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DEVELOPMENT OF AN AI-BASED PLATFORM FOR RECOMMENDING PROGRAMMING INSTRUCTION PLANS

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ABSTRACT

This research aims to develop and evaluate the effectiveness of AI-PINS (AI-based Programming Instruction Navigation System), a platform for recommending programming lesson plans for primary school teachers in municipal schools. It is designed within a six-theoretical framework: System Theory (IPOF), Agent Theory, Experiential & Adaptive Learning, Explainable AI (XAI), Information Theory, and Cognitive Load Theory. This platform consists of an AI-Agent Core that continuously recognises, analyses, and makes decisions based on real teaching data. The system applies DKT, CBR, RAG, Reinforcement Learning, and intelligent recommendation techniques to generate lesson plans that align with OBEC indicators and learner contexts. The evaluation consists of content validity (IOC ≥ 0.80), evaluation by 15 experts, statistical analysis of the mean, standard deviation, IOC, and Cronbach's Alpha ≥ 0.90, and the application of TAM 4.0 to measure acceptability. The evaluation results indicated that the system is most appropriate ($\bar{x}$ = 4.67, S.D. = 0.13) especially in the dimensions of Intelligence Quality and Decision Quality ($\bar{x}$ = 4.65 and 4.80, respectively). This is due to the efficiency of ML, NLP, RAG, and the Explainable Decision module, which includes XAI to explain to users the reasons for recommending learning management plans and selecting activities through the Dashboard. Regarding the necessity of XAI in the education system, the system also has the potential for continuous learning through MLOps Monitoring and is user-friendly ($\bar{x}$ = 4.53), supporting TAM 4.0 factors in municipal schools. In summary, AI-PINS is a robust, well-evaluated architecture that helps reduce teachers' workload, supports personalised learning, and has the potential to expand digital learning policies at the national level.

Keywords: *AI-Based Platform, Artificial Intelligence, Learning Management Plan, Primary School Teacher, Programming Fundamentals*

1. INTRODUCTION

Coding education has gained global importance. Many countries have incorporated coding into their basic education curricula. The Organization for Economic Co-operation and Development (OECD) [1] highlights that teaching coding from primary school helps develop students' logical and problem solving skills [2]. Policies in Finland, Singapore, and the United States have integrated artificial intelligence (AI) into coding instruction to enhance teaching effectiveness and promote personalized learning [3]. This method aligns with the mission of the National Digital Economy and Society Commission (NDEC). The NDEC oversees organizations and individuals in developing and using AI to advance Thailand and create essential educational resources for future AI technology development [4]. Thailand is currently developing a national strategy for teaching and learning as a foundation for national development. Strategy 3 focuses on developing and enhancing human resources [5]. It encourages educational institutions to create learning activities that yield tangible results, particularly in Computational Thinking and Debugging Skills [6], [7].

Improving the quality of coding education is essential for advancing programming. Despite its importance current teaching systems suffer from critical limitations and structural problems particularly due to a shortage of teachers with expertise in coding and artificial intelligence [7], [8]. As a result educational implementation lacks the necessary competence. The main issues are: 1) Teachers often rely on uniform teaching methods, making it difficult for students to develop skills in analyzing, and correcting errors. Although the same curriculum and learning plan are used teaching approaches differ, leading to unequal outcomes students with less background may fall behind peers with stronger preparation. Additionally learning materials sometimes fail to engage students, reducing instructional effectiveness [9], [10]. 2) Learning systems do not account for varying student abilities. While all students must follow the same

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curriculum, grading and assessment criteria vary among institutions. Consequently, teachers must adapt their methods such as using games to address code errors [11] to foster interest and enjoyment. When students engage more with coding, learning challenges decrease, and teachers can more effectively tailor lesson plans to match student abilities [12], [13].

An AI-powered platform for recommending programming lesson plans is being developed for primary school teachers in municipal schools. This platform can recommend teaching methods using a one-size-fits-all lesson plan [14], [15]. However, it introduces a new format focused on increasing student achievement. The platform follows a common-core structure with curriculum-based learning units and indicators [16]. The content includes an introduction, teaching methods, knowledge sheets, activities, desirable characteristics, ethics, and specified evaluation criteria. All this is based on past learning unit scores. Activity options for different student levels are added. These begin with writing algorithms [17], [18] then move to creating flowcharts [19], [20] and finally programming. All activities match the indicators listed in the lesson plan. The platform uses Agentic AI, which is developed from data sent to the system for memorization, and recording. Teachers set goals for what they want Agentic AI to help them achieve. Agentic AI assists them in meeting those goals or responding to various situations [21], [22]. The platform acts as a learning recommendation system to solve individual teaching problems. CBR recommends activities that have been effective for students [23], [24]. RAG is used to retrieve sample worksheets that match the topic [25] and organize learning paths to meet scoring criteria. The system records model improvements to update the knowledge base. In the future, teachers will use this as a complete automated programming lesson plan recommendation system [26], [27].

Despite the increasing use of Artificial Intelligence in education, existing systems provide limited support for teachers' instructional planning, particularly in primary programming contexts that require transparency and curriculum alignment. Most approaches focus on learner-level analytics while neglecting explainable, context-aware decision support for teachers. Therefore, this study aims to develop and evaluate AI-PINS, an AI-based Programming Instruction Navigation System that integrates intelligent agents and Explainable AI to support transparent instructional decision-making and reduce teacher workload in municipal primary schools.

2. THEORETICAL ARCHITECTURE

2.1 AI-Based Platform

In recent years, artificial intelligence has played a crucial role in the development of digital systems leading to the emergence of so-called AI-based platforms that use AI as the primary mechanism for automatically processing analyzing and generating decision-making outcomes. These platforms are recognized as the foundation for new innovations in various fields including the control of physical systems. This is because AI reduces human labor, increases the accuracy of situation assessment, and can learn and develop skills based on the data received. The world's transformation from a command-based digital system to one that can learn and analyze on its own makes AI-based platforms a truly central technology for developing new innovations [28], [29].

Empirical evidence in education suggests that AI-based platforms have been applied to automatically analyze and evaluate outcomes, such as coding comprehension/skills, error pattern analysis, and learning outcome analytics [28] demonstrating their potential for effective teaching. Education plays a crucial role in transforming learning in the 21st century by leveraging AI to monitor learning, analyze student knowledge and potentially create personalized learning paths tailored to student needs using appropriate learning materials, reducing the burden on teachers, and supports systematic personalized learning [29]. There is also an Adaptive Learning AI platform that lets learners use media appropriate to their actual potential, resulting in shorter learning time, better achievement, and higher engagement than in traditional learning. This development shows that an AI-based platform helps promote access to information and intelligently design learning paths for learners [30]. All of this reinforces the idea that AI-based platforms are the core architecture of the future.

Table 1: Synthesis of AI-Based Platform workflow

Component	Content	Ref.
AI Engine / Core Algorithm	Uses Deep Learning, CNN, ResNet, ML Ensemble, Attention Mechanism, and Predictive Model to process data.	[28], [31], [29], [30], [32].
Data Processing Pipeline	Stores/processes learning logs, interaction data, and historical teaching data in real time.	[28], [31], [9], [33], [34].
Component	Content	Ref.
Feature Extraction Module	Extracts learner characteristics such as learning speed, repetition, understanding level, and coding skill types.	[28], [31], [29],

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		[30], [33].
Personalized Recommendation	Recommends personalized learning paths, adaptive learning, and a suggestion engine.	[29], [30], [32], [35], [36].
Decision Support System	Helps teachers make decisions based on student behaviors data and exercise results. Strengths and weaknesses and the next class period.	[28], [31], [29], [37], [38].
Automated Assessment	Assesses outcomes such as understanding/coding skills. Error Pattern Analysis and Learning Outcome Analytics.	[28], [31], [29], [30], [37].
Knowledge Analytics Layer	Analyze student skills, progress, and weaknesses. Big-picture analytics for teacher dashboards.	[31], [29], [30], [32], [33].
UI/UX Front-End Interface	Dashboard: Single-page student analysis, Learning Analytics Visualization, Teaching Suggestion Screen.	[28], [29], [30], [32], [33], [38].
Cloud Integration / Deployment	Supports web-based platforms, online student data processing.	[28], [31], [29], [39], [40].
Workflow Optimization	Reduce teacher burden with AI-powered learning plan recommendations, content prioritization, and teacher dashboards.	[28], [31], [30], [32], [37], [38].
Predictive Analytics	Predict student areas where students will struggle. Predicting the success of exercises, predicting long-term performance.	[28], [31], [29], [41], [37], [40].
Monitoring & Tracking System	Tracking learning progress, interaction patterns, engagement, and weaknesses for individual learners.	[29], [30], [32], [33], [38], [42].
Scalability Architecture	Supports large numbers of students, grades, and teachers.	[28], [31], [40], [39].
Explainability / Model Transparency	Recommendation reasoning (XAI) with attention/ heatmap/ explanation to reduce teacher anxiety.	[28], [31], [33], [38].
Intelligent Collaboration	Supports teacher-administrator collaboration, such as viewing school-wide or class-wide data.	[29], [39], [40].
Automation Workflow System	Performs some of the manual tasks. Analysis–Decision–Automated Response.	[28], [31], [30], [32], [37], [38].

The overall research clearly shows that AI-based platforms are not just software or tools. They are a "decision-making ecosystem" comprised of databases, learning models, and automated situational responses. As AI advances toward real-time, federated learning, and explainable AI the capabilities of these platforms will only increase. This will create a society where data analysis and decision-making can be instantaneous, accurate, and contextually adaptable without always relying on humans.

2.2 Artificial Intelligence (AI)

Artificial Intelligence (AI) has become a key innovation in the digital age. Its goal is to enable computers to think, analyze, make decisions, and learn like humans by creating perception models and fostering experiential learning. This continuous development has led to technological advancements in expert systems, natural language processing, image recognition, and various forms of automation. Numerous studies have shown that AI combines machine intelligence with human logic, creating new capabilities that can enhance the quality of life, economy, and society. This is especially true in recent times, where machine learning technology has made remarkable advancements [43], [44].

Most researchers currently believe that deep learning, which has enabled AI to achieve significant advances in speed, accuracy, and self-learning, is unlikely to reverse [45], [46]. Meanwhile, AI is making strides in aesthetics and artistic creation across painting, music, literature, and design. Researchers have found that while AI can rapidly produce high-quality work, it still lacks the depth of emotion, life experiences, and unique human interpretations of meaning. This raises ethical questions about the true authorship of the work and the originality of the ideas [47], [48]. Another important dimension is the development of computational architectures towards the concept of the Standard Model of Machine Learning, with various learning processes such as supervised, unsupervised, and reinforcement learning working together as a single system. The goal of this concept is to create AI that can learn from all dimensions of human experience, or Panoramic Learning which is an important development for future AI that has increased learning capabilities and is more flexible.

