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Design and Expert Validation of AI-Supported Collaborative Digital Learning Model for Introductory Multimedia Course SPADA Indonesia

Muh. Al Amin[a,1,*], Ahmad Fatoni Dwi Putra [b,2]

[a]Institut Teknologi dan Bisnis Bina Adinata, Sulawesi Selatan, Indonesia
[b]Universitas Qamarul Huda Badaruddin, Nusa Tenggara Barat, Indonesia
[1] daeng.ngawing@gmail.com*; [2] ahmadfatoni@uniqhba.ac.id
* corresponding author

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ABSTRACT

This study develops and conceptually validates an AI-Supported Collaborative Digital Learning (AI-CDL) model for an Introduction to Multimedia course delivered through the national LMS, SPADA Indonesia. Using a Design and Development Research approach aligned with early-stage Design-Based Research, the study followed four phases: (1) contextual and needs analysis of course outcomes, commonly referred to as CPL (*Capaian Pembelajaran Lulusan*) and CPMK (*Capaian Pembelajaran Mata Kuliah*), existing learning activities, and available LMS affordances; (2) conceptual model design grounded in collaborative learning theory and multimedia learning principles; (3) development of project-based collaborative scenarios and supporting artefacts (learning paths, assessment rubrics, and responsible AI-use guidelines); and (4) conceptual validation through expert review and alignment with recent evidence syntheses on AI-supported collaboration in higher education. The resulting AI-CDL model operationalizes AI support across three layers intelligent content support, AI-supported collaboration, and AI-augmented production workflows mapped to key multimedia topics and implemented through SPADA activities. Expert feedback informed iterative refinements, particularly in task orchestration, assessment transparency, and ethical safeguards. This study contributes a validated design blueprint and transferable design principles for integrating AI into collaborative multimedia learning within a national-scale LMS. Future work will empirically evaluate learning processes and outcomes through classroom implementation and learning analytics.

1. Introduction

The rapid expansion of the digital economy has transformed how organizations communicate, market, and build user experiences, positioning multimedia competence as a core graduate capability in design, media, and digital business-oriented programs. Contemporary digital communication brand storytelling, social media campaigns, digital advertising, and interface design depends on purposeful integration of text, images, audio, video, and animation. Consequently, an Introduction to Multimedia course is increasingly expected to move beyond discrete technical instruction toward collaborative, project-oriented learning experiences that approximate authentic production practices and industry-relevant competencies [1].

In parallel, higher education has expanded online and blended learning infrastructures to increase flexibility and equity in access. In Indonesia, a key national initiative is SPADA Indonesia, a national

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Learning Management System (LMS) that supports asynchronous and synchronous interaction, structured assessment, and learning analytics. As a platform operating at national scale, SPADA Indonesia serves heterogeneous learners from diverse institutions and regions, amplifying common online learning challenges such as uneven access to devices and connectivity, variable instructor readiness, and difficulty maintaining high-quality collaboration across distance and time [2]. These constraints are especially salient for multimedia courses, where learning success depends not only on understanding concepts but also on iterative production cycles and sustained peer feedback.

Research on online collaborative learning and Computer-Supported Collaborative Learning (CSCL) has repeatedly shown that collaboration is not inherently beneficial; learning gains depend on the quality of cognitive, metacognitive, and socio-relational interaction. CSCL scholarship provides well-established design principles for structuring productive group work, including collaboration scripts (roles, phases, prompts), mechanisms for participation equity, and assessment strategies for individual contribution within group products. However, many CSCL-oriented designs were developed before the widespread availability of generative AI and therefore rarely specify how algorithmic tools should be embedded into collaborative processes nor how to preserve learner agency and constructive disagreement when AI can quickly generate answers [3].

A second strand of research examines AI in higher education [4], including intelligent tutoring, learning analytics, and generative AI applications for supporting explanation, feedback, and content creation. Evidence syntheses suggest AI can enhance collaborative learning by assisting group formation, monitoring interaction patterns, producing formative feedback, and summarizing discussion threads, potentially reducing coordination overhead and improving perceived support when aligned with pedagogical goals [5]. Yet the same literature also highlights risks automation bias, reduced critical engagement, academic integrity violations, privacy concerns, and unequal access indicating that AI integration is fundamentally an instructional design and governance problem, not a simple technology adoption choice [6].

