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A Comparative Study of Rule-Based and AI-Based Educational Robots for Vision-Based Waste Sorting

Emilia-Felicia Coșniță
National University of Science and Technology "Politehnica" Bucharest, Department of Theory of Mechanisms and Robots, Bucharest, Romania.
emilia.cosnita@stud.mec.upb.ro,
https://orcid.org/0009-0004-4362-5091

Păun Antonescu
National University of Science and Technology "Politehnica" Bucharest, Department of Theory of Mechanisms and Robots, Bucharest, Romania.
paun.antonescu@upb.ro
https://orcid.org/0000-0002-7569-8330

Simona-Elena Vârlan
Alexandru Ioan Cuza University of Iași, Faculty of Computer Science, Iași, Romania.
simona.varlan@info.uaic.ro,
https://orcid.org/0009-0007-0235-7459

Abstract: *The integration of educational robots in pre-university education provides valuable opportunities for developing technical and computational thinking skills. This study analyses the use of LEGO Mindstorms robots and artificial intelligence robots from the NextLab.tech platform for recognising and manipulating objects of different colours, aiming to simulate an automated sorting system for waste with identical shapes. The research focuses on the design and validation of a robotic system capable of object classification using rule-based deterministic methods and Machine Learning algorithms, integrated into a pick-and-place mechanism. System performance is evaluated using indicators such as classification accuracy, error rate, sorting time, productivity, and efficiency. The results enable a comparison between the two approaches and highlight the advantages of integrating computer vision into robotic control. The study also emphasises the role of these technologies in transitioning towards the active use of robots in applied educational processes.*

Keywords: *educational robotics; programming education; haptic interaction; trajectory control; hybrid robotic platforms.*

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1. Introduction

Artificial Intelligence (AI) has become one of the fastest-growing fields of computer science, with significant applications across industry, healthcare, transportation, and education. Since the Dartmouth Summer Research Project on Artificial Intelligence introduced the term *artificial intelligence* in 1955 (McCarthy et al., 1955), the field has evolved from symbolic approaches aimed at reproducing human reasoning towards intelligent systems capable of learning from data, perceiving their environment, and supporting autonomous or semi-autonomous decision-making. Classical definitions describe AI as the science of building machines capable of performing tasks that normally require human intelligence (Minsky, 2003; Rich et al., 2009), whereas more recent perspectives emphasise rational agents that perceive their environment and act to maximise predefined objectives (Russell & Norvig, 2021). Likewise, the OECD (2019) defines an AI system as a machine-based system that generates predictions, recommendations, or decisions to achieve human-defined objectives, while the European Union AI Act (Regulation (EU) 2024/1689) extends this definition by emphasising different levels of autonomy and adaptive capabilities after deployment (European Union, 2024). Beyond their technological potential, AI systems also raise important issues related to transparency, accountability, human rights, and trustworthy deployment (Leslie et al., 2021).

The rapid development of Machine Learning, Deep Learning, Computer Vision, and Natural Language Processing has accelerated the integration of AI into educational environments. Current research indicates that AI supports three major educational domains: institutional management, teaching activities, and student learning (Chen et al., 2020; Chassignol et al., 2018). Intelligent educational systems automate administrative tasks, assist curriculum development, provide personalised feedback, and adapt instructional content according to learners' characteristics and performance. Consequently, AI has become a key enabling technology for personalised learning environments and evidence-based educational decision-making (Holmes et al., 2022).

Educational robotics represents one of the most important practical applications of AI within STEM education. Unlike software-only learning environments, robotic platforms enable students to integrate programming, mechanics, sensor technologies, control systems, and artificial intelligence into real-world engineering activities. Numerous studies have shown that educational robots improve computational thinking, programming skills, problem-solving abilities, and collaborative learning while increasing students' motivation towards STEM disciplines (Benitti, 2012; Alimisis, 2013; Eguchi, 2014). Recent systematic reviews further demonstrate that the educational effectiveness of robotic platforms depends not only on their technological capabilities but also on their pedagogical integration and the degree of learner engagement (Xu & Ouyang, 2025). Similarly, research on social and intelligent tutoring robots highlights the complementary roles of Intelligent Tutoring Systems (ITS) and Robot Tutoring Systems (RTS), combining adaptive instructional strategies with social interaction to enhance both cognitive and motivational outcomes (Belpaeme et al., 2018; Latif et al., 2026).

Within computer science education, educational robots provide an authentic environment in which students can design, implement, and validate control algorithms, computer vision-based classification approaches, and autonomous robotic behaviours. Such project-based activities support the development of computational thinking and engineering design competencies while enabling learners to understand the interaction between mechanical architecture, sensing capabilities, control strategies, and artificial intelligence algorithms (Coșniță & Antonescu, 2025).

Against this background, the present study presents a comparative analysis of two educational robotic systems employed for automated object sorting, one based on a deterministic rule-based approach and the other integrating artificial intelligence-assisted classification algorithms. The research investigates the technical performance of the robotic systems by evaluating object identification accuracy, sorting and manipulation efficiency, execution time, and error rate, while also examining the influence of computer vision and classification algorithms on the overall system performance. In addition, the study explores the educational impact of students' involvement in the design, programming, implementation, and experimental validation of robotic systems by assessing the development of computational thinking, technical competencies, and teamwork skills. By combining experimental evaluation of robotic performance with the analysis of educational outcomes, this research highlights the role of educational robotic platforms in integrating artificial intelligence, and supporting project-based learning approaches.

