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Teaching Artificial Intelligence in Primary School: An Example-Based Approach Using ML for Kids and Scratch

Abstract

Introduction. The study addresses the challenge of integrating foundational artificial intelligence (AI) and machine learning concepts into primary education to foster early algorithmic thinking and digital literacy: *methodology and Methods.* The study used a mixed-methods design, combining document analysis of the national draft curriculum with an experimental intervention involving 21 second-grade students using ML for Kids and Scratch. Additionally, the study administered a diagnostic survey to 44 in-service Informatics teachers. *Results.* A five-stage integration model was established. Practical acoustic model training improved students' conceptual understanding of machine learning and increased their motivation to learn. Teachers showed strong interest in AI education (88.4%), and demand for specialized training courses was substantial (54.5%). *Scientific novelty.* The study validates a constructivist, block-based instructional pipeline linking supervised machine learning tools with visual block programming tailored to primary school standards - *practical significance.* The proposed framework and instructional scenarios offer direct guidelines for educators and curriculum designers implementing applied AI literacy in primary classrooms.

Keywords: artificial intelligence, primary education, ML for Kids, Scratch, digital literacy, pedagogical model.

Introduction. The rapid and pervasive advancement of digital technologies has fundamentally transformed societal structures, communication paradigms, and educational systems worldwide (Holmes & Tuomi, 2022). Among emerging computational breakthroughs, artificial intelligence (AI) has emerged as one of the most transformative catalysts reshaping modern education (Zawacki-Richter et al., 2019; Marr, 2022). As global economies shift toward data-driven, automated ecosystems, technological competence is no longer confined to traditional computer operation; it now demands early foundational literacy in intelligent systems (Chiu & Chai, 2020). Consequently, introducing artificial intelligence into school curricula has shifted from experimental pedagogical enrichment to an indispensable national strategic priority across

many educational jurisdictions (Touretzky et al., 2019; UNESCO, 2022).

Integrating foundational AI and machine learning concepts at the primary school level represents a strategic intervention to prepare future-ready learners (Dai et al., 2020). Early educational stages offer a prime cognitive window for demystifying how automated systems perceive data, make inferences, and influence daily interactions (Kim et al., 2021). However, a persistent pedagogical tension exists in early computing education: early-grade learners possess developing abstract thinking capacities and cannot engage with complex, syntax-heavy text-based programming languages (Tedre et al., 2021). To bridge the gap between traditional introductory computing practices and modern machine learning concepts, educational systems must leverage

visual, block-based programming environments and intuitive machine learning interfaces (Lane, 2021; Resnick et al., 2009).

Despite the growing global interest and high-level curriculum declarations, substantial pedagogical, infrastructural, and methodological challenges remain in primary AI implementation. In many emerging curricula, including the updated national standard framework for “Digital Literacy and Artificial Intelligence” in Kazakhstan (talqylau.bms.kz), clear instructional pipelines that connect supervised machine learning directly to accessible visual coding tools remain underdeveloped (Ministry of Education of the Republic of Kazakhstan, 2023). Successful implementation also requires rigorous assessment of in-service teacher readiness, infrastructural availability, and classroom-tested scaffolding strategies (Celik, 2023; Wang et al., 2023).

To address this gap, this paper investigates the practical integration of AI literacy in early primary classrooms. Specifically, this study aims to determine how artificial intelligence content can be systematically integrated into the primary school “Digital Literacy” curriculum through an applied visual programming approach using Machine Learning for Kids (ML for Kids) and Scratch 3.0. To achieve this objective, the study evaluates the updated national standard curriculum, diagnoses in-service teacher competence and infrastructural readiness, and empirically tests a classroom-level acoustic classification model with second-grade learners to formulate a structured five-stage pedagogical framework. Primary education represents a critical phase in a child’s cognitive, social, and communicative development (Piaget, 1952; Braun, 2016; Vygotsky, 1978). During these formative years, children acquire fundamental cognitive schemata, critical thinking capabilities, and early algorithmic reasoning (Kim et al., 2021; Liu et al., 2023). From a constructionist pedagogical perspective (Papert, 1980), learners internalize abstract concepts most effectively when they actively design, build, and manipulate tangible or visual artifacts.