Table 2: Synthesis of Artificial Intelligence workflow

Component	Content	Ref.
AI Definition & Core Concept	AI refers to intelligent systems that can process data, mimic human thinking, analysis, and decision-making to solve problems with reason and logic.	[43], [44], [49].
Machine Learning (ML)	Used to learn learner behavior, analyze programming fundamentals, and create personalized learning profiles for lesson planning.	[50], [45], [51], [52].
Deep Learning (DL)	Used to analyze patterns from large amounts of data, such as repeated errors, programming weaknesses, and learning log data.	[45], [53], [54].
Neural Network Structures	Help process complex data, such as exercise order, scores, progress, and predict learning outcomes.	[45], [53], [55].
Natural Language Processing (NLP)	Used to automatically summarize sample worksheets. Interpret student programming tasks, provide automated feedback, and generate recommendations for teachers.	[50], [51], [56].
Knowledge Representation & Reasoning	Provides rationale for teacher recommendations, such as identifying common errors, solutions, and appropriate instructional activity sequences.	[43], [46], [53].
Standard Model of Machine Learning	Models utilize the concept of integrating supervised, unsupervised, and sequential learning to create more accurate recommendation models.	[45], [55], [52].
AI Creativity & Generative AI	Generates worksheets, code samples, debugging explanations, and communicates with teachers in contextualized learning contexts.	[47], [48]
Human–AI Trust & Transparency (XAI)	Provides rationale for recommendations, ensuring teachers' confidence, such as "Why is this activity recommended?" or "What topic does this group of students have difficulty with?".	[48], [45].
AI Development Framework & Decision Support	Provides the core structure for designing AI-PINS systems, such as the student assessment module. Lesson Plan Recommendation Module and Learning Dashboard.	[49], [57], [58].
Future Generation AI (AGI/XAI)	AI-PINS aims to provide explainable AI to help teachers clearly understand the rationale and reduce anxiety about using AI in the classroom.	[46], [55], [52].

In short, AI today is moving beyond traditional command-based capabilities into an era of intelligent, self-aware systems that think, analyze, and adapt. This technological trend is not simply a programmatic development, but a shift in human perspectives on "intelligence" and the coexistence between humans and machines. AI is therefore not just a technology, but a new phenomenon in the development of human knowledge and civilization in this century.

Although Artificial Intelligence has been widely applied in educational systems, prior research remains limited in its support for teachers' instructional planning and decision-making. Most AI-based studies emphasize learner-level analytics, automated assessment, or content personalization, while offering minimal consideration of pedagogical reasoning and classroom constraints. Furthermore, many systems operate as black-box models, offering limited explainability, undermining teachers' trust and practical adoption. These limitations are particularly evident in primary school contexts, where instructional decisions must align with curriculum standards, institutional policies, and diverse learner needs. As a result, existing AI research does not yet offer a comprehensive, explainable framework that effectively supports teachers in real instructional environments.

To address these gaps, this study proposes the AI-PINS framework as an explainable and context-aware AI system for instructional planning. AI-PINS positions AI as a decision-support agent for teachers rather than a purely predictive tool, integrating Intelligent Agent Theory, Deep Knowledge Tracing, Case-Based Reasoning, and Retrieval-Augmented Generation within an IPOF architecture. By embedding Explainable AI mechanisms, the framework enables transparent reasoning behind instructional recommendations, enhancing teacher confidence and usability. Consequently, AI-PINS is essential for reducing teacher workload, supporting adaptive programming instruction, and ensuring alignment with learner diversity, curriculum indicators, and municipal school contexts.

2.3 Learning Management Plan

Developing a Learning Management Plan for the Programming Fundamentals course is a crucial component in guiding the teaching direction, lesson content, and learning activities to systematically develop students' programming skills. Literature studies show that programming fundamentals are challenging due to the complexity of logical concepts, programming language structure, and the need for both theoretical and practical understanding. Therefore, a good Learning Management Plan should establish a systematic sequence of learning units, teaching activities, and assessments to reduce cognitive anxiety and increase the chances of learning success [59]. It also helps students gain a clearer understanding of the program structure, which is an important approach in a Learning Management Plan to ensure sequential learning and maximum meaning for students [60].

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In developing countries, structural technological issues and students' knowledge bases have been found to significantly impact course success. Therefore, project-based learning support and blended learning approaches are recommended to provide students with space for continuous skill development [61]. Furthermore, coding instruction should be linked to Computational Thinking (CT) skills through a Learning Management Plan that clearly defines which activities promote these skills. Decomposition, pattern recognition, and algorithm design are used to ensure that programming instruction is not limited to syntax but also linked to logical problem-solving [62]. In terms of specific teaching methods, online Python exercises are designed with a progressive level of difficulty, and an automated, real-time feedback system that allows students to track their progress, and build confidence in programming [63]. Turtle graphics is also proposed to visualize code, help summarize programming briefs and provide motivation [64]. Games have been tested to teach basic coding and encourage participation in problem-solving which should be incorporated into lesson plans to accommodate the diversity of learners in Programming Fundamentals [65].

Table 3: Synthesis of Learning Management Plan workflow

Component	Content	Ref.
Alignment to Curriculum	The plan must align with the curriculum, indicators, objectives, key points, activity content, and expected learning outcomes.	[66], [67], [68], [69].
Learning Outcomes Design	Match learning outcomes with appropriate content, tasks, and activities using the RAG + DKT model → Help teachers select lesson plans that meet their goals.	[70], [67], [71], [72].
Content Structuring	Automatically prioritizes content. Based on the difficulty of Programming Fundamentals and the student's learning history.	[66], [73], [68], [72].
Learning Sequence Mapping	Analyzes the appropriate activity sequence, such as Exercise → Debug → Project → Reflection.	[73], [69], [74], [75].
Instructional Strategy Planning	AI recommends teaching strategies, such as Debug-first, Example-based, and Step-by-Step, based on learner error data.	[70], [76], [77], [78].
Learner Need Analysis	Uses learning history, strengths and weaknesses, and activity participation behavior to analyze learner levels and create recommended teaching plans.	[71], [76], [78], [72].
Task & Activity Design	Recommends appropriate activities, such as programming problems that align with Student Profile + Question Base (CBR).	[73], [71], [77], [78].
Assessment & Evaluation	The system uses Learning Analytics + DKT to assess understanding by topic and notify teachers via a dashboard.	[67], [71], [77], [79], [75].
Outcome-Based Planning (OBE)	The system can automatically match Learning Outcomes → Content → Activities using RAG.	[70], [67], [71], [75].
Feedback-Improve Cycle	Analyze results and automatically adjust the recommendation plan (Adaptive AI Plan).	[76], [79], [80].
Technology Enhanced Learning	AI-PINS is a 100% digital platform using a dashboard, recommendation AI, and an analytical engine.	[76], [77].
Critical & Analytical Skills Design	Design AI selects coding and debugging activities that practice high-level analytical thinking (HOTs).	[81], [77], [74].
Adaptive Teaching Plan	A plan that automatically adjusts based on real-time student data.	[82], [76], [83], [69].

Overall, it can be seen that an effective Learning Management Plan for Programming Fundamentals in the current era should be based on four key foundations: (1) hierarchical lesson structure to reduce cognitive load; (2) the use of proven teaching strategies; (3) continuous monitoring and evaluation systems that allow learners to develop according to their individual abilities; and (4) a flexible learning context that allows learning through images, games, or creative activity formats. This literature therefore provides an important theoretical basis for the development and design of basic programming lesson plans at the elementary, secondary, and tertiary levels that are aligned with digital learning skills and can be concretely extended to intelligent recommendation systems in the future.

2.4 Primary School Teacher

Primary school teachers play a crucial role in laying the foundation for 21st-century knowledge and skills, particularly in programming fundamentals that underpin computational thinking and logical problem-solving. The transformation of education in the digital age means that teachers' roles are no longer limited to content delivery, but also serve as learning designers, creating safe, fun, challenging, and easily understood learning contexts for primary school students who are still developing basic skills.

Instructing programming in primary school should begin with Scratch, a programming platform that connects abstract concepts to concrete forms, helping students understand loops and command structure. Primary school teachers must be able to connect programming fundamentals with games. Teachers must help students gradually progress from memorizing, understanding, applying, analyzing, evaluating, and creating code, adapting them to simple tasks or solving increasingly complex problems incrementally [84]. Teachers must design learning experiences that encourage trial and error without fear of failure [85]. Digital twins, or simulated environments for programming experimentation, have been shown to increase student engagement and reduce anxiety, fostering confidence and improved code debugging skills. The motivational dimension of coding activities helps students gain confidence and positive attitudes, which are the main drivers for primary school students to open their minds to learning programming. Finally, the use of blended learning for teaching Programming Fundamentals enables teachers to design flexible activities that better accommodate students' diverse backgrounds, making it especially suitable for primary school students [86].

Table 4: Synthesis of Primary School Teacher workflow

Component	Content	Ref.
Social & Emotional Competence	Teachers need to have emotional and social skills to understand the context of their learners and use Dashboard data to help analyze problems.	[87], [88].
Professional Attitude & Ethical Orientation	Positive attitudes toward technology/innovation are key factors in AI-PINS (Technology Adoption) adoption.	[89], [87], [90], [91].
Meaningful & Learner-Centered Pedagogy	Teachers emphasize meaningful learning, aligned with the AI-PINS Personalized Learning Path module.	[92], [93], [94].
Child Development & Psychology Knowledge	Teachers need to understand child development and use Dashboard data to interpret behavior and learning outcomes.	[87], [95], [88], [96].
Ability to Teach Students	Supporting learner differences, linked to the recommendation system. AI-PINS Individualized Plan.	[95], [96].
Digital Literacy & Web 2.0 Integration	Technology competence is a key foundation for using the AI-PINS platform.	[92], [97], [98].
Continuous Professional Development (CPD)	Teachers must continuously develop their technological and teaching capabilities for lifelong learning.	[89], [99], [94].
Teaching Practice & Field Experience	Teachers can use Learning Analytics data to analyze class performance and systematically adjust their plans.	[100], [99], [101], [98].
Pedagogical Mastery	The ability to design lesson plans, analyze students, and evaluate learning outcomes is well-suited to the AI-PINS automated lesson plan recommendation system.	[99], [101].
Early Career Challenges	New teachers have a high workload and lack experience. The AI-PINS system helps reduce workload and analyze data. and generate recommendations.	[102], [103].
Teacher Workforce Structure & Educational Context	School context differences influence the design of the AI-PINS system to support multiple contexts.	[104], [91].

In summary, the research indicates that Primary School Teachers in the context of Programming Fundamentals must be activity designers, motivating coaches, creative learning path facilitators, and builders of the foundations of logical thinking and confidence as they step into the digital world. The use of games, music, art, Digital Twins, and Blended Learning becomes an important tools that enable primary school children to access programming naturally, enjoyably, and continuously develop.

2.5 Programming Fundamentals

Programming Fundamentals is considered the most fundamental subject in the computer science and software engineering disciplines. It serves as the foundation for learning programming and developing algorithmic skills. Its goal is to provide students with an understanding of command structure, variables, data types, conditions, loops, functions, and logical problem-solving concepts. A literature review revealed that the key aspects of Programming Fundamentals extend beyond teaching language structure to developing computational thinking concepts, formative assessment, and the use of technology to support learning in real classrooms [105]. It is integrated into basic programming courses, aiming to teach students to think like problem solvers, break problems down, create algorithms, and translate them into logical code. It also provides students with a visual understanding of program operation and variable value changes, alleviating anxiety in students without a basic understanding and increasing their motivation to learn [106].

