

# Design of a robotics educational laboratory on a unified smart city platform with a three-level architecture

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## Abstract

The rapid development of robotics, cyber-physical systems, and smart city technologies requires new approaches to engineering education that ensure continuity between different educational levels and research activities. This paper presents the concept of a robotics educational laboratory based on a unified Smart City-type platform with a three-level architecture designed for secondary school pupils, university students, and research and development activities. Robot Operating System (ROS) is used as a core middleware that enables modularity, scalability, and integration of physical and digital components. The proposed platform supports IoT, Fog/Edge computing, cloud services, and digital twins, providing a continuous educational trajectory from basic STEM competencies to advanced applied research. The educational and research benefits of the proposed approach are discussed in the context of SMARTINDUSTRY.

**Keywords:** Educational Robotics, Smart City, Robot Operating System (ROS), STEM Education, Tripled Learning, IoT, R&D.

## 1. Introduction

The fast evolution of robotics and intelligent automation has significantly increased the demand for highly qualified engineers capable of working with cyber-physical systems and smart city infrastructures. Recent studies on robotics education and ROS-based learning environments demonstrate that unified platforms and realistic scenarios considerably improve learning outcomes and practical skills [1]-[4]. In addition, the integration of Fog/Edge/AIoT technologies with the Tripled Learning concept enables the creation of a continuous educational pathway that connects school education, university training, and research activities [5]-[7]. The proposed educational platform, like close analogues such as Duckietown, is not unique, but rather an example of the implementation of a new type of Research-Education Robotics Platforms (RERP), infrastructures that simultaneously serve as a laboratory, course, and experimental stand. Research-education robotics platforms are specialized, versatile, and often open-source systems designed to teach, simulate, and research AI, navigation, and control systems.

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\*SmartIndustry 2026: 3rd International Conference on Smart Automation & Robotics for Future Industry, March 26-27, Lviv, Ukraine

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Key platforms include versatile mobile bots (AgileX), modular manipulators (DOBOT), and simulation software (Webots, Gazebo, ROS), enabling hands-on training from K-12 to advanced postgraduate levels [11].

## **2. Concept of a Unified Smart City Platform**

The proposed educational laboratory emulates key components of a smart city infrastructure, including intelligent transportation systems, energy management, environmental monitoring, and public safety services. The platform combines physical robotic systems with virtual models and digital twins, enabling both experimental and simulation-based learning. A modular architecture based on IoT devices, robotic platforms, standardized communication protocols, and cloud-based data processing ensures scalability and flexibility.

Beyond physical infrastructure emulation, the proposed Smart City platform incorporates a cyber-physical control paradigm in which semantic task formulation, perception, and physical execution are tightly coupled in a closed-loop architecture. The platform thus evolves from a purely ROS-based robotic training environment toward a Physical AI-enabled ecosystem, where robots are capable of interpreting high-level human instructions and autonomously decomposing them into structured execution plans. This extension transforms the Smart City mock-up into a testbed for semantic-to-physical system integration.

## **3. Role of Robot Operating System (ROS)**

ROS serves as the core software framework of the proposed platform across all educational levels. ROS provides standardized communication mechanisms, reusable software components, and integration with simulation tools such as Gazebo and RViz. Its use enables seamless transition from simple educational tasks to complex multi-robot and smart city scenarios, as well as effective implementation of digital twins for urban infrastructure components.

In addition to serving as middleware, ROS acts as the execution backbone for higher-level cognitive modules. While perception, navigation, and control are handled through ROS nodes, high-level semantic reasoning modules (e.g., Large Language Models) operate as supervisory layers that generate structured action sequences without directly interacting with actuators. This separation of concerns ensures safety, modularity, and real-time reliability.

## **4. Three-Level Architecture of the Educational Laboratory**

### **4.1 Level 1: Secondary School Pupils**

The first level focuses on developing basic STEM competencies and motivation toward engineering disciplines. It employs educational robotics kits, visual programming environments, and simplified smart city scenarios such as traffic light control and environmental sensing. Game-based and gamified learning approaches are applied to increase engagement and learning effectiveness [8].

At this stage, students work with a unified mobile robotic platform featuring a differential drive base, a front-facing camera, an ultrasonic distance sensor, and a lightweight robotic manipulator (3–4 degrees of freedom). Control is performed manually via joystick or web interface, enabling direct understanding of kinematics, actuator control, and basic sensor feedback processing.

### **4.2 Level 2: University Students**

At the university level, students work with mobile robots, manipulators, and autonomous systems using high-level programming languages and ROS-based frameworks. The educational process includes modeling and simulation of urban processes, cloud integration, and basic machine learning techniques. The Tripled Learning approach is actively applied, combining education, research, and innovation within a single platform [6], [7].