2. Theoretical Background

2.1. Artificial Intelligence in Education

Artificial Intelligence (AI) has become one of the main drivers of digital transformation in modern education. Advances in Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Learning Analytics have enabled the development of intelligent educational systems capable of supporting teaching, learning, and educational management by adapting instructional content and learning strategies to individual learner characteristics (Chassignol et al., 2018; Chen et al., 2020).

Current research identifies three major application domains of AI in education: institutional administration, teaching support, and personalised learning (Chen et al., 2020). In educational management, AI-based systems automate repetitive tasks such as assessment, academic progress monitoring, resource management, and early identification of students at risk of academic failure. Within instructional activities, AI supports curriculum design, educational content generation, and personalised feedback, allowing educators to make evidence-based pedagogical decisions. From the learner's perspective, intelligent educational systems enable adaptive learning environments in which instructional materials, learning pace, and assessment strategies are dynamically adjusted according to students' knowledge levels and learning progress (Luckin et al., 2016; Holmes et al., 2022).

The effectiveness of AI in education relies on the integration of complementary digital technologies. According to Yuskovych-Zhukovska et al. (2022), cognitive services based on Machine Learning, Deep Learning, Natural Language Processing, speech recognition, and computer vision constitute the technological foundation of intelligent educational environments. These technologies support intelligent tutoring systems, automated assessment, learner modelling, and conversational educational agents capable of providing individualised assistance.

Immersive technologies, including Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR), further enhance AI-supported learning environments by enabling interactive simulations and experiential learning. Their integration with AI facilitates adaptive educational scenarios that improve conceptual understanding and practical skill acquisition, particularly in engineering and technical education (Yuskovych-Zhukovska et al., 2022).

Recent developments in the Internet of Things (IoT), edge computing, and AI-enabled mobile platforms have expanded intelligent educational applications beyond conventional computer laboratories. These technologies enable real-time collection and analysis of learning data while reducing processing latency, thereby supporting continuous monitoring of learner performance and adaptive educational interventions (Chen et al., 2020). Consequently, AI-powered educational applications can provide advanced functionalities such as speech recognition, automated translation, intelligent tutoring, and augmented reality directly on mobile devices, increasing the accessibility and flexibility of personalised learning.

Despite these benefits, the large-scale adoption of AI in education raises important challenges related to algorithmic transparency, data privacy, explainability of automated decisions, fairness in assessment, and the responsible use of educational data. Consequently, recent research emphasises the development of Trustworthy Artificial Intelligence, combining technological performance with ethical principles, data protection, and regulatory compliance, as reflected in both current educational research and the European Artificial Intelligence Act (Holmes et al., 2022; European Union, 2024).

2.2. Artificial Intelligence in Educational Robotics and Computer Science Disciplines

Educational robotics is an interdisciplinary field that integrates computer science, artificial intelligence, control engineering, and educational sciences to support the development of computational thinking, programming skills, and engineering competencies through hands-on learning activities. The integration of Artificial Intelligence (AI) into robotic platforms extends the capabilities of traditional educational robots by enabling adaptive behaviours, intelligent perception, and autonomous decision-making, thereby creating learning environments that can respond dynamically to learners' performance and interaction patterns (Chen et al., 2020; Xu & Ouyang, 2025).

Numerous studies have demonstrated that educational robotics enhances both technical and transversal competencies. A systematic review by Benitti (2012) showed that robotics-based learning improves STEM achievement, problem-solving abilities, and student motivation. Similarly, Mubin et al. (2013) concluded that the educational effectiveness of robotic platforms depends not only on their technological capabilities but also on their pedagogical integration into collaborative and project-based learning activities. Within computer science education, educational robots provide an important advantage over software simulations by allowing students to directly observe the relationship between algorithms, sensors, actuators, and the physical behaviour of robotic systems. This experiential approach facilitates the acquisition of programming, debugging, systems modelling, and computational thinking skills (Benitti, 2012; Eguchi, 2014).

Recent research further emphasises the role of educational robotics in fostering computational thinking. Coșniță and Antonescu showed that programming educational robots engages learners in algorithmic reasoning, decomposition, abstraction, debugging, and iterative problem-solving, while simultaneously increasing motivation and active participation in STEM learning activities (Coșniță & Antonescu, 2025). These findings support the integration of robotics laboratories as effective environments for developing both computational thinking and engineering design competencies.

The incorporation of AI technologies has significantly expanded the educational role of robotic platforms. Contemporary educational robots integrate Computer Vision, Machine Learning, and intelligent control algorithms, enabling autonomous perception and adaptive interaction during learning activities (Chen et al., 2020). In higher education, AI-enabled software robots have also been employed to automate educational and administrative processes and to provide personalised learning support, contributing to more flexible instructional models (Yeslyamov, 2024).

A comprehensive systematic review by Xu and Ouyang (2025), covering 92 empirical studies published between 2010 and 2023, identified learner agency and robot interactivity as the principal factors influencing the educational effectiveness of robotics. The authors proposed a conceptual framework describing four complementary learning approaches: learning about robots, learning through robots, learning from robots, and learning with robots, demonstrating that educational benefits increase as robots evolve from instructional tools to active learning partners.

Recent advances in Intelligent Tutoring Systems (ITS) and Robot Tutoring Systems (RTS) further illustrate the complementary roles of software intelligence and embodied robotic interaction. While ITS primarily supports learner modelling, adaptive instruction, and personalised feedback, RTS enhances social engagement through verbal and non-verbal interaction, adaptive scaffolding, and physical presence. Consequently, hybrid educational systems integrating AI-driven cognitive adaptation with robotic social interaction are increasingly proposed for engineering and computer science education (Belpaeme et al., 2018; Latif et al., 2026).