Currently, learning analytics and machine learning are being used to predict the risk of course failure, enabling instructors to design timely, individualized support. This learning model allows the curriculum to address differences among learners and reduce dropout rates in foundational subjects [107]. thereby making Programming Fundamentals more likely to serve as a platform for practicing logical thinking, problem-solving, and deep digital competencies within the context of 2 1 st-century skills.

Table 5: Synthesis of Programming Fundamentals workflow

Component	Content	Ref.
Algorithmic Thinking	The basic step-by-step thinking methodology that AI-PINS uses to assess learners' thinking paths before generating recommendations.	[108], [109], [110], [106].
Computational Thinking (CT)	The core of learner analysis, used to create CT-based recommendation models.	[111], [109], [112], [113].
Debugging & Error Handling	Used in AI-PINS's Debug Recommendation module to automatically identify errors.	[108], [114].
Problem Decomposition	Key data that AI-PINS uses to identify learners' weaknesses in each skill unit.	[115], [116], [117], [118].
Block → Text Transition	AI-PINS helps teachers design teaching paths from Scratch → Python/C.	[109], [119], [113], [105].
Pedagogy for PF (CT-first)	Uses AI-PINS to automatically generate lesson plans tailored to learner profiles and an active learning/example-first teaching style.	[112], [120].
Self-assessment & Feedback	The starting point for Learning Analytics and the automatic feedback model in AI-PINS.	[113], [121].
Learning Analytics in PF	Basic data for the AI-PINS Dashboard and Performance Prediction.	[117], [122].
IDE for PF (C-SOLVIS)	The concept of reducing cognitive load is the basis of the UI/UX for the AI-PINS Teacher Dashboard.	[123], [118].
Visual Tutor System (CGRAPHIC)	A conceptual framework for AI-PINS visualization (showing execution and error patterns).	[109], [112], [106], [124].
Human Cognitive Factors	Used to reduce the cognitive load between teachers and learners with a one-page Cognitive Load Design Dashboard.	[123], [118].
Multiparadigm Awareness	Used in recommendations to tailor activities to learners.	[125], [110], [117].
Industry Skill Alignment	AI-PINS uses this data to recommend activities aligned with the new digital skills guidelines.	[121], [126].

The literature overview concludes that Programming Fundamentals in the current era is not just about teaching grammar and programming commands, but rather about designing a learning environment that supports computational thinking, learning reflection, self-evaluation, and the use of AI/Analytics to support learner progress in the same direction: creating learners with a foundation in systems thinking, able to work with real code, analyze errors, and confidently develop programs in real situations.

3. THEORETICAL METHODLOGY

System Architecture of AI-PINS

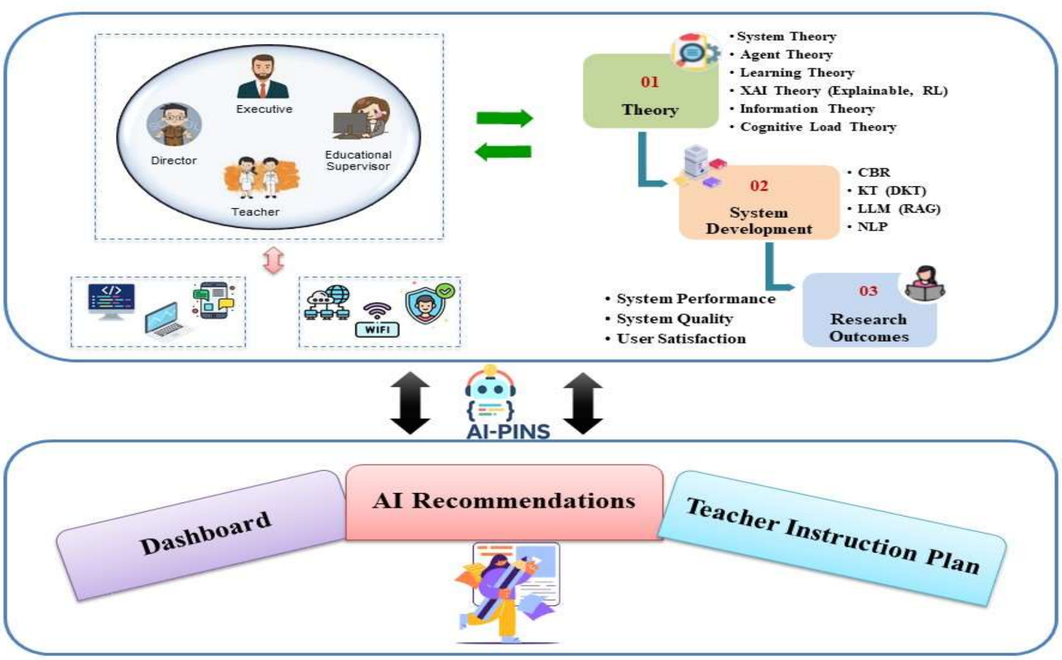

Figure 1: Figure 1: System Architecture : AI-PINS (AI-based Programming Instruction Navigation System)

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As shown in Figure 1, the AI-PINS architecture is an integrated AI-based framework designed to support programming lesson plan recommendations for primary school teachers in municipal school contexts. The architecture consists of four interconnected modules: (1) the Theory Layer, which provides the conceptual foundations including system theory, intelligent agent theory, learning theory, explainable AI, information theory, and cognitive load theory; (2) the System Development Layer, which operationalizes these theories through the AI Agent Core, data management, and intelligent algorithms; (3) the Research Outcome Layer, which delivers practical outputs such as learning analytics dashboards and instructional recommendations; and (4) the Evaluation Dimension, which systematically assesses system quality, intelligence quality, decision quality, learning quality, and user acceptance. All modules are connected through a continuous feedback loop, enabling adaptive learning, model refinement, and sustained system improvement based on real instructional data. These modules comprise:

3.1 Theory

This theory is the conceptual foundation for the development of the AI-PINS platform. Six main theoretical foundations are:

3.1.1 System Theory

System Theory (IPOF Model): Systems theory underpins AI-PINS's interconnected approach. The IPOF (Input–Process–Output–Feedback) model structures input from learning outcomes and teacher data. It processes with the AI Agent Core, outputs lesson plan recommendations, and refines through feedback. [127]. The IPOF framework is essential for system learning and ongoing development.

3.1.2 Intelligent Agent Theory

Agent Theory (Perceive–Decide–Act–Learn Cycle) is a theory of AI-agents that can make decisions and learn by themselves. It has a cycle consisting of Perceive–Decide–Act–Learn steps, enabling the system to perceive, analyze, make decisions, and learn from actual use cases to continuously improve the quality of recommendations. Research on agent-based learning systems in K–12 indicates that intelligent agents can effectively support learning and teaching tasks [128], [129]. This cycle is implemented in the AI-agent core of the AI-PINS system to recognize learning situations, analyze, make decisions, and propose appropriate practices for the school context. It automatically and rationally recommends teaching that adapts to real classroom data and time constraints in the class schedule.

3.1.3 Learning Theory

Learning Theory (Experiential and Adaptive Learning) determines the recommendations of AI-PINS, using the concept of learning from experience. (Experiential Learning) and Adaptive Learning to simulate teacher and student learning in a real-world context appropriate to the development of primary school children. This enables AI-PINS to efficiently create lesson plans that meet their needs. This aligns with research on Knowledge Tracing and Deep Knowledge Tracing, which found that they can track student development and more accurately analyze understanding [130], [131] leading to deeper learning, promoting computational thinking skills, and enabling teachers to systematically reflect on their teaching (Reflective Practice).

3.1.4 Explainable AI Theory

Explainable AI Theory (XAI/RL) enables AI-PINS to provide evidence for its recommendations. For example, it can explain why one lesson plan was chosen over another. Reasons could include lower-than-standard pre-test scores or student responses that indicate the need to review concepts. Research shows that Explainable AI for Education increases teachers' transparency, confidence, and acceptance of AI in teaching [132], [133]. Meanwhile, the technique Reinforcement learning enables the system to accumulate real-world performance data to improve the quality of instruction in subsequent rounds [134], [135] making AI-PINS a system that is both explainable and transparent and continuously adapts to real data.

3.1.5 Information Theory

The AI-PINS data management system ensures maximum efficiency and consistency in data quality management. The system must filter large volumes of data from student scores, past performance, lesson plans, and skill-training activities, so the AI module processes only data that informs decision-making. This is crucial for designing dashboards that reduce cognitive load and enhance teachers' understanding. Research on Visualization Literacy and Dashboards for Teachers indicates that good design can reduce cognitive load and enhance teachers' data analysis capabilities [136].

3.1.6 Cognitive Load Theory

The AI-PINS teacher experience design is based on Sweller's cognitive load reduction principles to reduce the system's memory and time-consuming workload for data analysis. This allows the dashboard and interface to be easily understood, with data displayed visually, graphs, and immediate analytical statistics. Research on Learning Analytics

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Dashboards indicates that well-designed visualizations facilitate faster decision-making and effectively reduce cognitive load [137], [138].

3.2 System Development Dimension

AI-PINS uses Data Management & Integration to collect and process historical student and teacher data. This data is then fed into the AI Agent Core, which utilizes various AI techniques, including Deep Knowledge Tracing (DKT) [130] Case-Based Reasoning (CBR), Natural Language Processing (NLP), Retrieval-Augmented Generation (LLM+RAG) [131] Recommender System, and Reinforcement Learning [134], [135]. The system's results are presented through a Dashboard for Learning Analytics and Instructional Recommendations for Teachers, which reports overall results and recommends programming lesson plans based on student learning outcomes from post-teaching records [138]. The process consists of three main steps:

3.2.1 Data Management & Integration

This process collects and integrates data from multiple sources, such as past scores, lesson plans, and learning outcome indicators. All data is stored in a central data warehouse to ensure readiness for processing [138]. Data security is ensured through encryption and access control (RBAC/ABAC) in this process.

3.2.2 AI Agent Core

The decision-making center of the system to generate and recommend lesson plans [128], [138]. It incorporates key techniques: (1) Deep Knowledge Tracing (DKT), which analyzes learner progress over time to track learning; (2) Case-Based Reasoning (CBR), which uses similar cases to provide recommendations to analyze similar cases; (3) Natural Language Processing (NLP), which analyzes text to understand the teacher's language; (4) Retrieval-Augmented Generation (RAG/LLM), which extracts real data to support the model's response generation; (5) Recommender System, which prioritizes appropriateness of activities and learning materials; and (6) Reinforcement Learning (RL), which improves decision-making based on rewards and post-teaching recordings. For adjusting strategies based on learning outcomes [134], [135].

3.2.3 System Outputs

The system's outputs are divided into two main parts: (1) Dashboard for Learning Analytics, which provides an overview of the learning outcomes of each student group [137], [138]. (2) Instructional Recommendations for Teachers, which recommends lesson plans, teaching activities, and teaching materials. Both parts work in conjunction with the XAI module to allow the system to select lesson plans for teachers and verify the source of recommendations [132], [133].

3.2.4 Feedback & Optimization

The system uses Active Learning and MLOps Monitoring to enable continuous learning and model improvement based on user feedback. This enables the system to learn from actual use, improve accuracy, and adapt to the context of use [137], [138].

