

Data-driven assessment competencies for AIoT-enhanced traffic management: A framework for educators

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Citation: Owan, V. J., Owan, M. V., & Bassey, B. A. (2026). Data-driven assessment competencies for AIoT-enhanced traffic management: A framework for educators. *Journal of Digital Educational Technology*, 6(2), Article ep2623. <https://doi.org/10.29333/jdet/19700>

ARTICLE INFO

Received: 03 May 2026

Accepted: 15 Aug. 2026

ABSTRACT

This paper, developed through a literature-informed conceptual synthesis, focused on how integrating Artificial Intelligence and the Internet of Things (AIoT) enables new approaches to urban traffic management through intelligent data collection, real-time analytics, and automated decision-making. Despite rapid technological advances, existing curricula and assessment frameworks provide little guidance for competency-based assessment, learning analytics, and institutional implementation in AIoT-enhanced traffic management education. Accordingly, the authors developed conceptual frameworks that support competency-based assessment and institutional implementation for AIoT-enhanced traffic management education. Drawing on contemporary literature in AIoT, competency-based education, learning analytics, authentic assessment, and digital education, two complementary conceptual frameworks were developed. The proposed Data-Driven Assessment Competency Framework (DACF) is associated competency domains, learning outcomes, authentic assessment tasks, evidence sources, AI-assisted analytics, educator judgement, analytic rubrics, feedback, and competency decisions. The accompanying AIoT Assessment Implementation Framework (AAIF) provides direction for strategic alignment, curriculum integration, infrastructure development, educator capacity building, and continuous evaluation to support sustainable institutional implementation. The authors further present competency progression levels, worked examples of assessments, analytic rubrics, assessment weighting, human-in-the-loop assessment practices, and quality assurance processes to support transparent and evidence-informed competency assessment. Unlike existing competency, digital education, or AI literacy frameworks, DACF and AAIF integrate competency mapping, authentic assessment, learning analytics, multi-source evidence, educator judgement, and institutional implementation within a unified model tailored to AIoT-enhanced traffic management education. Finally, the paper presents policy recommendations, a structured validation roadmap, and future research priorities to guide empirical validation and advance AIoT-enhanced traffic management education for smart city mobility.

Keywords: learning analytics, digital evidence, competency mapping, adaptive feedback, project-based learning, interoperability

INTRODUCTION

Artificial Intelligence of Things (AIoT), the integration of artificial intelligence (AI) with the Internet of Things (IoT), is rapidly transforming urban mobility management. By enabling continuous sensing, distributed computing, and data-driven control, AIoT systems are changing how cities monitor and regulate traffic (Siam et al., 2025). In smart cities, these systems employ sensor networks (interconnected devices that gather data), edge and fog computing (local processing of data near the source to reduce latency), and machine learning (algorithms that improve automatically through experience) to drive adaptive signals (traffic lights that adjust based on

conditions), real-time monitoring, and predictive routing (foreseeing and suggesting optimal travel paths). Documented benefits include improved traffic flow, safety, and environmental impact (Yusuf et al., 2025). Despite these advances, challenges such as data compatibility (the ability of different systems to work together), model validation (ensuring AI models are accurate), and stakeholder engagement (involvement of key participants) persist (Jagatheesaperumal et al., 2024). Today, AIoT traffic platforms extend beyond pilots to influence daily urban operations, using AI-based forecasting, connected vehicles (cars that communicate with networks), and safety monitoring for mobility planning (Wolniak & Stecuła, 2024).

These developments demand that system designers, managers, and regulators acquire integrated skills in AI, IoT, data analysis, and ethical judgment (Alakkari & Ali, 2025). However, a gap exists between technological progress and workforce preparedness, notably in the absence of clear curricular and assessment frameworks (Wolniak & Stecula, 2024). Technology-enhanced learning research also highlights limited assessment tools and inconsistent evaluation as barriers to practical adoption and to the development of robust competency models.

Although existing frameworks such as DigCompEdu, UNESCO AI competency frameworks, IoT curriculum models, and learning analytics frameworks are valuable, none integrates competency mapping, authentic AIoT traffic management assessment, learning analytics, evidence modelling, and institutional implementation within a single assessment architecture. This gap limits the ability of educators to design coherent competency-based assessment systems for AIoT-enhanced traffic management education. The present article addresses this limitation through the proposed Data-Driven Assessment Competency Framework (DACF) and AIoT Assessment Implementation Framework (AAIF).

To address these gaps, this article provides a clear, actionable framework that links AIoT advancements in traffic management with data-driven educational assessment. It clarifies essential concepts, identifies vital competencies, introduces the Data-Driven Assessment Competency Framework (DACF), and describes the AIoT Assessment Implementation Framework (AAIF) for institutional use. The article then discusses the policy implications and future research opportunities, underscoring the pressing need for education systems to keep pace with the realities of smart-city mobility (Lloret et al., 2025).

Unlike existing digital competency, AI literacy, and learning analytics frameworks, the proposed Data-Driven Assessment Competency Framework (DACF) and AIoT Assessment Implementation Framework (AAIF) are specifically designed for AIoT-enhanced traffic management education. The frameworks integrate competency mapping, authentic assessment, learning analytics, institutional implementation planning, and ethical governance within a unified domain-specific model. This integration extends existing frameworks by providing operational guidance for competency assessment in AIoT traffic management rather than general digital competence or AI literacy alone. Throughout this article, the term AIoT-enhanced traffic management education is used consistently to describe educational programmes, curricula, and professional training that prepare learners to design, implement, evaluate, and govern AIoT-enabled traffic management systems. This term encompasses related concepts, such as smart mobility education, AIoT-based traffic management training, and intelligent transportation education, as used in the broader literature.

METHODOLOGICAL APPROACH

This article is presented as a conceptual paper developed through a literature-informed conceptual synthesis rather than as a systematic review, scoping review, or empirical investigation. Its primary purpose is to develop theoretically grounded frameworks for competency-based and data-driven assessment in AIoT-enhanced traffic management education by integrating evidence and concepts drawn from multiple, complementary bodies of literature. Accordingly, the article does not seek to review all available publications exhaustively or to synthesise empirical findings statistically. Instead, it adopts a narrative synthesis approach to identify, compare, and integrate key concepts that inform the development of the proposed Data-Driven Assessment Competency Framework (DACF) and AIoT Assessment Implementation Framework (AAIF).

The literature informing this study was identified through iterative searches of major academic databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, and Google Scholar. Searches combined keywords and related terms, including *Artificial Intelligence of Things (AIoT)*, *traffic management*, *smart mobility*, *competency-based education*, *assessment frameworks*, *learning analytics*, *digital competence*, *educational assessment*, and *higher education*. Additional sources were identified through backward and forward citation tracking of influential publications and policy documents.

The selection of literature was guided by relevance to the study's objectives rather than by a formal review protocol. Priority was given to peer-reviewed journal articles, conference proceedings, international policy frameworks, and authoritative reports that addressed one or more of the following areas: (i) AIoT applications in intelligent transportation and smart mobility; (ii) competency-based education and assessment; (iii) digital competence and AI competency frameworks; (iv) learning analytics and evidence-centred assessment; (v) authentic assessment and rubric design; and (vi) institutional implementation of educational technologies. Sources that focused exclusively on technical AI or IoT development without educational implications, or that lacked direct relevance to competency assessment or implementation, were excluded from the conceptual synthesis.

The development of DACF and AAIF followed an iterative conceptual design process. First, the selected literature was analysed to identify recurring themes, competency requirements, assessment principles, implementation challenges, and governance considerations relevant to AIoT-enhanced traffic management education. Second, these themes were organised into coherent conceptual categories describing learner competencies, assessment evidence, learning analytics, feedback mechanisms, institutional readiness, curriculum integration, infrastructure, professional development, and quality assurance. Third, relationships among these categories were synthesised to develop two complementary frameworks. The Data-Driven Assessment Competency Framework (DACF) was designed to guide competency specification, evidence collection, assessment,

and feedback at the learner level, whereas the AIoT Assessment Implementation Framework (AAIF) was developed to support institutional planning, implementation, and continuous improvement.

The resulting frameworks therefore represent an integrative conceptual synthesis of current literature rather than empirically validated models. Their purpose is to provide theoretically grounded guidance for curriculum developers, educators, researchers, and higher education institutions seeking to design, implement, and evaluate competency-based assessment systems for AIoT-enhanced traffic management education. Empirical validation of both frameworks through expert review, pilot implementation, and multi-institutional studies is proposed as the next stage of this research programme.

CONCEPTUAL CLARIFICATION

Definition of Key Concepts

Three concepts underpin the proposed assessment frameworks: Artificial Intelligence of Things (AIoT), data-driven assessment, and competency-based learning. These concepts define the scope of the article, while the theoretical perspectives discussed in the next section explain how the proposed frameworks are designed and implemented.