Overall, current research indicates that the effectiveness of AI-supported educational robotics depends on the coherent integration of intelligent algorithms, robotic architecture, instructional design, and pedagogical objectives rather than on the complexity of AI algorithms alone (Benitti, 2012; Xu & Ouyang, 2025). This perspective provides the theoretical foundation for comparative studies evaluating both the technical performance and the educational value of different robotic platforms.

3. Methodology

This research is based on the hypothesis that the LEGO Mindstorms educational robotic platform, relying on deterministic control algorithms, and the NextLab.tech platform, integrating Artificial Intelligence (AI)-based perception and classification algorithms, are capable of performing automatic object recognition and pick-and-place manipulation on a conveyor system, enabling the implementation of an educational model for automated waste sorting.

It is further hypothesised that the differences in the hardware and software architectures of the two robotic platforms affect the overall performance of the sorting process. These differences can be quantitatively evaluated using engineering performance indicators, including classification accuracy, error rate, average sorting cycle time, system throughput, and overall sorting efficiency.

3.1. Objectives

The general objective of this research is to design, implement, and experimentally evaluate an educational robotic sorting system capable of recognising and automatically manipulating objects using two robotic platforms based on different control architectures.

To achieve this objective, the following specific research objectives were established:

O1. To implement and validate computer vision algorithms capable of recognising objects with identical geometry but different colours using the sensing capabilities available on the LEGO Mindstorms and NextLab.tech platforms.

O2. To design and implement an automated pick-and-place robotic system for manipulating classified objects and placing them into predefined storage containers.

O3. To comparatively evaluate two educational robotic sorting systems based on deterministic rule-based and AI-assisted Machine Learning classification approaches, considering the impact of algorithmic, hardware, sensing, and manipulation factors on overall system performance.

O4. To assess the performance of both robotic systems using quantitative engineering metrics, including classification accuracy, error rate, average sorting cycle time, throughput, and overall system efficiency.

O5. To evaluate the impact of students' active involvement in the design, programming, implementation, and experimental validation of a robotic sorting system on the development of computational thinking and technical competencies.

O6. To evaluate the impact of project-based educational robotics activities on students' perceptions of teamwork, consensus building, and active engagement in the learning process.

3.2. Research Aim

The primary aim of this research is to perform a comparative analysis of two educational robotic platforms, LEGO Mindstorms and NextLab.tech, regarding their capability to automatically recognise and manipulate objects with identical geometry but different colours in order to simulate an automated waste-sorting system representative of industrial recycling applications.

From an engineering perspective, the study focuses on the design, implementation, and experimental validation of a robotic workcell capable of performing automatic visual classification and pick-and-place operations using two different control strategies:

- deterministic rule-based object classification;
- AI-assisted object classification based on Machine Learning algorithms integrated into the NextLab.tech platform.

To ensure a controlled comparison, both robotic systems were evaluated under identical experimental conditions, including the same conveyor configuration, identical object geometry, identical sorting criteria, and equivalent operating parameters.

The comparative analysis aims to evaluate the influence of the perception system and control architecture on the overall performance of the robotic sorting process.

System performance is assessed using the following quantitative engineering performance indicators: classification accuracy; error rate; average sorting cycle time; system throughput; overall sorting efficiency.

These performance metrics provide an objective assessment of both the perception and manipulation capabilities of the robotic systems while enabling a quantitative comparison between deterministic and AI-assisted control strategies.

Beyond the technical evaluation, the proposed experimental protocol demonstrates the integration of computer vision, robotic manipulation, and Artificial Intelligence into an educational environment representative of industrial automation applications. The developed system enables students to experience the complete engineering workflow, including system design, robot programming, experimental validation, performance analysis, and optimisation of the robotic sorting process.

3.3. Research Questions

• *Focused on technical performance*

RQ1. To what extent are educational robotic platforms capable of accurately recognising objects of different colours using onboard cameras or dedicated sensing devices?

RQ2. What is the performance of the robotic sorting system in terms of classification accuracy, sorting cycle time, throughput, error rate, and overall system efficiency?

• *Focused on Artificial Intelligence*

RQ3. How does the implementation of computer vision and object classification algorithms affect the performance of the robotic sorting system?

RQ4. How do deterministic rule-based control and AI-assisted perception influence the technical performance of educational robotic platforms under identical experimental conditions?

• *Focused on Educational Impact*

RQ5. To what extent does students' active involvement in the design, programming, implementation, and experimental validation of a robotic sorting system contribute to the development of computational thinking and technical competencies ?

RQ6. To what extent do project-based educational robotics activities involving the design, development, programming, and testing of robots contribute to improving students' perceptions of teamwork, consensus building, and active engagement in the learning process?

3.4. Research Design

The present study adopts an applied experimental research design based on a mixed-method approach that combines quantitative evaluation of technical performance with qualitative assessment of educational outcomes. The research focuses on the design, implementation, and experimental validation of an educational robotic system for automatic object recognition and sorting using two robotic platforms based on different control architectures.

A controlled comparative experimental design was employed, in which both robotic platforms operated under identical experimental conditions. The experimental protocol was designed to evaluate the influence of the perception system and control architecture on the overall performance of the automated sorting process.

Two educational robotic systems were investigated:

System A – a *LEGO Mindstorms EV3* robotic platform implementing deterministic rule-based sensing and control algorithms;

System B – a *NextLab.tech* robotic platform integrating computer vision and Artificial Intelligence-based object classification algorithms.