A third relevant strand is multimedia learning theory, particularly Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML). These theories explain why novice learners may experience cognitive overload in multimedia contexts due to simultaneous processing of multiple representations and procedural steps. Theory-driven recommendations segmenting tasks, scaffolding complex workflows, using worked examples, and managing split attention can reduce extraneous load and support schema construction. However, multimedia learning theory primarily addresses cognition and information presentation; it does not fully specify how to orchestrate sustained collaborative multimedia production online, where learners must coordinate ideation, design, production, critique, revision, and reflection under time constraints and varied prior skill levels [7].

Taken together, the state of the art is strong but fragmented. Many course implementations are tool-centric, adding AI as optional support without systematically mapping AI functions to learning outcomes, collaboration processes, and assessment [8]. Meanwhile, AI-supported collaboration studies often examine isolated tasks in controlled settings or generic LMS environments, leaving the translation to national scale platforms under-specified. Finally, CSCL and multimedia learning theories provide complementary guidance, but they are rarely integrated into an actionable blueprint that teachers can implement within a specific LMS ecosystem while managing integrity, privacy, and equity constraints [9].

Despite advances in AI-supported collaboration, CSCL design, and multimedia learning theory, prior work rarely offers an end-to-end instructional design model that (i) maps AI functions to collaborative processes and assessed learning outcomes, (ii) supports the full multimedia production workflow from ideation through production, critique, revision, and reflection, and (iii) is implementable within a national-scale LMS while operationalizing safeguards for academic integrity, privacy, bias-awareness, and unequal access. As a result, instructors lack a practical yet theory-grounded blueprint for integrating AI into collaborative multimedia learning on SPADA Indonesia in ways that are pedagogically coherent, ethically defensible, and feasible under real constraints of learner heterogeneity [10].

To address this gap, the present study develops an AI-CDL tailored to the Introduction to Multimedia course delivered through SPADA Indonesia. The novelty lies not in using AI tools per se, but in providing an integrated instructional design that connects (a) collaborative learning orchestration, (b) multimedia learning principles for cognitive load management, and (c) human-centered, responsible AI use into a coherent, implementable framework. Unlike tool-centric course designs that treat AI as an add-on, and unlike generic collaboration frameworks that do not specify how AI should be embedded across assessed workflows, the AI-CDL model operationalizes AI support across three layers: intelligent content support, AI-supported collaboration, and AI-augmented production workflows aligned with topic-level competencies and project milestones. In addition, the study contributes implementable SPADA-based collaborative scenarios across key multimedia domains, supporting artefacts (AI-use guidelines, assessment rubrics, integrity-oriented task designs), and transferable design principles refined through conceptual validation via expert review and literature alignment [11], [12], [13].

An Introduction to Multimedia course combines conceptual learning with sustained creative production. Students must develop foundational understanding of multimedia concepts and design principles while building procedural fluency with tools and workflows and exercising judgment about audience, narrative coherence, and design rationale. In online settings, these demands intensify because learners start with heterogeneous skill levels and often face delays in receiving feedback. Collaboration can be pedagogically powerful by enabling peer modeling, shared troubleshooting, and iterative critique; however, it is also vulnerable to coordination overhead, participation imbalance, and shallow interaction. AI can plausibly mitigate some friction by reducing low-level overhead and structuring peer feedback, but only if tasks require learners to critique, revise, and justify AI outputs rather than accept them uncritically. For this reason, the model conceptualizes AI as a mediating artefact that supports collaborative sense-making and production, while keeping human deliberation central to meaning-making and evaluation [14], [15], [16].

At the same time, AI integration in assessed production tasks requires explicit governance. Generative tools can blur authorship boundaries, encourage over-reliance, and reproduce biases. Reliance on external AI services also raises privacy and sustainability concerns. These issues intersect with equity in national-scale contexts: students with stronger devices and connectivity may benefit disproportionately. Therefore, responsible AI integration must be operationalized through task design (process documentation and reflection), rubric criteria that value reasoning and revision, and clear guidance on acceptable AI use rather than treated as generic policy statements. The AI-CDL model addresses these constraints by embedding integrity and ethics safeguards as design components, not as afterthoughts [17], [18], [19].

