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A Conceptual Teaching Framework For AI-Ready IoT System Design in TVET Education

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ABSTRACT

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) is reshaping industry expectations of Technical and Vocational Education and Training (TVET) graduates, who are increasingly required to work with connected, data-driven systems. However, many IoT courses remain component-based, emphasizing sensors, microcontrollers, communication, and dashboards in isolation. While this approach enables students to build functional prototypes, it often limits their understanding of overall system architecture and data readiness for future AI integration.

This paper argues that the key challenge lies not in the absence of AI instruction, but in the way foundational IoT concepts are taught. It proposes a shift toward system-oriented and data-driven IoT education, where AI readiness emerges as a natural outcome of sound system design rather than advanced algorithm training. To support this shift, the paper introduces a conceptual teaching framework consisting of four layers: sensing, connectivity, data readiness, and application intelligence to guide the organization of IoT projects and laboratory activities. The proposed framework offers a practical approach for modernizing TVET IoT courses by promoting structured data generation and system-level thinking, while also providing a foundation for future empirical studies on AIoT learning outcomes.

Keyword: AI-ready IoT, system-oriented IoT education, data-driven IoT systems, conceptual teaching framework

INTRODUCTION

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has increasingly shaped the design and deployment of modern intelligent systems across various industries. Contemporary IoT systems extend beyond basic device connectivity and monitoring, relying instead on structured data pipelines that support analytics, prediction, and intelligent decision-making. Consequently, industry expectations for Technical and Vocational Education and Training (TVET) graduates have shifted toward competencies in system-level thinking and data-driven system design rather than isolated technical skills.

Despite this shift, many existing IoT courses continue to adopt a component-based teaching approach, in which sensors, microcontrollers, communication protocols, and dashboards are introduced as separate instructional units. While such an approach enables students to assemble functional prototypes, it often limits their understanding of IoT systems as integrated architectures. In these contexts, data is frequently treated as a final output for visualization rather than as a strategic asset that flows through the system and supports future intelligence. As a result, students may complete IoT projects successfully yet lack exposure to system-level design considerations required for future AI integration. Figure 1 illustrates the contrast between conventional component-based IoT teaching and a system-oriented approach that emphasizes data readiness for AI integration.

Recent discussions in AIoT and smart system development suggest that AI readiness does not primarily arise from the late introduction of machine learning algorithms. Instead, it is strongly influenced by how well IoT systems are designed from the outset, particularly in terms of architectural coherence, data continuity, and scalability. Without foundational exposure to system-oriented IoT design, efforts to incorporate AI at later stages risk becoming fragmented and superficial, highlighting a gap between prevailing teaching practices and the requirements of emerging AI-driven applications.

This paper argues that the core challenge lies not in the absence of AI-related instruction, but in the way foundational IoT concepts are structured and delivered. Addressing this challenge requires a shift toward system-oriented and data-driven IoT education, where AI readiness is treated as a natural outcome of sound system design rather than advanced algorithm-focused training. Accordingly, this paper proposes a conceptual teaching framework that reorganizes IoT learning around four functional layers: sensing, connectivity, data readiness, and application intelligence. The framework is intended to guide instructors in structuring IoT projects and laboratory activities so that student-developed systems generate clean, structured data and remain extensible for future AI integration.

