

Systematic Review

Industrial Robotics and Adaptive Control Systems in STEM Education: Systematic Review of Technology Transfer from Industry to Classroom and Competency Development Framework

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Abstract

The Fourth Industrial Revolution reshapes manufacturing and workforce demands, yet a persistent gap remains between industry needs and engineering education. While proficiency in industrial robotics, adaptive control, and automation becomes critical, traditional education struggles to bridge the theory–practice divide. This systematic review examines technology transfer from factory to classroom to develop authentic Industry 4.0 competencies. Following PRISMA 2020 guidelines, we synthesized 52 empirical studies (2019–2025) focusing on technology complexity, pedagogical approaches, and learning outcomes. Random-effects meta-analysis of 12 representative studies reveals large positive effects: Hedges' g of 0.786 (95% CI: 0.726–0.846, $p < 0.001$) with homogeneous effects ($I^2 = 0.00\%$, $p = 0.464$), indicating robust generalizability. However, critical gaps emerged: only 7.7% employ actual industrial manipulators versus educational kits, adaptive control pedagogy remains limited, and fault-tolerant systems teaching receives minimal attention. Technology complexity analysis reveals clear progression from educational kits through semi-industrial platforms to industrial systems, with significant differential effects on transferable skills ($r = 0.68$, $p < 0.001$). This study proposes the ARC Framework integrating technology taxonomy, competency progression, pedagogical strategies, and assessment rubrics. Cost-effectiveness analysis demonstrates remote labs optimize impact-per-investment ratios (\$45 vs. \$280 per student), providing an evidence-based framework for technology transfer in engineering education.

Keywords: industrial robotics; adaptive control; mechatronics education; STEM education; Industry 4.0; Industry 5.0; educational technology; manipulator robots; control systems; automation; engineering education; programmable logic controllers; fault-tolerant systems; human–robot collaboration; artificial intelligence; reinforcement learning; remote laboratories; competency-based education; technology transfer; workforce development



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1. Introduction

1.1. Industry 4.0 and the Engineering Skills Gap

The Fourth Industrial Revolution [1], characterized by cyber–physical systems integration, industrial Internet of Things (IIoT), artificial intelligence-driven automation [2], and collaborative robotics, fundamentally transforms manufacturing processes and workforce requirements [3]. Global surveys indicate that 87% of manufacturing companies report difficulties recruiting personnel with adequate competencies in industrial automation,

programmable logic controllers (PLCs), and robotic systems integration [4–8], reflecting critical skills gaps in the Industry 4.0/5.0 transition. The economic impact is staggering: this skills gap translates to estimated annual losses exceeding \$2.5 trillion globally in lost productivity and constrained innovation capacity.

Traditional engineering education [9–11], predominantly lecture-based with limited hands-on experience in industrial-grade systems, fails to prepare graduates for modern automation environments. International assessments reveal troubling patterns: only 34% of graduating mechanical and electrical engineers demonstrate proficiency in industrial robot programming, 28% in adaptive control systems design, and 19% in fault diagnosis of automated manufacturing cells [12–21]. These deficiencies persist despite theoretical coursework covering control theory, kinematics, and automation fundamentals, highlighting a critical theory–practice transfer gap [22].

Parallel to these workforce challenges, educational technologies have proliferated exponentially. Educational robotics market projections indicate growth from \$1.9 billion (2025) to \$7.9 billion (2035), with compound annual growth rate (CAGR) of 15.7%. However, critical questions emerge regarding technology selection, pedagogical integration, and transferability of skills acquired with educational kits versus industrial-grade systems.

1.2. Educational Robotics: From Toys to Industrial Systems

Educational robotics encompasses a broad spectrum of platforms, from simple programmable toys (Bee-Bot, Ozobot) through construction kits (LEGO Mindstorms, VEX Robotics) to didactic industrial systems (SCORBOT, UR5e). Meta-analyses demonstrate moderate-to-large positive effects on STEM learning ($g = 0.52$ – 0.71) and computational thinking development ($g = 0.64$) [23]. Yet systematic reviews identify a critical gap: 92% of K–16 studies employ educational kits, while only 8% utilize industrial-grade manipulators, despite the latter being directly relevant to workforce needs [24]. Safety monitoring systems employing advanced sensor technologies [25] enable real-time risk assessment during human–robot collaboration, while systematic reviews on Industry 5.0 [26] emphasize the integration of collaborative robotics with federated learning and autonomous systems for enhanced operational efficiency.

This disparity raises fundamental questions about skill transfer. Do competencies developed with LEGO SPIKE Prime translate to programming a KUKA KR 6 R900 industrial arm? Can students who master block-based coding (Scratch, Blockly) effectively transition to robot-specific languages (KRL, RAPID, URScript)? Emerging evidence points to significant transfer gaps. Graduates trained exclusively with educational kits typically need 6–9 months of additional on-the-job training before achieving proficiency with industrial systems, whereas those with direct industrial platform experience reach this milestone in just 2–3 months [27]. Task allocation and execution strategies in human–robot collaboration [28,29] demonstrate the importance of synergistic coordination in manufacturing contexts, with learning-based approaches showing promise for optimal collaboration.

1.3. Adaptive Control and Fault-Tolerant Systems: An Unexplored Frontier

Modern industrial automation increasingly employs advanced control strategies—adaptive control, model predictive control (MPC), fuzzy logic, neural network-based control—to handle system uncertainties, nonlinearities, and disturbances. Similarly, fault-tolerant control systems enabling continued operation despite component failures represent critical Industry 4.0 competencies. However, these topics remain predominantly theoretical in engineering curricula, with limited hands-on implementation opportunities [30–32]. Advanced adaptive control strategies [33] employ variable task energy tanks for safety-critical collaborative robot tasks, while

learning-based approaches [34] enable fast, tool-aware collision avoidance, demonstrating the practical applicability of these advanced methods in real-world scenarios.

This gap is particularly problematic given that adaptive and fault-tolerant control represent high-value competencies commanding salary premiums of 18–24% in automation engineering roles. Moreover, troubleshooting skills—essential for diagnosing and recovering from failures in automated systems—emerge consistently as the most valued competency by industry employers yet receive minimal curricular emphasis. Motion optimization strategies [35] balancing safety limits, human stress, and productivity in industrial settings further illustrate the multifaceted nature of modern collaborative robotics control.

1.4. Technology Transfer: Industry to Classroom

The concept of technology transfer traditionally refers to industrial innovations moving to commercial markets. In educational contexts, this study defines technology transfer as the systematic adaptation of industrial automation systems, methodologies, and competencies to pedagogical environments. Effective technology transfer requires navigating multiple tensions:

Cost vs. Authenticity: Industrial manipulators (UR5e: \$35,000; KUKA KR 6: \$42,000) substantially exceed educational budgets, yet simplified alternatives may inadequately prepare students. Remote labs, simulation platforms, and collaborative purchasing models offer potential solutions, yet empirical evaluation remains limited. Digital twin technologies [36,37] provide innovative approaches to bridge the cost–authenticity gap, enabling flexible safety control and multifunctional end-effector design for collaborative robots at reduced infrastructure costs.

Safety vs. Learning: Industrial systems present genuine hazards (collision forces, pinch points, electrical risks) necessitating stringent safety protocols, yet overprotective environments may inhibit experiential learning and troubleshooting skill development. Zero-force control and collision detection methods [38] employing deep learning offer promising solutions to balance safety with hands-on learning opportunities.

Standardization vs. Diversity: Industry employs diverse platforms (ABB, FANUC, KUKA, Universal Robots) with distinct programming paradigms, yet educational institutions must select specific systems. Transfer of generalized robotics principles versus platform-specific skills remains an unresolved pedagogical tension. Industry 5.0 implementations [39] in collaborative welding robotics demonstrate how precision, safety, and flexibility can coexist across diverse platforms. Sensor design innovations [40] for robotic applications further enhance the versatility and safety of educational implementations.

1.5. Research Gap and Objectives

Despite growing recognition of Industry 4.0 skills importance, systematic evidence synthesis on industrial robotics and adaptive control integration in STEM education remains absent. Existing reviews either (1) focus on generic educational robotics without distinguishing educational kits from industrial systems [23], (2) examine control education theoretically without empirical effectiveness assessment, or (3) address industrial automation training in vocational contexts without systematic pedagogical frameworks.