1. *Artificial Intelligence of Things (AIoT)*: Artificial Intelligence of Things (AIoT) refers to the integration of artificial intelligence with Internet of Things infrastructures to support distributed sensing, communication, data processing, and autonomous or semi-autonomous decision making in near real time (Siam et al., 2025). AIoT combines intelligent processing across edge, cloud, and connected devices to enable adaptive and predictive system responses (Siam et al., 2025; Xu et al., 2024). In traffic management, AIoT links roadside infrastructure, connected and autonomous vehicles, and communication networks to support adaptive signal control, incident detection, cooperative driving, and safer urban mobility (Jagatheesaperumal et al., 2024).
2. *Data-driven assessment*: Data-driven assessment refers to the systematic use of digital evidence to evaluate learning, support feedback, and inform instructional decisions (Ghashim & Arshad, 2023). Rather than relying on isolated assessment events, it draws on multiple sources of evidence generated during learning activities, including simulation outputs, sensor data, code repositories, digital submissions, and other learner artefacts. These evidence sources support continuous assessment of technical performance, problem solving, and competency development, particularly in AIoT learning environments (Badshah et al., 2023; Tabuenca et al., 2024).
3. *Competency-based learning and competencies*: Competency-based learning emphasises demonstrated mastery rather than time spent in instruction. Competencies are integrated combinations of knowledge, skills, and professional attitudes that learners apply in authentic situations. Within STEM education, competency models commonly include technical competence,

analytical reasoning, collaboration, and ethical practice, which are assessed through authentic tasks and performance-based assessment (Abichandani et al., 2022). In AIoT-enhanced traffic management, competency extends beyond technical proficiency to include responsible decision making on issues such as privacy, fairness, safety, and sustainability (Alakkari & Ali, 2025). These competencies form the basis of the Data-Driven Assessment Competency Framework developed later in this article.

Theoretical Underpinnings

The proposed Data-Driven Assessment Competency Framework (DACF) and AIoT Assessment Implementation Framework (AAIF) are informed by five complementary perspectives. Bloom's taxonomy explains how learning outcomes progress from basic to advanced cognitive performance. Constructivism explains why authentic learning experiences are central to assessment. Competency-based education defines the competencies that learners are expected to demonstrate. DigCompEdu identifies the capabilities educators need to design and manage digital assessment, while learning analytics explains how evidence from multiple sources can be collected and interpreted to support assessment decisions. Together, these perspectives establish the conceptual basis for the two frameworks.

The revised Bloom taxonomy explains learning as a progression from remembering and understanding to analysing, evaluating, and creating. This progression aligns with AIoT learning tasks such as problem analysis, model development, system integration, and policy evaluation (González-Mujico, 2024; Phanichsiti et al., 2025). Researchers further argue that assessment in AI, computational thinking, and AIoT education should address cognitive, psychomotor, and affective learning rather than focusing only on factual recall (Lubbe et al., 2025). In the DACF, Bloom's taxonomy guides the sequencing of learning outcomes and the design of assessment tasks that require increasingly complex cognitive performance.

Constructivist theory views learning as an active process in which learners build understanding through meaningful experiences. Researchers report that authentic datasets, project-based learning, and practical problem-solving activities help learners develop AI literacy and understand the behaviour of AI models more effectively (Hong & Kim, 2025). This perspective guides the design of authentic assessment activities within the DACF, where competence is demonstrated through projects, simulations, and realistic AIoT traffic management problems rather than through isolated examinations.

Competency-based education emphasises demonstrated mastery rather than completion of prescribed learning time. Assessment therefore focuses on integrated competencies that combine knowledge, practical skills, analytical reasoning, and professional judgement (Vargas et al., 2024). Within the DACF, competency-based education informs the identification of competency domains, observable performance indicators, and progression towards mastery. It also ensures that assessment

evaluates learners' ability to apply knowledge in authentic professional situations.

DigCompEdu provides guidance on the digital competencies educators require to design, implement, and evaluate technology-supported assessment. The framework places particular emphasis on data literacy, ethical use of digital technologies, and effective assessment practices (Mattar et al., 2022). Researchers have also developed rubric-based approaches that align educator competencies with clear performance criteria for assessing digital and AIoT-related learning (González-Mujico, 2024). Within the AAIF, DigCompEdu informs educator preparation and professional development so that digital assessment practices can be implemented consistently and responsibly.

Learning analytics provides the evidence base for data-driven assessment by supporting the systematic collection, integration, and interpretation of learner data. Researchers working in competency-based education show that combining assessment records, activity logs, and observational evidence improves decisions about learner progression while strengthening assessment quality and validity (Divjak et al., 2023). In AIoT education, evidence from code repositories, simulation outputs, system logs, and sensor data can be combined to evaluate competency development. Within the DACF, learning analytics links learning outcomes with multiple evidence sources, performance indicators, dashboards, and continuous feedback.

These theoretical perspectives complement one another in the design of the proposed frameworks. Bloom's taxonomy explains how learning progresses, constructivism guides the design of authentic assessment activities, competency-based education defines what learners are expected to demonstrate, DigCompEdu identifies the educator capabilities required for implementation, and learning analytics explains how assessment evidence is generated and interpreted. The DACF draws primarily on Bloom's taxonomy, constructivism, competency-based education, and learning analytics to organise learning outcomes, assessment activities, competencies, and evidence. The AAIF extends these principles by using DigCompEdu to guide educator preparation and institutional implementation. Together, these perspectives establish a coherent theoretical basis for the frameworks developed in this article.

COMPETENCY MAPPING FOR AIoT- ENHANCED TRAFFIC MANAGEMENT

Core Competency Domains

Competency mapping organises the skills, knowledge, and dispositions needed for AIoT-based traffic management into clear domains that guide curriculum design, teaching, and assessment. Studies on AI and digital competencies, IoT curricula, and Industry 4.0 and 5.0 training often group these requirements into three main areas: technical and technological competencies; cognitive and analytical competencies; and ethical and social competencies. These areas evolve as technology advances and social expectations shift (Okada et al., 2025; Santana & Díaz-Fernández, 2023).

Technical competencies refer to the ability to design, build, and manage AIoT systems across the full technology stack. Reviews of IoT curricula and information technology programmes emphasise skills in sensing and embedded hardware, networking and communication protocols, middleware, cloud and edge services, and user interfaces, as well as programming and data management (Gumina et al., 2024). AIoT-based traffic management involves deploying sensor networks, implementing vehicle-to-everything communication, building data pipelines, training and validating AI models for prediction and control, and integrating these components into secure, reliable systems (Abichandani et al., 2022). Broader work on AI-related competencies also points to programming and the effective use of AI and data tools as essential for applying AI in real-world settings (Santana & Díaz-Fernández, 2023).

Cognitive competencies are higher-level thinking skills required to work with complex socio-technical systems. Reviews of AI literacy and related competencies identify critical thinking, problem-solving, information analysis, and adaptability as key abilities (Okada et al., 2025). In AIoT traffic management, these skills support systems-level thinking about urban mobility, interpretation of diverse data streams, identification of unusual system behaviour, and the design and evaluation of routing or control strategies under uncertainty (Abichandani et al., 2022). The UNESCO AI competency framework describes this as a progression from understanding basic concepts to applying and creating AI-based solutions (Okada et al., 2025).

Ethical and social competencies focus on responsible and human-centred use of AIoT technologies. UNESCO frameworks for students and teachers emphasise fairness, transparency, privacy, awareness of social impact, and inclusive design, linking AI to broader goals such as social justice and sustainability (Okada et al., 2025). IoT education models also include professional ethics and social responsibility alongside technical training, often through project-based tasks that connect smart-city applications to public-interest and environmental concerns. In transport and logistics, research on digital competence also stresses the need to assess digital tools in relation to working conditions and safety (Stadin et al., 2024). For AIoT traffic systems, this means understanding how sensing and control decisions affect different groups, recognising risks of bias or exclusion, and designing responses that address privacy, fairness, environmental impact, and worker wellbeing.

Across all domains, effective competency mapping depends on clear learning outcomes, defined progression stages, and multiple methods for assessing performance. Evaluation frameworks for IoT programmes explain how technical skills, practical performance, teamwork, and ethical reasoning can be assessed through exams, project rubrics, peer and self-assessment, and mentor feedback aligned with professional standards (Abichandani et al., 2022). In fast-changing AIoT settings, such evidence-based approaches help track learner development, identify skill gaps, and support regular curriculum updates in line with technological and social change (Okada et al., 2025; Santana & Díaz-Fernández, 2023).

Table 1. Comparison of DACF with existing digital competency frameworks

Framework	Primary Focus	Assessment Guidance	AIoT Traffic Specificity	Main Limitation	DACF Extension
DigCompEdu	Teacher digital competence	Moderate	No	Generic digital education	AIoT competency assessment
UNESCO AI Framework	AI competencies	Moderate	No	Broad educational orientation	Traffic management competencies
IoT Curriculum Models	Technical IoT skills	Limited	Partial	Limited competency assessment	Data-driven assessment
Learning Analytics Models	Learning evidence	Strong	No	No AIoT competency mapping	Analytics linked to competencies
Proposed DACF	AIoT competency assessment	Comprehensive	Yes	Conceptual framework	Domain-specific integrated model

Alignment With Existing Standards

Aligning AIoT traffic competency mapping with established frameworks helps maintain consistency across curriculum design, professional training, and quality assurance. The European Framework for the Digital Competence of Educators, DigCompEdu, outlines six areas: professional engagement, digital resources, teaching and learning, assessment, learner empowerment, and support for learners' digital competence. It also includes progressive proficiency levels that can be adapted across sectors and technologies (Cabero-Almenara et al., 2020). Validation studies indicate that DigCompEdu and its Check-In tools achieve acceptable reliability, cover key aspects of educator digital competence, and are often preferred to alternative models (Cabero-Almenara et al., 2020). Reviews also confirm its internal consistency and international relevance, while noting the need for local adaptation and additional tools for specialised areas (Zeng et al., 2025).

UNESCO ICT and AI competency frameworks also stress core digital skills, critical thinking, ethical awareness, and the integration of technology into teaching and assessment (Ng et al., 2024). Recent adaptations of the DigCompEdu and P21 frameworks for AI education highlight assessment, ethical reasoning, and higher-order thinking across stages such as understanding, application, evaluation, and creation (Hong & Kim, 2025; Ng et al., 2024). However, some critics warn that broad digital competence frameworks may encourage rigid, technology-focused interpretations and may limit teacher flexibility if applied without adaptation (Falloon, 2020). Other reviews note that many frameworks give less attention to dispositions, attitudes, and well-being, focusing more on technical skills and information use (Chifla-Villón et al., 2025).