The platform at this stage maintains the same physical hardware used at Level 1, but introduces autonomous navigation modules including SLAM, AMCL localization, Nav2 stack, and sensor fusion pipelines. This continuity ensures a progressive transition from manual control to algorithmic autonomy without changing the hardware foundation.

### 4.3 Level 3: Research and Development (R&D)

The R&D level supports advanced research activities, including development of autonomous control algorithms, multi-robot coordination, system scalability studies, and digital twin implementation. A mixed Fog/Edge/AIoT/Robotics approach is used to validate solutions in realistic smart city scenarios and to facilitate technology transfer to educational levels [6]. At this stage, control interaction evolves from programmatic command execution to high-level semantic task specification. Instead of issuing low-level motion commands, users may formulate structured or natural language tasks, which are interpreted by supervisory cognitive modules and translated into executable robotic behaviors.

At this level, the laboratory adopts a Physical AI paradigm, integrating cognitive planning, real-time perception, and deterministic ROS2-based control within a unified cyber-physical feedback system. Task execution operates as a closed loop in which high-level intent is translated into structured plans, executed by reliable control modules, and continuously validated through sensor feedback.

## 5. Platform Architecture and Visualization

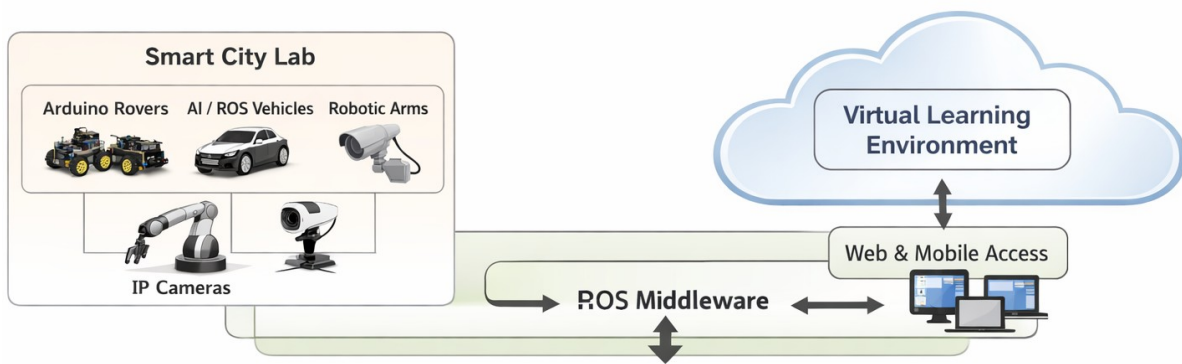
**Figure 1** illustrates the general architecture of the proposed robotics educational laboratory. The core physical component of the platform is a Smart City mock-up equipped with road markings, intersections, and infrastructure elements that emulate real urban environments. The mock-up hosts mobile robotic vehicles implemented on Arduino-based platforms for basic control and sensing tasks, as well as more advanced autonomous robotic cars powered by NVIDIA Jetson modules running ROS, enabling computer vision, SLAM, and AI-based navigation.

The laboratory also integrates robotic manipulators (robot arms) for modeling industrial automation scenarios. In addition, multiple camera systems provide real-time video streams. These cameras allow teleoperation, experiment monitoring, and session replay, which is particularly important for remote and hybrid learning formats.

The physical platform is connected to a cloud-based virtual environment that serves as its digital counterpart. This virtual layer includes simulation tools, digital twin models, learning management components, and data analytics services. Users can access the system through web and mobile interfaces to run simulations, monitor experiments, and analyze collected data from different educational levels. In addition to its middleware role, the platform architecture explicitly distinguishes Edge, Fog, and Cloud computing layers. Edge nodes, implemented on NVIDIA Jetson modules, perform real-time perception, SLAM, sensor fusion, and navigation tasks directly on robotic platforms, ensuring deterministic and low-latency control.

The Fog layer operates at the Smart City infrastructure level, coordinating communication between multiple robots and infrastructure elements within the laboratory environment. This layer enables localized orchestration, inter-robot data exchange, and distributed task execution without relying on constant cloud connectivity.

The Cloud layer provides long-term data storage, digital twin synchronization, learning management services, large-scale analytics, and remote user access. It supports experiment replay, performance evaluation, and scalability studies across educational and research scenarios. Such hierarchical distribution of computation ensures stable real-time execution at the physical level while enabling scalable system-wide analysis and experimentation. The architecture supports simultaneous multi-robot operation, allowing research on distributed coordination, network latency impact, bandwidth optimization, and system scalability in realistic Smart City conditions.



