Architecture-Driven Logic Design Strategies for Distributed Educational IoT Environments with Robotic Support

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Abstract: - The integration of artificial intelligence components and humanoid robotic platforms into adaptive educational software ecosystems requires clear architectural planning, secure data flows and reliable interfaces between user-facing applications, AI services, databases and robotic interaction modules. This paper proposes a formal architecture-driven framework for adaptive educational IoT environments with robotic support. The proposed architecture is represented as a directed graph, where nodes correspond to software, AI, data, security, and robotic components, while edges represent controlled data flows and communication interfaces. This model introduces metrics for end-to-end latency, communication overhead, reliability, traceability, and risk exposure. A small-scale simulation-based validation is presented for evaluating representative learning scenarios involving AI-based personalization, teacher supervision, secure logging, and humanoid feedback robots such as the QTrobot RD-V2 i7 and NAO. This proposed framework supports students with special education needs by combining predictable interaction, multimodal feedback, emotional literacy support, teacher control, and GDPR-compliant data management.

Key-Words: - artificial intelligence, distributed IoT, humanoid robots, adaptive learning, special educational needs, QTrobot, NAO, secure data flow, educational robotics.

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1 Introduction

Modern educational software and IoT systems are increasingly composed of distributed services, application programming interfaces (APIs), databases, learning-content repositories, analytics modules, user-facing applications, and robotic interaction components, [1], [2]. In such environments, the integration of a new intelligent feature rarely affects only a single isolated component. Instead, it requires coordinated changes across data models, service interfaces, processing pipelines, access-control mechanisms, and user interaction flows. The integration of artificial intelligence (AI) into an existing software ecosystem further increases architectural complexity. Beyond the implementation of a specific algorithm, AI-based processing requires structured metadata management, controlled access to input and output data, validation of generated results, and reliable delivery of outcomes to the intended user, service, or system component.

A previous architecture-driven Software-as-a-Service (SaaS) feature-integration case is used in this paper as an engineering reference for deriving reusable integration principles. In contrast, the present work extends this logic toward adaptive educational IoT environments with humanoid robotic support. The focus is therefore shifted from SaaS-based AI image processing to secure educational data flows, teacher-supervised AI personalization, robot-mediated feedback, and measurable architectural validation in learning scenarios for studentc with SEN, [3], [4].

The same architecture-driven logic can be adapted to educational software ecosystems that integrate AI modules and humanoid robotic platforms. In this context of supporting students with SEN, such ecosystems may include learner profiles, teacher dashboards, AI-based recommendation and personalization modules, learning content repositories, and robot-mediated feedback mechanisms. Humanoid social robots such as QTrobot RD-V2 i7 and NAO can serve as embodied interaction interfaces for structured learning activities, emotional literacy tasks, programming scenarios, social communication, and multimodal feedback, [5], [6], [7], [8], [9], [10].

The integration of humanoid robots should not be considered only as the introduction of a physical device into the learning environment. It requires a broader architectural framework in which the robot is connected to educational content, learner data, AI-based decision-making logic, teacher supervision, and secure data-management processes. Such a framework is particularly important in adaptive educational environments, where the system must respond to individual learner needs while ensuring reliability, transparency, and data protection, [3], [4], [10].

The contributions of the paper are: (i) it summarizes an architecture-driven refinement process for AI-enabled feature integration; (ii) it generalizes the process toward adaptive educational systems with humanoid robotic components; and (iii) it maps the proposed approach to project activities related to secure interfaces, adaptive learning, robot-assisted education, and technical validation.

The novelty of the current research lies in transferring architecture-driven integration principles to adaptive educational IoT systems with humanoid robotic support for students with SEN, defining secure layered data flows, introducing teacher-supervised AI personalization, integrating robot-mediated feedback, and proposing formal metrics for latency, reliability, communication overhead, logging, completeness, and pedagogical control.

Socially assistive robots and humanoid robots have been widely discussed as tools for supporting interaction, engagement, and learning in children with autism spectrum disorder (ASD) and other special educational needs, [5], [6], [9], [11]. Existing reviews emphasize both the potential of social robots to support communication and learning and the need for careful design, safety, acceptance, and pedagogical suitability. Studies involving NAO demonstrate applications in pedagogical and logopedic intervention, language interaction, imitation training, and human action recognition, [7], [8].