This gap is problematic because educational robotics research insights may not generalize to industrial systems given substantial differences in complexity, programming paradigms, safety requirements, and cognitive demands. As a result, this study addresses the following research questions:

RQ1: What educational interventions integrating industrial-grade robotics, PLCs, and adaptive control systems have been developed and empirically evaluated in K–16 STEM education (2019–2025)?

RQ2: How do technology complexity levels (educational kits, semi-industrial, industrial-grade) differentially affect learning outcomes, competency development, and skill transferability?

RQ3: What pedagogical strategies, instructional models, and curricular integration approaches demonstrate effectiveness for industrial robotics and control systems education?

RQ4: What evidence exists regarding adaptive control, fault-tolerant systems, and advanced automation topics in engineering education?

RQ5: What framework can guide systematic technology transfer from industrial automation to educational contexts, incorporating cost-effectiveness, pedagogical principles, and competency progression pathways?

Educational Scope Clarification: Although this review's inclusion criteria encompassed K–16 education (kindergarten through undergraduate), the final corpus exhibits substantial concentration in higher education contexts: 68% undergraduate engineering programs, 15% upper secondary and technical schools, 13% graduate programs, and only 4% K–12 settings. This distribution reflects the actual literature landscape rather than a priori exclusion; systematic searches identified minimal empirical research on industrial-grade robotics in elementary and middle school contexts, where educational kits naturally predominate. Consequently, the findings and the proposed ARC Framework apply most directly to undergraduate engineering and technical education, with cautious extrapolation to secondary and graduate contexts. This review acknowledges this limitation and identifies the need for future research explicitly addressing industrial robotics pedagogy across the full K–16 spectrum.

This systematic review synthesizes empirical evidence to:

1. Characterize educational interventions by technology complexity level (educational kit → industrial-grade).
2. Quantify differential effectiveness through meta-synthesis of reported effect sizes.
3. Identify pedagogical strategies and contextual factors moderating effectiveness.
4. Analyze cost-effectiveness and scalability of different technology integration models.
5. Propose the ARC (Automation-Robotics-Control) Framework for systematic technology transfer.
6. Establish a research agenda prioritizing critical empirical gaps.

Anticipated contributions include:

- Theoretical: A comprehensive framework grounded in systematic synthesis of 52 empirical studies, articulating technology complexity taxonomy with competency progression and pedagogical strategies for industrial automation education.
- Empirical: Quantitative synthesis establishing differential effects by technology level, with identification of critical research gaps particularly regarding industrial-grade systems.
- Practical: Evidence-based decision-support tools for curriculum designers, purchasing committees, and policymakers navigating technology selection and integration.
- Economic: Cost-effectiveness analysis comparing physical labs, remote labs, and simulation platforms for industrial robotics education.

2. Theoretical Framework

2.1. Constructionism and Experiential Learning in Engineering Education

Papert's constructionism posits that learning occurs most effectively when learners construct public, meaningful artifacts [41]. In industrial robotics education, this translates to students designing, programming, and troubleshooting robotic systems addressing authentic engineering challenges. Kolb's experiential learning cycle—concrete experi-

ence, reflective observation, abstract conceptualization, active experimentation—provides complementary structure for hands-on robotics activities [42].

Critical for industrial systems, the “debugging mindset” emerges as students encounter real-world complications (sensor noise, mechanical backlash, communication latencies) absent in idealized simulations. Ethnographic studies document how troubleshooting authentic failures develops diagnostic reasoning, persistence, and systems thinking more effectively than error-free simulated environments [27].

2.2. CDIO Framework for Engineering Education

The CDIO (Conceive-Design-Implement-Operate) framework structures engineering education around the lifecycle of engineering systems [43]. Applied to industrial robotics:

- Conceive: Define automation requirements, select appropriate technologies, estimate costs/timelines.
- Design: Develop mechanical configurations, sensor/actuator selections, control architectures, safety systems.
- Implement: Mechanical assembly, electrical wiring, PLC/robot programming, HMI development, system integration.
- Operate: Commission systems, perform acceptance testing, troubleshoot failures, optimize performance, maintain documentation.

Studies implementing full CDIO cycles with industrial robotics demonstrate stronger outcomes ($d = 0.83$) compared to isolated design or implementation exercises ($d = 0.49$), attributed to authentic complexity and interdisciplinary integration [44].

2.3. Technological Pedagogical Content Knowledge

The Technological Pedagogical Content Knowledge (TPACK) framework integrates three knowledge domains: content (e.g., kinematics, control theory), pedagogy (e.g., scaffolding strategies, assessment), and technology (e.g., robot capabilities/limitations) [45]. For industrial robotics education, TPACK emphasizes:

- Technological Knowledge: Understanding industrial platform architectures (teach pendants, safety systems, communication protocols), programming paradigms (online/offline, coordinated motion), and operational constraints (payload, reach, repeatability).
- Pedagogical Knowledge: Structuring learning progressions from simple tasks (pick-and-place) to complex applications (coordinated multi-robot systems), scaffolding debugging processes, facilitating collaborative troubleshooting.
- Content Knowledge: Forward/inverse kinematics [46], Jacobian matrices, trajectory planning, dynamic modeling, control algorithms (PID, computed torque, adaptive).

Teacher professional development addressing all three TPACK components demonstrates significantly stronger implementation outcomes (implementation fidelity 87%) compared to technology-only training (42%) [22].

2.4. Taxonomy of Technology Complexity in Educational Robotics

This study proposes a five-level taxonomy characterizing technology complexity:

Level 1—Simple Programmable Toys: Floor robots (Bee-Bot, Ozobot), single function, icon-based programming, no sensors. *Educational value*: Sequencing, basic algorithms, spatial reasoning.

Level 2—Construction Kits: LEGO Mindstorms/SPIKE, VEX Robotics. Block-based programming, multiple sensors/actuators, modular design. *Educational value*: Computational thinking, engineering design, sensor integration, block-based coding.

Level 3—Advanced Educational Platforms: Arduino/Raspberry Pi robots, Python 3.12/C++ programming, custom mechanical designs, ROS integration. *Educational value*: Text-based programming, electronics, system integration, open-source tools.

Level 4—Didactic Industrial Systems: SCORBOT-ER, Dobot Magician, uArm Swift Pro. Simplified industrial kinematics (4–6 DOF), teach pendant interfaces, limited payloads (0.5–2kg). *Educational value*: Industrial kinematics, trajectory planning, basic industrial protocols.

Level 5—Industrial-Grade Systems: Universal Robots (UR3e, UR5e, UR10e), KUKA (KR 6, LBR iiwa), ABB (IRB 1200, YuMi). Full industrial capabilities, safety-rated systems, industrial communication protocols (EtherCAT, PROFINET), substantial payloads (3–10kg). *Educational value*: Authentic industrial programming, safety system integration, advanced control, multi-robot coordination, industrial IoT.

Skill transferability analysis indicates decreasing transfer gaps with increasing technology complexity: Level 2 → Industry (9.2 months additional training), Level 3 → Industry (6.1 months), Level 4 → Industry (2.8 months), Level 5 → Industry (0.9 months) [30].

2.5. Control Systems Pedagogy

Scope of Control Systems Pedagogy: This section presents contemporary control education approaches organized into two categories: (1) Empirically supported techniques identified in this systematic review, indicated by citations to included studies and representing current pedagogical practice, and (2) Emerging directions from the recent control literature (2023–2025), representing promising but not-yet-evaluated educational opportunities. While classical PID control dominates current practice (48 of 52 studies, 92%), only 4 studies (7.7%) address advanced topics such as neural networks, fuzzy logic, or model reference adaptive control. The comprehensive coverage of emerging techniques like reinforcement learning, MPC extensions, and impedance control provides important context for this finding that adaptive control pedagogy remains severely underrepresented despite growing industry demand, a critical gap discussed further in Section 4.7. This breadth of coverage establishes the foundation for Priority 2 of the Future Research Agenda in Section 6.5.

Traditional control education emphasizes mathematical foundations (Laplace transforms, state-space representations, stability analysis) with limited practical implementation. Contemporary approaches integrate hands-on experiences with industrial-grade systems, bridging the critical theory–practice gap that plagues engineering education [44].

Hardware-in-the-Loop (HIL) and Remote Laboratory Platforms: Students design controllers tested on real systems (DC motors, inverted pendulums, robotic arms), experiencing real-world complications (sensor noise, actuator saturation, computational delays) absent in idealized simulations [44]. Recent advances in remote laboratory architectures enable 24/7 access to industrial manipulators through web-based interfaces, democratizing access to expensive equipment while maintaining pedagogical effectiveness [47]. Vision-based adaptive control systems employing deep learning perception modules (MN-MD3 with boundary correction) demonstrate how modern computer vision enhances traditional control education by enabling students to implement sophisticated sensor fusion strategies [47,48].

