Chapter 14
Seamless Data Integration for Predictive Learning Environments

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ABSTRACT

This research explores predictive learning structures in connected environments and shows that seamless integration of multi-purpose data through intelligent architectures enables adaptive and personalized learning. Leveraging the Internet of Things, artificial intelligence, and real-time analytics, educational systems are able to accurately predict learner behavior and performance and deliver targeted interventions. By introducing data-driven frameworks, this study addresses the technical, ethical, and cognitive requirements for designing such environments and outlines a roadmap for future education.

1. INTRODUCTION

In the current era, the spread of emerging technologies such as the Internet of Things (IoT), artificial intelligence (AI), and learning analytics has fundamentally transformed the way we teach and learn. One of the most important approaches in this transformation is the creation of predictive learning environments that contin-

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uously analyze learner performance and optimize their educational path based on data from the brain. Such environments require the integration of diverse data from heterogeneous sources, including smart sensors, educational platforms, interaction-based systems, and behavioral data, which must be integrated into secure, scalable, and compatible platforms (Moon et al., 2024).

Seamless Data Integration, as a key prerequisite for creating these environments, requires the design of infrastructures that can integrate multi-purpose and time-sensitive data streams with minimal latency and maximum accuracy. In connected education ecosystems, data is received not only from multiple sources but also from different levels – from the edge to the cloud. This data includes physiological information, location, classroom behaviors, learning histories, and even emotional and cognitive data, each of which is incomplete on its own but combined with each other can provide a comprehensive picture of the learning situation (Nozari, Szmelter-Jarosz, & Ghahremani-Nahr, 2022).

In the meantime, artificial intelligence plays a central role in analyzing hidden patterns in educational data. Machine learning models, especially in the field of supervised learning and deep learning, are able to predict learner behavior by training on combined data, warn of potential risks such as academic failure, and dynamically adapt educational content (Lee, 2007). This is especially important when educational systems are faced with cultural, cognitive, and behavioral diversity of learners; conditions that other traditional models are unable to respond to (Nozari, Fallah, Kazemipoor, & Najafi, 2021).

On the other hand, the Internet of Things (IoT) in the form of wearable sensors, smart peripherals, and interactive tools has enabled the continuous collection of precise, location-based data. Unlike traditional data that was collected after the learning event, this data is made available to analytics systems in real time, enabling timely learning decisions (Andrews, Owen, & Oye, 2025). However, the main challenge is integrating this data in a way that not only maintains analytical consistency, but also minimizes system latency and ensures data security (Nozari, Szmelter-Jarosz, & Ghahremani-Nahr, 2021).

In many current approaches, data integration is performed centrally and post-processed, which reduces efficiency in real-time learning environments. In contrast, the design of distributed architectures based on edge computing allows some of the analysis to be performed at the closest point to the data source, resulting in significantly faster decision-making and more accurate responses to learner changes (Aithal & Aithal, 2023). This paradigm shift in architecture also provides a platform for the scalability of educational infrastructures, so that educational environments can function appropriately in diverse conditions without dependence on central infrastructures (Nozari, Ghahremani-Nahr, & Szmelter-Jarosz, 2024).

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