3.2.5 User & Environment

This links the AI-PINS system to the actual work environment in municipal schools. There are 3 main user groups: (1) teachers, using AI-PINS Dashboard to analyze learning results and adjust learning management plans via XAI to enable teachers to understand and adjust teaching in accordance with the curriculum [127], [128], [129]. (2) educational supervisors, acting as learning facilitators between teachers and policy (Advisory Layer), using AI-PINS to analyze teaching quality and provide strategic advice (Supervisors) [130], [131]. (3) educational administrators, acting as policy level users (Strategic Level), using AI-PINS Decision Support System (DSS) to analyze and process overall school data to support administrators' decision-making in line with municipal education policies [132], [133]. (3) educational administrators, acting as policy level users (Strategic Level), using AI-PINS Decision Support System (DSS) to analyze and process overall school data to support administrators' decision-making in line with municipal education policies.

3.3 Research Outcomes Dimension

3.3.1 Technical Outcomes

The system's performance is evaluated using technical indicators, including Accuracy, Precision, Recall, and F1 - score, to measure the model's accuracy, performance, and stability [139]. This model's ability to predict and guide learning is validated through cross-validation and Confusion Matrix Analysis.

3.3.2 Application Outcomes

The system can be applied in real classrooms, producing results in the form of lesson plans, automated assessments, and policy decision support systems (DSS) to assist teachers in planning learning activities and administrators in formulating educational policies [140], [141], [142].

3.3.3 Practical and Policy Outcomes

The most important outcome of the research is the practical application of the system in Bang Yai Municipality. The AI-RTRO system has significantly improved security efficiency in the municipality. Automatic object and event detection enables faster responses to situations. The system also reduces the workload of officials who manually review CCTV footage, a time-consuming task that can easily lead to missed details. Furthermore, the data and statistics generated by the system help facilitate more efficient planning and policy decision-making. Community impact is another key outcome. An effective object detection system improves public safety and increases public confidence. The system also promotes a positive image of the municipality in its management of modern technology. Furthermore, the success of the system development allows Bang Yai Municipality to serve as a model for other local administrative organizations interested in developing similar systems. Based on the experience in developing and implementing the system, the researchers have summarized several key policy recommendations, including guidelines for the appropriate and effective use of artificial intelligence in public organizations, taking into account both opportunities and challenges; security and privacy measures that must be considered when using AI systems related to citizen data; and policies for developing AI personnel in public organizations to ensure sustainable system development and maintenance. These recommendations are not only beneficial to Bang Yai Municipality but also to the broader community. But it can still be applied to other agencies.

3.4 Evaluation Dimension

This quantitative and qualitative evaluation examines the model's validity and stability. The evaluation tools include:

3.4.1 Quantitative Evaluation

This examines the validity, reliability, and statistical appropriateness of the model.

3.4.1.1 Appropriateness

The appropriateness of the conceptual framework is measured using a 5-point Likert scale to assess the appropriateness of each component. The data were then analyzed to determine the mean ($\bar{x}$) and standard deviation (SD) to summarize the quantitative data [143].

3.4.1.2 Content Validity

Content validity is examined by at least five experts to calculate the Index of Conformity (IOC) for each question. This measures the appropriateness and reliability of the system, ensuring that the content is accurate and meets the objectives [144], [145].

3.4.1.3 Statistical Reliability & Validation

Advanced statistics are used to analyze and verify the quality of the instrument, including reliability using Cronbach's Alpha (≥ 0.90), factor analysis (CFA) to confirm that the theoretically designed evaluation dimensions are consistent with the actual statistical data, and key performance indicators (KPIs) to assess the overall quality of the system [145], [146], [147].

3.4.2 Qualitative Evaluation

This is used to verify and confirm the system's appropriateness, reliability, and practicality. It consists of:

3.4.2.1 Expert Opinions & Recommendations

This examines the appropriateness, accuracy, and completeness of the system. Data was collected through in-depth interviews for thematic summary and focus group discussions for coding and categorization, and then provided feedback for improvement before the system was implemented [148], [149].

3.4.2.2 Usability/Acceptance

Used to assess the system's ease of use, understandability, and level of acceptance. Data was collected through a usability test using the TAM 4.0 model, along with observations or post-system interviews [146], [150] to improve and confirm the system's completeness.

4. RESULT

The AI-PINS conceptual framework evaluation was designed under the concept of Evaluation Dimensions for the Conceptual Framework of AI Agent-Based Intelligent System Development, covering five main dimensions: (1) System Quality, (2) Intelligence Quality, (3) Decision Quality, (4) Learning Quality, and (5) User & Environment Quality. This evaluation aimed to evaluate a programming instructional management system for elementary school teachers. The evaluation consisted of:

4.1 System Quality

This system measures the efficiency, stability, security, and technical suitability of the AI-PINS system. It is used to verify the consistency and reliability of indicators such as processing speed, historical database connectivity, and dashboard display capabilities [151], [152], [153]. This evaluation assesses the completeness of the system structure and its ability to function under the designed conditions. It supports effective operation in real-world environments, including the appropriate integration of the IPOF module and the AI Agent Core.

4.2 Intelligence Quality

This focuses on model performance and reliability. and the intelligence of AI agents (Perceive–Decide–Act–Learn) in analyzing data and providing accurate recommendations using CBR, KT, and RAG. To achieve an Explainable AI (XAI) system that can explain the reasons for recommendations, it must support ML and NLP

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techniques appropriate to the real-world context and continuously adapt to new data [154], [155], [156], [157].

4.3 Decision Quality

The reasoning behind decisions generated or recommended by AI must be explainable and validated. This measures the accuracy, transparency, and ability to support the system's decision-making, such as recommending lesson plans, sequencing learning paths, and providing analytical feedback using the Explainable Decision Module, which demonstrates the reasons for decisions, and Rule-based Validation, which logically validates recommendations to ensure teachers understand the system's decisions. This includes generating outcomes that are logical and appropriate to the real context [151], [155], [157], [158].

4.4 Learning Quality

Emphasizes the system's ability to learn from data and experiences (Feedback Loop/Experiential Learning) to continuously improve performance from feedback. This includes applying the MLOps process and quality checks to ensure the system can continuously develop and adapt its learning. AI-PINS's learning assessment includes developing students' computational thinking (CT) and debugging skills, as well as designing lesson plans that align with the OBEC curriculum's Learning Outcomes (LOs) and satisfaction measurement [152], [153], [156].

4.5 User & Environment Quality

Measures the system's usability and understandability. (Understandability) and user acceptance levels measured satisfaction with the system's responsiveness to municipal school policies and contexts. The Technology Acceptance Model (TAM 4.0) framework was used to measure 1) PU (Perceived Benefits), displaying a dashboard summarizing learning plans and student scores; 2) PEOU (Ease of Use), ease of use; 3) TR (Trust, Accuracy, Transparency, and Security); and 4) BI (Biometrics), continuity of use and recommended for continued use in the next semester. Interviews with educational supervisors and administrators were also conducted to analyze readiness for practical implementation [151], [153], [154], [158].

The evaluation of the five dimensions of the developed conceptual framework demonstrated that the AI-PINS framework is comprehensive across technical, pedagogical, and policy aspects for practical application. This clearly impacts the application of AI-PINS in municipal school contexts. The framework effectively links theoretical constructs to practical applications in municipal schools, leading to sustained acceptance and confidence among teachers who use the system.

The results of the framework suitability assessment by 15 experts are shown in Table 6.

Table 6: Results of the framework suitability assessment by experts

Assessment list	Mean	S.D.	Opinions
1. System Quality	4.72	0.16	Excellent
1.1 The structure according to the IPOF model is complete and coherent.	4.80	0.41	Excellent
1.2 The system architecture design can support data and operations. In real-world environments	4.67	0.49	Excellent
1.3 The system is flexible and scalable to accommodate new needs.	4.67	0.49	Excellent
1.4 The integration of basic theory and design is consistent.	4.73	0.46	Excellent
2. Intelligence Quality	4.65	0.23	Excellent
2.1 The AI agent has the ability to perceive, analyze, decide, and act (Perceive–Decide–Act–Learn) efficiently.	4.73	0.46	Excellent
2.2 The AI system uses a variety of techniques (ML, NLP, RAG, XAI) appropriately for its purpose.	4.60	0.51	Excellent
2.3 The AI learns and adapts continuously from new data and feedback.	4.60	0.51	Excellent
2.4 The AI Core design is modern and complies with international standards.	4.67	0.49	Excellent
3. Decision Quality	4.80	0.17	Excellent
3.1 The system's decisions are accurate. Reliable and explainable.	4.87	0.35	Excellent
3.2 The decision support system is transparent and traceable.	4.67	0.49	Excellent
3.3 The decision outputs are consistent with actual user needs and problems.	4.87	0.35	Excellent
4. Learning Quality	4.67	0.44	Excellent
4.1 The system can learn experientially and adapt to the environment.	4.67	0.49	Excellent
4.2 The AI agent learns from historical data and feedback to improve accuracy and efficiency.	4.67	0.49	Excellent
4.3 The system uses MLOps for inspection to improve performance quality.	4.67	0.49	Excellent
5. User & Environment Quality	4.53	0.39	Excellent

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Assessment list	Mean	S.D.	Opinions
5.1 The system is designed to be appropriate for actual user use.	4.53	0.52	Excellent
5.2 The system is easily accessible, secure, and convenient to use.	4.60	0.51	Excellent
5.3 The system is designed with user acceptance in mind according to the TAM model.	4.47	0.52	High
Overall Summary	**4.67**	**0.13**	**Excellent**

From Table 6, the results of the evaluation of the appropriateness of the AI-PINS (AI-based Programming Instruction Navigation System) conceptual framework by 15 experts, covering 5 main dimensions, found that the overall appropriateness was at the highest level ($\bar{x}$ = 4.67, S.D. = 0.13) indicating the completeness of the structure according to the IPOF model and the ability to integrate basic theories with the AI system architecture perfectly. The system can support real data processing, is flexible and scalable to support new needs. The dimensions of intellectual quality and decision-making of AI-PINS were evaluated at the highest level ($\bar{x}$ = 4.65 and 4.80 respectively) because the system can process with ML, NLP, RAG and XAI techniques efficiently and reason through the Explainable Decision module which is consistent with the findings in the literature of Zaid M. Altukhi (2024/2025) [159] who stated that educational AI systems should have an explainable mechanism to reduce the ambiguity of the results. In addition, the evaluation results indicated that the system has the potential for continuous learning and development through the MLOps Monitoring process, consistent with the guidelines. Subhankar Maity's Human-Centric XAI (2024) [160] focuses on users learning from the system's reasoning and its suitability for users and the environment ($\bar{x}$ = 4.53). Experts found that the system is safe, easy to use, and consistent with technology acceptance factors in educational institutions, especially when it can be easily explained, as proposed by Sachini Gunasekara (2025) [161]. As a result, the AI-PINS conceptual framework is strong in both theory and practice and meets the design needs of modern educational AI systems that must be transparent, explainable, reliable, and support practical application in primary schools. It is also consistent with the TAM 4.0 model regarding Perceived Usefulness and Ease of Use, indicating a high level of technology acceptance in the context of municipal schools.