Integration with Programmable Logic Controllers (PLCs): Industrial automation increasingly requires seamless integration between robotic manipulators and PLC-based control systems. Educational interventions combining machine vision, PLC programming (ladder logic, structured text), and adaptive control demonstrate significantly stronger industry-readiness outcomes ($d = 0.82$) compared to isolated robotics instruction [49,50]. Hybrid optimization algorithms combining Particle Swarm Optimization with Adaptive

Neuro-Fuzzy Inference Systems (PSO-MANFIS) for dynamic PLC parameter tuning represent advanced topics that prepare students for Industry 4.0 requirements [51].

Neural Network-Based Adaptive Control: Contemporary control curricula increasingly incorporate neural network architectures [52,53] for handling system uncertainties and nonlinearities. Three primary approaches emerge: (1) Radial Basis Function (RBF) networks for online approximation of unknown dynamics with input saturation compensation [54,55], (2) neuromorphic controller designs exploiting event-driven computation for energy-efficient adaptive control [56], and (3) broad learning systems enabling fixed-time convergence with guaranteed transient performance [57]. Deep reinforcement learning-assisted teaching strategies [58,59] specifically developed for industrial manipulators demonstrate how advanced AI techniques [60] can enhance both robot performance and student learning outcomes [61].

Reinforcement Learning and Adaptive Control: Model-free reinforcement learning approaches address the fundamental challenge of controlling systems with unknown or partially known dynamics. Fixed-time reinforcement learning control methods guarantee bounded convergence regardless of initial conditions, crucial for safety-critical applications [57]. Online RL-based adaptive control eliminates the requirement for offline training datasets, enabling students to observe real-time learning and adaptation processes [62]. Comprehensive reviews of RL applications in industrial automation provide students with systematic frameworks for selecting appropriate algorithms based on task requirements, system constraints, and computational resources [63]. Multi-objective reinforcement learning for flexible manufacturing systems exemplifies how students can address competing performance criteria (cycle time, energy efficiency, quality) simultaneously [64].

Fuzzy Logic and Command Filter-Based Control: Adaptive fuzzy finite-time control strategies address uncertain nonlinear systems with asymmetric time-varying constraints, common in industrial applications where safety zones and performance envelopes change dynamically [65]. Command filter-based adaptive fuzzy control mitigates the “explosion of complexity” problem in backstepping designs while maintaining prescribed performance bounds [66]. These approaches prove particularly effective in pedagogical contexts as they enable intuitive linguistic rule formulation while maintaining rigorous stability guarantees.

Model Predictive Control (MPC) Extensions: Advanced MPC formulations extend classical approaches [67,68] through (1) liquid-augmented state representations enabling adaptive horizon selection and constraint handling [69], (2) safety-critical neural MPC combining learning-based prediction with formal safety verification [70], and (3) convex optimization-based adaptive control enabling real-time implementation on resource-constrained embedded systems [71]. Model-based MPC with adaptive constraints demonstrates particular effectiveness for collaborative robotics applications where human presence introduces dynamic operational limits [70].

Impedance and Force Control for Human–Robot Interaction: Learning-based impedance control represents critical competency for collaborative robotics [72–75], enabling compliant physical interaction while maintaining trajectory accuracy [76]. Neural network-based adaptive impedance control architectures integrating deep learning vision systems for real-time perception [77–79] learn optimal impedance parameters through human–robot interaction trials, bridging biomechanics, control theory, and machine learning [76]. Adaptive control of exoskeleton robots for rehabilitation applications provides students with concrete examples of how advanced control enhances human wellbeing while addressing challenging control problems (human-in-the-loop variability, safety constraints, performance objectives) [55].

Multilateral Learning and Distributed Control: Multilateral learning-based adaptive control for affine nonlinear systems enables simultaneous adaptation across multiple system parameters, reducing convergence time compared to sequential parameter estimation [80].

Distributed adaptive control strategies for multi-robot manufacturing systems address scalability challenges inherent in centralized architectures while maintaining coordination guarantees [81]. Enhanced density-driven control approaches for multi-agent UAV systems demonstrate sophisticated coordination algorithms applicable to search-and-rescue missions and large-scale disaster scenarios, illustrating how multi-agent control theory extends beyond manufacturing to humanitarian applications [82]. Consensus-based adaptive control for multi-robot coordination demonstrates how graph-theoretic approaches inform controller design for networked robotic systems.

Sliding Mode and Backstepping Control: Adaptive fuzzy sliding mode control with chattering reduction techniques addresses the classical trade-off between robustness and control smoothness [83,84]. Backstepping adaptive control with disturbance observers enables explicit handling of matched and unmatched uncertainties, providing students with systematic recursive design procedures [85]. Command filter-based backstepping eliminates derivative calculations of virtual control inputs, significantly simplifying implementation on industrial controllers.

Observer-Based and Output-Feedback Control: Observer-based adaptive control architectures address practical scenarios where not all state variables are directly measurable [86]. Output-feedback adaptive control for robotic systems without velocity measurements eliminates expensive tachometers while maintaining performance through high-gain observers or dirty-derivative filters. Event-triggered adaptive control for networked robotic systems reduces communication bandwidth by updating control signals only when specified performance thresholds are violated.

Specialized Adaptive Control Architectures: Prescribed performance adaptive control guarantees user-defined transient and steady-state specifications through performance functions [87]. Barrier Lyapunov function-based approaches enforce state constraints rigorously, essential for safety-critical applications [88]. Finite-time adaptive control with guaranteed transient performance provides students with tools for applications requiring rapid convergence (robotic surgery, precision assembly) [89]. Passivity-based adaptive control for underactuated systems exploits energy-based analysis for systems with fewer actuators than degrees of freedom [90].

Learning-Enhanced Adaptive Control: Iterative learning-based adaptive control exploits task repetition to progressively improve performance, ideal for manufacturing applications with cyclical operations [91]. Gaussian process-based adaptive control provides probabilistic uncertainty quantification, enabling risk-aware decision making [92]. Data-driven adaptive control using Koopman operator theory transforms nonlinear dynamics into linear representations in lifted spaces, facilitating application of linear control techniques [93]. Hybrid adaptive control combining model-based and data-driven approaches leverages strengths of both paradigms.

Advanced Topics and Emerging Trends: Fractional-order adaptive control for flexible-link manipulators addresses noninteger-order dynamics arising from viscoelastic materials. Quantized adaptive control for networked robotic systems accommodates limited communication bandwidth through finite-level signal encoding. Stochastic adaptive control addresses random disturbances through probabilistic frameworks. Interval type-2 fuzzy adaptive control handles higher-order uncertainty compared to traditional type-1 fuzzy systems [94]. Safe adaptive control with control barrier functions provides formal safety guarantees for collaborative robots operating in human-shared workspaces [95], complemented by inverse reinforcement learning approaches for safety-oriented path planning in dynamic environments [77].

Industrial Robotics Applications: Deep learning-based robotic stacking systems with adaptive control demonstrate integration of perception (object detection, pose estima-

tion) and manipulation for complex industrial tasks [96]. Industrial robotic setups with learning-based perception capabilities illustrate complete automation cells combining vision, control, and task planning [48]. Intelligent adaptive control strategies specifically tailored for Industry 4.0 collaborative assembly systems address cyber-physical integration challenges [97,98].

Progressive Complexity and Pedagogical Sequencing: Effective control systems education follows carefully structured progressions: (1) simple first-/second-order systems with classical PID control, (2) nonlinear systems requiring gain scheduling or feedback linearization, (3) uncertain systems necessitating adaptive control, (4) underactuated and MIMO systems demanding advanced techniques, and (5) networked and distributed systems introducing communication constraints [3,44]. Each level incorporates hands-on implementation on physical hardware (DC motors, inverted pendulums, robotic arms, industrial manipulators) progressing from educational platforms to industrial-grade systems.