In the present paper, QTrobot is considered as a possible robotic interaction layer for scenarios involving emotion recognition, emotional expression, and emotion regulation, [12]. NAO, in contrast, is considered a broader programmable humanoid platform suitable for educational, programming, movement-based, and interactive learning scenarios.

From a software-engineering perspective, robot-assisted learning cannot be reduced to the robot device alone. The robot must be integrated with secure data storage, interaction logs, personalization logic, content repositories, monitoring dashboards, and teacher-control mechanisms. Recent work on IoT, cloud/edge computing, and real-time analytics highlights the importance of layered architectures, traceability, and intelligent data-processing pipelines in AI-enabled systems, [3], [4]. These principles are transferable to educational robotics, where reliability, transparency, and controlled data flows are particularly important.

2 Architecture-Driven Planning Approach

The proposed approach is based on the idea that complex AI-enabled and robot-supported features should be planned before implementation through a structured refinement process. It transforms an initial problem or stakeholder need into a development-ready specification by combining architectural diagramming, data-flow analysis, interface definition, formal modeling, measurable metrics, and risk-oriented evaluation. Figure 1 (Appendix) summarizes the proposed architecture-driven refinement workflow. The process starts with problem identification, continues with architecture diagramming and AI/robot integration analysis, and ends with development-ready tasks supported by test, safety, reliability, and validation criteria.

Table 1 (Appendix) presents the proposed approach not only as a design sequence, but also as a methodological framework for reducing integration risks and supporting the reliable use of AI modules and humanoid robots in educational environments.

The original SaaS feature-integration case is used as an engineering foundation to derive reusable architectural principles. Although the original case concerns AI-generated image derivatives, its underlying logic is transferable to adaptive educational IoT environments (Table 2). In both cases, the system must coordinate AI-based processing, metadata management, secure data exchange, user interfaces, storage, monitoring, and feedback.

In the educational robotics scenario, the humanoid robot is treated as an interactive layer within a broader software ecosystem. Robots do not operate in isolation; rather, they receive commands, provide feedback, and participate in learning scenarios with the help of AI modules, learner profiles, content repositories, and teacher supervision interfaces. This interpretation supports unified learning environments that integrate software, artificial intelligence, and robotics platforms into a unified architecture.

Table 2. Transfer of architectural principles from the SaaS integration case to the educational robotics scenario

SaaS integration element	**Educational robotics equivalent**	**Role in the proposed architecture**
Front-end component	Learner or teacher interface	Provides access to tasks, dashboards, and interaction controls
API services	Secure communication layer	Enables controlled data exchange between software modules and robotic components
AI post-processing module	AI personalization or recommendation module	Supports adaptive selection of content, feedback, or next learning activity
Image metadata	Learner profile and interaction metadata	Stores information about learner progress, task status, and interaction history
Storage layer	Educational data repository	Maintains learning resources, profiles, logs, and system records
Delivery mechanism	Robot-mediated or screen-based feedback	Provides learning outcomes through visual, verbal, or robotic-mediated feedback
Monitoring and validation	Teacher dashboard and safety monitoring	Supports supervision, reliability checks, and pedagogical control

Source: created by the authors

3 Formal System Model and Evaluation Metrics

The proposed adaptive educational IoT architecture is represented as a directed graph $G = (V, E)$, where V is the set of system components and E is the set of directed communication links between them. The system components include learner interface, teacher dashboard, AI module, database, security services, and robotic interaction modules.

The set of nodes is defined as:

$$V = V_L \cup V_A \cup V_D \cup V_R \cup V_S \qquad (1)$$

where V_L denotes learner and teacher interaction components, V_A denotes AI personalization modules, V_D denotes data and content repositories, V_R denotes robotic interaction components, and V_S denotes security, monitoring, and logging services.

For a given learning interaction, the data-flow path is defined as:

$$P = \{v_1, v_2, \dots, v_k\} \qquad (2)$$

where $v_i \in V$ and $(v_i, v_{i+1}) \in E$. A typical path includes learner input, secure API communication, AI-based personalization, teacher approval, database logging, and robot-mediated feedback.

The end-to-end response time is defined as:

$$T_{total} = T_{input} + T_{API} + T_{AI} + T_{DB} + T_{teacher} + T_{robot} \qquad (3)$$

This metric measures the total time from the learner's initial input to the final screen-based or robot-mediated feedback. Here T_{input} is the time required to capture the learner input, T_{API} denotes the communication delay through the secure API layer. T_{AI} denotes the AI personalization time, T_{DB} denotes the time required for database access and logging time, $T_{teacher}$ denotes the time required for teacher approval, supervision, or intervention, T_{robot} denotes the time required for the robot to generate verbal, visual, gestural, or multimodal feedback.