**Figure 1:** Architecture of the ROS-based Smart City educational robotics platform with a physical Smart City mock-up, Arduino- and NVIDIA Jetson-based robotic vehicles, robotic manipulators, remote learning cameras, and a cloud-based virtual environment with web and mobile access

Figure 2 presents a visual representation of the physical Smart City laboratory implementation. The figure demonstrates the Smart City mock-up with road markings, intersections, and urban infrastructure elements integrated into the educational environment. Mobile robotic vehicles operating on Arduino platforms are shown performing basic navigation and control tasks, while more advanced autonomous robotic cars based on NVIDIA Jetson modules execute ROS-based perception and navigation algorithms. Robotic manipulators are deployed for industrial automation and logistics scenarios, and overhead and fixed-position cameras provide real-time video streaming to support remote and hybrid learning modes. The physical laboratory is conceptually linked to the cloud-based virtual environment, enabling synchronized experimentation, simulation, and digital twin visualization across web and mobile interfaces.



**Figure 2:** Physical implementation of the Smart City robotics educational laboratory with mobile robots, robotic manipulators, camera-based remote access, and integration with a cloud-based virtual learning environment

## 6. Related Work and Comparative Analysis

Several educational robotics initiatives aim to bridge theoretical knowledge and hands-on experience.

**Duckietown** is a globally recognized open and low-cost platform for teaching robotics, autonomous systems, and artificial intelligence through tangible robotic ecosystems and structured curricula. Originating at MIT, Duckietown provides modular hardware (Duckiebots) and urban-like physical environments with road markings, traffic signs, and intersections. Learners can experiment with perception, localization, navigation, and multi-robot coordination using ROS-based software stacks.

Duckietown is widely adopted in university-level courses and research laboratories and supports reproducible experimentation and benchmarking in autonomy research [9].

**The Construct AI** represents a cloud-first educational approach focused on ROS training and simulation. It offers browser-based access to simulators, structured learning paths, and remote interaction with real robots. The main advantage of this platform is accessibility, as learners can acquire ROS competencies without deploying local hardware. However, its reliance on simulation and limited physical interaction may reduce the depth of practical engineering skills acquired, particularly in complex cyber-physical and industrial scenarios [10].

In comparison, the proposed Smart City-based robotics educational laboratory integrates the strengths of both platforms. It combines hands-on physical experimentation with mobile robots and manipulators (similar to Duckietown) and cloud-based virtual environments with remote access (similar to The Construct). Moreover, it extends beyond educational use toward applied research and R&D by supporting Fog/Edge computing, AIoT integration, and digital twins, which are not fully addressed by the analyzed platforms. The growing demand for practice-oriented robotics and AI education has stimulated the development of accessible platforms that combine teaching and experimental validation within a single ecosystem. Traditional laboratory robots are often expensive, proprietary, and difficult to replicate across institutions, which limits scalability and reproducibility in engineering education. To address these constraints, recent research has focused on open, modular, and cost-effective robotic systems designed specifically for university-level learning environments.

One prominent direction is the development of ROS-compatible educational robots that expose students to industry-relevant software stacks while maintaining affordability. For example, the ROBOTONT platform provides an omnidirectional mobile robot tightly integrated with ROS, enabling experimentation in navigation, perception, and multi-sensor fusion while serving as a bridge between academic training and Industry 5.0 requirements [12]. Similarly, PlatROB introduces a reconfigurable open-hardware architecture with interchangeable locomotion and manipulation modules, allowing students to explore system-level integration and rapid prototyping concepts [13].

Another line of work emphasizes modular, curriculum-embedded frameworks that support long-term deployment in engineering programs. MecQaBot demonstrates how an open mechatronics architecture can be used across multiple courses to teach sensing, embedded programming, and autonomous behavior through hands-on experimentation [14]. Comparable educational goals are pursued by HOPPY, an open-source dynamic robot kit designed to connect theoretical modeling with experiments on real mechanical systems, particularly in control and locomotion studies [15]. Recent studies have also explored democratizing access to embodied artificial intelligence by leveraging very low-cost hardware. BricksRL integrates reinforcement learning workflows with consumer-grade robotic components, enabling physical training of AI agents without specialized infrastructure [16]. In parallel, the STRIDE platform investigates reconfigurable bipedal robots as an educational tool for studying locomotion, robustness, and nonlinear control in an accessible format [17].

These contemporary systems build upon earlier open educational robots such as the e-puck and Thymio, which demonstrated the pedagogical value of compact, reproducible hardware combined with open software ecosystems [18], [19]. Cloud-supported environments such as Open Roberta further extend accessibility by enabling browser-based programming and remote experimentation, reducing installation and maintenance barriers in classrooms [20].

Overall, the literature indicates a clear transition from isolated instructional tools toward integrated research-education robotics infrastructures characterized by affordability, modularity, and reproducibility. Such platforms enable experiential learning while simultaneously serving as testbeds for validating algorithms in autonomous systems, thereby aligning robotics education with the practical needs of embodied AI research.