Introducing AI literacy within this framework allows young children to explore computational

ideas beyond passive digital consumption (Ali et al., 2019; Druga & Ko, 2021). Early exposure to interactive computational models fosters curiosity, algorithmic problem-solving, and adaptive thinking-core competencies required in the 21st-century digital landscape (Kong et al., 2023; Su & Yang, 2022). Constructionist AI activities enable students to construct personal meaning through hands-on model exploration, grounding complex computational processes in concrete, experiential learning tasks (Druga & Ko, 2021; Lane, 2021). Educational researchers broadly agree that teaching AI in early childhood and primary schooling does not entail training children to become professional computer scientists or advanced code writers (Wong et al., 2020). Instead, foundational AI literacy focuses on building conceptual understanding of intelligent systems, human-computer interaction, and the societal implications of technology (Long & Magerko, 2020; Ng et al., 2021; Fridin, 2014). As Touretzky et al. (2019) conceptualize, K–12 AI education encompasses core Big Ideas: perception, representation and reasoning, learning from data, natural interaction, and societal impact. In primary education, this translates into distinguishing between rule-based, deterministic algorithms (conventional coding) and probabilistic, data-driven learning models (machine learning) (Tedre et al., 2021). By engaging with pattern recognition, data collection, and classification algorithms, students learn how machines process inputs and generalize predictive outputs (Lin et al., 2021; Su & Zhong, 2022).

To make abstract machine learning paradigms developmentally appropriate for young children (aged 7–8), visual block-based platforms are widely recognized as the standard instructional tool (Resnick et al., 2009). Tools such as ML for Kids coupled with Scratch 3.0 eliminate syntactical cognitive load, allowing learners to focus on the logical pipeline of supervised learning: gathering training data, training a model in the cloud, and programming sprites based on model predictions (Dai et al., 2020; Lane, 2021).

Empirical studies demonstrate that linking machine learning classifiers to visual outputs

(such as voice-controlled or gesture-controlled interactive characters) promotes learner engagement and computational thinking (Chiu et al., 2023; Druga & Ko, 2021). However, instructional transitions between stochastic model outputs and deterministic programming blocks often present cognitive friction, requiring explicit teacher scaffolding and structured instructional scaffolds (Tedre et al., 2021). Comprehensive AI literacy extends beyond technical model building to encompass critical reflections on data ethics, privacy, and algorithmic fairness (Crawford & Paglen, 2021; Holmes et al., 2019). Young learners must be equipped to evaluate how data is collected critically, question algorithmic decision-making, and understand digital safety considerations (Kong et al., 2023; Smakman et al., 2021; UNESCO, 2022).

Nevertheless, the classroom implementation of these concepts depends heavily on teacher competence, self-efficacy, and institutional infrastructure (Celik, 2023; Fan & Zhong, 2022). International studies highlight that while educators exhibit strong positive attitudes toward AI adoption, many feel underprepared in pedagogical content knowledge regarding machine learning and neural networks (Fan & Zhong, 2022; Wang et al., 2023). Addressing these instructional and infrastructural gaps through systematic teacher training and validated pedagogical models remains a vital prerequisite for successful AI integration in primary education (Chiu & Chai, 2020; Han et al., 2021).

Materials and Methods. This investigation used an explanatory sequential mixed-methods design, combining qualitative curricular analysis and experiential pedagogical intervention with a quantitative cross-sectional diagnostic survey (Creswell & Creswell, 2018). The qualitative strand evaluated the national standard curriculum and described classroom implementation of artificial intelligence (AI) literacy through block-based machine learning environments. The quantitative strand evaluated the technological readiness, competence profiles, infrastructural constraints, and professional development demands of in-service informatics educators. Participants

The empirical component involved two targeted participant groups: Primary School Students: A cohort of $N = 21$ second-grade students (aged 7–8 years) participated in the laboratory-based teaching experiment focusing on voice recognition model construction and visual programming. In-Service Educators: A total of $N = 44$ primary and secondary school educators teaching Informatics and Digital Literacy completed the structured survey. Within this cohort, 37.2% possessed 1–5 years of pedagogical experience, 32.6% had more than 10 years of teaching tenure, and 53.5% taught at the secondary level. Furthermore, 45.5% reported prior practical experience teaching AI-related modules.