The reliability of an interaction path is estimated as:

$$R_P = \prod_{i=1}^{k} R_i \qquad (4)$$

where R_i is the reliability of the i-th component or communication link included in the interaction path.

The architectural risk score for a given risk category j is defined as:

$$Risk_j = P_j \times I_j \qquad (5)$$

where P_j is the probability of occurrence of the j-th risk and I_j is the potential impact.

The total risk exposure of the architecture is calculated as:

$$Risk_{total} = \sum_{j=1}^{m} \omega_j + P_j \times I_j \qquad (6)$$

where ω_j is the weight assigned to the j-th risk category, and m is the total number of identified risk categories.

The next learning activity can be modeled as an optimization problem

$$a_{t+1} = arg\max_{a \in A} U(a | p_t, h_t, c_t) \qquad (7)$$

where a_{t+1} is the selected next learning activity, A is the set of available learning activities, p_t is the current learner profile, h_t is the interaction history, c_t is a pedagogical constraint set, and $U(a|p_t, h_t, c_t)$ is the utility function that evaluates the suitability of an activity a for the learner at the time t.

The formal model provides a basis for evaluating the layered architecture shown in Figure 2 (Appendix), where each functional layer can be mapped to a subset of nodes and each communication flow can be represented as a directed edge.

4 Architectural Scenarios for Adaptive Educational IoT Systems

Based on the information presented in Table 2, the proposed architecture can be described through a set of interconnected educational IoT scenarios. These scenarios illustrate how AI services, learner profiles, teacher dashboards, content repositories, and humanoid robotic platforms can operate together in a distributed adaptive learning environment. The aim is to present reusable architectural models for developing secure and scalable educational systems that leverage robotic support.

The architecture presented in Figure 2 (Appendix) illustrates the main functional organization of the proposed adaptive educational IoT system. The model combines learner and teacher interaction, secure communication, AI-based personalization, data and content management, and robotic feedback. Each layer has a specific role, but the system's effectiveness depends on the controlled interaction among layers.

The learner and teacher interaction layer provides access to educational activities, dashboards, and supervision tools. The secure communication layer ensures controlled data exchange between software modules, databases, AI services, and robotic platforms. The AI personalization layer supports selecting learning activities, feedback types, and adaptive pathways based on learner profiles and interaction history. The data and content management layer stores learner profiles, educational resources, interaction logs, and system metadata. The robotic interaction layer enables embodied feedback via platforms such as the QTrobot RD-V2 i7 and the NAO.

In this ecosystem, embodied feedback and communication can be provided via platforms such as the QTrobot RD-V2 i7 and the NAO, [7], [8], [13], [14]. This layered organization, illustrated in Figure 2 (Appendix), shows that humanoid robots are not treated as isolated devices but as integrated components of a broader educational IoT system. Their role is to provide structured, predictable, and multimodal feedback under the supervision of the teacher and according to predefined pedagogical and safety criteria.

The following scenarios represent the multi-layered architecture in Figure 2 (Appendix). Scenario 1 focuses on the interaction between learner data, AI-based personalization, and teacher supervision. Scenario 2 illustrates the role of the humanoid robot as an embodied feedback interface connected via the secure communication layer. Scenario 3 examines the secure data flow, monitoring, and logging of interactions throughout the architecture.

Scenario 1: AI-based personalization and teacher supervision

The first scenario concerns AI-based personalization under teacher supervision, where the learner completes a digital or robot-mediated learning task. The system records the task status, learner response, and interaction metadata. Based on these data, the AI module proposes the next activity, feedback type, or difficulty level. However, the teacher or specialist remains responsible for reviewing, approving, or adapting the recommended learning path.

The scenario is suitable for students with SEN, as adaptive solutions must remain transparent and pedagogically controlled. The AI module supports the teacher by providing recommendations, but does not replace human judgment. In terms of the architecture shown in Figure 2 (Appendix), this scenario primarily involves the learner and teacher interaction layer, the AI personalization layer, and the data and content management layer. By combining these layers, the teacher is able to support controlled adaptation while maintaining accountability for the pedagogical decision, [1], [2], [10].