Unlike prior AI-based educational studies that primarily focus on learner-level prediction and content personalization, this research advances AI toward an explainable, teacher-centered decision-support framework. While earlier systems often operate as black-box analytics tools, AI-PINS explicitly integrates Explainable AI to support transparent instructional planning. Furthermore, most existing research is situated in higher education or generic online environments, whereas this study is grounded in the real context of municipal primary schools. By embedding Deep Knowledge Tracing, Case-Based Reasoning, and Retrieval-Augmented Generation within an IPOF architecture, AI-PINS bridges the gap between data-driven intelligence and pedagogically accountable classroom practice.

5. DISCUSSION AND CONCLUSION

The evaluation of the AI-PINS (AI-based Programming Instruction Navigation System) framework by 15 experts found it to be the most appropriate ($\bar{x}$ = 4.67, SD = 0.13, IOC = 0.95), reflecting theoretical completeness and structural consistency. And the potential for application in the context of municipal schools, especially the Decision Quality dimension, which received the highest score ($\bar{x}$ = 4.80), indicating the transparency and ability to explain the reasons for decisions through the Explainable Decision and Rule-Based Validation modules, consistent with the results of the literature review indicating that AI systems that can provide explainable reasoning can increase user confidence and acceptance in teaching programs [132] [162]. The System Quality ($\bar{x}$ = 4.72) and Intelligence Quality ($\bar{x}$ = 4.65) dimensions reflect the stability of the architecture and the learning potential of AI-Agents through the Perceive–Decide–Act–Learn cycle, including ML, RAG, and XAI techniques, which is consistent with research that found that Generative AI has the potential to accelerate learning Python and reduce the gap for learners with different backgrounds. Learning Quality ($\bar{x}$ = 4.67) and User & Environment Quality ($\bar{x}$ = 4.53) are consistent with the TAM 4.0 conceptual framework that emphasizes usability and ease of use [163]. The evaluation results for each item ranged from 4.53 to 4.87 (SD 0.35–0.52) except for item 5.3 which was at a high level. The overall evaluation results confirm that the AI-PINS conceptual framework has a high level of content validity (IOC > 0.90) and is ready for development into a prototype for actual use, reflecting a balanced integration between AI intelligence, learning design, and user-friendliness, which is in line with the OECD Education 2030 policy guidelines and DEPA's digital education strategy that promotes the use of AI to

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enhance the quality of learning for teachers and students in the 21st century.

This study aimed to develop and evaluate the AI-PINS framework as an AI-based instructional decision-support system for programming education in municipal primary schools. The findings demonstrate that AI-PINS successfully integrates intelligent-agent mechanisms, explainable AI, and learning analytics to support transparent, context-aware instructional planning, achieving high expert-evaluated appropriateness across system, intelligence, and decision-quality dimensions. The framework effectively addresses teacher workload reduction and alignment with curriculum indicators, confirming its practical relevance. However, this research is limited by its reliance on expert-based evaluation and a specific municipal school context, which may constrain generalizability. Potential threats to validity include contextual dependency, limited longitudinal classroom deployment, and reliance on historical data quality. Future studies should therefore validate the framework through large-scale implementation and long-term analysis of learning outcomes.

REFERENCES:

[1] *Education Policy Outlook 2022*. in Education Policy Outlook. OECD Publishing, 2022. doi: 10.1787/c77c7a97-en.

[2] S. Forsström and M. Bond, "Computational Thinking Assessment in Primary and Secondary Education: A Meta-synthesis of tools, Methods and Pedagogical Approaches," *International Journal of Computer Science Education in Schools*, vol. 6, no. 4, Nov. 2024, doi: 10.21585/ijcses.v6i4.208.

[3] M. J. Cox and J. Voogt, " A K- 6 Computational Thinking Curriculum Framework: Implications for Teacher Knowledge" , [Online] . Available: https://www.researchgate.net/publication/316597429

[4] S. Y. Huang, W. Tarng, and K. L. Ou, " Effectiveness of AR Board Game on Computational Thinking and Programming Skills for Elementary School Students," *Systems*, vol. 11, no. 1, Jan. 2023, doi: 10.3390/systems11010025.

[5] R. Bahri *et al.*, "The Impact of Outcome-Based Education on Lecturers' Professional Growth in Vocational Programs," *International Journal of Academic Research in Progressive Education and Development*, vol. 14, no. 1, Mar. 2025, doi: 10.6007/ijarped/v14-i1/24862.

[6] R. Caballero, E. Martin-Martin, A. Riesco, and S. Tamarit, "A unified framework for declarative debugging and testing," *Inf Softw Technol*, vol. 129, Jan. 2021, doi: 10.1016/j.infsof.2020.106427.

[7] E. Kamburjan, N. Klungre, R. Schlatte, B. Johnsen, and M. Giese, "Programming and Debugging with Semantically Lifted States."

[8] E. Woodruff, " AI Detection of Human Understanding in a Gen- AI Tutor," *AI (Switzerland)*, vol. 5, no. 2, pp. 898–921, Jun. 2024, doi: 10.3390/ai5020045.

[9] J. Ulucan and M. Betul Yilmaz, "Effects of Coding and Robotics Activities on Computational Thinking and Problem-Solving Skills: A Meta Analysis Study," 2024. [Online] . Available: https://www.journalofcomputereducation.info/

[10] A. de Araujo, P. M. Papadopoulos, S. McKenney, and T. de Jong, " Automated coding of student chats, a trans-topic and language approach," *Computers and Education: Artificial Intelligence*, vol. 4, Jan. 2023, doi: 10.1016/j.caeai.2023.100123.

[11] A. Aqeel and M. Shree, "Engineering and Technology Impact Factor 7. 12│□Vol," *International Advanced Research Journal in Science*, vol. 10, no. 1, 2023, doi: 10.17148/IARJSET.2023.10116.

[12] R. Zazkis, P. Liljedahl, and N. Sinclair, " LESSON PLAYS: PLANNING TEACHING versus TEACHING PLANNING."

[13] Norwanto, "Designing Lesson Plan Based on Critical Thinking for Language Classes."

[14] T. Kabudi, I. Pappas, and D. H. Olsen, "AI-enabled adaptive learning systems: A systematic mapping of the literature," *Computers and Education: Artificial Intelligence*, vol. 2, Jan. 2021, doi: 10.1016/j.caeai.2021.100017.

[15] Oyebola Olusola Ayeni, Nancy Mohd Al Hamad, Onyebuchi Nneamaka Chisom, Blessing Osawaru, and Ololade Elizabeth Adewusi, " AI in education: A review of personalized learning and educational technology," *GSC Advanced Research and Reviews*, vol. 18, no. 2, pp. 261–271, Feb. 2024, doi: 10.30574/gscarr.2024.18.2.0062.

[16] S. X. Yin, D. Hoe-Lian Goh, and C. L. Quek, " Collaborative Learning in K- 12 Computational Thinking Education: A

Systematic Review," *Journal of Educational Computing Research*, vol. 62, no. 6, pp. 1440–1474, Oct. 2024, doi: 10.1177/07356331241249956.

[17] A. O. Sunday, F. J. Agbo, and J. Suhonen, "Co-design Pedagogy for Computational Thinking Education in K-12: A Systematic Literature Review," *Technology, Knowledge and Learning*, vol. 30, no. 1, pp. 63–118, Mar. 2025, doi: 10.1007/s10758-024-09765-y.

[18] G. Adorni *et al.*, "Development of algorithmic thinking skills in K-12 education: A comparative study of unplugged and digital assessment instruments," *Computers in Human Behavior Reports*, vol. 15, Aug. 2024, doi: 10.1016/j.chbr.2024.100466.

[19] M. M. Ibrohim, E. Siregar, and U. A. Chaeruman, "Scratch and Computational Thinking in Elementary School: A Meta-analysis," *AL-ISHLAH: Jurnal Pendidikan*, vol. 15, no. 3, pp. 2703–2715, Jul. 2023, doi: 10.35445/alishlah.v15i3.2326.

[20] A. O. Sunday, F. J. Agbo, J. Suhonen, I. Jormanainen, and M. Tukiainen, "Co-designing to develop computational thinking skills in Nigeria K-12 using scratch," *Educ Inf Technol (Dordr)*, vol. 30, no. 11, pp. 14925–14965, Jul. 2025, doi: 10.1007/s10639-025-13386-y.

[21] G. Kostopoulos, V. Gkamas, M. Rigou, and S. Kotsiantis, "Agentic AI in Education: State of the Art and Future Directions," *IEEE Access*, vol. 13, pp. 177467–177491, 2025, doi: 10.1109/ACCESS.2025.3620473.

[22] L. A. Dieker *et al.*, "Using an Artificial Intelligence (AI) Agent to Support Teacher Instruction and Student Learning," *78 | JOURNAL OF SPECIAL EDUCATION PREPARATION*, vol. 4, no. 2, 2024, doi: 10.33043/d8x.

[23] J. Mamcenko, E. Kurilovas, E. Kurilovas, and I. Krikun, "On application of case-based reasoning to personalise learning," *Informatics in Education*, vol. 18, no. 2, pp. 345–358, 2019, doi: 10.15388/infedu.2019.16.

[24] M. Skittou, M. Merrouchi, and T. Gadi, "A Recommender System for Educational Planning," *Cybernetics and Information Technologies*, vol. 24, no. 2, pp. 67–85, Jun. 2024, doi: 10.2478/cait-2024-0016.

[25] Z. Li, Z. Wang, W. Wang, K. Hung, H. Xie, and F. L. Wang, "Retrieval-augmented generation for educational application: A systematic survey," Jun. 01, 2025, *Elsevier B.V.* doi: 10.1016/j.caeai.2025.100417.

[26] J. Cárdenas-Cobo, C. Vidal-Silva, L. Arévalo, and M. Torres, "Applying recommendation system for developing programming competencies in children from a non-weird context," *Educ Inf Technol (Dordr)*, vol. 29, no. 8, pp. 9355–9386, Jun. 2024, doi: 10.1007/s10639-023-12156-y.

[27] P. Garcia-Calvés, J. Sabater-Mir, P. Aramendia, J. Corominas, and B. M. Perez Ruchat, "Recommenders for Improved Lesson Planning in Formal Education," 2023. doi: 10.3233/faia230689.

[28] V. Vudayagiri, "Web-Based AI Platform for Early Cancer Detection through Histopathological Image Analysis." [Online]. Available: www.ijfmr.com

[29] M. Ivanov, D. S. Cristea, M. Vlase, and D. Munteanu, "Navigating Learning Paths with EDSense: An AI-Powered Learning Platform," *Journal of Digital Pedagogy*, vol. 2, no. 1, pp. 14–24, 2023, doi: 10.61071/jdp.2375.

[30] L. Y. Tan, S. Hu, D. J. Yeo, and K. H. Cheong, "Artificial intelligence-enabled adaptive learning platforms: A review," Dec. 01, 2025, *Elsevier B. V.* doi: 10.1016/j.caeai.2025.100429.

[31] F. Lunghini, A. Fava, V. Pisapia, F. Sacco, D. Iaconis, and A. R. Beccari, "ProfhEX: AI-based platform for small molecules liability profiling," *J Cheminform*, vol. 15, no. 1, Dec. 2023, doi: 10.1186/s13321-023-00728-6.