A structured analytical matrix was applied to the draft standard curriculum for “Digital Literacy and Artificial Intelligence” (Grades 1–4), accessible on the national Center for Curriculum Analysis discussion platform (talqylau.bmsokz). The protocol systematically assessed thematic organization, grade progression, continuity of learning objectives, and depth of AI concepts - teacher Competence and Readiness Questionnaire: A multi-dimensional diagnostic survey utilizing 5-point Likert scales and structured category items. The instrument evaluated five core areas: theoretical understanding of AI concepts (machine learning, neural networks), practical application in everyday contexts, methodological capability to teach children, material and technical school infrastructure, and qualification upgrade demands. The questionnaire showed high internal reliability (Cronbach’s $\alpha = 0.86$). Standardized observational sheets and post-intervention reflective dialogues captured student motivation, algorithmic conceptualization, and technical hurdles during block-based model assembly. The research was conducted through four structured operational phases:

Phase 1: Curricular Document Analysis. Systematic qualitative content analysis of state curriculum documents, confirming the integration of the dedicated section “Media Literacy and Artificial Intelligence” into primary school standards.

Phase 2: Teacher Survey Administration. Electronic dissemination of the diagnostic instrument to active Informatics educators, yielding 44 fully validated responses.

Phase 3: Machine Learning Model Training (ML for Kids). In the classroom laboratory setting, second-grade students executed a hands-on “Voice Control” project. Within the ML for Kids environment, students initiated a “Sound Project” and generated discrete categorical labels: “background noise”, “Salem”, “jump” (sekir), “dance” (bile), and “run” (jygir). Each student provided 8 audio samples per class to build the training dataset. The system executed cloud-based supervised training (Learn & Test), and students verified real-time classification accuracy.

Phase 4: Block-Based Programming and Integration (Scratch). Students imported the verified machine learning model into Scratch 3.0 via custom extension blocks. Students constructed visual scripts linking recognized speech inputs to interactive sprite behaviors (e.g., triggering the Cat sprite’s dialogue “Oh, Salem!”, jumping across coordinate axes, or executing rhythmic dancing routines).

Ethical Consideration. The study followed the ethical principles of the Declaration of Helsinki and the Law of the Republic of Kazakhstan “On Personal Data and Their Protection” (No. 94-V of 21 May 2013). The intervention was conducted during regular scheduled lessons using publicly available educational software and did not involve collecting personal or sensitive data; therefore, it did not require formal ethics committee review under the applicable institutional regulations. The school administration granted permission, and parents or legal guardians were informed about the study and consented to their children’s participation. Teachers’ participation in the survey was voluntary and anonymous. All audio samples contained only short command words without identifying information and were deleted after the sessions; all data are reported in anonymized and aggregated form.

Results. Pedagogical Framework for AI Integration in Primary Education. Synthesizing the qualitative curriculum document analysis

with the classroom experimental outcomes resulted in a validated five-stage pedagogical model for introducing machine learning into primary curricula. The conceptual stage introduces fundamental concepts and distinguishes between deterministic, rule-based algorithms and statistical learning models through accessible real-life analogies. In the data collection stage, students gather, categorize, and label training data using acoustic samples. During the model training stage, learners construct and train a classification model within the ML for Kids environment. The application and programming stage enables students to visualize model inference by integrating trained blocks into Scratch 3.0 to animate sprite behaviors. Finally, the reflection and ethics stage supports structured, teacher-guided discussions on model accuracy, digital data privacy, and the ethical dimensions of automated systems.

Classroom Implementation and Student Outcomes. The experimental intervention conducted with second-grade students ($N = 21$) demonstrated high engagement and measurable conceptual acquisition. Hands-on acoustic data collection and immediate visual verification in Scratch significantly increased students’ motivation to learn, with reflective feedback highlighting positive experiences such as excitement when the computer recognized speech and animated the sprite. Students successfully grasped the fundamental four-step machine learning principle: the user speaks, the computer listens, the model learns, and the character executes the command. However, several learners encountered operational obstacles when linking model prediction blocks to conditional loops in Scratch, confirming the necessity of structured pedagogical scaffolding during visual coding activities.