Scenario 2: Robot-mediated feedback via QTrobot or NAO

This scenario focuses on robot-mediated feedback, in which the humanoid robot receives commands from the educational software environment via the secure communication layer shown in Figure 2 (Appendix). Depending on the learning task, learner profile, and selected pedagogical scenario, the robot can provide verbal feedback, facial expressions, emotions, gestures, movement-based prompts, or emotional-literacy cues.

QTrobot RD-V2 i7 is suitable for students with SEN and structured emotional literacy activities, such as recognizing, naming, expressing, and regulating emotions. It can be considered a humanoid social robot for research and education in the context of human-AI interaction. Its ROS-based interface provides access to robot functionality via publish/subscribe and service/client communication mechanisms, making it suitable for integration into a modular educational IoT architecture, [9], [10], [13], [14]. NAO can support broader educational scenarios, including programming tasks, imitation activities, movement-based learning, and interactive communication. The technical characteristics of NAO V6, such as cameras, microphones, loudspeakers, Ethernet, Wi-Fi, Bluetooth connectivity, and an embedded Intel Atom-based computing platform, allow it to support verbal feedback, imitation activities, motion-based interaction, and multimodal communication within teacher-controlled learning scenarios, [7], [8], [15].

From an infrastructure perspective, both robotic platforms require a stable local area network, secure Wi-Fi or Ethernet connectivity, a teacher or operator workstation, and access to the educational software platform. Depending on the implementation, an additional local server or edge device can host AI services, learner profile databases, monitoring dashboards, and logging mechanisms. This configuration supports a privacy-aware integration model in which sensitive learner data are processed in a controlled environment, while the humanoid robot serves primarily as an embodied interface for feedback and interaction. Compact edge platforms such as Raspberry Pi-based robotic systemc can also support sensing, control, and robotic behavior in experimental environments, [15].

Scenario 3: Secure Data Flow, Monitoring, and Interaction Logging

This scenario focuses on secure data flow, monitoring, and interaction logging in the proposed adaptive educational IoT environments. Robot-assisted educational activities may generate different types of data, including learner responses, task completion status, interaction events, feedback history, teacher annotations, and system status information. The data should be exchanged through secure interfaces and stored according to predefined access-control and data-protection rules. In Figure 2 (Appendix), this scenario mainly involves the secure communication layer and the data and content management layer.

The secure communication layer controls the exchange of information between the learner interface, artificial intelligence services, teacher dashboards, databases, and robotic platforms. The data and content management layer stores only the necessary learner profiles, educational resources, interaction log files, and system metadata, [3], [4], [10].

This scenario is important because adaptive educational systems for students with SEN require traceability, accountability, and supervision by teachers. Interaction logs and metadata can help teachers and specialists review the learning process, assess the relevance of feedback, and improve future learning scenarios. At the same time, the system must follow the principles of data minimization, controlled access, transparency, and secure storage so that sensitive student data remains protected within the educational software environment.

5 Scenario-based Architectural Verification and Validation Metrics

The proposed architecture was evaluated through an illustrative simulation-based technical assessment. The aim of this validation was to verify whether the architecture supports measurable, reliable, and traceable interaction flows under representative adaptive learning scenarios.

Three representative scenarios were considered: S1 – AI-based personalization with teacher supervision; S2 – robot-mediated feedback through QTrobot or NAO; and S3 – secure data-flow logging and monitoring.

Each scenario was executed in 100 repeated simulation runs using representative data-flow paths derived from the proposed layered architecture. The evaluated parameters included average latency, successful execution control, and architectural support for monitoring and safety (Table 3).

The reported values should be interpreted as illustrative simulation-based results intended to demonstrate the applicability of the proposed metrics rather than as measurements from a fully deployed classroom prototype.

Table 4 presents the main risks associated with AI and humanoid robot integration in adaptive educational IoT environments. The architectural measures support a secure, reliable, and pedagogically controlled implementation.

The risks presented in Table 4 indicate that the proposed architecture should be evaluated not only on technical criteria but also on pedagogical, ethical, and safety-related requirements. This is important when robotic platforms are used in learning scenarios involving students with SEN.