[32] W. Cao, Q. Wang, A. Sbeih, and F. Shibly, "(on-line) ©IBERAMIA and the authors Artificial Intelligence Based Efficient Smart Learning Framework for Education Platform," *Inteligencia Artificial*, vol. 23, no. 66, pp. 112–123, 2020, doi: 10.4114/intartf.vol20iss59pp123-127.

[33] W. Salah Eldin and A. Kaboudan, "AI-Driven Medical Imaging Platform: Advancements in Image Analysis and Healthcare Diagnosis."

[34] J. Ruggaber, K. Ahmic, J. Brembeck, D. Baumgartner, and J. Tobolář, "AI-For-Mobility—A New Research Platform for AI-Based Control Methods," *Applied Sciences (Switzerland)*, vol. 13, no. 5, Mar. 2023, doi: 10.3390/app13052879.

[35] A. Damayanti, R. Kurniawan, A. Shalli Anziila, T. Rahmawati, Rafi, and I. Fauzi, "Benefits of AI-Based Application in Facilitating English Learning," *Jurnal Pendidikan Dasar dan Menengah*, vol. 3, no. 2, pp. 135–145, Sep. 2025, doi: 10.69743/edumedia.v3i2.48.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[36] M. Betaubun, D. Eva, L. Rokhmah, and J. Budiasto, " Personalized Pathways to Proficiency: Exploring the Synergy of Adaptive Learning and Artificial Intelligence in English Language Learning," 2023. [Online] . Available: www.techniumscience.com

[37] G. R. Naik, " AI Based Inventory Management System Using Odoo," *INTERANTIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT*, vol. 07, no. 08, Aug. 2023, doi: 10.55041/ijsrem25510.

[38] R. Orsenigo *et al.*, "OPeNet: an AI-based platform implemented to facilitate clinical reasoning by primary care practitioners, as well as the virtuous co- management of chronic patients during and after the COVID-19 pandemic in Italy," Nov. 01, 2022, *Walter de Gruyter GmbH*. doi: 10.1515/dx-2022-0040.

[39] Addakula Lavanya and T. Murali Krishna, " An AI and Cloud Based Collaborative Platform for PlantDisease Identification, Tracking and Forecasting for Farmers," *international journal of engineering technology and management sciences*, vol. 6, no. 6, pp. 527– 537, Nov. 2022, doi: 10.46647/ijetms.2022.v06i06.091.

[40] J. Bauer *et al.*, " ForeSight - Platform Approach for Enabling AI-based Services for Smart Living," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Springer, 2019, pp. 204–211. doi: 10.1007/978-3-030-32785-9_19.

[41] A. Ahmed, P. Boopathy, and S. Sudhagara Rajan, "Artificial intelligence for the novel corona virus (COVID- 19) pandemic: Opportunities, challenges, and future directions," *International Journal of E-Health and Medical Communications*, vol. 13, no. 2, Jul. 2022, doi: 10.4018/IJEHMC.20220701.oa5.

[42] C. and M. Methods in Medicine, "Retracted: Network Information Security Platform Based on Artificial Intelligence for the Elderly' s Health ' Integration of Physical, Medical, and Nursing Care,'" *Comput Math Methods Med*, vol. 2023, no. 1, Jan. 2023, doi: 10.1155/2023/9756383.

[43] M. Dhiman, M. Tonk, R. Kaur, and A. Kaur, "Real World of Artificial Intelligence – A Review," *Journal of Technology Management for Growing Economies*, vol. 11, no. 2, pp. 41– 47, Nov. 2020, doi: 10.15415/jtmge.2020.112005.

[44] S. I. R, S. A. S, and V. A. S, "3 Candidate of Technical Sciences, Associate Professor, Technologies and organizations of the forest complex," *International Journal of Engineering Research and Technology*, vol. 13, no. 11, p. 33, 2020, doi: 10.37624/IJERT/13.11.2020.3631-364000.

[45] F. A. Rego-Rodríguez, L. Germán-Flores, and A. A. Vitón- Castillo, " Artificial intelligence and machine learning: present and future applications in health sciences," Oct. 05, 2022, *AG Editor (Argentina)*. doi: 10.56294/mw20229.

[46] H. A. Kautz, "The third AI summer: AAAI Robert S. Engelmore Memorial Lecture," *AI Mag*, vol. 43, no. 1, pp. 105–125, Mar. 2022, doi: 10.1002/aaai.12036.

[47] M. Raj, J. Berg, and R. Seamans, "Art-ificial Intelligence: The Effect of AI Disclosure on Evaluations of Creative Content," 2023.

[48] R. Gu, " Research on the Reasonable Application Strategy of AI Technology in the Field of Artistic Creation," *Arts Studies and Criticism*, vol. 5, no. 5, p. 319, Dec. 2024, doi: 10.32629/asc.v5i5.3076.

[49] W. Gao, Q. Qi, L. Dong, and C. Liu, " Application of Artificial Intelligence in Innovation Experiment Management System Engineering," 2018.

[50] N. Kühl, M. Schemmer, M. Goutier, and G. Satzger, "Artificial intelligence and machine learning," *Electronic Markets*, vol. 32, no. 4, pp. 2235– 2244, Dec. 2022, doi: 10.1007/s12525-022-00598-0.

[51] V. Voronkova and V. Nikitenko, "Artificial Intelligence as a Global Problem of Modernity: Technological, Ontological, Anthropological Dimensions," *Newsletter on the Results of Scholarly Work in Sociology, Criminology, Philosophy and Political Science*, vol. 2, no. 3, pp. 52–67, Sep. 2021, doi: 10.61439/cpgr2192.

[52] N. Kühl, M. Goutier, R. Hirt, and G. Satzger, *Machine Learning in Artificial Intelligence: Towards a Common Understanding*. [Online] . Available: https://hdl.handle.net/10125/59960

[53] T. Standard and F. JrCOLLEGE, " Engineering MAMIDI SAI AKASH ARTIFICIAL INTELLIGENCE (Biologically Inspired Intelligent Robots using Artiicial Intelligence)."

[54] S. S. Diware, "A Review on Can AI Replace Humans?," *Int J Res Appl Sci Eng Technol*, vol. 11, no. 5, pp. 3420–3422, May 2023, doi: 10.22214/ijraset.2023.52373.

[55] Z. Hu and E. P. Xing, "Toward a 'Standard Model' of Machine Learning," *Harv Data Sci Rev*, Oct. 2022, doi: 10.1162/99608f92.1d34757b.

[56] Z. Gong, "Artificial Intelligence in the 21st Century," *Research on Intelligent Manufacturing and Assembly*, vol. 2, no. 1, pp. 52– 59, Mar. 2023, doi: 10.25082/rima.2023.01.002.

[57] L. T. Al-Ameri and E. K. Hameed, "Artificial Intelligence: Current Challenges and Future Perspectives," Apr. 30, 2023, *Al- Kindy College of Medicine, University of Baghdad*. doi: 10.47723/kcmj.v19i1.1017.

[58] Z. Cao, "Development and Application of Artificial Intelligence," 2017.

[59] U. Omer, M. S. Farooq, and A. Abid, "Introductory programming course: review and future implications," *PeerJ Comput Sci*, vol. 7, pp. 1–33, 2021, doi: 10.7717/PEERJ-CS.647.

[60] J. Waite and S. Sentance, " Teaching programming in schools: A review of approaches and strategies Raspberry Pi Foundation," 2021. [Online]. Available: www.raspberrypi.org

[61] I. Eteng, S. Akpotuzor, S. O. Akinola, and I. Agbonlahor, "A review on effective approach to teaching computer programming to undergraduates in developing countries," *Sci Afr*, vol. 16, Jul. 2022, doi: 10.1016/j.sciaf.2022.e01240.

[62] Y. Zeng, W. Yang, and A. Bautista, "Teaching programming and computational thinking in early childhood education: a case study of content knowledge and pedagogical knowledge," *Front Psychol*, vol. 14, 2023, doi: 10.3389/fpsyg.2023.1252718.

[63] I. Amorim, P. B. Vasconcelos, and J. P. Pedroso, " Kumon- Inspired Approach to Teaching Programming Fundamentals," in *OpenAccess Series in Informatics*, Schloss Dagstuhl- Leibniz- Zentrum fur Informatik GmbH, Dagstuhl Publishing, Sep. 2024. doi: 10.4230/OASIcs.ICPEC.2024.5.

[64] J. Insuasti, E. Insuasty, and A. Baron, "Didactics of the Fundamentals of Computer Programming with a Computational Thinking Approach Based on Turtle Graphs," *Academia y Virtualidad*, vol. 18, no. 2, pp. 65–80, Aug. 2025, doi: 10.18359/ravi.7533.

[65] J. Arnedo-Moreno and D. García-Solórzano, " Programming Fun(damentals) : Using commercial video games to teach basic coding to adult learners," *Entertain Comput*, vol. 52, Jan. 2025, doi: 10.1016/j.entcom.2024.100850.

[66] M. C. C. Musingafi, I. Mhute, S. Zebron, and K. E. Kaseke, " Journal of Education and Practice www.iiste.org ISSN," Online, 2015. [Online]. Available: www.iiste.org

[67] Z. UIN Syarif Hidayatullah Jakarta, "THE DEVELOPMENT OF TEACHER PROFESSIONALISM THROUGH THE IMPROVEMENT OF COMPETENCY IN THE INSTRUCTIONAL PLANNING."

[68] B. C. Greiman, M. A. Bedtke, and A. E. Teacher, " EXAMINING THE INSTRUCTIONAL PLANNING PROCESS TAUGHT IN AGRICULTURAL EDUCATION TEACHER PREPARATION PROGRAMS: PERSPECTIVES OF UNIVERSITY FACULTY," 2008.

[69] S. Wilson and J. Mcchesney, "From course work to practicum: Learning to plan for teaching mathematics," 2018.

[70] C. Gu, X. Zheng, and G. Li, "Teaching reform and practice based on OBE concept: Taking the course of Python programming and practice as an example," *SHS Web of Conferences*, vol. 166, p. 01026, 2023, doi: 10.1051/shsconf/202316601026.

[71] P. T. Phuong Thao, "TRAINING LESSON PLAN DESIGNING SKILLS FOR MATHEMATICS TEACHER EDUCATION STUDENTS TOWARDS THE DEVELOPMENT OF STUDENTS' QUALITY AND COMPETENCE," *International Journal of Education and Social Science Research*, vol. 05, no. 02, pp. 152– 160, 2022, doi: 10.37500/ijessr.2022.5210.

[72] N. Andini, "Planing A Lesson For English Langguage Teaching (Speaking Course) In The Milenium Era," European Alliance for Innovation n. o. , Jan. 2020. doi: 10.4108/eai.5-8-2019.2289813.

[73] M. J. Hofer and J. B. Harris, " W&M ScholarWorks W&M ScholarWorks Topics and Sequences in Experienced Teachers' Instructional Topics and Sequences in Experienced Teachers' Instructional Planning: Addressing a ~30-Year Literature Gap Planning: Addressing a ~30- Year Literature Gap. " [Online]. Available: https://scholarworks.wm.edu/educationbookchapters

[74] Y. Jafarzadeh, S. Kord, M. Kazemiyan, and B. Kazemikani, " RELATIONSHIP BETWEEN TEACHING AND TENDENCY TO LESSON PLAN IN HEALTH WORKING TRAINERS OF MAZANDARAN MEDICAL SCIENCE UNIVERSITY," 2014.