For AIoT-based traffic management, these frameworks serve as useful guides but not complete solutions. They outline key areas such as assessment, ethics, and learner empowerment, but often do not explain how to assess complex AIoT tasks, such as configuring multi-layer sensor systems, deploying edge AI controllers, or balancing privacy, safety, and sustainability in traffic scenarios. Studies in IoT education and project-based learning suggest that these abilities are better assessed through practical work supported by analytics. This includes multi-criteria rubrics aligned with IoT system layers and professional practice, peer and self-assessment within extended projects, and learning analytics that track activity and generate performance indicators and feedback (Abichandani et al., 2022). AIoT-enhanced traffic management education programmes also use validated AI and digital literacy measures, often with pre- and post-assessments, to track growth in learners' competence (Hong & Kim, 2025).

The proposed AIoT traffic competency mapping, therefore, aligns with DigCompEdu and UNESCO-style frameworks to support consistency and transfer across settings, while extending them with domain-specific descriptors and assessment approaches grounded in project work, rubric-guided evaluation, and learning analytics. This approach retains the benefits of established standards while ensuring that the assessment reflects learners' actual ability to design, implement, and manage AIoT traffic systems responsibly. To clarify how the proposed Data-Driven Assessment Competency Framework (DACF) extends existing digital competency and assessment models, **Table 1** compares its focus and scope with widely adopted frameworks. The comparison identifies the unique domain-specific contributions of DACF while acknowledging the foundational role of established frameworks.

Table 1 shows that established frameworks such as DigCompEdu, the UNESCO AI competency framework, IoT curriculum models, and learning analytics models each contribute important guidance for digital competence, AI literacy, assessment, or data-informed teaching. However, none integrates these elements into a unified framework tailored to competency assessment in AIoT-enhanced traffic management education. The proposed Data-Driven Assessment Competency Framework (DACF) extends these existing approaches by combining competency mapping, authentic AIoT traffic management tasks, multi-source evidence, learning analytics, and implementation guidance within a single domain-specific assessment model. This integration enables a more comprehensive and contextually relevant approach to assessing learners' competencies in AIoT-enhanced traffic management.

DATA-DRIVEN ASSESSMENT STRATEGIES FOR AIoT COMPETENCY DEVELOPMENT

Principles

Assessment in AIoT education should mirror the data-intensive work found in smart environments by incorporating continuous sensor-based data collection, real-time analytics, and adaptive intervention, all of which are recognised as key features of Education 4.0 and AIoT-enabled learning environments (Ghai et al., 2025). Consequently, assessment for AIoT competency works best when it is continuous, analytics-based, and performance-centred. Education 4.0 models explain that IoT devices and sensors enable continuous monitoring of learning processes and environments, moving assessment away from one-off tests toward ongoing

observation of engagement, participation, and attainment (Ahad et al., 2018). In AIoT-supported education, behavioural, interaction, and performance data can be used to inform timely feedback and automated support tailored to learner needs (Ghai et al., 2025). Research on dispositional learning analytics suggests that formative traces and activity patterns can predict academic performance and the risk of withdrawal, enabling early support and more personalised learning (Tempelaar et al., 2024). When considered through the lenses of assessment of learning, assessment for learning, and assessment as learning, data-driven AIoT assessment can record attainment, guide feedback and adjustment, and involve learners in interpreting evidence, enabling them to manage their own learning more effectively (Williams, 2023).

Methods and Tools

1. *Simulated, synthetic, and live datasets*: Open traffic datasets and simulation platforms support repeatable tasks such as congestion prediction, anomaly detection, and incident response, making scenario-based assessment possible. Reviews of IoT curricula stress the value of realistic sensor data streams for linking learning activities to real-world IoT system layers (Abichandani et al., 2022). AI-supported education also increasingly uses synthetic or simulated data to broaden the range of tasks, reduce privacy concerns, and strengthen model-based feedback, for example, through generated datasets for analysis and evaluation exercises (Zaman et al., 2025). In AIoT traffic laboratories, these datasets enable a fair comparison of modelling, deployment, and decision-making under controlled yet realistic conditions.
2. *Learning analytics dashboards and IoE-style monitoring*: Learning analytics and Internet of Everything-based educational models combine data from learning management systems, IoT devices, and assessment events to visualise patterns in attention, engagement, and achievement over time (Ahad et al., 2018). Institution-level models describe analytics-supported assessment systems in which dashboards help educators and leaders design flexible and learner-centred assessment strategies (Williams, 2023). In AIoT-enhanced traffic management education, dashboards can consolidate code contributions, model metrics, simulation outputs, sensor performance, and engagement indicators into a single view to support feedback, resource planning, and curriculum review.
3. *AI-based adaptive feedback and tutoring*: AIoT-supported learning environments use AI algorithms to monitor learner behaviour and performance and deliver personalised support, such as adjusting task difficulty or recommending learning materials (Ghai et al., 2025). Studies on AI-supported formative assessment report improved achievement, greater motivation, and deeper reflective learning compared with traditional approaches (Alazemi, 2024). Large language model-based tutoring systems can also support dialogic feedback, automated questioning, and integrity-aware assessment linked to analytics systems (Owan et al., 2023). In addition, AI-assisted peer assessment systems use analytics to enhance feedback quality and support instructor oversight, thereby improving scalability and consistency (Darvishi et al., 2022). Even so, research stresses the need to validate these

tools for fairness, transparency, and ethical fit, especially given continuing concerns about privacy, equity, and commercial influence in AI-supported assessment (Williams, 2023).

Assessment Modes

Formative assessment in AIoT-enhanced traffic management education naturally generates rich data. Frequent quizzes, coding tasks, simulations, and laboratory checkpoints generate continuous records that support assessment for learning and assessment as learning (Alazemi, 2024; Williams, 2023). When these are integrated into dispositional learning analytics systems, educators can better anticipate outcomes, understand how learning dispositions interact with practice patterns, and adjust support for different learner profiles (Tempelaar et al., 2024).

Summative assessment usually centres on capstone projects or integrated practical examinations in which learners design and justify AIoT solutions to complex problems such as urban traffic optimisation. Analytics can support these high-stakes decisions through cohort-level performance analysis, rubric benchmarking, and identification of common strengths and weaknesses for programme improvement (Williams, 2023). Studies using predictive models to estimate attainment of course and programme outcomes from historical data suggest that institutions can use such tools to evaluate and calibrate assessment systems and to build scenario-based evaluations that align with professional practice (Zaman et al., 2025). In AIoT-enhanced traffic management education, predictive models based on formative and behavioural data can indicate competence trends early enough for support to be given, while longer-term analytics help keep summative standards aligned with changing industry expectations and technological developments (Ahad et al., 2018; Tempelaar et al., 2024).

Example Tasks and Rubrics

Representative AIoT traffic assessment tasks should mirror real-time, multi-source decision-making situations while making technical, analytical, and ethical competence visible.

1. *Multi-intersection traffic signal control project*: Learners design, train, and deploy an AI or reinforcement learning controller in a SUMO-style simulation environment using realistic sensor inputs, including loop detectors, cameras, and connected vehicles, combined with edge-oriented architectures (Kwon et al., 2025). Evaluation focuses on congestion duration, average delay, queue length, and emissions or fuel consumption, consistent with traffic engineering and AIoT studies comparing control algorithms using delay and environmental measures (Chavhan et al., 2025). Rubrics may assess system design and implementation through state and action representation, training stability, and deployment reliability. Model performance and evaluation may examine improvements over baseline control using suitable metrics, such as mean absolute error or F1 score, supported by sensitivity or ablation checks commonly used in AIoT forecasting and anomaly detection research (Bhatti et al., 2024; Trilles et al., 2024). Analytical reasoning considers how well learners justify architectural and

Table 2. Worked assessment example for an AIoT traffic signal control project

Component	Description
Learning task	Design, implement, and evaluate an AI-based adaptive traffic signal controller for a four-intersection urban road network using SUMO simulation and reinforcement learning.
Competency assessed	AIoT system design; machine learning implementation; traffic data analytics; ethical and responsible AI deployment.
Evidence collected	Python source code; SUMO simulation outputs; model performance dashboard; technical report; learner reflection.
Evidence sources	GitHub repository; simulation logs; traffic sensor datasets; learning management system submissions.
Performance metrics	Average vehicle delay; queue length reduction; traffic throughput; model accuracy; computational efficiency; compliance with ethical and privacy requirements.

Table 3. Analytic rubric for the AIoT traffic signal control project

Assessment Criterion	Beginning (1)	Developing (2)	Proficient (3)	Advanced (4)
System implementation	The system fails to operate correctly	Partially functional implementation	Functional implementation meeting project requirements	Fully optimised, reliable implementation with efficient integration
AI model performance	Performance below baseline	Moderate improvement over baseline	Significant improvement using appropriate evaluation metrics	Excellent optimisation supported by comprehensive validation
Data interpretation	Limited interpretation of traffic data	Basic interpretation with minor errors	Correct interpretation supported by appropriate analyses	Critical interpretation with well-justified optimisation decisions
Ethical reasoning	Ethical issues are largely ignored	Basic discussion of privacy and fairness	Good consideration of ethical, privacy, and safety issues	Comprehensive evaluation including fairness, explainability, accountability, and sustainability

reward design choices and explain trade-offs such as lower delay versus higher emissions. Ethical and socio-technical reflection addresses fairness across routes, data quality and bias, safety, explainability, and compliance with privacy and security expectations in traffic data use (Pandya et al., 2025).