Table 3. Illustrative simulation-based validation and interpretation of representative interaction scenarios

Scenarios	Average latency	Success rate	Results and interpretation
AI-based personalization with teacher supervision	185 ms	98%	Supports fast teacher–controlled adaptation and timely AI-based recommendation generation
Robot-mediated feedback through QTrobot or NAO	320 ms	96%	Show the highest latency due to robot-command generation, communication with the robotic platform, and feedback execution.
Secure data-flow logging and monitoring	140 ms	99%	Provides complete traceability with low technical overhead and reliable logging of interaction events

Source: created by the authors

Table 4. Reliability, safety, and data protection risks in AI-enabled and humanoid robot-assisted educational IoT environments

Risk category	Description	Mitigation measure
Data protection risk	Learner profiles, interaction logs, and educational records may contain sensitive information.	Apply data minimization, access control, anonymization, and GDPR-aware storage policies
Reliability risk	Service failure or network delay may interrupt the learning process or robotic response.	Monitoring, fallback procedures, and local recovery mechanisms.
Robot behavior risk	Unexpected robot actions may affect learner comfort or safety, or trust in the system	Predefined scenarios, teacher control, and emergency stop procedures
Pedagogical risk	Technology may dominate the learning process rather than support educational objectives and individual learners' needs.	Teacher-controlled scenarios, alignment with pedagogical goals, and adaptation to individual learning needs
Integration risk	Inconsistencies may occur between AI services, databases, dashboards, and robot-control commands	Use versioned interfaces, architecture documentation, and integration testing procedures.
Transparency and traceability risk	AI recommendations or robot-mediated feedback may be difficult to interpret or review after the interaction	Maintain interaction logs, explainable decision records, and teacher-accessible monitoring dashboards
Security risk	Unauthorized access to learner data, robot control services, or the teacher dashboard may compromise system integrity	Apply HTTPS/TLS communication and JWT?OAuth2 authorization, RBAC/ ABAC access control, encrypted storage, and SIEM-like monitoring

Source: created by the authors

To support traceability, quantification, and future validation of prototypes, objective indicators, target values, and validation methods have been added to the qualitative risk categories, as shown in Table 5.

Table 5. Quantitative risk indicators and validation methods

Risk Category	Quantitative Indicators	Target Values	Validation methods
Data protection	Number of unauthorized access attempts resulting in successful access	0	Access-log inspection and authorization testing
Reliability	Successful execution rate of representative interaction scenarios	≥ 95%	Repeated scenario execution and success-rate calculation
Robot behavior	Number of unsafe or non-whitelisted robot commands	0	Command whitelist testing and safety-rule verification
Pedagogical Control	Percentage of AI recommendations reviewed or approved by the teacher	100%	Teacher dashboard log review
Traceability	Percentage of interaction events successfully recorded in the log system	≥ 99%	Comparing event logs and checking audit trails

Source: created by the authors

6 Discussion

The proposed architecture-driven approach demonstrates that integrating AI and humanoid robotic platforms into adaptive educational IoT environments should be treated as a coordinated engineering process rather than the isolated addition of intelligent or robotic components. The main value of the approach lies in the early clarification of system layers, interfaces, data flows, risks, and responsibilities. The model shows how AI-based personalization, teacher supervision, secure data management, and robot-mediated feedback can operate together in a secure and traceable way.

The formal and simulation-based evaluation indicates that the proposed architecture provides a measurable framework for integrating AI-based personalization, teacher supervision, secure data management, and robot-mediated feedback. The graph-based representation makes it possible to define metrics that support objective assessment of system behavior. Compared with a baseline non-layered architecture, the proposed model improves traceability, separates educational decision-making from robotic execution, and introduces explicit control points for security and teacher supervision.

The transfer from the SaaS integration case to the educational robotics scenario shows that the same architectural principles can be applied across different application domains. In the SaaS case, the system coordinates AI-generated outputs, metadata, APIs, storage, validation, and delivery mechanisms. In the educational robotics scenario, the same logic is applied to learner profiles, AI-based personalization, learning content, interaction logs, teacher supervision, and robot-mediated feedback. Therefore, the contribution of the proposed model is not limited to a specific software implementation but rather to the definition of reusable architectural logic for complex AI-enabled systems.

The relevance of this approach is supported by recent research on social and humanoid robots in special education. Reviews on social humanoid robots for children with autism spectrum disorder (ASD) emphasize both the potential of these platforms to support communication and learning and the need for careful design, safety, and appropriate use conditions, [5], [6], [9], [10], [11].