[75] X. Xia and W. Lv, "Optimized Model of Experimental Teaching Plan Based on Improved by Clear Theory," in *E3S Web of Conferences*, EDP Sciences, Jun. 2021. doi: 10.1051/e3sconf/202127503031.

[76] A. Alexiou, "Using Active Learning to Teach Critical and Contextual Studies: One Teaching Plan, Two Experiments, Three Videos. ," in *International Conference on Higher Education Advances*, Universidad Politecnica de Valencia., 2022, pp. 619–627. doi: 10.4995/HEAd22.2022.14863.

[77] I. R. Indra Astutik and M. A. Rosid, " Integrated Information System Teaching Plan in College Using FAST Method and Twitter Bootstrap," *Kinetik: Game Technology, Information System, Computer Network, Computing, Electronics, and Control*, pp. 163– 170, Apr. 2018, doi: 10.22219/kinetik.v3i2.588.

[78] N. A. Aflahah and H. Nadia, "Exploring EFL Students' Experience in Developing Daily Lesson Plan for Teaching English for Toddler," *ELLITE: Journal of English Language, Literature, and Teaching*, vol. 7, no. 2, pp. 95– 99, Nov. 2022, doi: 10.32528/ellite.v7i2.8659.

[79] Z. Robinson Wolf, " Evidence- Based Teaching Plan, Test, and Evaluation on Caring for Healthcare Provider Second Victims," *PATIENT SAFETY*, vol. 5, no. 2, Jun. 2023, doi: 10.33940/001c.77630.

[80] C. van Diggele, A. Burgess, and C. Mellis, "Planning, preparing and structuring a small group teaching session," Dec. 01, 2020, *BioMed Central Ltd*. doi: 10.1186/s12909-020-02281-4.

[81] J. E. Mason, "The cult of culture: An analysis and plan for teaching about The cult of culture: An analysis and plan for teaching about organizational culture organizational culture," 1992, doi: 10.25669/nakx-eys9.

[82] Y. Liang, "Practical Deficiencies and Routing Optimization of Professional Teaching Plan in Higher Vocational Colleges" , doi: 10.23977/aetp.2020.41012.

[83] Julia. Koppich, Carla. Asher, and Charles. Kerchner, *Developing Careers, Building a Profession The Rochester Career in Teaching Plan*. Distributed by ERIC Clearinghouse, 2002.

[84] S. R. Sobral, "Bloom's taxonomy to improve teaching- learning in introduction to programming," *International Journal of Information and Education Technology*, vol. 11, no. 3, pp. 148– 153, Mar. 2021, doi: 10.18178/ijiet.2021.11.3.1504.

[85] M. Lu and Z. Hu, "Digital Twin- Enhanced Programming Education: An Empirical Study on Learning Engagement and Skill Acquisition," *Computers*, vol. 14, no. 8, Aug. 2025, doi: 10.3390/computers14080322.

[86] A. D. Samala *et al.*, "Top 10 Most- Cited Articles Concerning Blended Learning for Introductory Algorithms and Programming: A Bibliometric Analysis and Overview," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 5, pp. 57–70, 2023, doi: 10.3991/ijim.v17i05.36503.

[87] O. V. Varetska, O. V. Nikulochkina, O. S. Tonne, A. I. Kuzminskyi, O. A. Bida, and V. V. Vdovenko, "Revista Românească pentru Educaţie Multidimensională Primary School Teacher' s Social Competence in the Postgraduate Education," *Revista Romaneasca pentru Educatie Multidimensionala*, vol. 11, no. 4, pp. 309–327, 2019, doi: 10.18662/rrem/192.

[88] A. Simion* and C. Stan, "Emotional Identity Formation In Primary School Children In A Formal Context," Cognitive-Crcs, Jun. 2019, pp. 322– 329. doi: 10.15405/epsbs.2019.06.40.

[89] " PROSPECTIVE PRIMARY SCHOOL TEACHER VIEWS ON PERSONAL AND PROFESSIONAL QUALITIES."

[90] Dwiwarna and R. B. Rahadian, "The Most Considered Type of Student Characteristics by Primary School Teacher," *International Journal on Integrating Technology in Education*, vol. 7, no. 3, pp. 29– 42, Sep. 2018, doi: 10.5121/ijite.2018.7303.

[91] F. J. Melara- Gutiérrez and I. González-López, " Teacher training for effective teaching," *Education in the Knowledge Society*, vol. 22, 2021, doi: 10.14201/eks.25290.

[92] S. Ustilaitė, S. Poteliūnienė, A. Juškevičienė, and S. Sabaliauskas, " How do Primary School Teachers Create Meaningful Learning Environment to Motivate Students?," *Pedagogika*, vol. 149, no. 1, pp. 53–81, May 2023, doi: 10.15823/p.2023.149.3.

[93] L. Szabo Bejenar and L. Szabo Bejenar, "Primary school education," E-ISSN, 2010.

[94] S. Author, C.-T. Teo, and J. Ee, "Title Primary Teachers' Attributes and Attitudes in Primary Teachers' Attributes and Attitudes in Singapore," 2003.

[95] S. Ghimire, "Knowledge of Primary School Teacher Regarding Learning Disabilities in School Children," vol. 6, no. 1, pp. 29–35, [Online]. Available: www.nepjol.info,

[96] " cognitive- styles- of- primary- school-teachers-58e9nwp23c011".

[97] J. Yu, S. Sukumaran, H. Li, and J. Zeng, " Examine Primary School Teachers' Attitudes Towards Technology Integration in Primary Education," *Environment-Behaviour Proceedings Journal*, vol. 8, no. 26, pp. 383–388, Oct. 2023, doi: 10. 21834/ e-bpj.v8i26.5193.

[98] J. Blannin, " The Role of the Teacher in Primary School Web 2.0 Use," 2015.

[99] V. Grinyova and O. Rezvan, " MODERNIZATION OF PRIMARY SCHOOL TEACHERS' TRAINING: FROM KNOWLEDGE TO COMPETENCE APPROACH," *Advanced Education*, no. 6, pp. 111–114, Dec. 2016, doi: 10.20535/2410-8286.85955.

[100] Z. Guo and X. Jiang, "Reform and Practice of Practice Teaching for Primary Education Specialty," 2018.

[101] O. Dubaseyuk, O. Voznyuk, and O. Uminska, " SIMULATION OF THE PROCESS OF FORMATION AND DEVELOPMENT OF PEDAGOGICAL MASTERY IN PRIMARY SCHOOL TEACHERS (BASED ON THE EXPERIENCE OF PAVLYSH SECONDARY SCHOOL)," *Zhytomyr Ivan Franko state university journal. Pedagogical sciences*, no. 1(116), pp. 5–19, Mar. 2024, doi: 10.35433/pedagogy.1(116).2024.1.

[102] T. Dilci and G. Dervişoğlu Kalkan, "THE PROBLEMS THAT PRIMARY SCHOOL TEACHERS' ENCOUNTER IN THE FIRST FIVE YEARS IN THEIR PROFESSIONS." [Online]. Available: http://egitim.cu.edu.tr/efdergi

[103] M. Amir, S. Hussain, and S. Muhammad, " Identification of the Need for Teacher Training at The Primary School Level," *International Research Journal of Education and Innovation*, vol. 3, no. 1, pp. 165–176, Mar. 2022, doi: 10.53575/irjei.v3.01.16(22)165-176.

[104] M. Huo, N. Zhao, Y. Zhao, and W. Van Den Noortgate, " Who is teaching in Chinese primary schools? A profile of the primary education workforce in Chinese county areas," *PLoS One*, vol. 16, no. 1 January, Jan. 2021, doi: 10.1371/journal.pone.0245549.

[105] K. D. Lee, " Undergraduate Topics in Computer Science Python Programming Fundamentals Second Edition." [Online]. Available: http://www.springer.com/series/7592

[106] A. Michailidi, " Learning Computer Programming: Start from Scratch!" [Online]. Available: http://www.clab.edc.uoc.gr/HSci2010

[107] R. Harimurti, E. Ekohariadi, M. Munoto, I. G. P. Asto B, and E. T. Winanti, "Analysis of Programming Skills Concept in Developing Problem Solving Skills," *Jurnal Pendidikan Teknologi dan Kejuruan*, vol. 25, no. 1, pp. 43– 51, Apr. 2019, doi: 10.21831/jptk.v25i1.22638.

[108] R. Cortinovis, P. F. Bolton, and R. Caceffo, " An Open List of Computer Programming Student' s Common Problems and its Leverage in Teaching Practice," 2023.

[109] J. Insuasti, E. Insuasty, and A. Baron, "Didactics of the Fundamentals of Computer Programming with a Computational Thinking Approach Based on Turtle Graphs," *Academia y Virtualidad*, vol. 18, no. 2, pp. 65–80, Aug. 2025, doi: 10.18359/ravi.7533.

[110] P. Bailes, L. Brough, and C. Kemp, *Fundamentals, Prospects and Challenges for Totally Functional Programming Style*.

[111] A. Rojas-López and F. J. García-Pẽalvo, " Initial learning scenarios based on the computational thinking evaluation for the course Programming fundamentals at INACAP," in *ACM International Conference Proceeding Series*, Association for Computing Machinery, Oct. 2019, pp. 6–12. doi: 10.1145/3362789.3362802.

[112] J. Rodríguez-Vidal and Á. García-Beltrán, " Impact of C- coding self- assessment exercises on exam performance: A study in engineering education," *Computer Applications in Engineering Education*, vol. 32, no. 2, Mar. 2024, doi: 10.1002/cae.22706.

[113] O. Luis de Oliveira, A. Maria Monteiro, and N. Trevisan Roman, " Programming fundamentals and human factors: an empirical study of three variables."

[114] J. C. Dehnert and A. Stepanov, "Fundamentals of Generic Programming." [Online]. Available: http://www.springer.de/comp/lncs/index.html.

[115] "AC 2007-145: A NEW PARADIGM TO IMPROVE COMPUTER EDUCATION

FOR ENGINEERING STUDENTS: APPLYING INDUSTRY- BASED SOFTWARE DEVELOPMENT CYCLE INTO PROGRAMMING PRACTICES A New Paradigm to Improve Computer Education for Engineering Students: Applying Industry- based Software Development Cycle into Programming Practices.”

[116] D. Mandrioli, P. Di, M. Piazza, L. Da Vinci, and M. Pradella, “Programming Languages shouldn’t be ‘too Natural.’”

[117] P. Van Roy, “Programming Paradigms for Dummies: What Every Programmer Should Know.”

[118] A. J. Fernández and J. M. Sánchez, “CGRAPHIC: Educational software for learning the foundations of programming,” *Computer Applications in Engineering Education*, vol. 11, no. 4, pp. 167–178, 2003, doi: 10.1002/cae.10048.

[119] E. Börger, “A practice-oriented course on the principles of computation, programming and system design and analysis.” [Online]. Available: http://www.di.unipi.it/AsmBook/.