Table 2 presents a worked example that illustrates how DACF can be applied in practice. Rather than describing assessment principles in the abstract, it demonstrates how a representative AIoT traffic management task can be organised into clearly defined competencies, evidence sources, and performance measures.

Table 2 illustrates that competency assessment extends beyond the evaluation of the final technical product. Multiple forms of evidence, including source code, simulation outputs, dashboards, reports, and reflective accounts, collectively support a more comprehensive judgement of learner competence. Such triangulation strengthens the validity of assessment and aligns with evidence-centred assessment principles. Assessment quality depends on explicit performance criteria. **Table 3** presents an example analytic rubric showing how technical performance, analytical reasoning, and ethical judgement can be evaluated across progressively higher levels of competence.

The rubric in **Table 3** illustrates how observable performance indicators can improve scoring consistency, support formative feedback, and facilitate the integration of assessment evidence with learning analytics within DACF. Although weighting may vary across institutions and courses, assessment should balance technical implementation with analytical reasoning, ethical judgement, and communication.

1. *Streaming sensor data analysis and anomaly detection laboratory:* Learners analyse live or recorded multi-source data streams, including traffic volume, speed, and pollution, and build streaming or TinyML-based anomaly detection or forecasting solutions, as commonly reported in AIoT monitoring studies (Bhatti et al., 2024). Rubric

dimensions may assess data handling and feature engineering for evolving streams and resource-constrained devices, the selection and tuning of detection models, and the proper use of evaluation metrics such as accuracy, precision, recall, F1 score, root mean square error, and mean absolute percentage error (Trilles et al., 2024). Operational reasoning focuses on how learners interpret false positives and false negatives and how well they propose mitigation strategies for edge deployment.

2. *Ethics and governance dossier for AIoT traffic systems:* Learners prepare a policy and risk analysis report for a city-scale AIoT traffic deployment, drawing on work in IoT ethics, big data governance, and AI accountability (Pandya et al., 2025). Rubric criteria may distinguish conceptual understanding of ethical principles such as privacy, fairness, transparency, accountability, and data ownership, the quality of governance proposals covering consent, data minimisation, audit trails, explainable models, and incident response, and careful thinking about trade-offs such as safety versus surveillance or optimisation versus equity (Kitto & Knight, 2019).

3. *Computational thinking and design thinking mini-projects:* Short design sprints or prototypes may assess problem decomposition, algorithm design, creativity, and collaboration. AIoT learning platforms can support problem-solving, creativity, and algorithmic reasoning, which should be clearly represented in rubric descriptors (Phanichsiti et al., 2025). Final judgements may combine evidence from code repositories, simulations, system metrics, peer and self-assessments, and reflective writing. Multidimensional rubrics that include ethical reasoning, creativity, and AI tool use can support feedback, self-assessment, and peer review (Phuong et al., 2025). However, poorly explained rubrics may encourage rigid or formulaic responses (Kola, 2022). Rubrics should therefore use clear descriptors and explain how analytics and performance evidence contribute to broader competency judgements.

Table 4. Competency progression model within the Data-Driven Assessment Competency Framework (DACF)

Competency Domain	Novice	Intermediate	Advanced	Expert
Technical competence	Understands basic AIoT concepts, sensors, traffic data, and programming with close guidance.	Implements AIoT tools to solve structured traffic management problems with moderate supervision.	Independently designs, develops, and evaluates AIoT traffic management systems using appropriate algorithms, simulations, and data pipelines.	Optimises and innovates AIoT traffic management solutions, integrating emerging technologies, scalability, and system resilience.
Analytical competence	Interprets simple datasets and basic traffic patterns.	Analyses traffic datasets, selects suitable analytical methods, and explains findings.	Integrates multiple data sources, justifies modelling decisions, and evaluates alternative traffic management strategies.	Synthesises complex evidence to develop strategic recommendations for dynamic traffic systems under uncertainty.
Ethical and professional competence	Demonstrates awareness of privacy, fairness, and responsible AI use.	Applies ethical principles during AIoT projects and recognises potential risks.	Evaluates governance, cybersecurity, explainability, inclusiveness, and regulatory compliance.	Leads responsible AIoT practice by integrating ethical governance, stakeholder engagement, sustainability, and public accountability into system design.

DESIGNING THE DATA-DRIVEN ASSESSMENT COMPETENCY FRAMEWORK (DACF)

1. *Competency domains and progression levels:* Competencies should be drawn from the literature and expert input and organised into a small set of teaching domains with clear stages of progression (Sidhu et al., 2023). Progression levels enable educators to distinguish between learners who are acquiring foundational knowledge and those capable of independently designing, evaluating, and improving AIoT-enabled traffic management solutions. Such descriptors support curriculum sequencing, rubric development, formative feedback, and programme-level evaluation by defining observable expectations at successive stages of learner development. **Table 4** presents an example competency progression model incorporated within DACF.

Table 4 presents competency development as a progression from foundational knowledge to independent application and innovation, supporting curriculum planning, assessment, and feedback. The progression descriptors provide explicit expectations for curriculum planning, rubric construction, learning analytics, formative feedback, and programme-level competency evaluation.

2. *Learning outcomes aligned with Bloom's taxonomy:* Learning outcomes should align with Bloom's taxonomy levels and connect directly to specific competencies. Matrix-based mapping of outcomes, tasks, and grade data enables estimation of competency attainment at cognitive levels and supports traceability in digital learning environments.

3. *Indicators and evidence models:* Each competency level should include a limited number of observable indicators to support consistency in reporting. These indicators may combine system performance metrics, artefact quality assessed with rubrics, and process data such as collaboration or persistence. Rubrics need clear behavioural anchors and shared glossaries to ensure consistent assessor interpretation (Vargas et al., 2024).

4. *Multi-source data channels:* Evidence may include learning management system logs, simulation traces, IoT sensor streams, code submissions, video interaction data, and portfolio artefacts. Earlier work on multi-source IoT-

based evaluation explains how such streams can support large-scale analysis of engagement and learning behaviour (Kamruzzaman et al., 2023).

5. *Assessment metrics and analytics:* Analytics components should convert raw data into interpretable measures, such as competency attainment indices, Bloom-weighted scores, and indicators of assessment reliability. Learning analytics-based competency frameworks suggest that these metrics support both detailed learner feedback and course-level monitoring (Pei et al., 2024; Vargas et al., 2024).

6. *Learner- and instructor-facing visualisations:* Dashboards should work as open student models that make knowledge states and learning gaps visible. Effective designs combine linked views such as competency profiles, progression charts, topic difficulty maps, and drill-down analyses to support teaching decisions and personalised feedback (Liao et al., 2024). These tools need careful introduction and explanation because they can also increase learner anxiety.

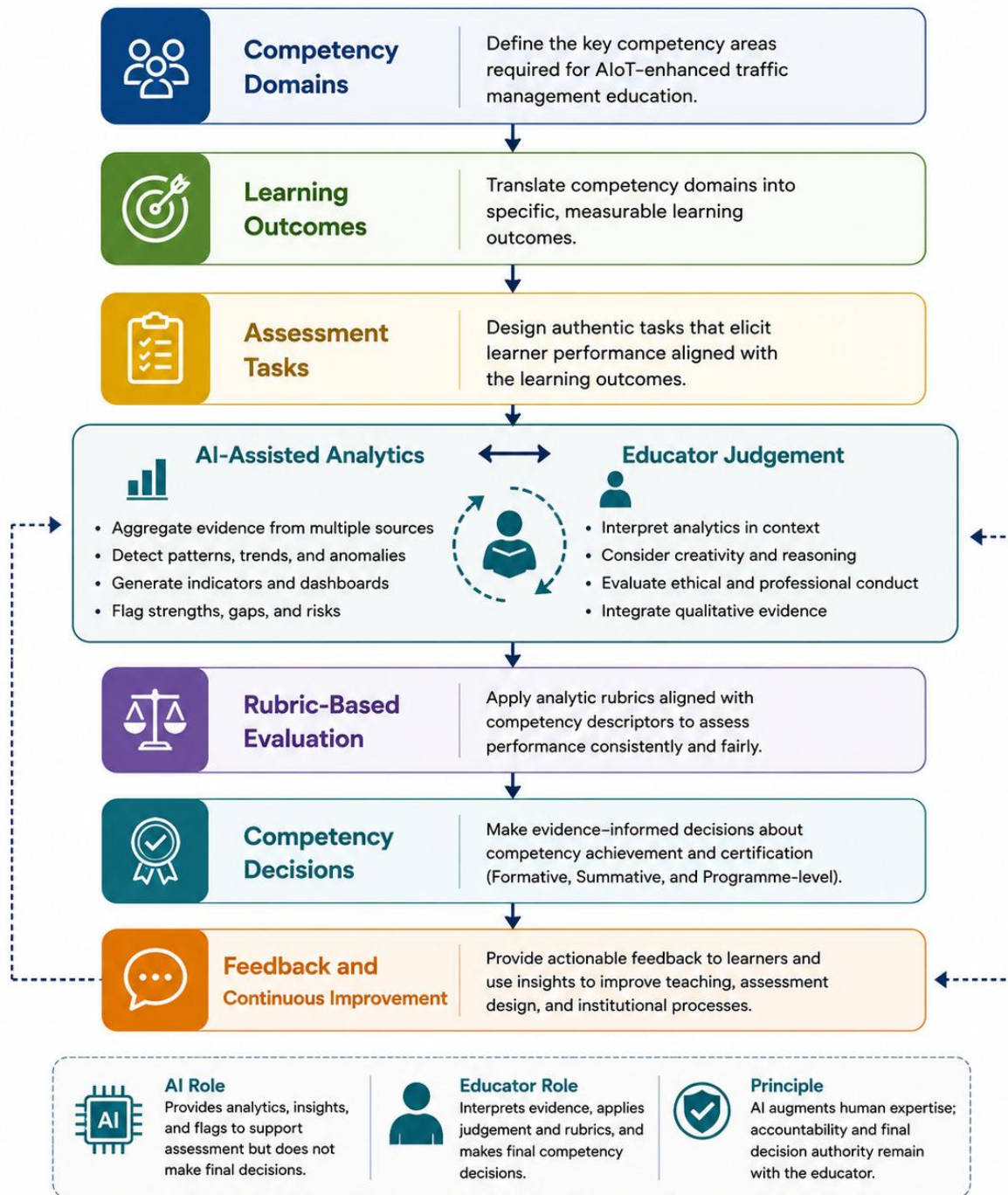
Table 5 summarises the components of DACF and their implementation requirements.

