deep Learning (DL) functions as a reinforcement tool for virtual practicum through interactive simulations and intelligent troubleshooting. This context is highly significant since vocational learning requires hands-on skills, which are often constrained by limitations in laboratories, equipment, and costs. The contribution of DL can be described through three main aspects:

a. AI-driven Simulation
   1) DL creates virtual environments where students can practice splicing, fusion, OTDR testing, and network configuration.
   2) These environments are safe, cost-efficient, and accessible repeatedly without consuming physical materials.
   3) Research by Chen et al. (2023) shows that DL-based simulations accelerate students' practical skill acquisition by up to 40% faster compared to conventional methods.

b. Intelligent Troubleshooting
   1) DL is capable of error detection and diagnosis by recognizing recurring patterns in students' mistakes.
   2) The system can provide real-time feedback in the form of corrective suggestions without waiting for teacher intervention.
   3) This approach aligns with Experiential Learning Theory (Kolb, 1984), which emphasizes the importance of a cycle of direct experience, reflection, conceptualization, and application.

c. Equity and Accessibility

   DL functions as a compensation mechanism for facility limitations, providing equal opportunities for vocational high school (VHS) students in regions with restricted laboratory access. Research by Rahman et al. (2022) indicates that DL-based simulations can improve skill retention by 30–40% among students who lack direct hands-on practice. Beyond its technical benefits, the implementation of DL in fiber optic learning also carries a dimension of industry relevance. Students are not only equipped with theoretical knowledge but also trained to face real-world field conditions, which are often dominated by troubleshooting challenges. Consequently, DL strengthens the role of vocational schools (VHS) as providers of industry-ready workforces in the context of the Fourth Industrial Revolution (Industry 4.0) and digital transformation.

3.1.3 Strengthening Infrastructure and Enhancing Teacher Competence in Implementing Adaptive Learning with Deep Learning

The successful integration of Deep Learning (DL) in vocational education, particularly in fiber

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optic learning at vocational high schools (VHS), is determined not only by algorithmic capabilities but also by the readiness of infrastructure and teacher competence as key enabling factors.

a. Technological Infrastructure, three key elements of infrastructure are required:
   1) Hardware: Implementing DL requires high-performance devices, particularly GPUs/TPUs, to train and run models. Without adequate hardware, real-time modeling will be hindered, reducing system effectiveness.
   2) High-speed internet connectivity: DL-based simulations and troubleshooting demand stable connections to access cloud-based platforms and AI-integrated LMS. Poor internet infrastructure will limit students' access to materials and virtual laboratory simulations.
   3) Cloud and big data systems: For optimal personalized learning, student data must be securely collected, stored, and processed. Cloud computing ensures scalable storage and processing capacity while enabling real-time analytics to support adaptive learning (Huang et al., 2024).

   In addition, data security and privacy concerns must be addressed. Student data management should comply with data governance principles, including encryption, access control, and adherence to digital privacy regulations. Without clear governance, DL implementation risks algorithmic bias and ethical violations.

b. Teacher Competence

   The second critical aspect is the competence of vocational teachers, who act as both facilitators and orchestrators in integrating DL system recommendations into classroom practice. Required competencies include:
   1) AI and DL literacy: Teachers must understand the fundamentals of DL models (e.g., how systems detect student error patterns and recommend remediation). This knowledge allows teachers to evaluate the validity of algorithmic outputs and connect them to learning contexts (Tan et al., 2025).
   2) Digital pedagogical skills: Beyond mastering technical content, teachers need to transform DL analytical results into learning strategies that are humanistic, inclusive, and tailored to student needs.
   3) Evaluative and reflective capacity: Teachers must remain the ultimate decision-makers (teacher-in-the-loop), ensuring system recommendations are not applied rigidly but are integrated with pedagogical intuition and local knowledge.

   Zary's (2025) study on the AI-based teaching factory model emphasizes that teachers' roles are not replaced by technology; rather, they become even more crucial as mediators between technology and students. Teachers are not merely users but also co-designers of adaptive learning practices.

c. Synergy Between Infrastructure and Teacher Competence

   Strengthening infrastructure without enhancing teacher capacity leads to technological determinism, where technology exists but cannot be fully utilized. Conversely, skilled teachers without sufficient infrastructure face technical constraints (Masykuri, et al, 2025). Therefore, successful DL integration requires synergy: robust digital infrastructure, clear data governance policies, and sustainable professional development programs for vocational teachers. This perspective can be framed as a socio-technical system model, in which the interaction between technology, human actors (teachers), and institutions determines the effectiveness of DL-based adaptive learning. In other words, DL integration is not merely a technological issue but a comprehensive transformation of the vocational education ecosystem.

3.2 Discussion

The integration of Deep Learning (DL) in vocational education has recently begun to be recognized as a strategic step rather than merely a technological experiment. Vocational education fundamentally requires practical skills that students must truly master, making adaptive learning systems

that can adjust to individual needs highly important. With DL, the learning process of students can be mapped more comprehensively from task completion patterns and recurring errors to levels of conceptual understanding (Masykuri, et al, 2025). Based on these data, the system can recommend remedial materials or enrichment exercises with greater precision. This differs from conventional learning, which is generally uniform for all students, without considering differences in learning pace and style (Navas-Bonilla et al., 2025).

In the specific context of fiber optic learning at vocational high schools (VHS), the implementation of DL has shown significant impact. Fiber optics involves not only theoretical knowledge but also technical skills such as cable splicing and network troubleshooting. Typically, the limited availability of practice tools makes it difficult for teachers to provide equal hands-on experience to all students. DL can fill this gap: AI-driven simulations can adjust levels of difficulty according to students' abilities, enabling them to practice step by step. Beyond that, DL can also act as a "virtual assistant" that provides instant feedback when students make mistakes in simulations. This allows learners to receive immediate guidance from the system without always waiting for teacher intervention (Budiarto et al., 2025).

Despite its potential, DL implementation in vocational high schools inevitably faces challenges. Two main aspects must be addressed: infrastructure and teacher competence. From an infrastructure perspective, schools need to provide adequate hardware and network capacity, including cloud-based systems to ensure simulations are accessible anytime. Without this support, DL adoption often remains at the discourse level. At the same time, teachers play a crucial role in interpreting system recommendations. While DL may suggest which students require remedial support, the final decision lies in the teacher's hands. Therefore, AI literacy for teachers is essential, ensuring that students do not become passive users but are instead guided by educators who can critically evaluate, adapt, and enrich system recommendations (Granström & Oppi, 2025). In sum, the integration of DL in vocational education particularly in fiber optic learning at VHS should be viewed as a collaboration between technology and human expertise. DL systems assist in mapping and directing the learning process, while teachers remain the central authority ensuring that learning aligns with classroom context and student needs. With adequate infrastructure and competent educators, DL holds great potential to make fiber optic learning more adaptive, effective, and industry-relevant (Ramansyah, et al, 2024).

CONCLUSIONS

Based on the above review, it is evident that Deep Learning (DL) can be a "game changer" in vocational education, particularly in fiber optic learning at vocational high schools (SMK). First, DL supports the creation of more adaptive and personalized learning, where each student receives materials tailored to their abilities and learning styles. Second, through AI-driven simulations and intelligent troubleshooting, students can practice more safely, flexibly, and in ways that closely mirror real-world industry conditions. Third, the success of such integration largely depends on robust infrastructure (devices, networks, and platforms) as well as teachers' competencies in leveraging technology while continuing to serve as the primary mentors for students. DL should not be seen merely as an additional technology but rather as a foundation for transforming vocational education into a system that is more relevant, inclusive, and responsive to the challenges of the future workforce.

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