Both robotic systems perform automated pick-and-place operations by detecting objects transported on a conveyor belt, classifying them according to predefined visual characteristics, and placing them into the corresponding collection containers.

For the LEGO Mindstorms EV3 platform, object classification is performed using deterministic decision rules based on the measurements provided by the integrated sensors. In contrast, the NextLab.tech platform employs a simplified Machine Learning classification model trained using a small experimental dataset collected by the participating students. The classification process relies on elementary visual features, namely the dominant object colour and object size.

The comparison of these two control strategies provides the experimental design required to investigate the influence of AI-assisted computer vision on robotic sorting performance (RQ3) and to analyse the performance differences between deterministic rule-based control and AI-assisted object classification (RQ4).

The technical performance of both robotic systems is evaluated using objective quantitative engineering metrics, including classification accuracy, classification error rate, average sorting cycle time, system throughput, and overall system efficiency.

These performance indicators enable an objective assessment of both perception and manipulation capabilities while providing a quantitative comparison of the implemented control strategies. The analysis directly addresses the research questions related to object recognition performance and robotic manipulation efficiency (RQ1 and RQ2).

The educational component of the study aims to evaluate the impact of students' active involvement in the design, programming, implementation, and experimental validation of a robotic sorting system on the development of computational thinking, technical skills, and collaborative competencies. The educational outcomes are assessed using two complementary evaluation instruments. The development of computational thinking and technical skills is objectively measured by comparing students' performance in pre-test and post-test assessments, whereas students' perceptions of teamwork, consensus building, and active engagement in the learning process are investigated through a post-study questionnaire administered after the experimental activities. This combined evaluation approach provides a comprehensive assessment of both measurable learning outcomes and students' perceived educational experiences and directly addresses Research Questions RQ5 and RQ6.

Table 1. Alignment of research questions with measurement instruments

Research Question	Measurement Instrument
RQ1	Classification accuracy; classification error rate; object recognition success rate
RQ2	Classification accuracy; classification error rate; sorting cycle time; throughput; overall system efficiency
RQ3	Comparative analysis of classification accuracy, error rate, processing time, sorting cycle time, and system efficiency
RQ4	Comparative evaluation of classification accuracy, error rate, sorting cycle time, throughput, and overall efficiency
RQ5	Pre-test/Post-test questionnaires; assessment of computational thinking and technical skills
RQ6	Student perception of engagement and teamwork

3.5. Implementation

To evaluate the performance of the automated sorting system developed using LEGO Mindstorms and the AI-based robot from the NextLab.tech platform, the experiment was conducted over a number of k experimental rounds. In each round, a fixed number of N objects was processed. For a given round i, we recorded $N_{correct}$ correctly sorted objects, T_{total} as the total duration of the round, and $N_{incorrect}$ as the number of incorrectly sorted objects. For each round, we calculated accuracy, average time per object, overall efficiency per round, as well as their arithmetic mean and standard deviation.

System stability (standard deviation) was calculated in order to assess the consistency of performance:

$$\sigma = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}(x_i - \bar{x})^2} \tag{1}$$

Where $\bar{x}$ is the mean of the indicator and x_i will be replaced with accuracy, average time, efficiency, error rate.

To ensure a controlled comparison, both robotic systems were evaluated under identical experimental conditions, and each experimental scenario was repeated multiple times. The implementation was carried out under controlled laboratory conditions. Quantitative data: N = 8 pieces/round, K = 15 rounds/student, total of 120 pieces/student/robot.

A total of 166 students from classes specialised in mathematics–computer science, intensive computer science, and natural sciences participated in the study. Fifteen experimental trials were selected to obtain a sufficient number of repeated observations for assessing the repeatability and operational stability of the robotic systems and for computing descriptive statistical indicators (mean and standard deviation). Repeating the experiments under identical operating conditions reduced the influence of random variations caused by object positioning, mechanical operation of the robot, and the classification process. Each trial included eight objects, allowing the complete recognition, pick-and-place, and sorting cycle to be evaluated without interrupting the experimental workflow or overloading the conveyor system. This configuration represented a practical compromise between experimental duration, measurement repeatability, and controlled performance evaluation. Using their own program, each student tested each robotic system by processing 120 objects/robot (15 rounds × 8 objects/round), a number considered sufficient to perform an experimental comparison between the two approaches.

System A (see Figure 1) – the color sorter robot (programmed with LEGO Mindstorms EV3) has a fixed position, the object "comes" to it, and it has fewer degrees of freedom and fewer positioning errors. The input data are provided by a LEGO colour sensor with fixed predefined values. The evaluated performance indicators include classification accuracy, average processing time, and efficiency.