Figure 1 illustrates how competencies are translated into evidence and competency decisions through continuous feedback.

Figure 1 presents DACF as an evidence-based assessment cycle in which feedback informs subsequent learning and assessment activities. AI-assisted analytics aggregate evidence from sources such as simulation outputs, sensor data, code repositories, learning management systems, portfolios, and learner reflections to identify performance patterns and competency gaps. These outputs support, rather than replace, educator judgement. Educators interpret the evidence within its educational, disciplinary, and ethical setting and apply analytic rubrics to evaluate complex aspects of performance, including problem-solving, ethical reasoning, and collaboration. Final competency decisions therefore combine analytical evidence with professional judgement, supporting transparent and accountable assessment. DACF may be applied iteratively by aligning competency expectations, assessment tasks, evidence sources, rubrics, analytics, feedback, and quality assurance with programme requirements.

Table 5. Summary of the Data-Driven Assessment Competency Framework (DACF)

Framework Component	Purpose	Required Evidence	Assessment Metrics	Primary Users	Implementation Requirements
Competency domains	Define AIoT competency areas	Curriculum documents, competency maps	Coverage across domains	Curriculum designers, educators	Literature review and expert consensus
Learning outcomes	Translate competencies into measurable outcomes	Course specifications	Bloom taxonomy alignment	Educators	Outcome mapping
Observable indicators	Describe expected learner performance	Rubrics, behavioural indicators	Competency attainment	Assessors	Standardised descriptors
Evidence sources	Collect evidence of competence	Simulation logs, code repositories, sensor streams, portfolios	Completeness and triangulation	Educators	Digital assessment ecosystem
Assessment metrics	Quantify performance	Rubric scores, analytics indicators	Accuracy, latency, competency indices	Educators	Learning analytics tools
Dashboards	Visualise learner progress	LMS and analytics data	Progress indicators	Students, educators	Dashboard infrastructure

**Figure 1.** Data-Driven Assessment Competency Framework (DACF) (Source: Authors' own elaboration)

FRAMEWORK FOR IMPLEMENTATION AND CAPACITY BUILDING (AAIF)

Domains of Action

The AIoT Assessment Implementation Framework (AAIF) links competency-based assessment with the institutional conditions required for AIoT-supported education. It connects strategic planning, curriculum integration, educator capacity, infrastructure, learning analytics, ethical governance, and continuous evaluation with DACF, addressing implementation requirements beyond those covered by generic educational technology models.

1. *Strategic alignment*: Institutional strategies for digital and smart education should recognise AIoT as a means of developing Education 4.0 and 5.0 capabilities, including data literacy, complex problem-solving, interdisciplinary work, and responsive assessment and administration (Badshah et al., 2023). Successful adoption of IoT and AI depends not only on technology but also on leadership commitment, governance, and clear privacy, security, and ethics policies (Kamruzzaman et al., 2023). Institution-wide standards, oversight, and alignment with accreditation and quality assurance are also important (Ilieva et al., 2025). Strategic alignment should therefore establish clear AIoT and data-driven assessment goals, ethical data-use and academic integrity policies, and governance units to coordinate implementation. Partnerships with municipalities, industry, and government agencies can further support access to authentic projects, real data, and shared infrastructure (Kamruzzaman et al., 2023).

2. *Curriculum integration*: Reviews of IoT and AIoT-enhanced traffic management education suggest that isolated courses have limited effects, whereas programmes that integrate AIoT experiences and data-driven thinking across the curriculum produce stronger outcomes (Abichandani et al., 2022). Smart learning ecosystems can engage learners in authentic, data-rich projects involving schools, universities, city agencies, and industry (Tabuenca et al., 2024). Education 4.0 and 5.0 likewise emphasise interdisciplinary, problem-based learning, with AI, IoT, and advanced connectivity serving as cross-cutting enablers (Phanichsiti et al., 2025). Within AAIF, curriculum integration involves mapping programme outcomes to AIoT competencies and DACF indicators, embedding authentic projects across levels of study, and supporting interdisciplinary teams in designing learning and assessment.

3. *Infrastructure and tooling*: AIoT-based education requires connectivity, IoT devices, cloud or edge platforms, analytics engines, and interoperable learning systems (Badshah et al., 2023; Ghai et al., 2025). Institutions with limited resources may face constraints relating to bandwidth, device access, interoperability, and maintenance costs (Ghai et al., 2025). Low-cost, open-source hardware, remote and virtual laboratories, and shared cloud resources may reduce costs and expand access (Abichandani et al., 2022). Within AAIF, infrastructure planning includes scalable network and cloud capacity,

reusable AIoT kits and simulation tools, secure data pipelines, and technical support with preventive maintenance.

4. *Educator capacity building*: Educator knowledge, data literacy, and confidence remain major barriers to AI and AIoT adoption (Kim, 2024). Educators may value AI for problem-based and reflective assessment but require sustained professional development and supportive institutional cultures (Kim, 2024). AIoT-specific professional development has also been associated with improved teacher knowledge, practical performance, and attitudes towards AIoT teaching (Kitcharoen et al., 2024). Within AAIF, capacity building covers competence in AI and IoT platforms, assessment and data literacy for interpreting DACF dashboards, pedagogies that preserve authenticity and learner agency, and ethics, privacy, and equity in data use (Badshah et al., 2023). It also recognises progression from basic tool use to active design and partnership with AI systems (Kim, 2024).

5. *Continuous evaluation and improvement*: IoT adoption and quality assurance research indicates that implementation requires ongoing evaluation of technical performance and educational impact (Ahanger et al., 2020). Important factors include usability, technical support, financial barriers, self-efficacy, surveillance concerns, and training effectiveness (Ghashim & Arshad, 2023). Smart education initiatives should also examine learner engagement, well-being, competency development, and ethical issues surrounding data collection (Badshah et al., 2023; Kamruzzaman et al., 2023). Within AAIF, continuous evaluation involves tracking learner outcomes through DACF metrics, monitoring educator practice, assessing institutional readiness and constraints, and using evidence to revise curricula, infrastructure, and policy in line with flexible AI integration models (Abbasnejad et al., 2025).

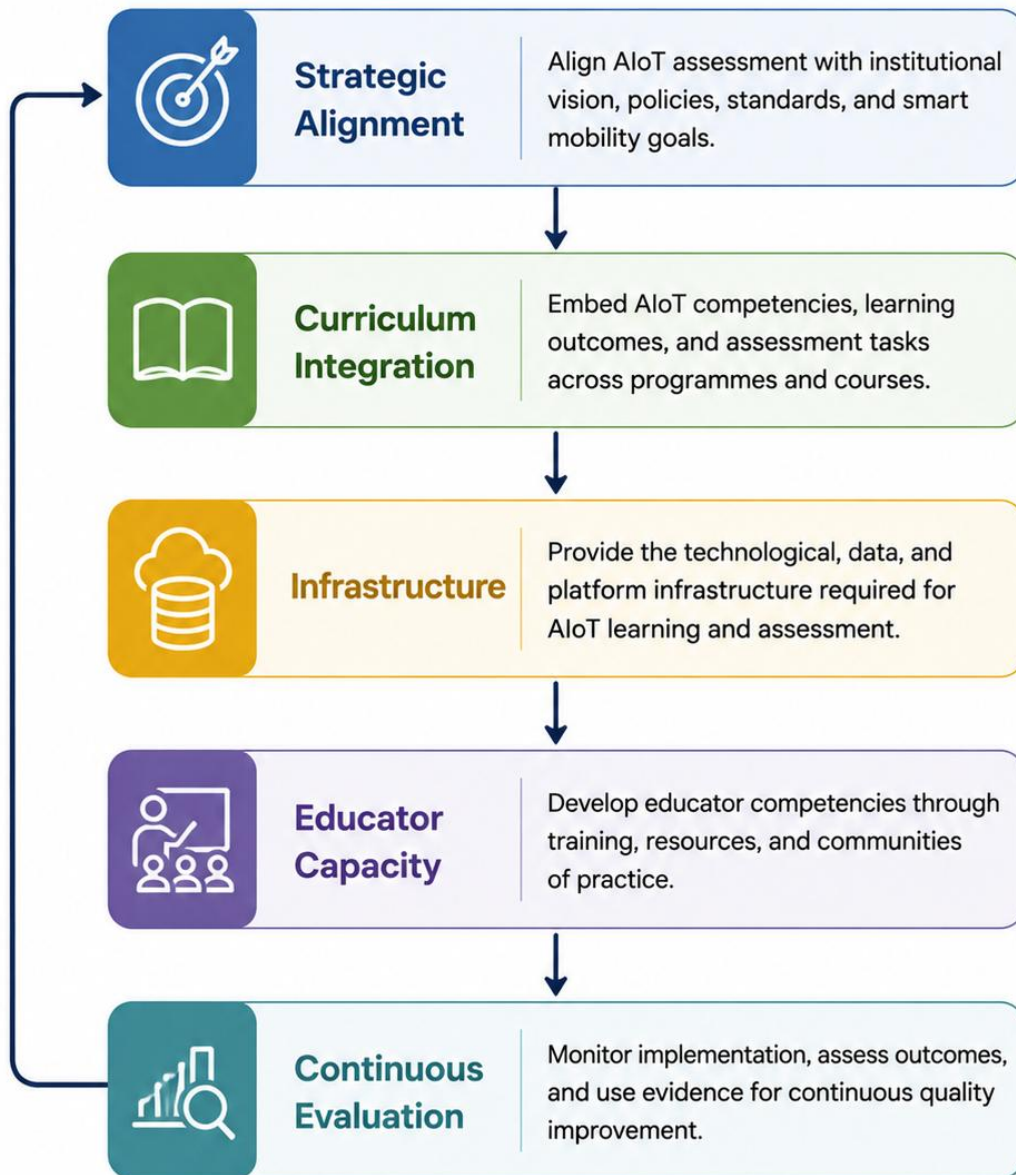
Table 6 indicates that effective implementation depends on coordinated institutional action rather than isolated technological investments. Strategic planning, curriculum integration, infrastructure, educator development, and continuous evaluation work together to support sustainable implementation of AIoT-based assessment. The relationships among the implementation domains are illustrated in **Figure 2**. Unlike DACF, which focuses on learner assessment, AAIF depicts the institutional processes required to sustain AIoT-enabled assessment practices. **Figure 2** presents implementation as a continuous improvement cycle. Evidence generated during evaluation informs subsequent strategic planning, curriculum revision, infrastructure enhancement, and professional development, thereby supporting long-term institutional capacity building.