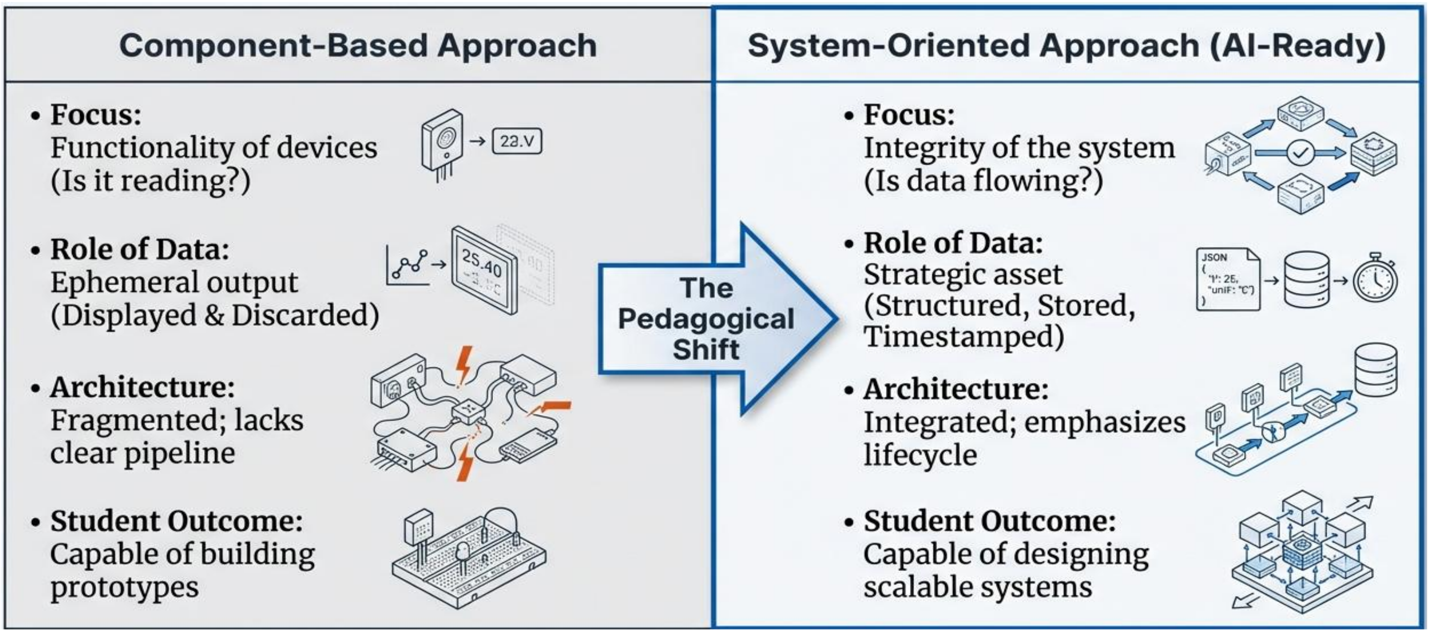

Figure 1: Conceptual shift from component-based IoT teaching toward a system-oriented, AI-ready approach.

The contribution of this paper is twofold. First, it clarifies key limitations of component-based IoT teaching in supporting AI-ready system development. Second, it introduces a practical conceptual framework that aligns IoT education with emerging paradigms in computer science and technology. While the framework is not empirically evaluated in this study, it provides a structured foundation for future implementation-based investigations in AIoT-focused TVET education.

Fundamental Issues in Current IoT Teaching Practices

Despite the rising importance of AI-enabled, data-driven systems, many IoT courses still focus on getting individual components to work rather than on designing coherent systems. This approach is useful for introducing basic skills but leaves several important gaps in preparing learners to design AI-ready IoT systems.

To overcome these limitations, IoT teaching needs a fundamental shift in perspective. Figure 1 illustrates this transition, contrasting the fragmented nature of component-based tasks with the holistic requirements of AI-ready systems. While traditional methods focus on whether a device works, the proposed system-oriented approach prioritizes data integrity and architectural continuity, ensuring systems remain scalable and prepared for future intelligence.

FROM COMPONENT-BASED IOT TO SYSTEM-ORIENTED AI-READY IOT

IoT content is often organized around separate blocks such as sensors, microcontrollers, communication, and dashboards, each taught as its own topic. Students can usually wire devices, configure protocols, and display readings, but they often see these as isolated tasks instead of parts of a single architecture. As a result, they struggle to think about end-to-end data flow, modularity, and scalability, and many projects remain one-off prototypes rather than systems that can be extended or maintained. Figure 1 illustrates how this component-based approach contrasts with a system-oriented view that emphasizes continuous data flow and integration.

Data Treated as Output, Not an Asset

In typical labs, sensor data is used mainly to drive a gauge, a chart, or a simple rule such as turning a device on or off. When data is treated only as something to display, students are rarely asked to consider its structure, quality, or long-term use. They may not think about how data is labelled, stored, timestamped, or cleaned, even though these choices determine whether it can later support analytics or AI models. Functional prototypes are therefore built on fragile or ad-hoc data practices, which limits their suitability for any serious AI-enabled extension. For example, in smart agriculture projects, the focus shifts from reading a single moisture sensor to managing an entire open farming system (Anekwong Yoddumnern, 2024).

AI Separated from Foundational IoT Learning

To respond to demand for AI skills, many programs place AI content in standalone, advanced modules that come after basic IoT courses. While administratively convenient, this reinforces the idea that AI is an optional add-on rather than a natural continuation of IoT system design. Students are asked to “do AI” without having first learned how architecture, data flow, and design decisions influence what AI can realistically achieve. This often leads to AI exercises that feel disconnected from earlier work and remain at the level of demonstrations rather than integrated, system-level solutions. Many graduates remain insufficiently prepared. Recent reviews indicate that workforce readiness now hinges on the ability to interact with and develop AI-driven technologies, a skill often missing in traditional vocational curricula (Deckker, 2025).