Teacher Readiness, Competence Distribution, and Technical Infrastructure. The diagnostic survey conducted among in-service Informatics teachers ($N = 44$) established clear competence distributions across key theoretical, practical, and infrastructural dimensions:

- professional profile and experience: among the respondents, 37.2% possessed 1–5 years of teaching experience, 32.6% had more than 10

years of pedagogical practice, and 53.5% taught at the secondary level. Additionally, 45.5% reported prior practical experience delivering AI-related instructional units, whereas 40.9% had not previously covered these topics;

- theoretical knowledge: teachers' understanding of fundamental AI concepts such as machine learning and neural networks was rated as moderate by 55.8%, fully prepared by 27.9%, and not prepared by 16.3%. When explaining the distinction between deterministic algorithmic solutions and AI models, 54.5% rated their preparedness as moderate, 22.7% as fully prepared, and 22.7% as not prepared;

- practical and methodological competence: a total of 47.7% of teachers reported being fully prepared to provide real-life examples of AI, 43.2% rated their knowledge as moderate, and only 9.1% felt unprepared. In applying generative AI platforms such as ChatGPT, 54.5% reported being fully prepared and 45.5% indicated a moderate level. Respondents rated their readiness to explain complex topics and organize practical AI tasks as moderate, at 54.5% and 52.3%, respectively. In the domain

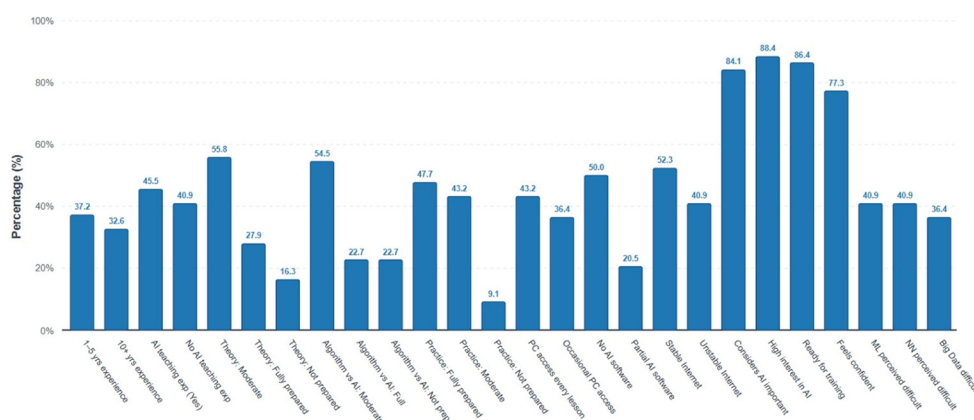
of ethics and safety, 45.5% felt fully prepared and 45.5% reported moderate readiness;

- technical infrastructure: while 43.2% of schools provided computer access in every lesson, 36.4% provided only occasional access. In 50.0% of schools, specialized software for AI instruction was absent, and in 20.5% it was only partially available. Internet connectivity was stable in 52.3% of institutions, with 40.9% reporting periodic instability;

- motivation and professional development demands: teachers expressed strong professional motivation, with 84.1% recognizing AI as essential for students, 88.4% displaying high instructional interest, and 86.4% stating readiness to improve their qualifications. Educators identified machine learning (40.9%), neural networks (40.9%), and big data (36.4%) as the most challenging topics. To address these gaps, educators prioritized professional development courses (54.5%), ready-made instructional materials (43.2%), and improved school hardware equipment (43.2%), favoring offline workshops (34.1%) and structured online courses (31.8%) (Figure 1).

Figure 1

Percentage distribution of teacher competencies, technical infrastructure, and professional development needs



As shown in Figure 1, teachers' professional development needs focus on both competency building and practical implementation support. Professional development courses emerged as the most frequently selected form of support, indicating educators' preference for systematic training to strengthen their AI-related knowledge and teaching skills. At the same

time, the relatively high demand for ready-made instructional materials and improved school hardware suggests that teachers perceive successful AI integration not only as a matter of individual competence but also as dependent on adequate methodological and technological resources. Regarding training formats, respondents preferred offline workshops and

structured online courses, reflecting the need for both hands-on interaction and flexible, organized learning opportunities. Overall, the results indicate that teachers are highly motivated to integrate AI into education but require targeted professional development, practical teaching resources, and appropriate infrastructure to translate this motivation into classroom practice.