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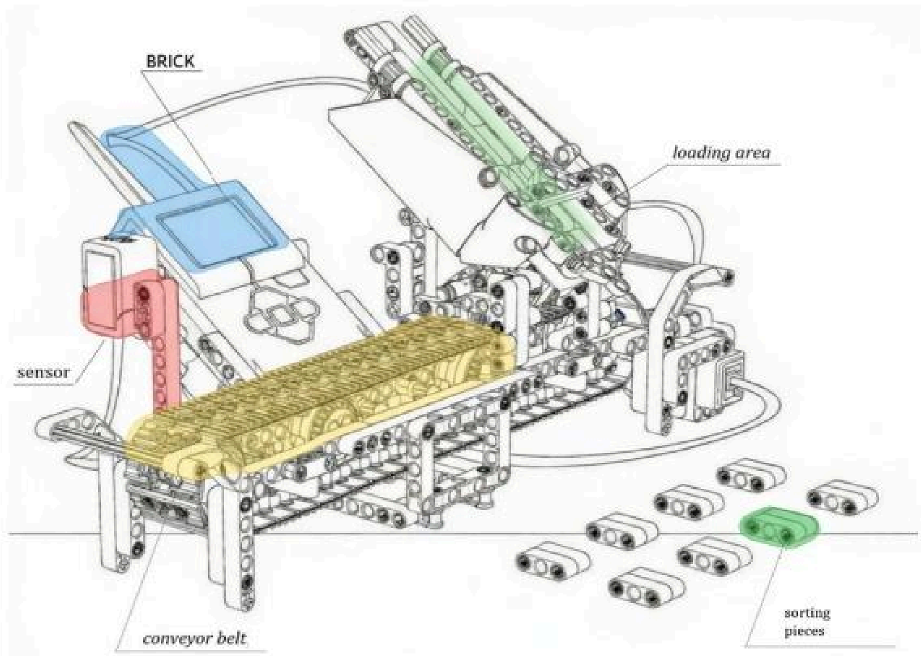

Figure 1. System A - Classical Programmed Robot

System B (see Figure 2) – the AI robotic arm has an NVIDIA Jetson Nano board mounted at the base of the arm and is connected to a video camera. The robot uses neural networks to identify objects in real time. The input is provided through a webcam (pixel data). It "sees" the difference between a red cube and a green one and "tracks" the object. If a cube is moved, the AI recalculates its trajectory and follows it. It has a high level of adaptability and can recognise objects with mixed colours.

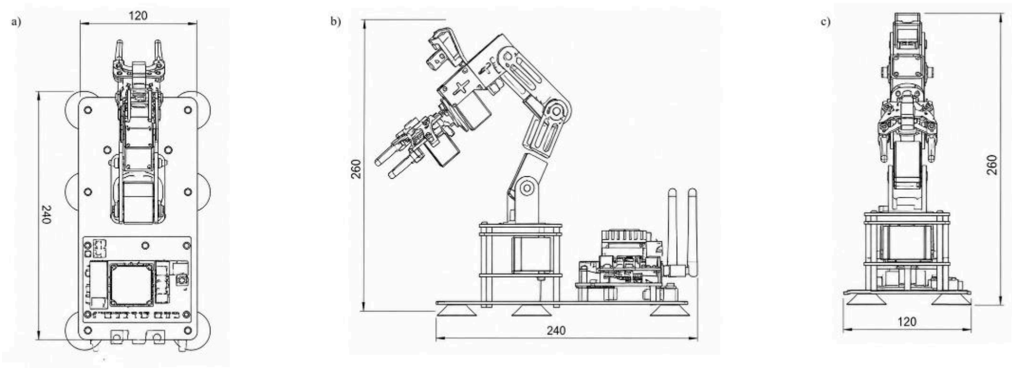

Figure 2. System B - AI-based Robot with Classification Algorithms
a) Top View; b) Side View; c) Rear View

For RQ1, RQ2, RQ3, and RQ4, students built, programmed, and tested the two robotic systems. In each class, the students participating in the study were organized into teams consisting of 4–5 members. Each team received two kits (one LEGO Mindstorms kit and one kit for the robot developed on the NextLab.tech platform) and was tasked with building an identical sorting robot prototype. The programming activity was performed individually by each student within the team, with each student developing and testing their own control program on the robot built by the team.

Each student tested their developed program by performing 15 experimental runs, with 8 objects processed in each run. For each test, students recorded the total processing time, the number of correctly sorted objects, and the number of incorrectly sorted objects. The same experimental procedure was applied to both the LEGO Mindstorms programmed robot and the robotic system developed on the NextLab.tech platform. This enabled a direct comparison between the deterministic rule-based approach and the artificial intelligence-assisted approach under similar experimental conditions.

The artificial intelligence component was implemented using the NextLab.tech platform, which integrates machine learning functionalities for object classification based on images captured by the robot's camera. The classification model was trained using a supervised learning approach, based on a labeled image dataset collected under controlled experimental conditions. During the data acquisition stage, the main environmental parameters, including camera position, lighting conditions, and workspace configuration, were kept constant to ensure the consistency and reproducibility of the experiments.

After the training stage, the classification model was integrated into the robotic application to enable real-time object recognition and the initiation of the pick-and-place manipulation task. The performance of the AI-based robotic system was evaluated using quantitative indicators such as classification accuracy, error rate, average sorting time, productivity, and overall system efficiency. To ensure the comparability of the results, both robotic systems were tested under equivalent experimental conditions, and each experimental scenario was repeated multiple times.

The data collected by the students were subsequently processed and statistically analyzed. The analysis included the calculation of mean values and standard deviations for the main performance indicators, enabling the evaluation of experimental stability and an objective comparison between the deterministic rule-based robotic system and the system assisted by artificial intelligence algorithms.

To investigate RQ5, an online pre-test/post-test assessment was administered before and after the experimental activities. Each assessment consisted of 30 objective multiple-choice items, and scoring was performed automatically by the online assessment platform, providing students with immediate feedback.

The assessment was structured as follows:

- 20 items evaluated computational thinking competencies based on the framework proposed in Fostering Computational Thinking Through Educational Robots (Coșniță & Antonescu, 2025), covering five dimensions: problem decomposition (C1), abstraction (C2), algorithm design (C3), iteration (C4), and generalization (C5);
- 5 items assessed knowledge related to the mechanics of robotic systems;
- 5 items evaluated competencies associated with control strategies used in robot programming and operation.