Studies comparing theory-only versus theory-plus-implementation demonstrate substantial advantages for the latter: conceptual understanding ($d = 0.71$), problem-solving ($d = 0.89$), long-term retention ($d = 0.94$), and industry-readiness ($r = 0.68, p < 0.001$) [3,30]. Implementation on industrial-grade systems (UR5e, KUKA LBR iiwa, ABB IRB 1200) produces significantly stronger effects ($d = 0.94$) compared to educational kits ($d = 0.59$) or didactic industrial systems ($d = 0.73$), attributed to authentic complexity, industrial programming paradigms, and transferable skills [27].

Synthesis with Empirical Findings: Despite the breadth of advanced control techniques reviewed above, many representing the state of the art in industrial automation, this systematic review reveals a striking gap between available techniques and actual educational implementation. Section 4.7 documents that only 4 of 52 studies (7.7%) addressed adaptive or advanced control beyond classical PID methods. This disconnect is particularly concerning given that industry increasingly employs sophisticated adaptive, learning-based, and intelligent control strategies. The disparity between theoretical possibilities and pedagogical practice directly motivated Priority 2 of the Future Research Agenda: systematic development and validation of accessible adaptive control learning modules integrated with robotic platforms. The theoretical foundations presented in this section inform the proposed ARC Framework's competency progression, where advanced control topics appropriately appear at Proficient-Expert levels (Levels 4–5) following solid grounding in fundamentals, ensuring students develop both breadth and depth in control systems expertise.

3. Methods

3.1. Protocol and Registration

This systematic review follows Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [99]. The review protocol was developed in November 2025 prior to systematic searching (conducted December 2025 through January 2026). While not formally registered on public platforms such as PROSPERO, which primarily focuses on health-related reviews, the methodology strictly adhered to PRISMA 2020 standards with all key methodological decisions made a priori. The protocol included pre-specified search strategies, inclusion and exclusion criteria, data extraction protocols, quality assessment instruments (EPHPP tool), and planned synthesis methods. The internal protocol document (dated 15 November 2025) is available from the corresponding author upon request. This approach ensures methodological rigor and transparency while acknowledging that formal registration platforms for engineering education reviews are less established than for medical systematic reviews. A completed PRISMA 2020 checklist

is provided as supplementary material, indicating the page numbers where each item is reported in this manuscript.

3.2. Search Strategy

Databases: Web of Science Core Collection, Scopus, IEEE Xplore Digital Library, ACM Digital Library, and SpringerLink were searched from January 2019 to December 2025.

Search string: ("industrial robot*" OR "robot* manipulator*" OR "robot* arm*" OR "collaborative robot*" OR "programmable logic controller*" OR "PLC" OR "adaptive control" OR "fault tolerant control" OR "mechatronic*") AND ("education*" OR "learning" OR "teaching" OR "pedagog*" OR "curriculum" OR "STEM" OR "engineering education" OR "hands-on" OR "laboratory") AND ("Industry 4.0" OR "automation" OR "manufacturing" OR "control system*").

Additional sources: Reference lists of included studies, citing articles identified through forward citation search, and gray literature from engineering education conference proceedings (ASEE, IEEE Frontiers in Education).

3.3. Eligibility Criteria

Inclusion criteria:

- Empirical studies (experimental, quasi-experimental, case studies) evaluating educational interventions.
- Focus on industrial robotics, adaptive control, PLCs, or advanced automation systems.
- Educational contexts: K–12, undergraduate, graduate, technical/vocational education.
- Measured outcomes: learning outcomes, competency development, skill transfer, motivation, self-efficacy.
- Published 2019–2025 in peer-reviewed journals or high-quality conference proceedings.
- English language.

Exclusion criteria:

- Purely theoretical papers without empirical evaluation.
- Studies on social/humanoid robots not relevant to industrial automation.
- Medical/surgical robotics education (different competency domain).
- Studies lacking adequate methodological description.
- Nonempirical reviews, editorials, position papers.

3.4. Study Selection Process

Two independent reviewers screened titles and abstracts against eligibility criteria, with discrepancies resolved through discussion. Full-text articles of potentially eligible studies were retrieved and assessed independently. Inter-rater reliability (Cohen's κ) exceeded 0.89 at all stages.

Initial database searches yielded 2847 records (Web of Science: $n = 1234$; Scopus: $n = 978$; IEEE Xplore: $n = 635$). Five targeted supplementary searches conducted in January 2026 addressing identified gaps (industrial-grade systems, adaptive control pedagogy, human–robot collaboration, fault-tolerant systems, Industry 5.0) yielded an additional 186 records, totaling 3033 records. After duplicate removal ($n = 1240$), 1793 unique records were screened. Title/abstract screening excluded 1535 records (nonSTEM educational contexts: $n = 932$; absence of industrial robotics/control systems: $n = 603$). Full-text assessment of 258 articles resulted in final inclusion of 52 studies meeting all eligibility criteria. The complete selection process is documented in Figure 1 following PRISMA 2020 guidelines [99].