A Cyclical Process

AAIF can be implemented as a cyclical, multi-level change process informed by large-scale IoT and AIoT implementations. The cycle begins with a foundation stage, in which institutions establish strategy, governance, ethical and data-protection policies, partnerships, and readiness analyses covering infrastructure, staff capacity, learner access, and regulatory requirements (Ilieva et al., 2025). The integration

Table 6. Summary of the AIoT Assessment Implementation Framework (AAIF)

Domain	Purpose	Expected Users	Required Resources	Expected Outputs
Strategic alignment	Align AIoT assessment with institutional strategy	University management	Policies, governance	Institutional readiness
Curriculum integration	Embed competencies across courses	Programme teams	Curriculum mapping	AIoT learning pathways
Infrastructure	Support AIoT learning	ICT personnel	Cloud services, sensors, LMS	Reliable assessment ecosystem
Educator capacity	Develop staff competence	Academic staff	Professional development	Competent educators
Continuous evaluation	Improve implementation	QA units	Learning analytics	Continuous improvement

**Figure 2.** AIoT Assessment Implementation Framework (AAIF) (Source: Authors' own elaboration)

stage involves co-designing AIoT-rich curricula, mapping outcomes to DACF competencies, embedding initial projects and assessments, and delivering foundational professional development for educators (Abichandani et al., 2022; Kitcharoen et al., 2024).

During operation, institutions deploy AIoT systems, data pipelines, and dashboards within authentic learning activities and give ongoing technical and pedagogical support in line with institutional policies (Tabuenca et al., 2024). The evaluation stage gathers multi-source evidence on learning outcomes, engagement, perceptions, costs, and sustainability,

and analyses factors associated with adoption and learning gains (Ahanger et al., 2020). Finally, scaling and institutionalisation use pilot evidence to refine standards, accreditation criteria, and curriculum guidelines, extending successful practice across departments and improving infrastructure and professional development over time (Abbasnejad et al., 2025; Ilieva et al., 2025). The cycle is iterative rather than strictly linear, with feedback loops linking all stages.

POLICY, EQUITY, AND FUTURE DIRECTIONS

Adoption Challenges and Future Directions

The adoption of AIoT-supported assessment faces interconnected challenges relating to privacy, bias, infrastructure, educator capacity, and institutional governance. AIoT systems may collect large volumes of behavioural and other sensitive data, creating risks of breaches, misuse, surveillance, unfair assessment, and weak accountability where automated decisions lack transparency (Adel, 2024; Elhassani et al., 2025; Ghai et al., 2025; Vindigni, 2025).

Unequal access to devices, connectivity, and technical support may also limit participation, particularly in rural and low-income settings, while high infrastructure costs may concentrate AIoT benefits within better-resourced institutions (Adel, 2024; Bulathwela et al., 2024; Kamruzzaman et al., 2023; Vesna et al., 2025). Shared infrastructure, low-cost technologies, and privacy-preserving approaches may help widen access and reduce dependence on centralised data systems.

Successful implementation also depends on educator competence in AI, IoT, data literacy, assessment design, and ethical decision-making, supported by professional development, interdisciplinary collaboration, and institutional governance (Badshah et al., 2023; Elhassani et al., 2025). Future systems are likely to integrate learning analytics, sensor-generated data, and automated feedback more closely, increasing the importance of explainability, fairness, human oversight, privacy protection, and energy efficiency.

Further research should test DACF and AAIF across different institutional and geographical settings to examine their effects on competency development, assessment quality, educator practice, equity, governance, and sustainability. Such evidence would guide further refinement and adaptation of both frameworks.

Policy Suggestions

1. *Digital infrastructure and access:* Governments and development agencies should invest in reliable connectivity, affordable devices, and low-bandwidth or offline-capable AI solutions to reduce digital exclusion (Kamruzzaman et al., 2023; Vesna et al., 2025). Public-private partnerships and smart city initiatives can also help fund AIoT infrastructure and shared platforms, reducing costs and widening access.
2. *Ethical and data governance frameworks:* National and institutional policies should require privacy-preserving technologies such as encryption, federated learning, and differential privacy, along with fairness-aware algorithms and transparency protocols (Xu et al., 2024). Existing frameworks, such as the GDPR and OECD principles, are useful starting points, but they require careful adaptation for educational use (Elhassani et al., 2025).
3. *Accreditation and standards:* Accreditation bodies can include AI and AIoT competencies, along with ethical requirements such as data protection, accessibility, and

sustainability, within programme standards. This helps ensure that adoption supports inclusive educational quality rather than narrow technical training alone (Kamruzzaman et al., 2023).

4. *Funding and capacity building:* Focused funding should link infrastructure investment with educator training and AI and data literacy initiatives, especially in underserved regions (Hong & Kim, 2025). Policies that strengthen local research capacity and support balanced international collaboration can also help address long-standing North-South inequalities in AI-for-education research (Elhassani et al., 2025).

5. *Accountability and oversight:* Institutions should establish interdisciplinary ethics or AI governance committees to review AIoT tools, monitor algorithmic effects, and ensure alignment with human rights-based principles (Elhassani et al., 2025). Equity and bias audits should form part of routine quality assurance to identify systematic disparities, assess data and model quality, and ensure appropriate human oversight. Where substantial bias is identified, corrective measures, including model revision or withdrawal, should be undertaken before continued use.

6. Policy implementation should also prioritise affordable access, accessible design, open resources, shared infrastructure, and participation by learners and educators in the development and evaluation of AIoT systems.

Validation Roadmap for DACF and AAIF

As a conceptual framework paper, the present study does not report empirical validation of DACF or AAIF. The proposed validation strategy consists of three stages, progressing from expert review to pilot implementation and multi-institutional evaluation (Table 7).

The first stage should establish the conceptual adequacy of DACF and AAIF through expert judgement. Specialists in AI, Internet of Things technologies, traffic engineering, educational assessment, learning analytics, and curriculum development should evaluate the frameworks for relevance, clarity, completeness, coherence, and practical applicability, supported where appropriate by content validity indices and qualitative feedback. The second stage should examine their operational performance in authentic teaching environments. DACF may be applied through project-based assessments, simulations, coding tasks, and learning analytics, while AAIF may guide curriculum integration, infrastructure, educator development, and governance. Evaluation should examine reliability, usability, feasibility, perceived fairness, feedback quality, learner acceptance, and competency development. The final stage should examine the frameworks across institutions operating under different educational, technological, and organisational conditions. Such studies should assess transferability, local adaptation, curriculum alignment, institutional readiness, educator adoption, learner performance, and implementation sustainability. As conceptually developed frameworks, DACF and AAIF also require further psychometric and implementation research before routine use. Future studies should examine their validity, reliability, usability, feasibility, cost implications, and effects on curriculum quality and graduate preparedness.

Table 7. Proposed validation roadmap for the Data-Driven Assessment Competency Framework (DACF) and AIoT Assessment Implementation Framework (AAIF)

Stage	Participants	Validation Activities	Data Sources	Reliability and Validity Checks	Intended Outcomes
Expert review	8–12 experts in AI, IoT, traffic engineering, educational assessment, learning analytics and curriculum design	Structured review of framework components, competency descriptors, indicators, rubrics, and implementation processes	Expert rating forms, qualitative comments	Item-level Content Validity Index (I-CVI), Scale-level Content Validity Index (S-CVI), modified kappa coefficients, inter-expert agreement	Establish content validity, clarity, relevance, completeness and feasibility
Pilot implementation	Undergraduate or postgraduate students enrolled in AIoT traffic management courses and participating educators	Classroom implementation of DACF assessment tasks and AAIF institutional processes	Rubric scores, simulation logs, learning analytics, dashboards, educator observations, learner feedback questionnaires	Internal consistency (Cronbach's alpha or McDonald's omega where appropriate), inter-rater reliability, usability evaluation, implementation fidelity	Evaluate practicality, reliability, usability, acceptability and initial educational effectiveness
Multi-institution evaluation	Universities implementing AIoT traffic management or related smart mobility programmes	Cross-institutional implementation and comparative evaluation	Institutional reports, assessment outcomes, interviews, analytics dashboards, programme documentation	Measurement invariance where appropriate, external validation, cross-context comparison, scalability assessment	Determine generalisability, institutional adaptability, sustainability and broader framework usefulness

These limitations define the scope of the present work and identify priorities for further refinement and empirical evaluation.