Similar conclusions are reported in studies on distance special education delivery through social robots, where robot-mediated interaction requires structured scenarios, supervision, and evaluation of user satisfaction, [6]. These findings support the position adopted in this paper that humanoid robots should be integrated through a controlled educational and technical framework rather than used as isolated devices.

The proposed model is also consistent with studies involving NAO in educational and therapeutic contexts. The use of NAO has been demonstrated in applications such as language interaction with children with autism, imitation learning, the recognition of human actions, and multimodal human-robot interaction, [7], [8], [15]. The architecture of these applications requires communication between robot functions, training scenarios, interaction data, and supervision mechanisms. It is important to secure an integration layer that connects robotic platforms to AI-based personalization modules and teacher-controlled interfaces.

The QTrobot RD-V2 i7 and NAO can be considered as complementary platforms within the proposed architecture. QTrobot is more directly suited to scenarios involving expressive social interaction and emotions, while NAO is better suited to interactive learning activities. QTrobot has ROS-based access to the robot's functionalities through publish/subscribe and service/client interfaces, which supports its integration into modular software architectures, [13]. NAO is connected to a programmable humanoid platform with 25 degrees of freedom, cameras, microphones, speakers, Ethernet, Wi-Fi, Bluetooth connectivity, and an embedded computing platform based on Intel Atom, making it suitable for multimodal educational interaction, [14]. These technical characteristics justify the need for a common communication and control layer in the proposed architecture.

It is important to ensure data protection and system reliability. Adaptive and robotic learning environments can process learner profiles, educational records, interaction metadata, and feedback events. For this reason, secure API communication, access control, interaction logging, and data minimization must be defined at the architectural level. Recent research on IoT, cloud/edge computing, and AI highlights the importance of multi-layered architectures, real-time data processing, traceability, and intelligent data pipelines in connected systems, [3], [4]. These principles are applicable to educational robotics, especially when the target users are students with special educational needs.

In the current study, validation was performed for technical and simulation-based scenarios and does not yet include a full pedagogical experiment with students with SEN. The proposed metrics assess architectural feasibility, latency, reliability, and traceability, but they do not yet measure long-term learning outcomes, emotional engagement, or clinical/ pedagogical effectiveness. Future work will include prototype implementation, teacher-led scenario testing, ethical approval procedures, and evaluation with real users in controlled educational settings.

References:

[1] Zhang, X., Ding, Y., Huang, X., Li, W., Long, L., Ding, S. Smart Classrooms: How Sensors and AI Are Shaping Educational Paradigms. *Sensors*, 2024, 24, 5487. https://doi.org/10.3390/s24175487.

[2] Tsipianitis, D., Misirli, A., Lavidas, K., Komis, V. IoT Devices and Their Impact on Learning: A Systematic Review of Technological and Educational Affordances. *IoT*. 2025, 6, 45. https://doi.org/10.3390/iot6030045.

[3] Khattach, O., Moussaoui, O., Hassine, M. End-to-End Architecture for Real-Time IoT Analytics and Predictive Maintenance Using Stream Processing and ML Pipelines.*Sensors* 2025, 25, 2945. https://doi.org/10.3390/s25092945.

[4] Ficili, I., Giacobbe, M., Tricomi, G., Puliafito, A. From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI. *Sensors* 2025, 25, 1763. https://doi.org/10.3390/s25061763.

[5] Puglisi, A., Caprì, T., Pignolo, L., Gismondo, S., Chilà, P., Minutoli, R., Marino, F., Failla, C., Arnao, A, Tartarisco, G., et al. Social Humanoid Robots for Children with Autism Spectrum Disorders: A Review of Modalities, Indications, and Pitfalls. *Children*. 2022, 9, 953. https://doi.org/10.3390/children9070953.

[6] Lytridis, C., Bazinas, C., Sidiropoulos, G., Papakostas, G., Kaburlasos, V., Nikopoulou, V., Holeva, V., Evangeliou, A. Distance Special Education Delivery by Social Robots. *Electronics* 2020, 9, 1034. https://doi.org/10.3390/electronics9061034.

[7] She, T., Ren, F. Enhance the Language Ability of Humanoid Robot NAO through Deep Learning to Interact with Autistic Children. *Electronics*. 2021, 10, 2393. https://doi.org/10.3390/electronics10192393.

[8] Alnafjan, A., Alghamdi, M., Alhakbani, N., Al-Ohali, Y. Improving Imitation Skills in Children with Autism Spectrum Disorder Using the NAO Robot and a Human Action Recognition. *Diagnostics*. 2025, 15, 60. https://doi.org/10.3390/diagnostics15010060.