The use of equivalent assessments before and after the educational intervention enabled direct comparison of students' performance and provided an objective measure of the development of computational thinking and technical competencies.

To address RQ6, a post-study questionnaire was administered at the end of the experimental activities to collect students' perceptions regarding their educational experience, with particular emphasis on teamwork, consensus building, and active engagement in project-based educational robotics activities.

3.6. Performance Indicators Tracked

Transport time

$$t = \frac{d}{v} \tag{2}$$

Sorting rate (accuracy) measures classification precision. It indicates how accurately the robot identifies objects.

$$\text{Accuracy}(\%) = \frac{N_{correct}}{N_{total}} \times 100 \tag{3}$$

where $N_{correct}$ is the number of correctly sorted objects and N_{total} is the total number of processed objects.

System efficiency measures system productivity of the robotic system. It indicates how many objects are correctly sorted per unit of time.

$$\eta = \frac{N_{correct}}{T_{total}} \tag{4}$$

where T_{total} is the total operating time.

Error rate represents the proportion of incorrectly sorted objects.

$$E_r = \frac{N_{incorrect}}{N_{total}} \tag{5}$$

where $$N_{incorrect} = N_{total} - N_{correct} \tag{6}$$

Mean sorting time (for RQ2) is the average time required to process a single object.

$$T_{mean} = \frac{T_{total}}{N_{total}} \tag{7}$$

where T_{total} is the total operating time and N_{total} is the total number of processed objects.

System productivity is expressed as objects per second or objects per minute.

$$P = \frac{N_{total}}{T_{total}} \tag{8}$$

Table 2. Comparison between the two systems

System	Mean accuracy, $\overline{Accuracy}$ (%)	Mean sorting time, T_{mean} (s)	Efficiency, η (objects/s)	Error rate, E_r(%)
System A (Rule-Based)	91.70 %	2.96	0.31	8%
Standard deviation, σ	9.05%	0.39	0.07	0.09%
System B (AI-Based)	84.20%	7.0	0.12	16%
Standard deviation, σ	11.05%	0.92	0.015	0.11%
Variation	$\Delta Accuracy =$ -7.5	ΔT_{mean}=4.04s	$\Delta\eta =$ -0.19	ΔE_r=8%

We compared: $\Delta\, Accuracy = \overline{Accuracy_B} - \overline{Accuracy_A}$ (9)

$$\Delta\eta = \overline{\eta_B} - \overline{\eta_A} \tag{10}$$

3.7. Results and Discussion

From the strictly performance-based perspective of sorting:

System A > System B (11)

The comparative analysis of the two educational robotic platforms revealed differences in the performance of the deterministic rule-based control system and the AI-assisted robotic system integrating computer vision algorithms. The experimental results indicate that System A (LEGO Mindstorms EV3), characterised by a fixed-base mechanical architecture and deterministic control strategy, achieved superior performance in terms of object classification accuracy and overall operational efficiency. The system attained an average classification accuracy of 91.7% and a throughput of 0.31 objects/s, demonstrating stable and repeatable behaviour throughout the experimental trials.

In contrast, System B (NextLab.tech), which integrates computer vision and Artificial Intelligence-based object classification, achieved an average classification accuracy of 84.2% and a throughput of 0.12 objects/s. Although the perception subsystem provides more advanced object recognition capabilities, the overall system performance is influenced by the increased complexity of the operational workflow, which includes object detection, visual classification, pose estimation, manipulator repositioning, trajectory correction, and execution of the pick-and-place operation.

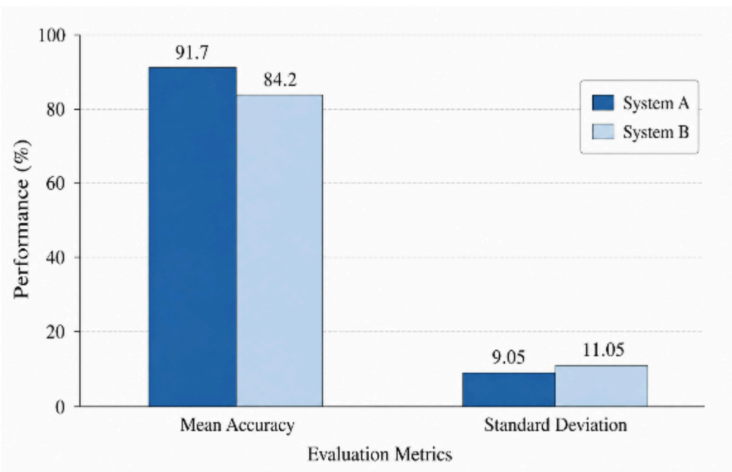

Figure 3. Comparison of mean accuracy and standard deviation for System A and System B

The comparative analysis (see Figure 3) shows a performance difference of ΔAccuracy = −7.5% and an efficiency difference of Δη = −0.19 objects/s in favour of System A. Under the investigated experimental conditions, these results suggest that the mechanical architecture and control strategy had a greater influence on overall system performance than the increased sophistication of the AI-assisted classification algorithm.

From the perspective of operational efficiency, System A achieved a sorting throughput of 0.31 objects/s, whereas System B achieved a throughput of 0.12 objects/s. The observed reduction in throughput is primarily associated with the additional processing stages required by the AI-assisted platform, including image acquisition, feature extraction, object classification, localisation, and manipulator trajectory adjustment prior to the execution of the pick-and-place operation. These additional computational and mechanical operations are likely to increase the sorting cycle time and consequently reduce the overall productivity of the robotic system.