[120] D. E. Comer, “Principles of Program Design Induced From Experience With Principles of Program Design Induced From Experience With Small, Public Programs Small, Public Programs.” [Online]. Available: https://docs.lib.purdue.edu/cstech/266

[121] M. C. Okur, “TEACHING OBJECT ORIENTED PROGRAMMING AT THE INTRODUCTORY LEVEL.”

[122] N. F. M. Noor, A. Saad, A. B. Ibrahim, and N. M. Noor, “THE ACCEPTANCE OF AN EDUCATIONAL INTEGRATED DEVELOPMENT ENVIRONMENT TO LEARN PROGRAMMING FUNDAMENTALS,” *Information Technologies and Learning Tools*, vol. 93, no. 1, pp. 135–151, Feb. 2023, doi: 10.33407/itlt.v93i1.5102.

[123] S. Al-Fedaghi and E. Haidar, “Programming Is Diagramming Is Programming,” *Journal of Software*, pp. 410–422, Sep. 2019, doi: 10.17706/jsw.14.9.410-422.

[124] J. Castro, J. Cortadella, J. Gabarró, A. García, and E. Vidal, “PROGRAMMING 1 and SUSTAINABILITY,” in *SEFI 2022 - 50th Annual Conference of the European Society for Engineering Education, Proceedings*, European Society for Engineering Education (SEFI), 2022, pp. 1041–1049. doi: 10.5821/conference-9788412322262.1261.

[125] V. K. Proulx and K. E. Gray, “Design of Class Hierarchies: An Introduction to OO Program Design,” 2006.

[126] D. Colton and A. Curtis, “Programming Proficiency in One Semester: Lessons Learned,” 2010. [Online]. Available: http://isedj.org/8/48/

[127] A. H. Hasan and M. F. Hilmi, “Input Process Output (IPO) AI Chatbot as Personal Learning Assistant for Programming Coursework,” *Malaysian Journal of Distance Education*, vol. 22, no. 1, 2022, doi: 10.36777/mjde2022.22.1.2.

[128] S. Zhang, C. D. Jaldi, N. L. Schroeder, A. A. López, J. R. Gladstone, and S. Heidig, “Pedagogical agent design for K-12 education: A systematic review,” *Comput Educ*, vol. 223, Dec. 2024, doi: 10.1016/j.compedu.2024.105165.

[129] K. M. Xu *et al.*, “Social presence: A key factor in embedding a pedagogical agent into online learning in primary education,” *British Journal of Educational Technology*, 2025, doi: 10.1111/bjet.70006.

[130] D. Kim, S. Kim, and Y. Jo, “Knowledge Tracing in Programming Education Integrating Students’ Questions,” Jan. 2025, [Online]. Available: http://arxiv.org/abs/2502.10408

[131] U. Lee *et al.*, “From Prediction to Application: Language Model-based Code Knowledge Tracing with Domain Adaptive Pre-Training and Automatic Feedback System with Pedagogical Prompting for Comprehensive Programming Education,” Aug. 2024, doi: 10.13140/RG.2.2.25134.11847.

[132] H. Khosravi *et al.*, “Explainable Artificial Intelligence in education,” *Computers and Education: Artificial Intelligence*, vol. 3, Jan. 2022, doi: 10.1016/j.caeai.2022.100074.

[133] L. Cabral, R. Pinto, and G. Gonçalves, “AI-powered learning analytics dashboards: a systematic review of applications, techniques, and research gaps,” *Discover Education*, vol. 4, no. 1, p. 525, Nov. 2025, doi: 10.1007/s44217-025-00964-y.

[134] Z. Fu, “Integrating Reinforcement Learning with Dynamic Knowledge Tracing for personalized learning path optimization,” *Sci Rep*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-23900-4.

[135] J.-Y. Chen, S. Saeedvand, and I.-W. Lai, “Adaptive Learning Path Navigation Based on Knowledge Tracing and Reinforcement

Learning," Jun. 2023, [Online]. Available: http://arxiv.org/abs/2305.04475

[136] Y. Liu, S. Pozdniakov, and R. Martinez-Maldonado, " The effects of visualisation literacy and data storytelling dashboards on teachers' cognitive load."

[137] D. A. Sprenger and A. Schwaninger, "Video demonstrations can predict the intention to use digital learning technologies," *British Journal of Educational Technology*, vol. 54, no. 4, pp. 857– 877, Jul. 2023, doi: 10.1111/bjet.13298.

[138] M. van Kessel, I. Molenaar, C. A. N. Knoop-Van Campen, M. de Jonge, and N. Saab, " Primary School Teacher Perspectives on Effective Dashboard Use in the Classroom: Skills, Knowledge, and Contextual Conditions," *Journal of Learning Analytics*, vol. 12, no. 2, pp. 279–292, Aug. 2025, doi: 10.18608/jla.2025.8493.

[139] M. C. Okur, " TEACHING OBJECT ORIENTED PROGRAMMING AT THE INTRODUCTORY LEVEL."

[140] J. Whitehill and J. Locasale- Crouch, " Automated Evaluation of Classroom Instructional Support with LLMs and BoWs: Connecting Global Predictions to Specific Feedback."

[141] J. Hu, "Teaching Evaluation System by use of Machine Learning and Artificial Intelligence Methods," *International Journal of Emerging Technologies in Learning*, vol. 16, no. 5, pp. 87– 101, 2021, doi: 10.3991/ijet.v16i05.20299.

[142] X. Mao, " Online education quality assessment model based on deep learning," *Discover Artificial Intelligence*, vol. 5, no. 1, Dec. 2025, doi: 10.1007/s44163-025-00421-7.

[143] G. K. Michelon, W. K. G. Assunç, A. Assunção, P. Grünbacher, and A. Egyed, " Analysis and Propagation of Feature Revisions in Preprocessor- based Software Product Lines. " [Online] . Available: https://www.sqlite.org/src/info/7b4583f932ff0933

[144] E. Avinç and F. Doğan, " Digital literacy scale: Validity and reliability study with the rasch model," *Educ Inf Technol (Dordr)*, vol. 29, no. 17, pp. 22895–22941, Dec. 2024, doi: 10.1007/s10639-024-12662-7.

[145] J. Alqurni, " Assessing the Usability of E-Learning Software Among University Students: A Study on Student Satisfaction and Performance," *International Journal of Information Technology and Web Engineering*, vol. 18, no. 1, 2023, doi: 10.4018/IJITWE.329198.

[146] C. H. Lai and C. Y. Lin, " Analysis of Learning Behaviors and Outcomes for Students with Different Knowledge Levels: A Case Study of Intelligent Tutoring System for Coding and Learning (ITS-CAL)," *Applied Sciences (Switzerland)*, vol. 15, no. 4, Feb. 2025, doi: 10.3390/app15041922.

[147] L. Tang, J. Gu, and J. Xu, "Constructing a Digital Competence Evaluation Framework for In-Service Teachers' Online Teaching," *Sustainability (Switzerland)*, vol. 14, no. 9, May 2022, doi: 10.3390/su14095268.

[148] M. Yu, " An AI- driven tools assessment framework for english teachers using the Fuzzy Delphi algorithm and deep learning," *Sci Rep*, vol. 15, no. 1, Dec. 2025, doi: 10.1038/s41598-025-25466-7.

[149] D. Gomes, " A Comprehensive Study of Advancements in Intelligent Tutoring Systems Through Artificial Intelligent Education Platforms," in *Improving Student Assessment With Emerging AI Tools*, IGI Global, 2024, pp. 213–244. doi: 10.4018/979-8-3693-6170-2.ch008.

[150] F. Alhashem, " Development and Psychometric Validation of an E Learning Competency Survey for Educators. " ," *Educational Point*, vol. 2, no. 2, Nov. 2025, doi: 10.71176/edup/17424.

[151] R. Fiati and D. K. Mutiara N, " INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION journal homepage : www. joiv. org/ index. php/ joiv INTERNATIONAL JOURNAL ON INFORMATICS VISUALIZATION Exploring M- Learning User Information Systems through the Development of a Comprehensive Technology Acceptance Model. " [Online] . Available: www.joiv.org/index.php/joiv

[152] S. Kodumuru *et al.*, "Towards developing a learning analytics dashboard for a massive online robotics competition."

[153] C. Wang, J. T. D. Ng, N. P. H. López, and X. Hu, " Preliminary Evaluation of Learning Analytics Dashboard for College Teachers' Online Professional Learning," in *Proceedings - 2024 IEEE International Conference on Advanced Learning Technologies, ICALT 2024*, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 83– 85. doi: 10.1109/ICALT61570.2024.00030.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[154] Y. Shaengchart, N. Bhumpenpein, and P. Limna, "วารสารสหวิทยาการจัดการ มหาวิทยาลัยราชภัฏบุรีรัมย์ Interdisciplinary Journal of Buriram Rajabhat University Determinants of Google's Gemini AI Chatbot Adoption Among Higher Education Students in Bangkok, Thailand".

[155] J. Paladines and J. Ramírez, "A systematic literature review of intelligent tutoring systems with dialogue in natural language," *IEEE Access*, vol. 8, pp. 164246–164267, 2020, doi: 10.1109/ACCESS.2020.3021383.

[156] S. B. P. Utami, N. Riska, R. Rusilanti, and A. Gumelar, "Evaluation of Content Validity for an Educational Media Instrument to Enhance Early Childhood Education (PAUD) Teachers' Nutrition Knowledge," *Jurnal Pendidikan dan Pembelajaran Indonesia (JPPI)*, vol. 5, no. 4, pp. 1801–1808, Aug. 2025, doi: 10.53299/jppi.v5i4.2531.

[157] R. A Rahmat, S. B. Saidi, and N. S. Mohd Nasir, " Content Validity of Digital Knowledge using CVI Method," *Environment-Behaviour Proceedings Journal*, vol. 9, no. SI20, pp. 21–28, Jul. 2024, doi: 10.21834/e-bpj.v9isi20.6092.

[158] J. Du and D. Dewitt, "Technology acceptance of a wearable collaborative augmented reality system in learning chemistry among junior high school students," *Journal of Pedagogical Research*, vol. 8, no. 1, pp. 106–119, Mar. 2024, doi: 10.33902/JPR.202425282.

[159] Z. M. Altukhi and S. Pradhan, "Systematic Literature Review: Explainable AI Definitions and Challenges in Education Literature Review," 2024.

[160] S. Maity and A. Deroy, "Human-Centric eXplainable AI in Education," Oct. 2024, [Online]. Available: http://arxiv.org/abs/2410.19822

[161] S. Gunasekara and M. Saarela, "Explainable AI in Education: Techniques and Qualitative Assessment," *Applied Sciences (Switzerland)*, vol. 15, no. 3, Feb. 2025, doi: 10.3390/app15031239.

[162] S. Elnaffar, F. Rashidi, and A. Z. Abualkishik, " Teaching with AI: A Systematic Review of Chatbots, Generative Tools, and Tutoring Systems in Programming Education," Oct. 2025, [Online]. Available: http://arxiv.org/abs/2510.03884

[163] J. Katona and K. I. K. Gyonyoru, "AI-based Adaptive Programming Education for Socially Disadvantaged Students: Bridging the Digital Divide," *TechTrends*, Sep. 2025, doi: 10.1007/s11528-025-01088-8.