[9] Cano, S., Díaz-Arancibia, J., Arango-López, J., Libreros, J.E.; García, M. Design Path for a Social Robot for Emotional Communication for Children with Autism Spectrum Disorder (ASD). *Sensors*. 2023, 23, 5291. https://doi.org/10.3390/s23115291.

[10] Horstmann, A., Mühl, L., Köppen, L., Lindhaus, M., Storch, D., Bühren, M., Röttgers, H., Krajewski, J. Important Preliminary Insights for Designing Successful Communication between a Robotic Learning Assistant and Children with Autism Spectrum Disorder in Germany. *Robotics*. 2022, 11, 141. https://doi.org/10.3390/robotics11060141.

[11] Nadeem, M., Barakat, J., Daas, D., Potams, A. A Review of Socially Assistive Robotics in Supporting Children with Autism Spectrum Disorder. *Multimodal Technol. Interact.* 2025, 9, 98. https://doi.org/10.3390/mti9090098.

[12] Nagae, T., Lee, J. Understanding Emotions in Children with Developmental Disabilities during Robot Therapy Using EDA. *Sensors*. 2022, 22, 5116. https://doi.org/10.3390/s22145116.

[13] LuxAI. QTrobot Computation and networking. LuxAI Documentation, [Online]. https://docs.luxai.com/docs/modules/processor (Accessed Date: January 15, 2026).

[14] Aldebaran/Softbank Robotics. NAO Documentation, NAOqi 2.8 for NAO V6, [Online]. http://doc.aldebaran.com/2-1/index_dev_guide.html (Accessed Date: January 15, 2026).

[15] Sapundzhi, F., Rahman, M., Georgiev, S. Todorov, V. Design of the Human Following Robot Using Raspberry Pi. *Recent Advances in Computational Optimization; Studies in Computational Intelligence, vol 1237; Springer*, 2026. pp. 153–164.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

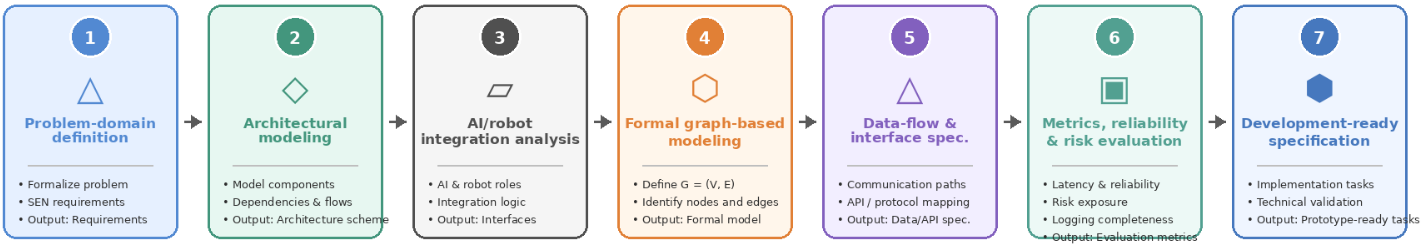

Fig. 1: Extended architecture-driven workflow from problem-domain definition to formal modeling, metric-based evaluation, and development-ready specification