Discussion. The empirical outcomes of this study show that integrating artificial intelligence (AI) elements into primary education offers transformative pedagogical opportunities while also introducing specific operational and ethical challenges (Chiu & Chai, 2020). When evaluating instructional benefits, educators identified the development of higher-order cognitive and algorithmic thinking skills (36.4%) and the facilitation of personalized learning pathways (25.0%) as the most significant advantages of early AI literacy. These findings corroborate previous research by Dai et al. (2020), which emphasized that visual block-based machine learning platforms scaffold computational logic while reinforcing learner autonomy.

Conversely, educators expressed valid concerns regarding potential systemic vulnerabilities associated with early technology exposure (Smakman et al., 2021). Teachers' primary risk was increased children's cognitive dependence on automated technologies (36.4%), mirroring earlier concerns raised by Luckin et al. (2016) about passive reliance on technology. In addition, digital data security (25.0%) and preserving academic integrity (25.0%) emerged as key concerns. These findings reinforce international recommendations that primary AI curricula must incorporate data ethics, model transparency, and child-safe data management practices from the outset (Crawford & Paglen, 2021; UNESCO, 2022). Qualitative student feedback and observational data from the ML for Kids and Scratch interventions provide strong empirical support for constructivist learning models in AI education (Druga & Ko, 2021; Papert, 1980). Young learners demonstrated notable motivation when training acoustic recognition models with their own voices and observing interactive sprite responses in real

time. This experiential approach demystified complex computational principles, enabling primary students to grasp the conceptual mechanics of supervised learning without encountering syntactical barriers (Ali et al., 2019; Kong et al., 2023).

However, the transition from model training in ML for Kids to visual programming in Scratch revealed cognitive friction for a subset of students. Linking probabilistic model predictions with deterministic conditional structures in Scratch required explicit teacher-led scaffolding. As Tedre et al. (2021) note, teaching machine learning requires distinct pedagogical strategies from conventional programming, necessitating structured templates and scaffolded visual tasks for early primary learners. To support effective curricular integration, survey respondents emphasized the need to expand hands-on practical exercises (42.9%) and implement specialized teacher professional development programs (38.1%). Given that over half of teachers demonstrated moderate theoretical understanding of machine learning and neural networks (55.8% and 54.5%, respectively), ongoing professional development programs focused on applied AI pedagogy are critical (Celik, 2023; Fan & Zhong, 2022). Furthermore, technical infrastructure requires targeted institutional upgrades to resolve current deficits, such as the complete absence of specialized AI software in 50.0% of schools and periodic internet instability in 40.9% of classrooms (Wang et al., 2023).

Conclusion. Integrating artificial intelligence (AI) elements into the primary school "Digital Literacy" curriculum is an essential strategic step toward modernizing early technological education and equipping young learners with foundational 21st-century competencies (Ministry of Education of the Republic of Kazakhstan, 2023). By combining the Machine Learning for Kids (ML for Kids) platform with the Scratch 3.0 visual programming environment, primary school students navigate the entire machine learning lifecycle—from acoustic data gathering and supervised model training to block-based code execution and socio-ethical reflection. The empirical outcomes confirm that

introducing early machine learning through a five-stage pedagogical framework fosters foundational algorithmic literacy, demystifies data processes, and enhances creative problem-solving without imposing syntactical cognitive overload. While primary teachers demonstrate positive professional attitudes toward AI adoption, successful national scaling requires targeted professional development programs, ready-to-use pedagogical resources, and improved computing infrastructure across primary classrooms. Future research should focus

on longitudinal assessments of AI literacy retention among early learners, the development of standardized computational assessment metrics, and cross-regional comparative analyses accounting for linguistic and cultural variations in technology-enhanced primary classrooms.

Conflict of Interest. The authors declare no conflict of interest regarding the publication of this manuscript. No financial, personal, or professional relationships have influenced the research design, data collection, analysis, interpretation, or writing of this paper.

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