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

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Abstract: *The integration of educational robots in pre-university education provides relevant opportunities for developing technical and computational thinking skills. This study analyzes the use of LEGO Mindstorms robots and artificial intelligence robots from the NextLab.tech platform for recognizing and manipulating objects of different colors, 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 comparison between the two approaches and highlight the advantages of integrating computer vision into robotic control. The study also emphasizes the role of these technologies in transitioning toward 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 toward 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 emphasize rational agents that perceive their environment and act to maximize 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 emphasizing 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 personalized feedback, and adapt instructional content according to learners' characteristics and performance. Consequently, AI has become a key enabling technology for personalized 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 toward 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, machine vision techniques, and autonomous robotic behaviors. Such project-based activities facilitate the development of computational thinking and engineering design competencies while enabling learners to understand the interaction between mechanical architecture, sensing, control strategies, and AI algorithms (Coșniță & Antonescu, 2025).

Against this background, the present study investigates the educational and technical implications of integrating AI into educational robotics by comparing two robotic sorting systems: a rule-based LEGO Mindstorms EV3 platform and an AI-assisted robotic platform developed using NextLab.tech. The comparison focuses on object recognition accuracy, sorting efficiency, processing time, and operational stability, while also evaluating the contribution of project-based robotic activities to the development of students' computational thinking and their interest in STEM careers.

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 personalized 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 personalized 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 modeling, and conversational educational agents capable of providing individualized 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 personalized 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 emphasizes 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 behaviors, 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 behavior of robotic systems. This experiential approach facilitates the acquisition of programming, debugging, systems modeling, and computational thinking skills (Benitti, 2012; Eguchi, 2014).

Recent research further emphasizes the role of educational robotics in fostering computational thinking. Coșniță and Antonescu demonstrated 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 personalized 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 modeling, adaptive instruction, and personalized 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 recommended 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 hypothesized 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 recognizing 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 recognizing objects with identical geometry but different colors 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 the performance of deterministic rule-based classification and AI-assisted classification based on Machine Learning algorithms implemented on the two educational robotic platforms.

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 develop an application-oriented educational framework enabling high-school students to acquire practical competencies in robotics, computer vision, Artificial Intelligence, and industrial automation through the implementation and validation of a robotic sorting application.

O6. To investigate the pedagogical transition from using robots as instructional tools for *learning about robotics* and *learning through robotics* toward their use as intelligent collaborative systems supporting *learning from robots* and *learning with robots*, according to the learner–robot relationship framework proposed by Xu and Ouyang (2025).

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 recognize and manipulate objects with identical geometry but different colors 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 fair 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 framework 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 optimization of the robotic sorting process.

From an educational perspective, the study also investigates a progressive transition from using robots primarily as demonstrative instructional tools (*learning about robotics* and *learning through robotics*) toward employing intelligent robotic systems as active learning partners (*learning from robots* and *learning with robots*), in accordance with the learner–robot relationship framework proposed by Xu and Ouyang (2025).

3.3. Research Questions

• *Focused on technical performance*

RQ1. To what extent are educational robotic platforms capable of accurately recognizing objects of different colors 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' involvement in the design, programming, implementation, and experimental validation of the robotic sorting system contribute to the development of computational thinking and technical competencies?

RQ6. To what extent does the transition from passive use of educational robots toward active interaction through the development and implementation of custom sorting algorithms increase high-school students' interest in pursuing studies and careers in engineering, robotics, and computer science?

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 color and object size.

The comparison of these two control strategies provides the experimental framework required to investigate the influence of AI-assisted computer vision on robotic sorting performance (RQ3) and to analyze 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; manipulation accuracy; system throughput; 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).

In addition to the technical evaluation, the study investigates the educational impact of involving students in the design, programming, implementation, and experimental validation of the robotic sorting system. Educational outcomes are assessed using pre-test and post-test questionnaires, allowing the evaluation of students' computational thinking skills, technical competencies, and interest in engineering and computer science. This component of the study addresses the educational research questions concerning competency development and the transition from passive interaction with educational robots toward active participation through the development and implementation of custom robotic control algorithms (RQ5 and RQ6).

Table 1. Alignment of research questions with measurement instruments

Research Question	Measurement Instrument
RQ1 & RQ2	Sorting error rate
RQ3 & RQ4	Processing time (ms)
RQ5 & RQ6	Pre-test/Post-test Questionnaires

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:

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

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

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 is provided by a LEGO color sensor (fixed values). Performance indicators: accuracy, average time, efficiency.