Source: created by the authors

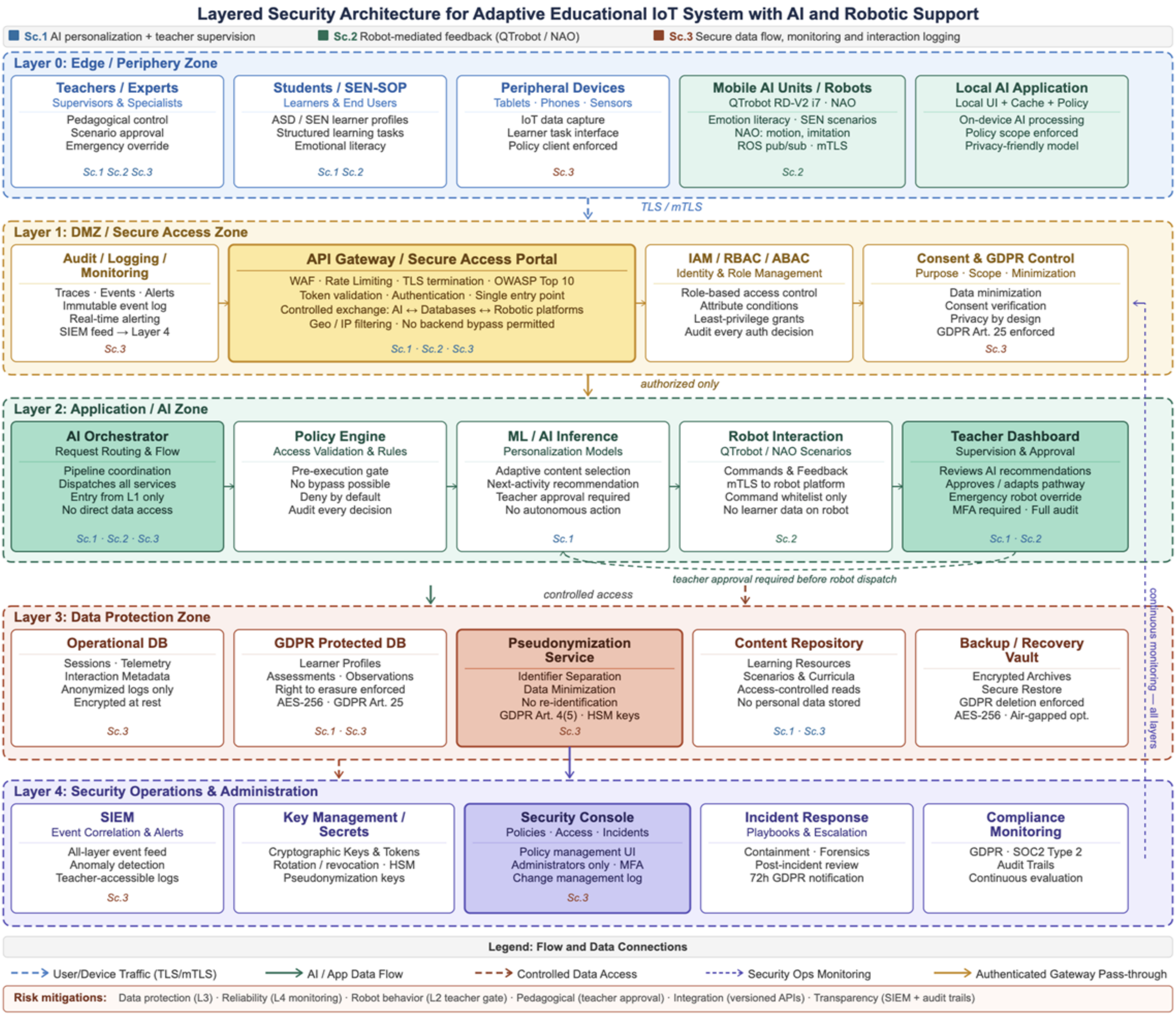

Fig. 2: Layered security architecture of the adaptive educational IoT system with AI and robotic support

Source: created by the authors

Table 1. Stages of the architecture-driven planning and specification process

	Stage	Purpose	Application in the proposed system	Output
1	Problem-domain definition	Formalizes the educational and technological problem	Defines the need for secure AI-supported and robot-assisted learning for students with SEN	Problem description and stakeholder requirements
2	Architectural modeling	Represents components, services, dependencies, and data flows	Models learner profiles, teacher dashboards, AI services, content repositories, APIs, and Humanoid robots	Architecture and interaction scheme
3	AI/robot integration analysis	Defines the role of AI modules and robotic platforms	Specifies personalization logic and robot-mediated feedback through QTrobot/NAO	Integration logic and interface requirements
4	Formal graph-based modeling	Defines system nodes, edges, interaction paths, and formal evaluation variables	Represents learner interfaces, AI modules, repositories, robotic components, and security services as a directed graph	Formal system model and interaction paths
5	Data-flow and interface specification	Defines communication paths and access-control points	Describes secure exchange of learner data, AI outputs, logs, and robot commands	Data-flow and API specification
6	Metrics, reliability and risk evaluation	Identifies risks related to security, reliability, and interaction	Establishes criteria for predictable robot behavior, data protection, traceability and teacher control	Validation and safety criteria
7	Development specification	Converts the model into implementation tasks	Defines tasks for software modules, AI components, dashboard, databases, and robot interfaces	Technical specification and task list

Source: created by the authors