Based on the identified research gap and positioning, this study aims to develop and conceptually validate an AI-CDL model for the Introduction to Multimedia course delivered through SPADA Indonesia. In the context of Indonesian higher education, the formulation of learning outcomes follows the national outcome-based education framework, commonly expressed through CPL (*Capaian Pembelajaran Lulusan*) and CPMK (*Capaian Pembelajaran Mata Kuliah*). CPL refers to the Program Learning Outcomes, which describe the competencies expected to be achieved by graduates of a study program, while CPMK refers to the Course Learning Outcomes, which specify the competencies that students should attain upon completing a particular course and which contribute to the achievement of the broader CPL.

Accordingly, this study seeks to: (1) analyze the pedagogical characteristics of the course and identify opportunities for AI integration; (2) propose a layered AI-CDL conceptual model and implementation logic that aligns course-level learning outcomes (CPMK) with program-level competencies (CPL) through AI-mediated collaborative learning activities; (3) develop exemplar project-based collaborative scenarios and supporting artefacts that can be implemented using SPADA features; and (4) discuss the pedagogical, technical, and ethical implications of AI integration within a national LMS context, generating transferable design principles for future empirical evaluation.

By doing so, the study contributes a theory-grounded and context-sensitive blueprint for integrating AI-supported collaboration into multimedia-oriented courses at scale while maintaining alignment with the CPL–CPMK learning outcome framework commonly used in Indonesian higher education.

2. Method

This study employed a Design and Development Research (DDR) approach aligned with early-stage Design-Based Research (DBR) to develop and conceptually validate an AI-CDL model for an Introduction to Multimedia course delivered via SPADA Indonesia. The study focused on design rigor and conceptual validation rather than classroom experimentation. The methodological logic follows iterative cycles of (1) contextual analysis, (2) model design, (3) scenario and artefact development, and (4) conceptual validation and revision [20], [21].

The study addressed four research questions (RQs), aligned with the study objectives:

RQ1: What course characteristics and learning-outcome requirements indicate high-leverage opportunities for AI-supported collaboration in an Introduction to Multimedia course?

RQ2: What conceptual AI-CDL model can align learning outcomes with AI-mediated collaborative processes and multimedia learning principles?

RQ3: What implementable learning scenarios and supporting artefacts can operationalize the model within the LMS affordances?

RQ4: To what extent is the proposed model conceptually valid in terms of pedagogical coherence, feasibility, ethical alignment, and theoretical consistency?

The development context was a 3-credit Introduction to Multimedia course for early-semester undergraduate students. The design artefacts produced in this study included: (a) the AI-CDL conceptual model and its component definitions, (b) an outcome-to-activity alignment matrix, (c) topic-level collaborative scenarios (tasks, roles, prompts, tools, assessment), (d) assessment rubrics emphasizing process evidence and reflection, and (e) responsible AI-use guidelines (integrity, privacy, bias awareness).

2.1. Phase 1: Contextual and Needs Analysis (RQ1)

Data were collected through document analysis of: (1) course syllabus/RPS and weekly topic plan, (2) intended learning outcomes at program/course level (CPL/CPMK), (3) assessment scheme and rubric drafts (if available), and (4) the existing LMS course configuration (modules, forums, assignments, quizzes, synchronous meeting integration). In addition, an LMS affordance audit was conducted to identify which platform features could support collaborative scripting (e.g., group assignments, discussion forums, peer feedback mechanisms, submission workflows).

Data analysis in this phase used a structured coding framework with three lenses: (a) outcome requirements (knowledge, skills, collaboration/communication), (b) workflow demands of multimedia production, and (c) constraints (time, access, heterogeneity, integrity risks). Outputs were summarized as a needs-analysis report and a list of "AI integration points" mapped to topics and learning outcomes [22], [23].

2.2. Phase 2: Conceptual Model Design (RQ2)

Model design followed a synthesis process combining: (1) requirements from Phase 1, and (2) evidence-based design principles from prior research on AI-supported collaborative learning, CSCL orchestration, and multimedia learning (CLT/CTML). The model was constructed iteratively through three steps:

1) Component specification: defining model constructs (pedagogical foundations, collaborative processes, AI support functions, and LMS implementation layer);
2) Layered AI mapping: operationalizing AI support into three layers intelligent content support, AI-supported collaboration, and AI-augmented production workflows each linked to targeted learning outcomes and risks (e.g., automation bias);
3) Alignment matrix creation.

The phase output was a draft AI-CDL model diagram and a written model specification describing assumptions, boundary conditions, and implementation logic [24].