CONCLUSION

AIoT is transforming traffic management by placing data-intensive and automated decision-making at the centre of urban mobility systems. These developments create educational demands that extend beyond technical skills to analytical reasoning, systems thinking, and ethical judgment. This article responds through the Data-Driven Assessment Competency Framework (DACF) and the AIoT Assessment Implementation Framework (AAIF). DACF translates AIoT competencies into assessable learning outcomes supported by multiple evidence sources, including project work, learning analytics, and reflective artefacts. AAIF complements this approach by addressing the institutional conditions required to embed such assessment across strategy, curriculum, infrastructure, professional development, and governance. Effective implementation requires investment in educator capacity, interoperable infrastructure, and sound data governance. Ethical and equity concerns also require attention because bias, surveillance, and unequal access may weaken trust and deepen existing inequalities. The frameworks should therefore be treated as developing rather than fixed models. Pilot studies, cross-institutional evaluations, and implementation research are needed to validate indicators, refine assessment instruments, and examine how analytics and AI-enabled feedback affect learning. Neither DACF nor AAIF has yet undergone empirical validation through expert review, pilot implementation, or cross-institutional evaluation. They should therefore be regarded as theoretically grounded frameworks requiring further empirical refinement before widespread adoption in AIoT-enhanced traffic management education.

Author contributions: **VJO:** conceptualization, methodology, investigation, visualization, writing – original draft, writing – review & editing; **MVO:** investigation, writing – original draft, writing – review & editing; **BAB:** validation, supervision, writing

– review & editing. All authors approved the final version of the article.

Funding: No external funding is received for this article.

Ethics declaration: The authors stated that ethical approval was not applicable to this study because the article was based solely on a literature-informed conceptual synthesis and did not involve human participants, animals, personal data, or primary data collection.

AI statement: The authors stated that generative artificial intelligence was not used to generate the substantive content, arguments, analysis, frameworks, or conclusions presented in this article. ChatGPT and Grammarly were used only for language polishing, grammatical refinement, and improvement of the clarity and readability of the manuscript. The authors retained full responsibility for the content, interpretation, and final version of the article.

Declaration of interest: The authors declared no competing interest.

Availability of data and materials: All data generated or analyzed during this study are available for sharing when appropriate request is directed to corresponding author.

REFERENCES

- Abbasnejad, B., Soltani, S., Taghizadeh, F., & Zare, A. (2026). Developing a multilevel framework for AI integration in technical and engineering higher education: Insights from bibliometric analysis and ethnographic research. *Interactive Technology and Smart Education*, 23(1), 49-79. <https://doi.org/10.1108/ITSE-12-2024-0314>
- Abichandani, P., Sivakumar, V., Lobo, D., Iaboni, C., & Shekhar, P. (2022). Internet-of-things curriculum, pedagogy, and assessment for STEM education: A review of literature. *IEEE Access*, 10, 38351-38369. <https://doi.org/10.1109/ACCESS.2022.3164709>
- Adel, A. (2024). The convergence of intelligent tutoring, robotics, and IoT in smart education for the transition from Industry 4.0 to 5.0. *Smart Cities*, 7(1), 325-369. <https://doi.org/10.3390/smartcities7010014>

- Ahad, M. A., Tripathi, G., & Agarwal, P. (2018). Learning analytics for IoE-based educational model using deep learning techniques: Architecture, challenges and applications. *Smart Learning Environments*, 5, Article 7. <https://doi.org/10.1186/s40561-018-0057-y>
- Ahanger, T. A., Tariq, U., Ibrahim, A., Ullah, I., & Bouteraa, Y. (2020). ANFIS-inspired smart framework for education quality assessment. *IEEE Access*, 8, 175306-175318. <https://doi.org/10.1109/ACCESS.2020.3019682>
- Alakkari, K., & Ali, B. (2025). Artificial intelligence of things: A review. *Babylonian Journal of Internet of Things*, 2025, 113-120. <https://doi.org/10.58496/BJIoT/2025/006>
- Alazemi, A. F. T. (2024). Formative assessment in artificial integrated instruction: Delving into the effects on reading comprehension progress, online academic enjoyment, personal best goals, and academic mindfulness. *Language Testing in Asia*, 14, Article 44. <https://doi.org/10.1186/s40468-024-00319-8>
- Badshah, A., Ghani, A., Daud, A., Jalal, A., Bilal, M., & Crowcroft, J. (2023). Towards smart education through Internet of Things: A survey. *ACM Computing Surveys*, 56(2), Article 26, 1-33. <https://doi.org/10.1145/3610401>
- Bhatti, M. A., Song, Z., Bhatti, U. A., & Syam, M. S. (2024). AIoT-driven multi-source sensor emission monitoring and forecasting using multi-source sensor integration with reduced noise series decomposition. *Journal of Cloud Computing*, 13, Article 65. <https://doi.org/10.1186/s13677-024-00598-9>
- Bulathwela, S., Pérez-Ortiz, M., Holloway, C., Cukurova, M., & Shawe-Taylor, J. (2024). Artificial intelligence alone will not democratise education: On educational inequality, techno-solutionism and inclusive tools. *Sustainability*, 16(2), Article 781. <https://doi.org/10.3390/su16020781>
- Cabero-Almenara, J., Romero-Tena, R., & Palacios-Rodríguez, A. (2020). Evaluation of teacher digital competence frameworks through expert judgement: The use of the expert competence coefficient. *Journal of New Approaches in Educational Research*, 9(2), 275-293. <https://doi.org/10.7821/naer.2020.7.578>
- Chavhan, S., Doswada, R., Gupta, D., Gunjal, S., & Rodrigues, J. J. P. C. (2025). Next generation intelligent traffic signal control: Empowering electronics consumers with edge-AIoT capabilities. *IEEE Transactions on Consumer Electronics*, 71(1), 1926-1934. <https://doi.org/10.1109/TCE.2025.3529300>
- Chiffla-Villón, M. R., Chiffla-Villón, M. P., Suárez-Guarter, E. M., & Guevara-Viejó, F. (2025). Multidimensional assessment and validation of digital competencies in university teacher education: A confirmatory factor analysis. *Frontiers in Education*, 10, Article 1597095. <https://doi.org/10.3389/feduc.2025.1597095>
- Darvishi, A., Khosravi, H., Sadiq, S., & Gašević, D. (2022). Incorporating AI and learning analytics to build trustworthy peer assessment systems. *British Journal of Educational Technology*, 53(4), 844-875. <https://doi.org/10.1111/bjet.13233>
- Divjak, B., Svetec, B., Horvat, D., & Kadoić, N. (2023). Assessment validity and learning analytics as prerequisites for ensuring student-centred learning design. *British Journal of Educational Technology*, 54(1), 313-334. <https://doi.org/10.1111/bjet.13290>
- Elamrani Elhassani, A., Oulamine, A., & Elbarhoumi, F. (2025). Rethinking the adoption of artificial intelligence in higher education: A bibliometric study of barriers, ethical issues, and governance challenges. *International Journal of Digitalization and Applied Management*, 2(2), 97-116. <https://doi.org/10.23882/ijdam.25216>
- Falloon, G. (2020). From digital literacy to digital competence: The teacher digital competency (TDC) framework. *Educational Technology Research and Development*, 68(5), 2449-2472. <https://doi.org/10.1007/s11423-020-09767-4>
- Ghai, A., Sharma, R., Altınay, Z., Altınay, F., Dağlı, G., & Jasola, S. (2025). Personalized learning in education through AIoT: Adaptive systems for student engagement and performance. *NEU Journal for Artificial Intelligence and Internet of Things*, 4(1), 96-103. <https://doi.org/10.32955/neuaiit202541958>
- Ghashim, I., & Arshad, M. (2023). Internet of Things (IoT)-based teaching and learning: Modern trends and open challenges. *Sustainability*, 15(21), Article 15656. <https://doi.org/10.3390/su152115656>
- González-Mujico, F. de L. (2024). Measuring student and educator digital competence beyond self-assessment: Developing and validating two rubric-based frameworks. *Education and Information Technologies*, 29(11), 13299-13324. <https://doi.org/10.1007/s10639-023-12363-7>
- Gumina, S., Patten, K., & Gerdes, J. (2024). The evolution of IoT education within an IT curriculum. *Education and Information Technologies*, 29(6), 6723-6752. <https://doi.org/10.1007/s10639-023-12088-7>
- Hong, J., & Kim, K. (2025). Impact of AIoT education program on digital and AI literacy of elementary school students. *Education and Information Technologies*, 30(1), 107-130. <https://doi.org/10.1007/s10639-024-12758-0>
- Ilieva, G., Yankova, T., Ruseva, M., & Kabaivanov, S. (2025). A framework for generative AI-driven assessment in higher education. *Information*, 16(6), Article 472. <https://doi.org/10.3390/info16060472>
- Jagatheesaperumal, S. K., Bibri, S. E., Huang, J., Rajapandian, J., & Parthiban, B. (2024). Artificial intelligence of things for smart cities: Advanced solutions for enhancing transportation safety. *Computational Urban Science*, 4, Article 10. <https://doi.org/10.1007/s43762-024-00120-6>
- Kamruzzaman, M. M., Alanazi, S., Alruwaili, M., Alshammari, N., Elaiwat, S., Abu-Zanona, M., Innab, N., Elzaghmouri, B. M., & Alanazi, B. A. (2023). AI- and IoT-assisted sustainable education systems during pandemics, such as COVID-19, for smart cities. *Sustainability*, 15(10), Article 8354. <https://doi.org/10.3390/su15108354>
- Kim, J. (2024). Leading teachers' perspective on teacher-AI collaboration in education. *Education and Information Technologies*, 29, 8693-8724. <https://doi.org/10.1007/s10639-023-12109-5>