System stability was evaluated by analysing the standard deviation of both classification accuracy and sorting cycle time. System A exhibited a standard deviation of 9.05% for classification accuracy and 0.39 s for the sorting cycle time, whereas System B presented higher variability, with corresponding values of 11.05% and 0.92 s, respectively. The increased variability observed for System B suggests greater sensitivity to positioning accuracy, experimental conditions, and the accumulation of mechanical and control-related errors throughout the execution of the sorting task.

The experimental findings indicate that the integration of Artificial Intelligence algorithms does not necessarily result in superior overall performance of an educational robotic system. Within the investigated experimental configuration, system performance appeared to be influenced by the combined effects of the perception algorithm, the mechanical architecture of the robotic platform, and the implemented control strategy. Consequently, optimisation of educational robotic systems intended for automated sorting applications should consider not only the accuracy of AI-based perception algorithms but also the kinematic characteristics of the robotic mechanism and the efficiency of the manipulation strategy.

Overall, the results suggest that the performance of an educational robotic sorting system should be evaluated as an integrated mechatronic system rather than solely from the perspective of the implemented Artificial Intelligence algorithm. The interaction between perception, motion planning, manipulator control, and mechanical architecture likely influenced classification accuracy, operational stability, and overall system efficiency. Under the experimental conditions considered in this study, the deterministic robotic platform exhibited superior technical performance despite employing a less sophisticated perception strategy.

3.7.1. Interpretation of the Educational Outcomes (RQ5 and RQ6)

The educational evaluation conducted on a sample of 166 students demonstrates that project-based educational robotics activities contributed both to the development of cognitive and technical competencies and to the enhancement of collaborative learning processes. Regarding RQ5, the comparative analysis of pre-test and post-test results revealed students' progress in the evaluated domains: computational thinking, mechanics, and control strategies. The assessment of algorithmic competencies was based on the framework proposed by Coșniță and Antonescu (2025), including the dimensions of problem decomposition, abstraction, algorithm design, iteration, and generalization. The results confirm that students' active involvement in the design, programming, implementation, and experimental validation of robotic systems provided an effective context for the practical application of computer science and engineering concepts.

verall, the findings associated with RQ5 and RQ6 demonstrate that educational robotics activities contribute not only to the development of computational thinking and technical competencies but also to the formation of transversal skills related to teamwork, communication, consensus building, and collaborative problem-solving within an engineering design context.

3.7.2. Assessment of Computational Thinking and Technical Competency Development *(see Figure 4)*

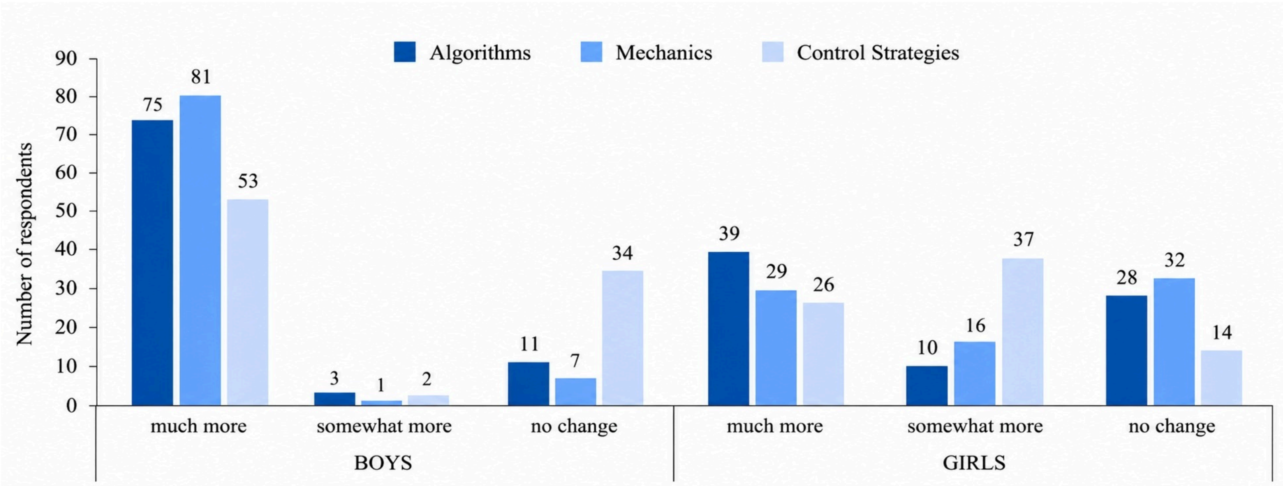

Figure 4.Graph illustrating the development of computational thinking and technical competencies

The comparative analysis of the assessment results revealed differences between male and female students regarding the level of improvement achieved between the initial and final evaluations. For male students, the most significant improvements were observed in the areas of mechanics and algorithm design, where more than 84% of participants achieved higher scores in the post-test compared with the pre-test. These results demonstrate the effectiveness of hands-on robotic construction and programming activities in developing technical and algorithmic competencies.

Regarding control strategies, the improvement was lower compared with the other evaluated components, with 38.2% of male students maintaining results similar to those obtained in the initial assessment. This outcome may be explained by the higher complexity of robotic control concepts, which require the simultaneous integration of programming knowledge, algorithmic reasoning, and hardware operation principles.

For female students, the results indicate a lower level of improvement compared with male students, with the most relevant difference identified in the area of control strategies, where 48.1% of participants achieved results that did not show improvement compared with the initial evaluation. These differences indicate variations in the rate of competency development between the analyzed groups; however, they do not support conclusions regarding fundamental differences in technical performance between male and female students.