Taken together, these issues reveal a clear gap between how IoT is currently taught and what is actually needed for AI-ready system development. Closing this gap requires restructuring foundational IoT teaching around system-oriented thinking and data-driven design, so that AI becomes a logical next step rather than an afterthought.

Rethinking IoT Education Toward AI Readiness

The limitations outlined above show that improving AI readiness is not simply a matter of adding an extra AI module on top of existing IoT courses. Instead, it requires rethinking how foundational IoT concepts are sequenced and connected, so that learners see IoT systems as continuous data pipelines rather than collections of parts.

In this view, AI readiness becomes the result of good IoT system design, not a separate advanced skill reserved for later stages. When students learn from the beginning to plan clear data flows, ensure continuity, and think about scalability, the systems they build are naturally easier to extend with analytics and AI.

Refocusing IoT education toward AI readiness therefore means treating system architecture, data handling, and modular design as core learning outcomes, not optional extras. Embedding these ideas into early IoT instruction helps learners understand how each design decision affects data quality, system flexibility, and the feasibility of adding intelligence later on.

This shift in perspective provides the foundation for the conceptual teaching framework introduced in the next section, which organizes IoT learning around system-oriented principles and offers a practical structure for AI-ready projects and laboratory activities.

PROPOSED CONCEPTUAL TEACHING FRAMEWORK FOR AI-READY IOT SYSTEMS

This section introduces a teaching framework that reorganizes IoT learning around system-oriented, data-driven principles. It treats AI readiness as the result of good IoT system design, not as a separate topic to be added at the end. The framework is meant to help instructors plan projects and labs so that students develop a clear sense of architecture and data flow across the whole system. The framework mirrors the architecture of industrial AIoT solutions, where similar layered approaches have been successfully implemented in community-based IoT learning centres (Anekwong Yoddumnern, 2024).

Framework overview

The framework consists of four layers: sensing, connectivity, data readiness, and application intelligence. Each layer captures a core function of an IoT system and shows how early design choices affect what is possible later. The model is technology-neutral, so it can be implemented with different boards, networks, or platforms while keeping the same underlying structure. Figure 2 summarizes these layers and how they work together to support AI-ready IoT system design.

Sensing layer

The sensing layer covers how data is captured from the physical environment. Here, students learn to think beyond wiring sensors and reading values and instead consider whether the data collected is meaningful for the problem they are trying to solve. Attention is given to relevance, consistency, and sampling strategy so that sensing is understood as the starting point of system behavior, not just a hardware exercise.