- Kitcharoen, P., Howimanporn, S., & Chookaew, S. (2024). Enhancing teachers' AI competencies through artificial intelligence of things professional development training. *International Journal of Interactive Mobile Technologies*, 18(2), 4-15. <https://doi.org/10.3991/ijim.v18i02.46613>
- Kitto, K., & Knight, S. (2019). Practical ethics for building learning analytics. *British Journal of Educational Technology*, 50(6), 2855-2870. <https://doi.org/10.1111/bjet.12868>
- Kola, I. M. (2022). Using analytical rubrics to assess technological solutions in the technology classroom. *International Journal of Technology and Design Education*, 32, 883-904. <https://doi.org/10.1007/s10798-020-09635-5>
- Kwon, H., Jang, J., Kim, J., Seo, D., & Jeon, S. (2025). Implementation of a real-time analysis simulation system for traffic signal control algorithms to reduce vehicle exhaust emissions and improve traffic flow. *IEEE Access*, 13, 76109-76120. <https://doi.org/10.1109/ACCESS.2025.3564623>
- Liao, X., Zhang, X., Wang, Z., & Luo, H. (2024). Design and implementation of an AI-enabled visual report tool as formative assessment to promote learning achievement and self-regulated learning: An experimental study. *British Journal of Educational Technology*, 55(3), 1253-1276. <https://doi.org/10.1111/bjet.13424>
- Lloret, Á., Peral, J., Ferrández, A., Auladell, M., & Muñoz, R. (2025). A data-driven framework for digital transformation in smart cities: Integrating AI, dashboards, and IoT readiness. *Sensors*, 25(16), Article 5179. <https://doi.org/10.3390/s25165179>
- Lubbe, A., Marais, E., & Kruger, D. (2025). Cultivating independent thinkers: The triad of artificial intelligence, Bloom's taxonomy and critical thinking in assessment pedagogy. *Education and Information Technologies*, 30, 17589-17622. <https://doi.org/10.1007/s10639-025-13476-x>
- Mattar, J., Ramos, D., & Lucas, M. (2022). DigComp-based digital competence assessment tools: Literature review and instrument analysis. *Education and Information Technologies*, 27, 10843-10867. <https://doi.org/10.1007/s10639-022-11034-3>
- Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K. W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, 55(3), 1082-1104. <https://doi.org/10.1111/bjet.13411>
- Okada, A., Sherborne, T., Panselinas, G., & Kolionis, G. (2025). Fostering transversal skills through open schooling supported by the CARE-KNOW-DO pedagogical model and the UNESCO AI competencies framework. *International Journal of Artificial Intelligence in Education*, 35, 1953-1998. <https://doi.org/10.1007/s40593-025-00458-w>
- Owan, V. J., Abang, K. B., Idika, D. O., Etta, E. O., & Bassey, B. A. (2023). Exploring the potential of artificial intelligence tools in educational measurement and assessment. *Eurasia Journal of Mathematics, Science and Technology Education*, 19(8), Article em2307. <https://doi.org/10.29333/ejmste/13428>
- Pandya, V. K., Joshi, K. R., & Modha, V. P. (2025). Practical and theoretical ethics in the age of IoT and big data: Navigating the digital landscape with implications for educational performance. *International Journal of Innovative Research in Computer Science and Technology*, 13(2), 1-5. <https://doi.org/10.55524/ijrcst.2025.13.2.1>
- Pei, B., Cheng, Y., Ambrose, A., Dziadula, E., Xing, W., & Lu, J. (2024). LearningViz: A dashboard for visualizing, analyzing and closing learning performance gaps—A case study approach. *Smart Learning Environments*, 11, Article 56. <https://doi.org/10.1186/s40561-024-00346-1>
- Phanichsiti, S., Nilsook, P., & Piriyaawong, P. (2025). Advance organizer integrating visual-based programming via artificial intelligence of things to enhance advanced computational thinking competency. *International Journal of Information and Education Technology*, 15(7), 1355-1367. <https://doi.org/10.18178/ijiet.2025.15.7.2337>
- Phuong, H. Y., Le, T. T., & Pham, T. T. (2025). Assessment for learning or assessment for scoring? Washback of analytic rubrics in Vietnamese EFL classrooms. *Language Testing in Asia*, 15, Article 32. <https://doi.org/10.1186/s40468-025-00371-y>
- Santana, M., & Díaz-Fernández, M. (2023). Competencies for the artificial intelligence age: Visualisation of the state of the art and future perspectives. *Review of Managerial Science*, 17, 1971-2004. <https://doi.org/10.1007/s11846-022-00613-w>
- Siam, S. I., Ahn, H., Liu, L., Alam, S., Shen, H., Cao, Z., Shroff, N., Krishnamachari, B., Srivastava, M., & Zhang, M. (2025). Artificial intelligence of things: A survey. *ACM Transactions on Sensor Networks*, 21(1), Article 9, 1-75. <https://doi.org/10.1145/3690639>
- Sidhu, N. S., Allen, K. J., Civil, N., Johnstone, C. S. H., Wong, M., & Taylor, J. A. (2023). Competency domains of educators in medical, nursing, and health sciences education: An integrative review. *Medical Teacher*, 45(2), 219-228. <https://doi.org/10.1080/0142159X.2022.2126758>
- Stadin, M., Asplund, S., Nyman, T., Svartengren, M., & Hellman, T. (2024). Digital competence is a must: Manager and safety representative perspectives on evolving job skills and balancing digital work environments in transportation, logistics, and home care. *Computers in Human Behavior Reports*, 16, Article 100486. <https://doi.org/10.1016/j.chbr.2024.100486>
- Tabuenca, B., Uche-Soria, M., Grellier, W., Hernández-Leo, D., Balcells-Falgueras, P., Gloor, P., & Garbajosa, J. (2024). Greening smart learning environments with artificial intelligence of things. *Internet of Things*, 25, Article 101051. <https://doi.org/10.1016/j.iot.2023.101051>
- Tempelaar, D., Rienties, B., & Giesbers, B. (2024). Dispositional learning analytics and formative assessment: An inseparable twinship. *International Journal of Educational Technology in Higher Education*, 21, Article 57. <https://doi.org/10.1186/s41239-024-00489-8>
- Trilles, S., Hammad, S. S., & Iskandaryan, D. (2024). Anomaly detection based on artificial intelligence of things: A systematic literature mapping. *Internet of Things*, 25, Article 101063. <https://doi.org/10.1016/j.iot.2024.101063>

- Vargas, H., Heradio, R., Farias, G., Lei, Z., & de la Torre, L. (2024). A pragmatic framework for assessing learning outcomes in competency-based courses. *IEEE Transactions on Education*, 67(2), 224-233. <https://doi.org/10.1109/TE.2023.3347273>
- Vesna, L., Sawale, P. S., Kaul, P., Pal, S., & Murthy, B. S. N. V. R. (2025). Digital divide in AI-powered education: Challenges and solutions for equitable learning. *Journal of Information Systems Engineering and Management*, 10(21s), 300-308. <https://doi.org/10.52783/jisem.v10i21s.3327>
- Vindigni, G. (2025). Data-driven disparities: How AI applications in education may perpetuate or mitigate inequality. *European Journal of Science and Modern Technologies*, 1(4), 4-54. [https://doi.org/10.59324/ejsmt.2025.1\(4\).02](https://doi.org/10.59324/ejsmt.2025.1(4).02)
- Williams, P. (2023). AI, analytics and a new assessment model for universities. *Education Sciences*, 13(10), Article 1040. <https://doi.org/10.3390/educsci13101040>
- Wolniak, R., & Stecula, K. (2024). Artificial intelligence in smart cities—Applications, barriers, and future directions: A review. *Smart Cities*, 7(3), 1346-1389. <https://doi.org/10.3390/smartcities7030057>
- Xu, H., Seng, K. P., Ang, L. M., & Smith, J. (2024). Decentralized and distributed learning for AIoT: A comprehensive review, emerging challenges, and opportunities. *IEEE Access*, 12, 101016-101052. <https://doi.org/10.1109/ACCESS.2024.3422211>
- Yusuf, O., Rasheed, A., & Lindseth, F. (2025). Leveraging big data and AI for sustainable urban mobility solutions. *Urban Science*, 9(8), Article 301. <https://doi.org/10.3390/urbansci9080301>
- Zaman, F. H., Imtiaz, J., Iqbal, M., & Mir, A. W. (2025). AI-based prediction of program learning outcomes for an engineering undergraduate degree. *Computer Applications in Engineering Education*, 33(6), Article e70092. <https://doi.org/10.1002/cae.70092>
- Zeng, M., Abdullah, Z., & Cheah, K. S. L. (2025). Pre-service teachers' digital competence: A systematic review of factors, frameworks, and global patterns. *International Journal of Learning, Teaching and Educational Research*, 24(8), 218-247. <https://doi.org/10.26803/ijlter.24.8.10>