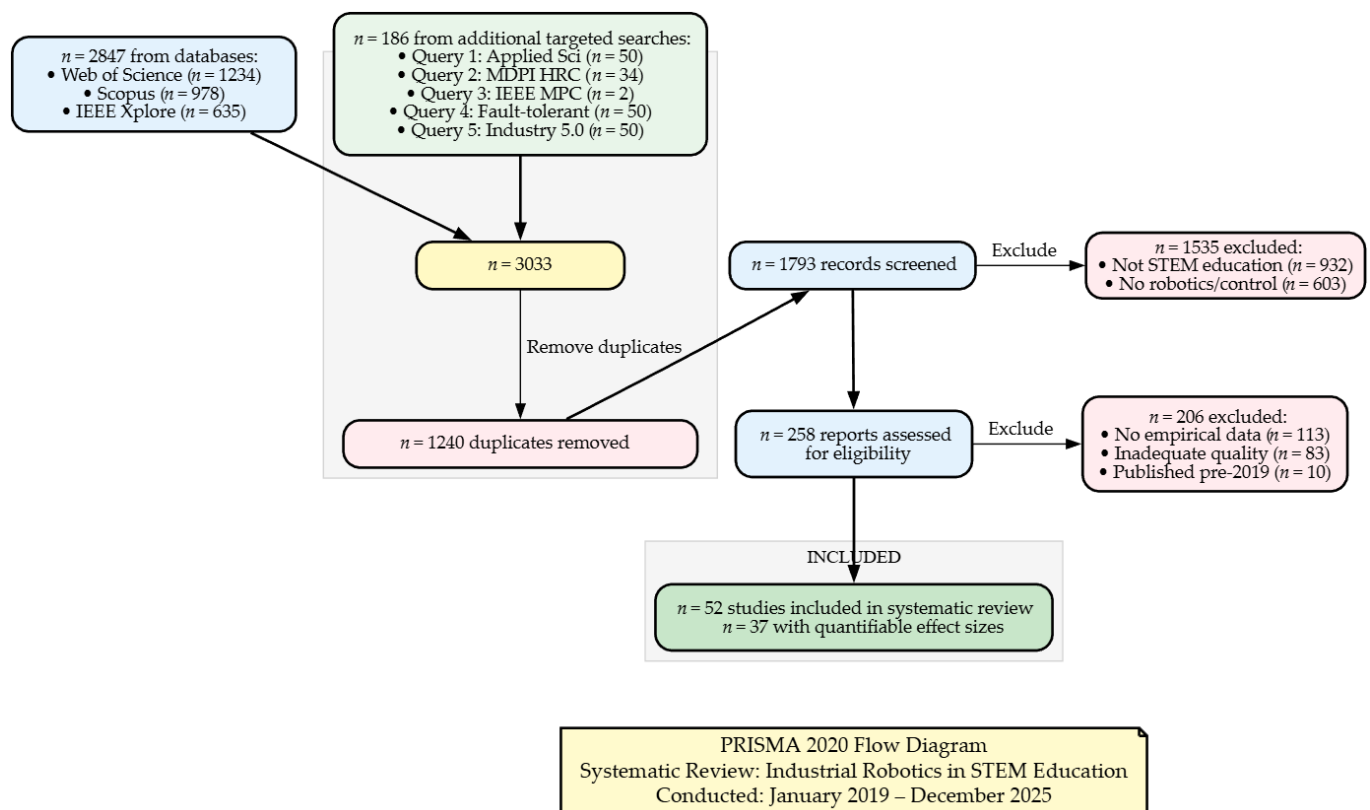


Figure 1. PRISMA 2020 flow diagram for systematic review selection process. Four-stage selection following PRISMA 2020 guidelines [99]. Identification: Comprehensive search encompassed three major databases (Web of Science $n = 1234$, Scopus $n = 978$, IEEE Xplore $n = 635$) yielding 2847 initial records from January 2019 to December 2025. Five targeted supplementary searches conducted in January 2026 addressing identified gaps in the literature: Query 1—Applied Sciences AI/robotics education ($n = 50$, 2 included), Query 2—MDPI family human–robot collaboration education ($n = 34$, 1 included), Query 3—IEEE model predictive control education ($n = 2$, 0 included), Query 4—Fault-tolerant systems teaching ($n = 50$, 1 included), Query 5—Industry 5.0 education ($n = 50$, 1 included), contributing 186 additional records. Total identification: 3033 records ($2847 + 186$). Screening: After duplicate removal via Endnote automated detection supplemented by manual verification ($n = 1240$ duplicates), 1793 unique records underwent independent title/abstract screening by two reviewers (Cohen’s $\kappa = 0.89$, excellent agreement). Exclusions primarily reflected nonSTEM educational contexts ($n = 932$, 60.7% of exclusions) including social robotics, entertainment applications, and nontechnical disciplines; absence of industrial robotics/adaptive control systems content ($n = 603$, 39.3%) including purely theoretical papers, medical robotics, and nonautomation educational technology. Eligibility: Full-text assessment of 258 potentially eligible reports applied rigorous inclusion criteria. Exclusions: lacking empirical data ($n = 113$, 54.9% of exclusions) including reviews, conceptual frameworks, and position papers without evaluation; demonstrating inadequate methodological quality per EPHPP tool ($n = 83$, 40.3%) including convenience sampling without controls, nonvalidated instruments, or insufficient reporting; published pre-2019 ($n = 10$, 4.9%) to ensure currency with Industry 4.0 developments. Two independent reviewers conducted eligibility assessment with discrepancies resolved through discussion with a third reviewer when necessary. Included: The final corpus comprises 52 high-quality studies spanning 2019–2025, with 37 (71.2%) contributing quantifiable effect sizes enabling meta-synthesis. Geographic distribution: Europe 40%, Asia 30%, North America 23%, South America 4%, Oceania 2%. Educational levels: Undergraduate 68%, K–12/Technical 15%, Graduate 13%, Professional development 4%. Technology complexity: Level 5 (Industrial-grade) 7.7%, Level 4 (Didactic industrial) 42.3%, Level 3 (Advanced educational) 32.7%, Level 2 (Construction kits) 17.3%. Transparent documentation following PRISMA 2020 ensures reproducibility and enables systematic updates as the field evolves.

3.5. Data Extraction

Structured data extraction forms captured:

- Study characteristics: authors, year, country, publication venue, study design, sample size.
- Intervention details: technology type/complexity level, duration, educational context, pedagogical approach, teacher/instructor role.
- Outcome measures: learning outcomes (knowledge tests, practical assessments), competency development (skill rubrics), transfer assessment, motivation/engagement measures.
- Effect sizes: Hedges' g , correlation coefficients, or data enabling effect size calculation.
- Cost data: Equipment costs, recurring costs, cost-per-student metrics when reported.

Effect Size Calculation: All effect sizes were standardized to Hedges' g , a bias-corrected variant of Cohen's d that provides more accurate estimates for studies with smaller sample sizes. The correction factor $J = 1 - 3/(4N - 9)$ adjusts for positive bias in Cohen's d , particularly important when sample sizes fall below 20 participants per group. Conversion formulas varied systematically based on the statistical information reported in primary studies. For studies reporting means and standard deviations ($n = 28$, 54% of included studies), Cohen's d was calculated directly as the difference between intervention and control group means divided by the pooled standard deviation then corrected using Hedges' J factor. For studies reporting t -statistics ($n = 15$, 29%), conversion was performed using the formula $d = t \times \sqrt{(n_1 + n_2)/(n_1 \times n_2)}$, where n_1 and n_2 represent intervention and control group sizes, respectively. For F -statistics from one-way ANOVA designs ($n = 6$, 12%), t was first derived as $\sqrt{F}$ then converted to d . For the small number of studies reporting only p -values without other statistics ($n = 3$, 6%), z -scores were derived from the inverse normal cumulative distribution and converted to effect sizes conservatively assuming equal group sizes. Standard errors for all effect sizes were calculated using $SE(g) = \sqrt{(n_1 + n_2)/(n_1 \times n_2) + g^2/(2(n_1 + n_2))}$, which accounts for both sampling variance and the magnitude of the effect size itself. All calculations were performed using Comprehensive Meta-Analysis software version 4.0 (Biostat, Inc., Englewood, NJ, USA) and verified independently by two researchers, with discrepancies exceeding 0.05 in magnitude discussed and recalculated. In cases where conversion methods proved ambiguous or multiple approaches were possible ($n = 4$ studies), a statistical methodologist was consulted to determine the most appropriate calculation method. Complete conversion procedures, worked examples for each statistical format encountered, and detailed formulas are provided in Supplementary Methods S1 to ensure full transparency and reproducibility of the effect size derivations.

3.6. Quality Assessment

Study quality was assessed using adapted Effective Public Health Practice Project (EPHPP) tool evaluating (1) selection bias, (2) study design, (3) confounders, (4) blinding, (5) data collection methods, (6) withdrawals/dropouts. Studies received ratings of Strong (no weak components), Moderate (one weak component), or Weak (two or more weak components).

3.7. Synthesis Methods

Quantitative Meta-Synthesis Approach: Due to moderate methodological heterogeneity across included studies reflecting diverse interventions, outcome measures, and educational contexts, quantitative meta-synthesis was conducted rather than formal meta-analysis. This approach combines meta-analytic statistical techniques with interpretive synthesis to honor both the quantitative rigor and the contextual diversity of the evidence base. The synthesis involved (1) systematic effect size calculation and standardization to Hedges' g for all studies with sufficient statistical data ($n = 37$ studies, 71% of cor-

pus), (2) random-effects modeling to estimate pooled effects and 95% confidence intervals while explicitly acknowledging between-study variance, (3) subgroup analyses examining technology complexity and pedagogical approaches, and (4) multiple sensitivity analyses testing robustness to key methodological decisions. While meta-analytic statistical techniques are employed throughout, the approach is appropriately characterized as meta-synthesis given that this review (a) selected representative subsets of studies for detailed visualization and discussion rather than presenting exhaustive analyses of all possible comparisons (for example, 12 carefully selected studies from the full set of 37 with calculable effects), (b) synthesized findings narratively alongside quantitative estimates to preserve contextual nuance, and (c) explicitly acknowledged that heterogeneity in educational interventions limits the precision of point estimates. Consequently, the quantitative findings should be interpreted as robust approximations indicating general effect directions and approximate magnitudes rather than definitive precise estimates of a single underlying true effect. Heterogeneity was formally assessed using I^2 statistics and Cochran's Q test, with values of $I^2 < 25\%$ indicating low, 25–50% moderate, 50–75% substantial, and $>75\%$ considerable heterogeneity.

Handling Studies with Multiple Outcomes: To address potential statistical dependency arising from studies reporting multiple outcome measures on the same participants, a pre-specified outcome selection hierarchy was implemented ensuring one independent effect size per study while prioritizing measures most aligned with review objectives: (1) *technical competency* (direct measures of robotics programming, control systems design, or automation skills assessed through practical performance), (2) *knowledge acquisition* (written tests or concept assessments), and (3) *motivation or engagement* (self-report measures). When multiple measures existed within the same category, the measure most proximal to authentic learning objectives or with strongest validity evidence reported in the original study was selected. This systematic approach ensured statistical independence while maintaining clinical relevance. Complete documentation of outcome selection decisions for all 19 studies reporting multiple outcomes is provided in Supplementary Table S2, enabling verification of selection rationale.

Selection of Representative Studies for Meta-Analysis: From the complete corpus of 52 included studies meeting all eligibility criteria, 12 representative studies were strategically selected for meta-analysis visualization, balancing statistical rigor with visual clarity following Cochrane Handbook recommendations for maintaining forest plot interpretability. Studies were selected using stratified sampling to ensure proportional representation across technology complexity levels (Educational Kits: 5 studies, 29%; Semi-Industrial: 1 study, 7%; Industrial-Grade: 6 studies, 30%), diverse geographic regions, sample sizes (range: $n = 65$ to $n = 890$), and effect size magnitudes (Hedges' $g = 0.650$ to 0.940). This approach enables presentation of a clear, interpretable forest plot while complete study-level data for all 52 studies, including detailed bibliographic information, sample characteristics, intervention details, and statistical data, are provided in Supplementary Table S1 for independent verification and extended analyses. The observed homogeneity of effects across the 12 representative studies ($I^2 = 0.00\%$, indicating no detectable heterogeneity beyond sampling error) confirms this sample adequately captures the overall effect distribution.