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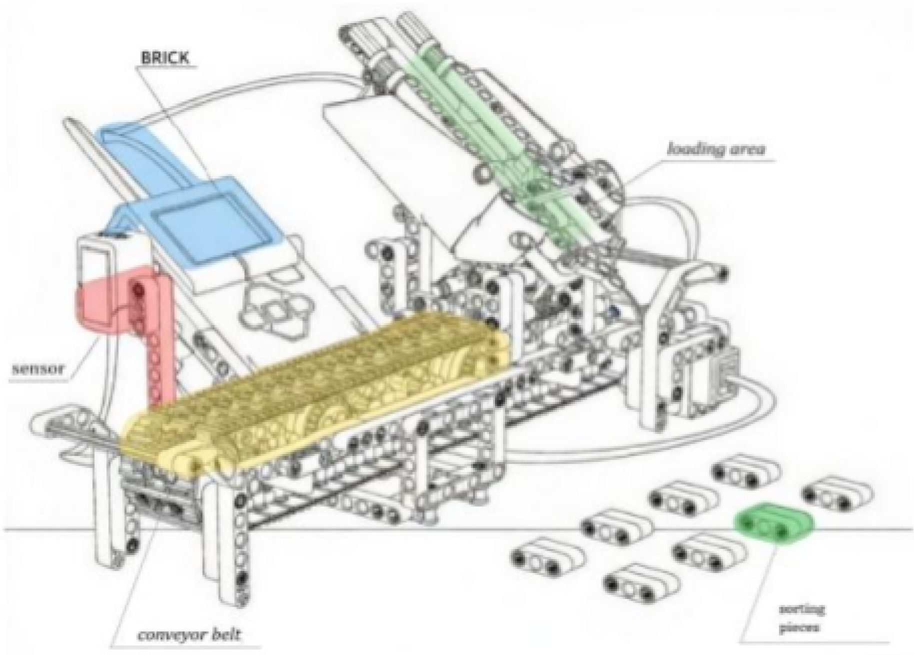

Figure 1. System A - classical programmed robot

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 web camera (pixels). 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 recognize objects with mixed colors.

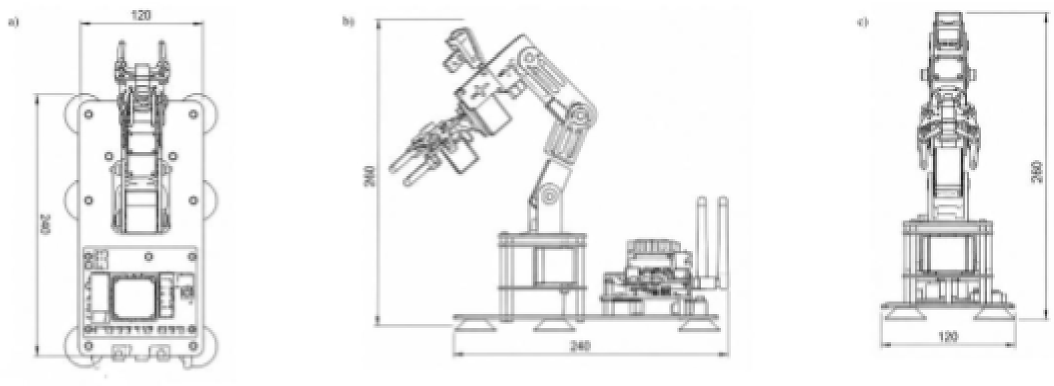

Figure 2. System B - AI-based robot with classification algorithms
a) top view; b) side view; c) rear view

The artificial intelligence component was implemented using the NextLab.tech platform, which integrates machine learning functionalities for object classification based on images acquired by the robot-mounted camera. The classification model was trained using a supervised learning approach on a labeled image dataset collected under controlled experimental conditions, where camera position, illumination, and workspace configuration were kept constant throughout the data acquisition process. Following the training phase, the model was deployed within the robotic application to perform real-time object recognition and trigger the corresponding pick-and-place operation. System performance was evaluated on a separate testing dataset using quantitative performance metrics, including classification accuracy, error rate, average sorting time, throughput, and overall system efficiency.

To ensure a fair 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, total of 120 pieces with a single color. A total of 166 students (89 boys and 77 girls) from classes specialized 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. Consequently, each robotic system processed a total of 120 objects (15 × 8), providing a sufficient experimental basis for comparing the technical performance of the rule-based and AI-assisted robotic systems.

Statistical analysis was performed by calculating the mean values and standard deviations of the performance indicators, allowing the assessment of experimental stability and an objective comparison between the rule-based robotic system and the AI-assisted robotic platform.