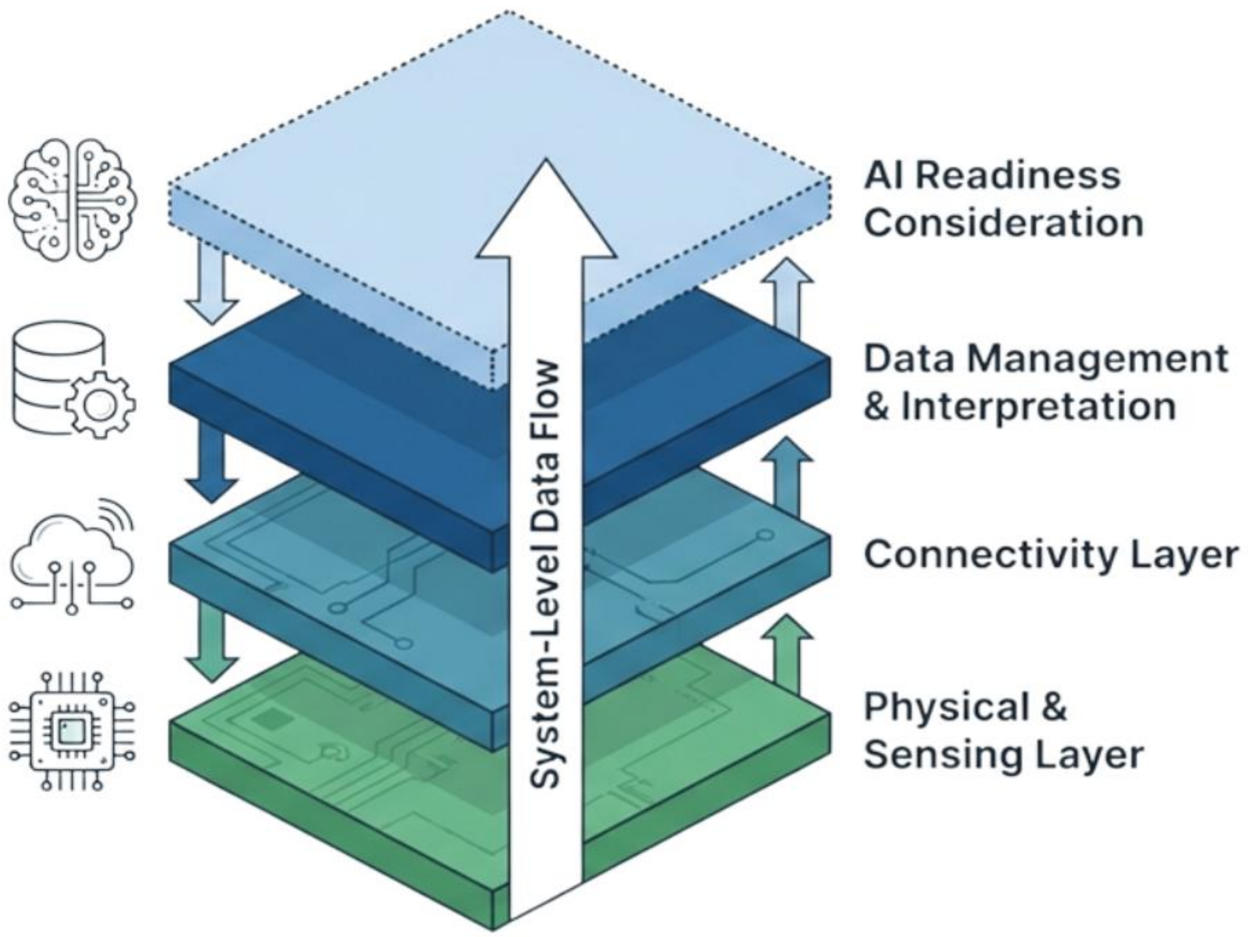

Figure 2: Proposed conceptual teaching framework for AI-ready IoT system design, illustrating the progression from sensing and connectivity to data readiness and application intelligence.

Connectivity layer

The connectivity layer focuses on how data moves through the system. Communication choices are discussed in terms of their impact on continuity, reliability, and integration with other components. By presenting connectivity as part of an end-to-end data pipeline, students are encouraged to connect protocol decisions with latency, scalability, and overall system robustness.

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Data readiness layer

The data readiness layer is the main departure from typical IoT teaching. Instead of stopping at display or basic control, this layer asks how data is structured, labeled, stored, and maintained over time. Students work with ideas such as formats, timestamps, and basic quality checks, and begin to see that well-prepared data is what makes later analysis or AI realistically possible. This layer acts as the bridge between "working IoT project" and "AI-capable system." Figure 3 illustrates this transformation, showing how raw sensor values (left) are converted into structured, machine-readable data (right) through labeling, timestamps, and consistent formatting.

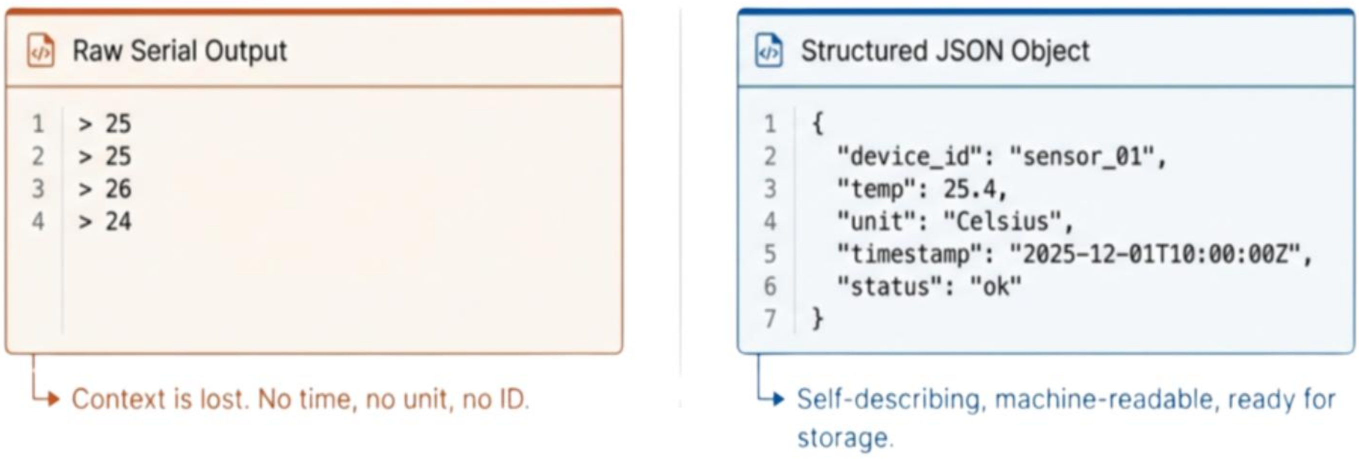

Figure 3: Illustration of data readiness through comparison between raw sensor output and structured, machine-readable data.