2.3. Phase 3: Scenario and Supporting Artefact Development (RQ3)

To operationalize the model, topic-level scenarios were authored using a standard scenario template containing: learning objectives, collaborative task phases, group roles, expected interaction products, AI usage instructions, prompts/examples, assessment criteria, and reflection questions. Scenarios were developed for representative domains including multimedia foundations, graphic design, audio/podcasting, video production, animation, and digital marketing integration [25].

Supporting artefacts were developed to ensure enactment feasibility: (a) rubric structures emphasizing process documentation and reasoning, (b) student-facing responsible AI-use guidelines, and (c) instructor orchestration notes (timing, facilitation moves, and risk mitigation for integrity and equity).

2.4. Phase 4: Conceptual Validation via Expert Review (RQ4)

1) Expert Panel and Selection Criteria
   Conceptual validation was conducted through expert review. A purposive expert panel of 5 experts was recruited across three domains: (1) instructional design/DBR and online learning, (2) multimedia education and project-based learning, and (3) AI in education and educational technology. Experts met the following criteria: (a) minimum 5 years of relevant experience, and at least one of (b) peer-reviewed publications in related areas, (c) experience designing or teaching online/blended courses, or (d) professional involvement in curriculum or learning design. Experts provided informed consent and were offered anonymized participation [26].
2) Validation Instrument
   Experts evaluated the model and scenarios using a structured validation rubric consisting of 22 items across four dimensions:
   a. Pedagogical coherence (alignment between outcomes, activities, collaboration scripts, and assessment)
   b. Feasibility (implementability within LMS constraints and typical course conditions),
   c. Ethical and integrity alignment (privacy, bias awareness, and plagiarism risk mitigation),
   d. Theoretical consistency (consistency with CSCL principles and CLT/CTML considerations).

   Items were rated on a 1-5 Likert scale and accompanied by open-ended prompts requesting revision suggestions and identification of risks or missing components.
3) Expert Review Procedure
   The review procedure consisted of one round. In Round one, experts received the model specification, scenario pack, and rubric via email. Responses were compiled into a structured feedback report. The research team revised the model and scenarios following predefined decision rules.
4) Analysis of Expert Feedback
   Quantitative ratings were summarized using descriptive statistics (mean and item-level agreement). To support content validity claims, content validity indices were computed. Qualitative feedback was analyzed using thematic coding to identify recurring issues and actionable revisions. A revision log documented each change, the corresponding expert input, and the rationale.
5) Reproducibility and Audit Trail
   To ensure reproducibility, the study maintained an audit trail consisting of: (a) analyzed course documents list, (b) LMS affordance audit checklist, (c) model versions and alignment matrices, (d) scenario templates and final scenario pack, (e) expert review instrument, (f) anonymized expert feedback summaries, and (g) revision logs mapping feedback to implemented changes.
6) Ethical Considerations
   This study involved expert participants only and did not collect student learning data. Experts provided informed consent; data were anonymized in reporting and stored securely. Any external AI tools referenced in the scenarios were framed with privacy-aware guidance and integrity constraints to minimize risks during future implementation [27], [28], [29].

3. Results and Discussion

This section reports the outcomes of an early-stage Design-Based Research process by presenting (1) the design artefacts produced and (2) conceptual validation findings from expert review. As the present study focuses on design and validation of an instructional model rather than classroom experimentation, the results are reported as design outputs and validation evidence, not as learning outcome effects.

3.1. Design Outcomes: AI-CDL Model and Implementable Artefacts

The primary design outcome is an AI-CDL model for the Introduction to Multimedia course implemented in SPADA Indonesia. The model specifies how AI is integrated as a pedagogical scaffold rather than an add-on tool. As illustrated in Figure 1, The architecture organizes AI support into three layers: (a) intelligent content support, (b) AI-supported collaboration, and (c) AI-augmented production workflows. Each layer is explicitly linked to collaborative processes and cognitive load considerations informed by CLT/CTML.