3.6. Performance Indicators Tracked

Transport time:

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

Sorting rate (accuracy) measures classification precision. It shows how well the robot identifies objects.

$$\text{Accuracy}\,(\%) = \frac{\text{N}_{\text{correct}}}{\text{N}_{\text{total}}} \ \text{X} \ 100 \tag{3}$$

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

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

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

where T_{total} is total operating time.

Error rate represents the proportion of incorrectly sorted objects.

$$E_r = \frac{\text{N}_{\text{incorrect}}}{\text{N}_{\text{total}}} \tag{5}$$

where $$N_{incorrect} = N_{total} - N_{correct} \quad (6)$$

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

$$T_{mean} = \frac{T_{total}}{N_{total}} \quad (7)$$

where T_{total} is total operating time and N_{total} is total number of processed objects.
System productivity (objects/second or objects/minute).

$$P = \frac{N_{total}}{T_{total}} \quad (8)$$

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		$\Delta\eta =$ -0.19	

We compared: $$\Delta\, Accuracy = \overline{Accuracy_B} - \overline{Accuracy_A} \quad (9)$$
$$\Delta\eta = \overline{\eta_B} - \overline{\eta_A} \quad (10)$$

3.7. Results and Discussion

From the strictly performance-based perspective of sorting:

$$\text{System A} > \text{System B} \quad (11)$$

The comparative analysis of the two educational robotic platforms revealed significant 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), characterized 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 behavior 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.

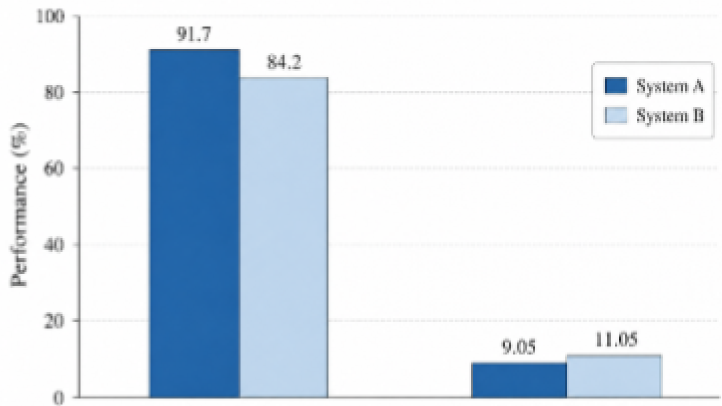

Figure 3. Comparison of mean accuracy and standard deviation for System A and System B

The comparative analysis (see figure 3) shows a performance difference of ΔAccuracy = −7.5% and an efficiency difference of $\Delta\eta = -0.19$ objects/s in favor of System A. Under the investigated experimental conditions, these results indicate 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 processed 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, localization, and manipulator trajectory adjustment prior to the execution of the pick-and-place operation. These additional computational and mechanical operations increase the sorting cycle time and consequently reduce the overall productivity of the robotic system.

System stability was evaluated by analyzing 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 was determined by the combined influence of the perception algorithm, the mechanical architecture of the robotic platform, and the implemented control strategy. Consequently, optimization 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 demonstrate 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 directly 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.

Interpretation of the Educational Outcomes (RQ5 and RQ6)

The educational component of the study was conducted on a sample of 166 high school students, comprising 89 males and 77 females, enrolled in Mathematics–Computer Science, Mathematics–Computer Science (Intensive Computer Science), and Natural Sciences programs.

The educational evaluation investigated the contribution of the design, programming, and experimental validation of educational robotic systems to the development of students' technical competencies and interest in STEM disciplines.

Furthermore, the study examined the transition from using robots as demonstrative learning tools (*learning about robotics* and *learning through robotics*) toward their active use as learning partners (*learning from robots* and *learning with robots*), following the learner–robot relationship framework proposed by Xu and Ouyang (2025).

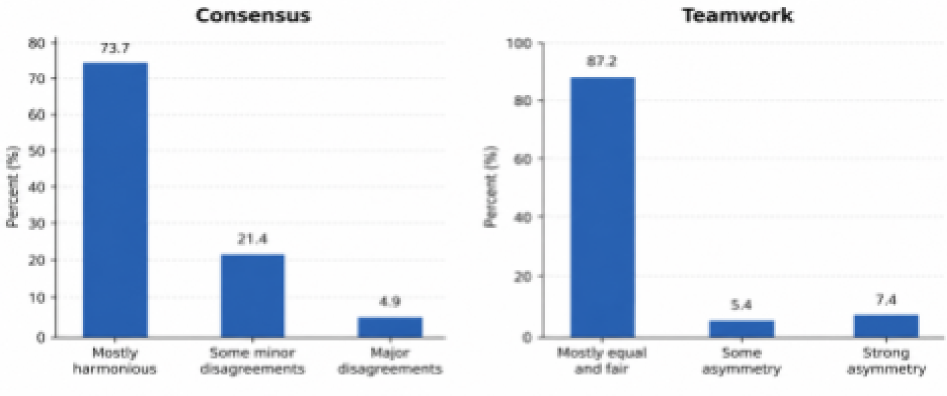

Figure 4. Feedback on: a) consensus building; b) teamwork

Consensus During Laboratory Activities

The results presented in figure 4.a) 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 provided favorable conditions for collaborative robotic design and programming activities.