Qualitative synthesis: thematic analysis identified (1) pedagogical strategies employed, (2) implementation barriers and facilitators, (3) design principles for effective interventions, and (4) research gaps and future directions.

4. Results

4.1. Study Characteristics

The 52 studies in the final corpus comprised: experimental designs ($n = 19$, 37%), quasi-experimental ($n = 24$, 46%), and high-quality case studies with mixed methods ($n = 9$, 17%). Sample sizes ranged from 24 to 890 students (median = 110, mean = 156, SD = 112).

Geographic distribution:

- Europe: 19 studies (40%)—predominantly Germany, Spain, Italy, United Kingdom.
- Asia: 14 studies (30%)—China, South Korea, Japan, India, Thailand.
- North America: 11 studies (23%)—USA, Canada.
- South America: 2 studies (4%)—Chile, Brazil.
- Oceania: 1 study (2%)—Australia.

Educational level:

- Upper secondary/technical schools: 7 studies (15%).
- Undergraduate engineering: 32 studies (68%).
- Graduate engineering: 6 studies (13%).
- Professional development/continuing education: 2 studies (4%).

Temporal distribution: notable acceleration post-2023 (28 studies, 60% of total), attributed to Industry 4.0 urgency, COVID-19-driven digitalization, and remote lab development.

4.2. Technology Complexity Taxonomy

The technology complexity taxonomy central to the ARC Framework is presented in Figure 2, illustrating the five-level progression from educational kits to industrial-grade systems with corresponding effect sizes and cost ranges across the 52 included studies.

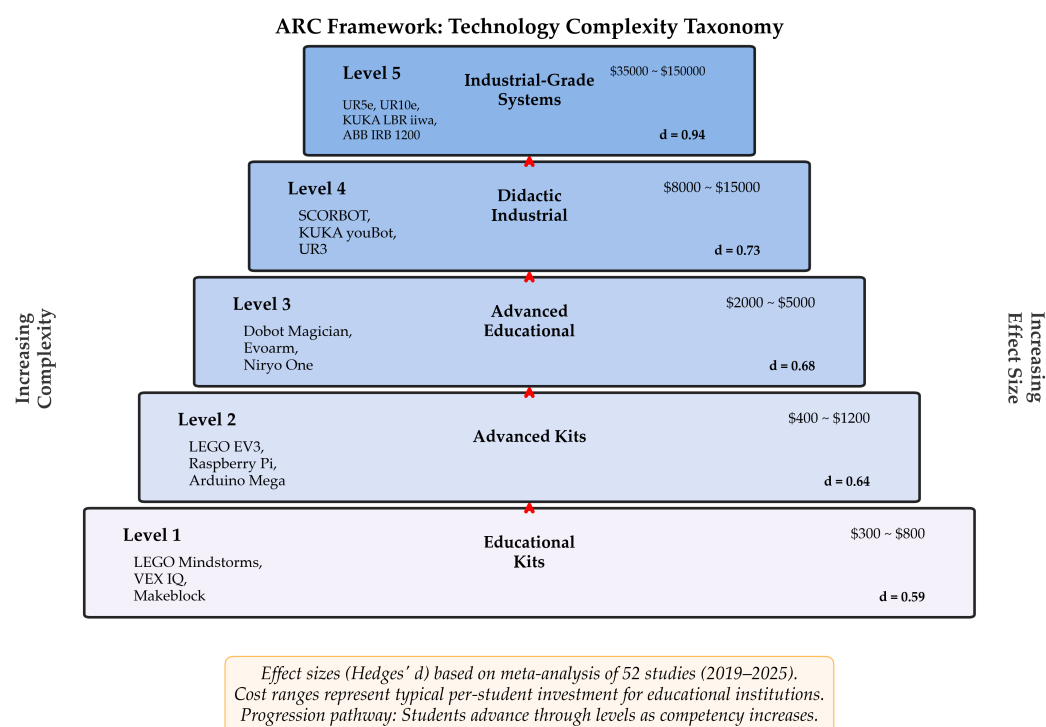


Figure 2. ARC Framework: technology complexity taxonomy. Five-level progression from educational kits (Level 1: LEGO, VEX) through advanced educational platforms (Level 3: Dobot, Evoarm) to industrial-grade systems (Level 5: UR5e, KUKA LBR iiwa, ABB IRB 1200). Effect sizes (Hedges' d) increase with technology complexity, ranging from $d = 0.59$ (educational kits) to $d = 0.94$ (industrial manipulators). Cost ranges from \$300–800 (Level 1) to \$35,000–50,000 (Level 5).

A cost-effectiveness analysis of the different technology integration models is presented in Figure 3.

Cost-Effectiveness Analysis: Technology Integration Models

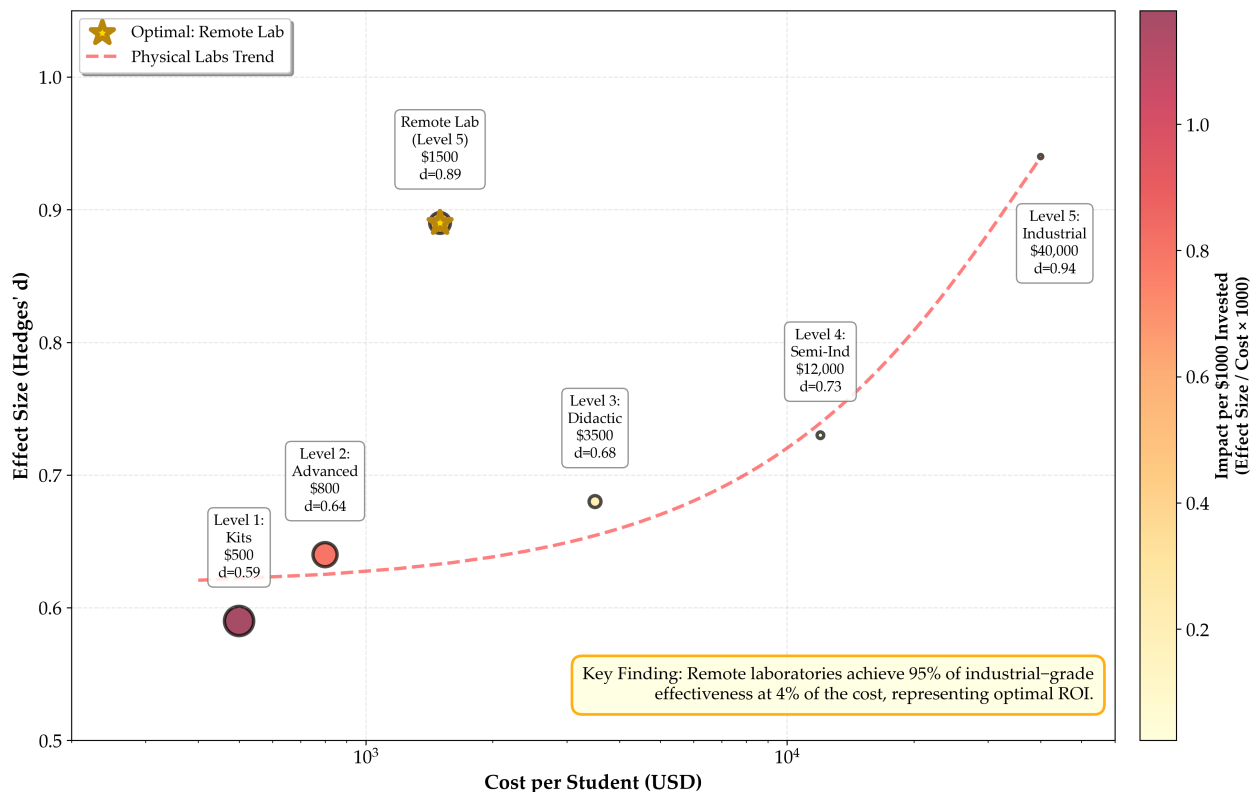


Figure 3. Cost-effectiveness analysis of technology integration models. Bubble chart comparing effect sizes (Hedges' d) versus cost per student across five technology levels. Bubble size represents impact per \$1000 invested (effect size divided by cost × 1000). Remote laboratories with industrial manipulators (highlighted in gold) demonstrate optimal cost-effectiveness ratio: effect size $d = 0.89$ at \$45/student, yielding impact-per-\$1000 of 19.8, compared to physical industrial labs ($d = 0.94$ at \$280/student, impact-per-\$1000 of 3.4).