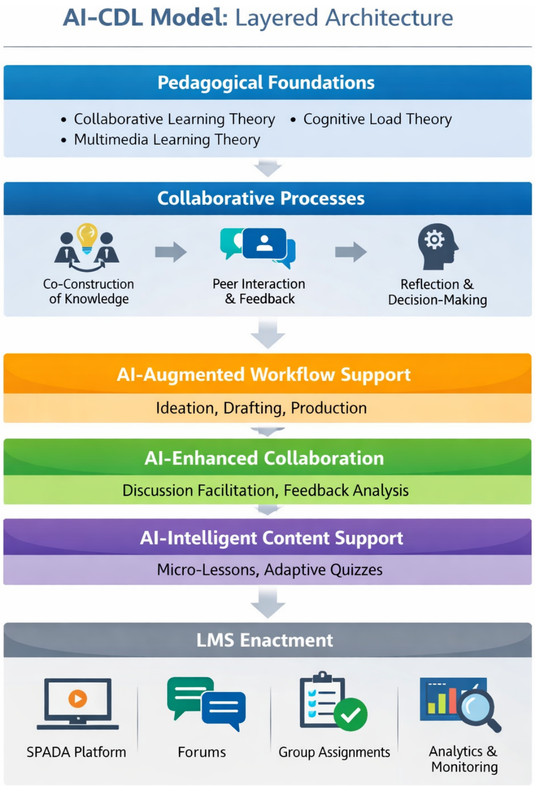

Fig. 1. AI-CDL Model

3.2. Conceptual Validation Results: Expert Review Evidence

Conceptual validation was conducted via a structured expert review to evaluate the AI-CDL model in terms of pedagogical coherence, feasibility, ethical alignment, and theoretical consistency. A purposive panel of five experts (N = 5) was recruited to represent the interdisciplinary scope of the model, comprising specialists in instructional design and online learning (n = 2), multimedia education and project-based learning (n = 2), and artificial intelligence in education (n = 1). All experts met the selection criteria of having a minimum of five years of professional experience and at least one of the following qualifications: peer-reviewed publications, formal curriculum or instructional design experience, or sustained teaching practice in higher education. Expert characteristics are summarized in Table 1.

Experts reviewed the AI-CDL model specification presented in Figure 1, together with the accompanying scenario pack using a validation instrument consisting of 22 items (k = 22) across four dimensions: pedagogical coherence (6 items), feasibility (6 items), ethical and integrity alignment (5 items), and theoretical consistency (5 items). Each item was rated on a five-point Likert scale (1 = not appropriate, 5 = highly appropriate) and complemented with open-ended comment fields to capture qualitative feedback and suggested revisions.

Table 1. Expert Panel Profile

Expert Code	Domain of Expertise	Years of Experience	Evidence of Expertise
E1	Instructional Design & DBR	12 years	Online curriculum design; DBR publications
E2	Instructional Design & Online Learning	8 years	LMS-based course development; faculty trainer
E3	Multimedia Education	9 years	Teaching multimedia production & PBL
E4	Multimedia & Digital Media	7 years	Industry-oriented multimedia curriculum
E5	AI in Education & Ethics	10 years	Research on AI-supported learning systems

Quantitative validation results are presented in Table 2. Overall, experts rated the AI-CDL model high in pedagogical coherence, The model achieved a mean score of 4.48, The ethical and integrity alignment dimension received a mean score of 4.44, and The highest rating was observed in theoretical consistency, with a mean score of 4.56. the feasibility dimension obtained a mean score of 4.18, reflecting expert concerns related to instructional workload, orchestration complexity, and variability in technological infrastructure across institutions.

Content validity was assessed using Aiken's V, which is particularly suitable for small expert panels ($N \leq 10$). A predefined acceptability threshold of $V \geq 0.75$ was applied. All dimensions met or exceeded this threshold, indicating acceptable to high content validity. Items flagged for revision were primarily concentrated in the feasibility and assessment transparency dimensions, suggesting that while the conceptual structure was judged coherent and theoretically sound, implementation guidance required further clarification and refinement.

Table 2. Expert Validation Metrics

Validation Dimension	No. of Items	Mean Rating (1–5)	Aiken's V	Interpretation
Pedagogical Coherence	6	4.48	0.87	High validity
Feasibility	6	4.18	0.78	Acceptable, needs refinement
Ethical & Integrity Alignment	5	4.44	0.85	High validity
Theoretical Consistency	5	4.56	0.90	Very high validity
Overall	22	4.42	0.85	High conceptual validity

3.3. Discussion: Positioning Against Prior Approaches and Theoretical Tensions

Compared with tool-centric AI adoption approaches commonly reported in higher education where AI is introduced as optional assistance without systematic outcome–assessment alignment the AI-CDL model contributes an integrated learning design blueprint linking AI functions to collaborative processes, assessed competencies, and ethics safeguards. In contrast to generic CSCL scripting frameworks that provide orchestration logic but do not specify AI's role across the multimedia production lifecycle, AI-CDL operationalizes AI support from ideation to revision while preserving human deliberation as the locus of decision-making. This positioning addresses a recurring gap identified in recent reviews: the need to move from isolated AI applications toward coherent, implementable instructional designs that remain theory-grounded and context-sensitive.