Overall, the pre-test/post-test results confirm that students' involvement in project-based educational robotics activities contributes to the development of computational thinking and technical competencies. The integration of mechanical design, algorithm development, robot programming, and experimental testing provided an authentic learning environment that supported the practical application of computer science and engineering concepts.

3.7.3. Consensus During Laboratory Activities

The results presented in Figure 5a indicate a high level of consensus among participants regarding the implementation of the laboratory activities. A total of 73.7% of the respondents perceived the collaborative environment as harmonious, whereas 21.4% reported the presence of minor disagreements among team members. Only 4.9% indicated the existence of major disagreements. Overall, the distribution of responses suggests that the laboratory environment wprovided favourable conditions for collaborative robotic design and programming activities.

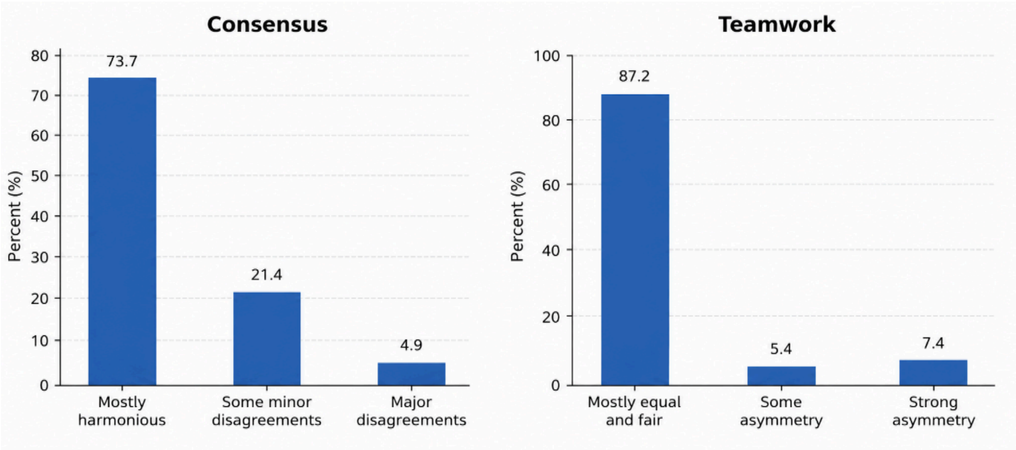

Figure 5. Feedback on: a) consensus building; b) teamwork

3.7.4. Perception of Team Collaboration

The responses regarding teamwork (see Figure 5b) indicate that 87.2% of the participants considered the distribution of responsibilities within the teams to be equitable. A further 5.4% perceived moderate imbalances in task allocation, while 7.4% reported significant asymmetry in team participation. These findings suggest that project-based robotics activities were associated with collaborative learning and effective task sharing for the majority of participating students.

4. Conclusions

The present study investigated the technical performance and educational applicability of two educational robotic systems designed to simulate an automated waste-sorting process: a rule-based robotic platform (LEGO Mindstorms EV3) and an AI-assisted robotic platform implemented using NextLab.tech.

The experimental results indicate that the rule-based robotic system achieved superior technical performance under the experimental conditions considered. Compared with the AI-assisted mobile robotic platform, the deterministic system exhibited higher classification accuracy, greater sorting efficiency, shorter processing time, and lower variability across repeated experimental trials. In contrast, the AI-based system introduced additional computational and kinematic complexity associated with object detection, visual classification, robot positioning, trajectory correction, and object manipulation. These sequential operations were associated with increased overall processing time and higher temporal variability, resulting in reduced operational stability.

The comparative analysis suggests that Artificial Intelligence alone does not guarantee superior robotic performance. The obtained results indicate that the overall performance of an educational robotic system appears to depend on the interaction between multiple engineering components, including the mechanical architecture, the control strategy, the positioning mechanism, and the robustness of the perception and manipulation processes. Consequently, the effectiveness of AI-based robotic systems should be evaluated as a property of the integrated mechatronic system rather than of the classification algorithm alone.

From an educational perspective, the study supports the applicability of both robotic platforms for supporting project-based STEM learning. The implementation of computer vision algorithms, robotic manipulation, and simplified machine learning models provided students with practical experience in programming, robotic control, and system integration. Moreover, the experimental activities were associated with the development of computational thinking, problem-solving skills, and a better understanding of the interdependence between mechanical design, sensing technologies, control algorithms, and Artificial Intelligence.

The educational evaluation further suggests that involving students in the design, programming, testing, and optimisation of robotic systems contributes to increased engagement in laboratory activities and supports interest in engineering and computer science disciplines. Within the limits of the collected data, the results suggest the gradual transition from passive educational use of robots (*learning about robotics* and *learning through robotics*) towards active learning scenarios (*learning from robots* and *learning with robots*), where students participate directly in developing and validating robotic solutions.

Overall, the findings indicate that the technical performance of educational robotic systems cannot be attributed exclusively to the sophistication of the AI algorithm. Instead, it appears to emerge from the integration of perception, mechanical design, control architecture, and system stability. Although the AI-assisted platform did not outperform the deterministic system under the investigated experimental conditions, its higher engineering complexity and educational potential support its inclusion in robotics and AI-oriented educational activities, where understanding the interaction between algorithms and physical systems represents an important learning objective.

Finally, the results suggest that educational robotics provides an effective experimental framework for introducing Artificial Intelligence concepts in secondary education while simultaneously supporting the development of interdisciplinary competencies in robotics, automation, computer vision, and intelligent control systems.

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