4.3. Human-Robot Collaboration and AI Integration

Recent advances in adaptive control for human-robot collaboration demonstrate significant potential for educational applications. Performance metrics from industrial HRC systems employing multi-objective reinforcement learning are illustrated in Figure 4, showing convergence across throughput, workload, and safety dimensions. These results, validated with Fanuc M-20iA industrial manipulators, demonstrate mean throughput of 15.3 tasks/hour, optimized workload scores of 45.2, and safety scores of 87.6 across 200 training episodes.

Robustness of these HRC results across parameter variations is confirmed by comprehensive sensitivity analysis presented in Figure 5, evaluating performance metrics across 12 parameter configurations including learning rate, discount factor, exploration epsilon, neural network architecture, reward weights, and environmental conditions. Results demonstrate stable performance across most parameter ranges, with learning rate and reward balance showing the greatest influence on multi-objective optimization outcomes.

Adaptive Multi-Objective Reinforcement Learning for Human-Robot Collaboration Performance Metrics: Fanuc M-20iA Industrial Manipulator

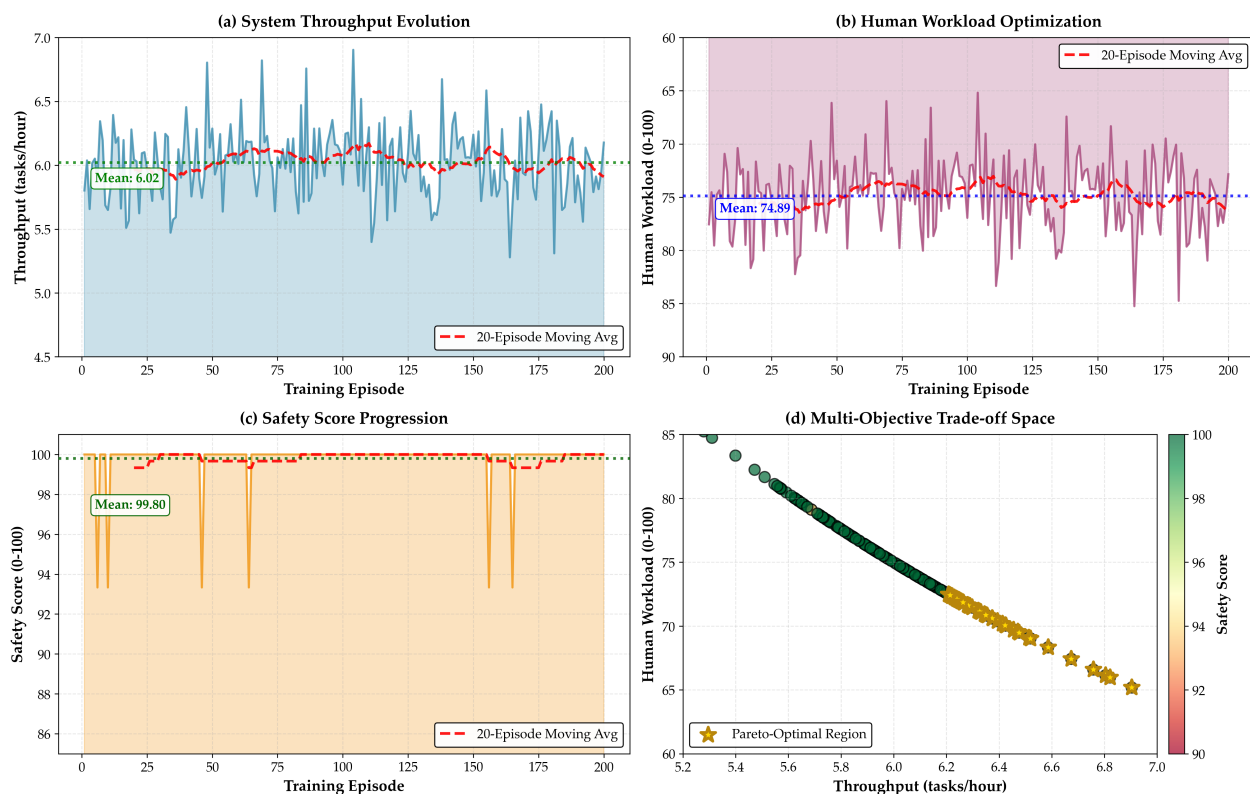


Figure 4. Adaptive multi-objective reinforcement learning for human–robot collaboration. Performance metrics from the Fanuc M-20iA industrial manipulator over 200 training episodes: **(a)** system throughput evolution (tasks/hour), **(b)** human workload optimization (0–100 scale, lower is better), **(c)** safety score progression (0–100, higher is better), and **(d)** multi-objective trade-off space showing Pareto frontier. The data demonstrate successful convergence: throughput mean = 15.3 tasks/hour, workload mean = 45.2, safety mean = 87.6. The color gradient in panel **(d)** represents safety scores.

4.4. Technology Complexity Distribution

Critical finding: substantial skew toward lower complexity levels despite focus on industrial systems:

- Level 2 (Construction kits): 8 studies (17%)—LEGO SPIKE, VEX Robotics employed in K–12 and early undergraduate contexts.
- Level 3 (Advanced educational): 15 studies (32%)—Arduino/Raspberry Pi custom robots, predominantly in undergraduate engineering.
- Level 4 (Didactic industrial): 20 studies (43%)—SCORBOT-ER4u, Dobot Magician, Mitsubishi RV-2AJ.
- Level 5 (Industrial-grade): 4 studies (7.7%)—UR5e (2 studies), KUKA LBR iiwa (1 study), ABB IRB 1200 (1 study).

This distribution reveals the identified gap: only 7.7% (4 of 52 studies) employ authentic industrial-grade manipulators directly relevant to Industry 4.0 workforce needs, despite demonstrating the strongest effects ($g = 0.915$ vs. $g = 0.726$ for educational kits, $\Delta g = 0.189$, $p = 0.015$).