**Table 1**

Comparative Analysis of Educational Robotics Platforms

Feature / Platform	Duckietown	The Construct AI	Proposed Smart City Platform
Physical robotic environment	Yes	Limited (remote only)	Yes (mobile robots, manipulators, smart city mock-up)
ROS-based middleware	Yes	Yes	Yes (core integration layer)
Cloud and remote access	Partial	Full	Full (web and mobile access)
Scalability to real-world scenarios	Limited	Simulation-oriented	High (smart city scale, digital twins)
Support for R&D activities	Moderate	Moderate	High
Educational continuity (school-university-R&D)	Moderate	Moderate	High

## 7. Educational Impact and Discussion

The proposed laboratory ensures continuity of learning from school to research activities, supports interdisciplinary education, and brings educational tasks closer to real industrial and urban challenges. The use of ROS and smart city scenarios significantly enhances practical skills, systems thinking, and innovation-oriented competencies.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Google's Gemini (version 2.5 Pro) and OpenAI's ChatGPT (versions o4 and 5 Thinking). ChatGPT o4 was used for literature classification and structure organization, while Gemini and ChatGPT 5 were used for language improvement and documentation review. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## 8. Author Contributions

The authors jointly developed the concept of a unified Smart City-based robotics educational laboratory with a three-level architecture. Roman T. Hasko proposed the methodological framework integrating ROS, Fog/Edge/AIoT technologies, the Tripled Learning concept into a continuous educational pathway and design of the platform architecture. Olexandra L. Hasko contributed to the analysis of educational scenarios. Nataliia I. Melnykova contributed to the system requirements for different learning levels. Anastasiia O. Kushnirova contributed to the conceptual development of the platform structure. All authors contributed equally to manuscript preparation and final editing. The table systematizes existing approaches to accessible robotics education, illustrating a shift from single-purpose teaching devices toward integrated ecosystems that simultaneously support instruction, experimentation, and validation of autonomous system algorithms. This comparison informed the design choices and pedagogical positioning of the proposed framework in this study.

Platform	Primary Educational Focus	Hardware Accessibility	Software Ecosystem	Research Integration	Distinctive Features
Duckietown	Autonomous driving, perception, multi-robot coordination	Low-cost, modular miniature vehicles and infrastructure	Python, ROS-based tooling, simulation + physical twin	Designed as a combined course and experimentation environment	City-scale scenario enables reproducible autonomy experiments
ROBOTONT	ROS-oriented robotics engineering education	Medium-cost but fully reproducible academic platform	Native ROS integration	Strong alignment with industrial robotics workflows	Omnidirectional mobility for advanced navigation studies
PlatROB	System integration and rapid prototyping	3D-printable, reconfigurable hardware	Open-source control stack	Supports experimentation with multiple robot morphologies	Interchangeable locomotion/manipulation modules
MecQaBot	Mechatronics and embedded AI education	Affordable modular design	Custom open framework with standard middleware	Long-term curriculum deployment across courses	Scalable architecture used with large student cohorts
HOPPY	Dynamics, control, and legged locomotion	Low-cost educational kit	Open-source modeling and control tools	Bridges theoretical coursework with physical validation	Focus on dynamic behaviors rather than wheeled motion
BricksRL	Reinforcement learning on physical robots	Very low-cost, consumer components	RL frameworks connected to embedded hardware	Enables embodied AI experimentation in classrooms	Rapid training-feedback loop for real-world RL
STRIDE	Bipedal locomotion and nonlinear control	Build-it-yourself, research-grade low-cost system	Open control and simulation environment	Used to study robustness and gait generation	Reconfigurable morphology for experimentation

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e-puck	Introductory embedded and swarm robotics	Compact, widely reproducible educational robot	Lightweight open software stack	Historically used in large-scale teaching labs	Early benchmark for open educational robotics
Thymio II	Pre-university and undergraduate education	Fully open-hardware educational design	Visual + text-based programming interfaces	Emphasis on accessibility and classroom adoption	Designed specifically for pedagogical usability
Open Roberta	Remote programming and algorithmic thinking	No local installation required	Browser-based programming with robot connectivity	Enables hybrid and remote learning	Eliminates deployment barriers in educational settings

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## Purpose of the Appendix:

The table systematizes existing approaches to accessible robotics education, illustrating a shift from single-purpose teaching devices toward integrated ecosystems that simultaneously support instruction, experimentation, and validation of autonomous system algorithms. This comparison informed the design choices and pedagogical positioning of the proposed framework in this study.

## 9. Conclusions

The presented concept of a robotics educational laboratory based on a unified Smart City platform with a three-level architecture creates favorable conditions for modern engineering education and applied research. The proposed approach supports sustainable development of competencies required for smart cyber physical systems and provides a foundation for further practical implementation and evaluation.

## Declaration on Generative AI

During the preparation of this work, the author used AI tools in order to: Grammar and spelling check.

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