However, expert feedback also highlighted tensions consistent with the broader literature. First, AI summarization and idea generation may suppress productive cognitive conflict by accelerating convergence and masking divergent viewpoints. To mitigate this, revised scenarios require structured divergence steps and explicit justification of final design decisions. Second, AI outputs can introduce hallucinations or culturally biased content that undermines learning quality and inclusivity. The model therefore incorporates bias-awareness reflection prompts and requires comparison with primary learning materials. Third, integrity risks are substantial in generative workflows; experts recommended shifting assessment emphasis from final products to process evidence which has been incorporated into the rubrics.

This study has important limitations. Most notably, it does not report classroom learning outcomes, collaboration effectiveness metrics, or before after comparisons because it is an early-stage design and conceptual validation study. Effectiveness claims are therefore not asserted as empirical findings. In addition, reliance on external AI services introduces variability in output quality, cost and access constraints, and privacy concerns. Potential failure cases include: (a) automation bias and over-trust in AI suggestions, (b) reduced student agency if AI outputs are adopted without critique, (c) inequitable benefit distribution due to device/connectivity differences, and (d) increased cognitive load if AI scaffolds are overused or poorly timed. These risks were explicitly addressed in revised design safeguards, but they require empirical testing.

4. Conclusion

This study developed and conceptually validated an AI-Supported Collaborative Digital Learning (AI-CDL) model for an Introduction to Multimedia course delivered through the national LMS, SPADA Indonesia. Using a Design and Development Research approach aligned with early-stage Design-Based Research, the study addressed a persistent gap in prior work by integrating collaborative learning theory, multimedia learning principles, and human-centered AI use into a coherent and implementable instructional design framework. The AI-CDL model operationalizes AI support across three interconnected layers intelligent content support, AI-supported collaboration, and AI-augmented production workflows explicitly aligned with learning outcomes, collaborative processes, and assessment requirements. Rather than positioning AI as a replacement for human judgment, the model frames AI as a mediating scaffold that supports coordination, reflection, and iterative multimedia production while preserving learner agency and productive cognitive engagement. The design is further supported by concrete artefacts, including outcome-aligned collaborative scenarios, assessment rubrics emphasizing process evidence, and responsible AI-use guidelines addressing integrity, privacy, bias-awareness, and equity. Conceptual validation through structured expert review indicated high pedagogical coherence, theoretical consistency, and ethical alignment, with feasibility rated as acceptable but contingent on careful instructional orchestration and institutional support. Expert feedback informed targeted refinements, particularly in task sequencing, assessment transparency, integrity safeguards, and accommodation of access constraints, strengthening the model's practical viability. This study contributes to the AI in education literature by shifting the focus from tool-centric adoption toward instructional design as the primary locus of responsible AI integration. However, as an early-stage DBR study, it does not report empirical learning outcomes or comparative effectiveness. Future research should empirically evaluate the AI-CDL model through classroom implementation, learning analytics, and comparative designs to examine its impact on learning outcomes, collaboration quality, and learner experience. Collectively, the AI-CDL model offers a transferable, theory-grounded blueprint for integrating AI-supported collaborative learning into multimedia courses within national-scale digital learning environments.

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AUTHORS BIBLIOGRAPHY

Muh. Al Amin was born in Bategulung. He is a permanent lecturer and researcher in the Digital Business Study Program at ITEB Bina Adinata. He earned his bachelor's degree in Informatics Engineering and his master's degree in Vocational Technology Education. His primary research interests include Mobile Programming, the Internet of Things (IoT), Cloud Computing, Machine Learning, and Educational Technology. He has actively published scientific works in various accredited national journals and international conference proceedings, and is involved in the development of innovative digital learning solutions based on immersive technologies and artificial intelligence. He also serves as a principal investigator for several research grants funded by the Ministry

Ahmad Fatoni Dwi Putra was born in Central Lombok. He is a permanent lecturer and researcher in the Computer Science Study Program at Qamarul Huda Badaruddin Bagu University. He earned his bachelor's degree in Informatics Engineering and his master's degree in Information Technology. His primary research interests include the Internet of Things (IoT) and Machine Learning.