Application intelligence layer

The application intelligence layer represents how the system could support smarter behavior once suitable data is available. In this framework, students are not required to implement full AI models; rather, they design the system so that intelligent functions could be plugged in later. This helps them see AI as a natural extension of the architecture and data they have already built, instead of a separate, opaque add-on.

Instructional implications

For teaching, the framework offers a clear progression from basic hardware interaction to future-ready system design. Organizing labs and projects by layers encourages students to ask, at each step, how their decisions affect the rest of the system and its ability to evolve. This provides a practical way to align IoT education with emerging AIoT practices, while keeping the approach flexible enough for different programs, resources, and institutional contexts.

Table 1: Proposed Assessment Criteria for the Data Readiness Layer

Criteria	Novice (1-2)	Competent (3-4)	AI-Ready (5)
Data Structure	Raw values only (e.g., 25)	Labeled values (e.g., temp: 25)	Standardized format (e.g., JSON {"t": 25, "unit": "C"})
Temporal Context	No timing information	Manual timing	Automated Timestamping (ISO 8601 format)
Data Continuity	Real-time view only	Short-term logging	Persistent storage/database ready for export

DISCUSSION

The proposed framework directly targets the main weaknesses of current IoT teaching by shifting attention from isolated components to system-level, data-driven design. It gives learners a clear structure for seeing how choices at each layer affect overall system behaviour and the ability to extend a prototype into a more capable solution.

A key strength of the framework is its explicit focus on data readiness as a design goal, not an afterthought. By treating data as a continuous asset that must be generated, shaped, and maintained across the system, it aligns classroom projects with how AIoT systems actually succeed or fail in practice. This encourages students to think beyond short-term display functions and begin considering how their systems could support analytics and AI in the future.

For TVET settings, the framework remains practical because it is conceptual and platform-agnostic. Educators can map it onto existing boards, tools, and project briefs, using the layers to structure labs, project milestones, or assessment rubrics without needing major infrastructure changes. In this way, programs can gradually modernize their IoT curriculum while staying close to industry-relevant system design principles. Successful integration requires alignment with institutional goals, often framed within an Enterprise Architecture (EA) approach to manage digital complexity in TVET (Noor et al., 2025).

Crucially, the framework is not intended to replace hands-on work or to force advanced AI content into early courses. Instead, it strengthens the foundation so that when AI topics are introduced whether in later modules or further study. Students are ready to connect them to robust architectures and clean data pipelines. This ensures that TVET graduates remain technically proficient and aligns with recent calls for a 'closed-loop' training model where industry needs directly influence teaching implementation (Zhang et al., 2025). This helps close the gap between current IoT teaching practices and the demands of AI-ready system development.

CONCLUSION

This paper has highlighted how common, component-based approaches to IoT teaching make it difficult for learners to design systems that are truly ready for AI. These approaches often stop at getting devices to work and data to appear on a screen, without developing the system-level thinking and data discipline required for intelligent, data-driven applications.

In response, the paper has proposed a conceptual teaching framework that restructures IoT learning around four layers: sensing, connectivity, data readiness, and application intelligence. By tracing how design decisions at each layer affect system extensibility and the possibility of adding AI later, the framework positions AI readiness as a natural outcome of sound IoT system design rather than early algorithm-focused instruction. The framework contributes toward a standardized pedagogical model for the AIoT era. Future iterations must also consider ethical frameworks and equitable access to digital infrastructure to ensure inclusive workforce development (Yoddumnern, 2024)

The framework offers a practical way to align IoT education with current technological developments, especially in TVET environments where hands-on work and resource constraints must be balanced. Because it is technology-agnostic, instructors can use it to organize projects and labs, encourage system-level reasoning, and foreground data-driven design without committing to specific platforms.

Future evaluations could employ practical methods such as classroom deployment with structured rubrics, analysis of student design artifacts, and comparison of system scalability between traditional and framework-guided projects.

Although the effectiveness of the framework has not yet been tested empirically, it provides a clear structure for future classroom studies. Subsequent work can investigate how using this framework influences students' understanding of system architecture, the quality of their designs, and their readiness to engage with AI-enabled IoT applications. Through such studies, the framework can further support the evolution of IoT education toward sustainable, AI-ready system development.

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