Perception of Team Collaboration

The responses regarding teamwork (see figure. 4.b) 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 promoted collaborative learning and effective task sharing for the majority of participating students.

Perceived Development of Technical Competencies *(see figure 5)*

The analysis revealed differences between male and female students regarding their perceived development of technical competencies acquired during the experimental activities.

Male students reported substantial improvement in mechanical design and algorithm development, with more than 84% indicating a high level of perceived progress in these domains. However, progress related to control strategies was perceived less positively, with 38.2% of the respondents reporting no substantial improvement compared with their initial level of competence.

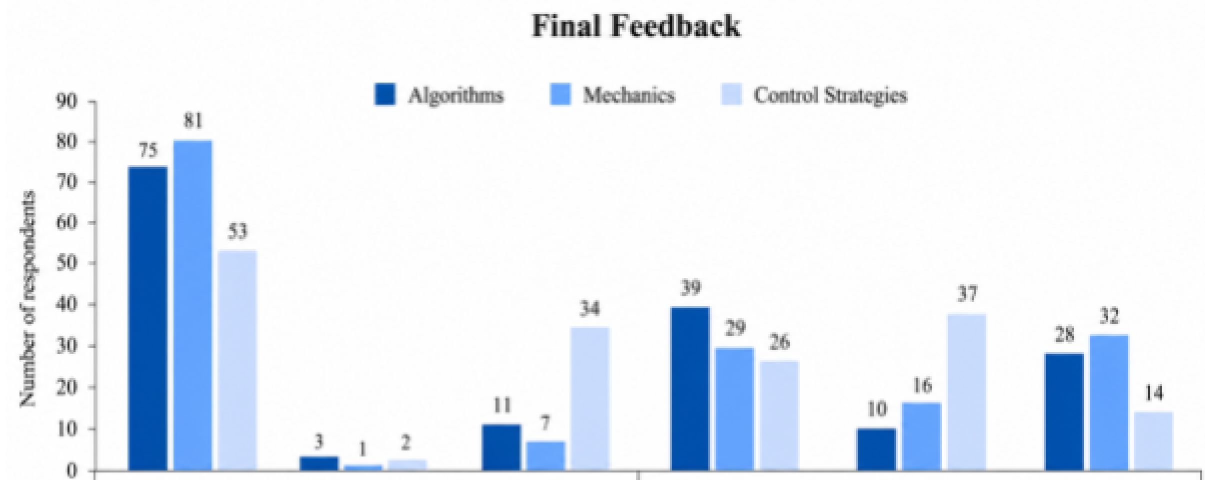

Figure 5. Feedback on self-perceived knowledge acquisition

Female students reported lower levels of perceived progress across the evaluated technical domains. The most pronounced difference was observed in control strategies, where 48.1% of the respondents indicated that their competency level had either remained unchanged or decreased relative to their initial self-assessment. These findings reveal differences in students' perceptions of competency development; however, they do not provide evidence of objective differences in technical performance between male and female participants.

Interpretation with Respect to the Research Questions

The obtained results provide evidence supporting RQ5, indicating that students' participation in the design, programming, and experimental validation of educational robotic systems was associated with a perceived improvement in technical competencies and computational thinking skills.

Regarding RQ6, the observed career preferences and the high level of engagement reported during the experimental activities suggest that project-based educational robotics may contribute to strengthening students' interest in engineering and computer science disciplines. However, this conclusion should be interpreted within the scope of the collected data and reflects participants' self-reported perceptions rather than demonstrating a causal relationship between participation in the educational activities and subsequent career choice.

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 increased the overall processing time and resulted in higher temporal variability and reduced operational stability.

The comparative analysis demonstrates that Artificial Intelligence alone does not guarantee superior robotic performance. The obtained results indicate that the overall performance of an educational robotic system depends 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 confirms 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 promoted 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 optimization 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 also support the gradual transition from passive educational use of robots (*learning about robotics* and *learning through robotics*) toward 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 emerges 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 highlight that educational robotics provides an effective experimental framework for introducing Artificial Intelligence concepts in secondary education while simultaneously developing interdisciplinary competencies in robotics, automation, computer vision, and intelligent control systems.

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