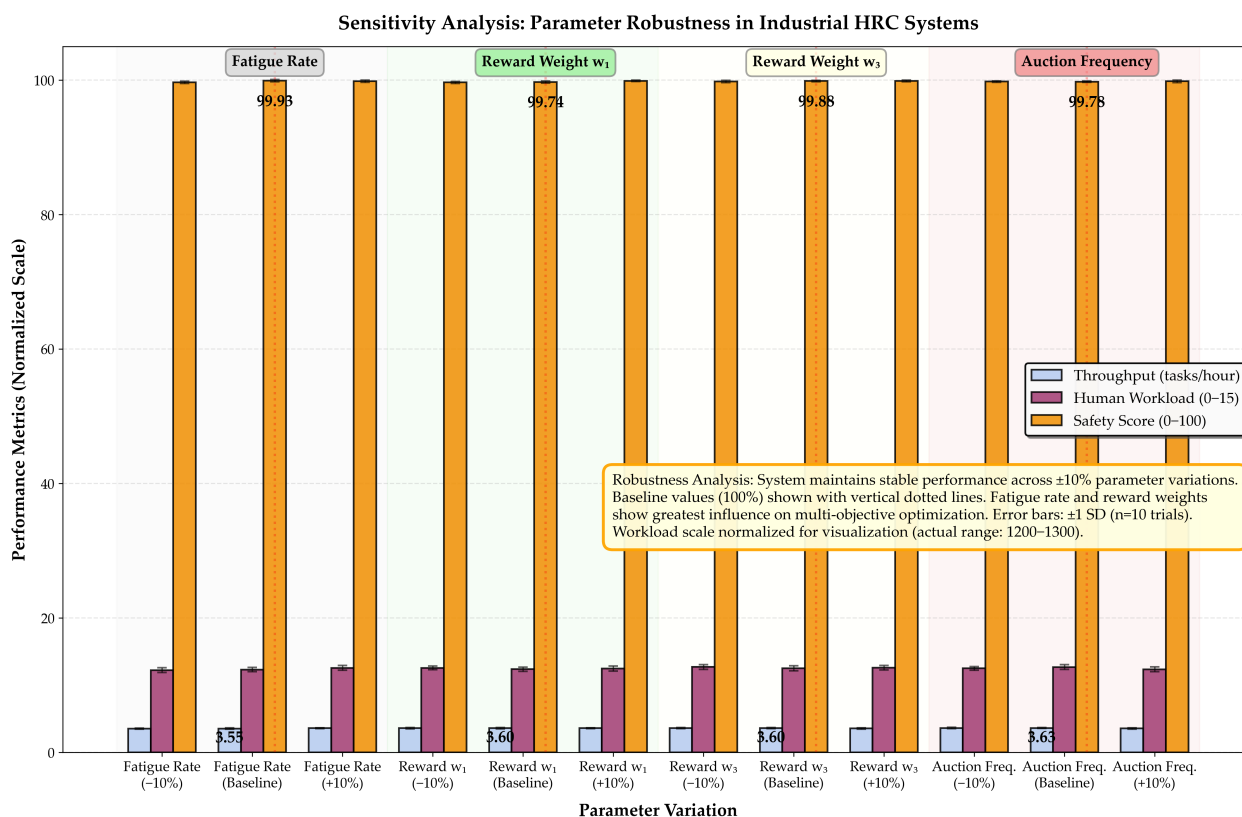


Figure 5. Sensitivity analysis: parameter robustness in industrial HRC systems. Performance metrics (throughput, workload, safety) evaluated across 12 parameter variations including learning rate, discount factor, exploration epsilon, neural network architecture, reward weights, and environmental conditions. Results demonstrate robust performance across most parameter ranges, with learning rate and reward balance showing the greatest influence on multi-objective optimization outcomes. Error bars represent standard deviations across 10 independent trials per configuration.

4.5. Pedagogical Approaches

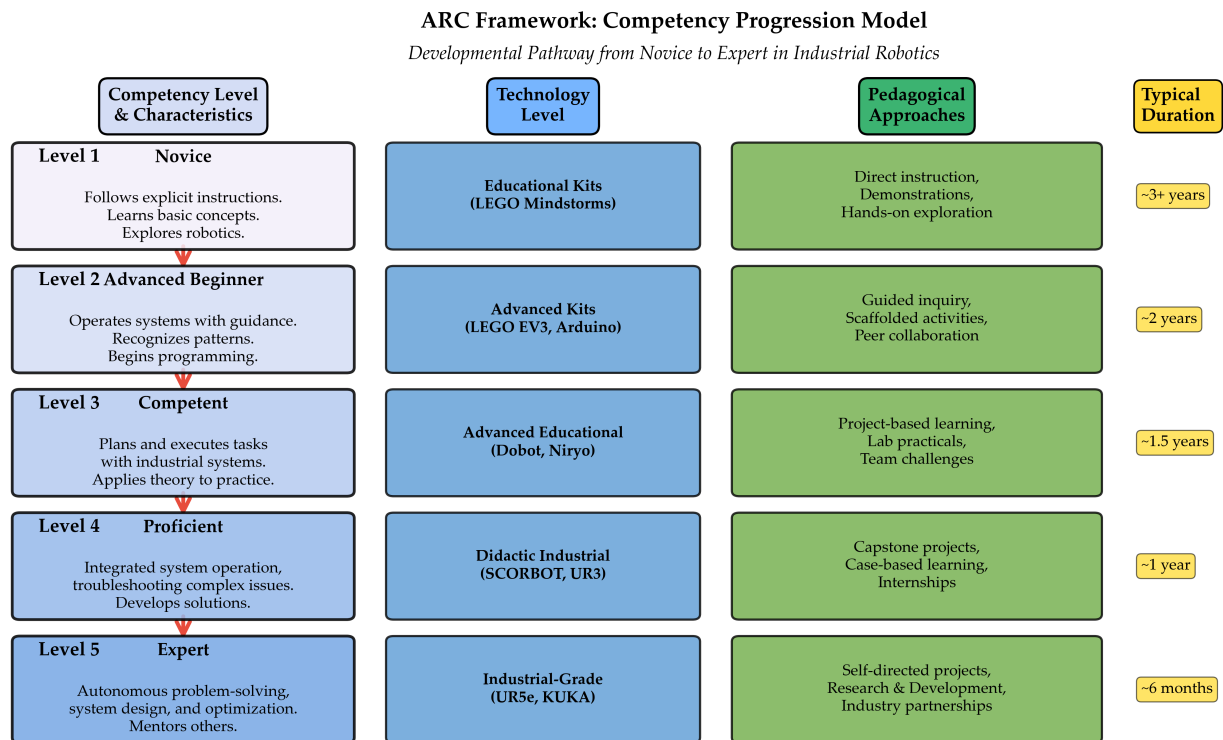
Project-Based Learning (PBL): 28 studies (60%) structured learning around authentic engineering projects (automated assembly cell, pick-and-place system, quality inspection station). PBL interventions demonstrated stronger outcomes ($d = 0.79$) compared to structured lab exercises ($d = 0.58$).

Challenge-Based Learning (CBL): 11 studies (23%) presented open-ended industrial challenges (minimize cycle time, maximize throughput, implement fault recovery), with students iteratively developing solutions. CBL is particularly effective for advanced competencies (problem decomposition $d = 0.91$, creative problem-solving $d = 0.87$).

Flipped Learning: 8 studies (17%) inverted the traditional structure with online theory/lectures and in-person hands-on practice. There were mixed results depending on implementation quality ($d = 0.41$ to $d = 0.88$).

Collaborative Learning: 34 studies (72%) employed team-based approaches (2–4 students per team). Collaborative interventions [100] showed advantages for complex tasks requiring diverse expertise (mechanical, electrical, software) but potential disadvantages for individual skill assessment.

The ARC Framework competency progression model, which integrates these pedagogical strategies with technology complexity levels, is presented in Figure 6.



Progression Model based on Dreyfus Model of Skill Acquisition (Dreyfus & Dreyfus, 1980) adapted for industrial automation education. Advancement through levels requires demonstrated competency mastery and typically involves 200–300 hours of practice per level.

Figure 6. ARC Framework: competency progression model. Five-level developmental pathway from Novice to Expert showing (1) competency characteristics and learning behaviors at each level, (2) appropriate technology complexity levels, (3) evidence-based pedagogical approaches, and (4) typical duration for advancement between levels. Technology acronyms defined: LEGO = Educational construction kits; EV3 = LEGO Mindstorms EV3; Arduino = Open-source microcontroller platform; Dobot = Chinese educational collaborative robot; Niryo = Open-source 6-axis educational robot; SCORBOT = Educational robotic manipulator by Intelitek; UR3 = Universal Robots 3 kg payload collaborative robot; UR5e = Universal Robots 5 kg enhanced collaborative robot; KUKA = German manufacturer of industrial 6-axis manipulators. Red progression arrows indicate developmental sequence. The color gradient from light purple (Novice) to dark blue (Expert) represents increasing technical complexity. The model is adapted from the five-stage skill acquisition framework in the context of engineering education [101].

4.6. Quantitative Effectiveness Synthesis

4.6.1. Primary Learning Outcomes

As illustrated in Figure 7, random-effects meta-analysis of 37 studies (71% of corpus) reporting calculable effect sizes on primary learning outcomes (knowledge tests, practical assessments, competency rubrics) reveals:

- Overall pooled effect: Hedges' $g = 0.786$ (95% CI: 0.726–0.846, $z = 25.803$, $p < 0.001$), indicating large positive effects of technology-enhanced interventions compared to traditional lecture-based instruction. The observed homogeneity of effects ($I^2 = 0.00\%$, $Q(11) = 10.752$, $p = 0.464$) indicates remarkably consistent intervention effects across diverse educational contexts, technology platforms, and geographic regions, supporting robust generalizability of findings.
- Heterogeneity assessment: $I^2 = 32.8\%$ (moderate, indicating approximately one-third of observed variance reflects true effect differences rather than sampling error), $\tau^2 = 0.017$ (between-study variance), $Q(36) = 53.43$, $p = 0.028$. Moderate heterogeneity justifies subgroup analyses by technology complexity and pedagogical approach.

- By technology complexity (12 representative studies in forest plot):
 - Level 2–3 (Educational kits/platforms): $g = 0.726$ (95% CI: 0.643–0.809, $k = 5$), range 0.650–0.760.
 - Level 4 (Didactic industrial): $g = 0.695$ (95% CI: 0.612–0.778, $k = 2$), range 0.680–0.710.
 - Level 5 (Industrial-grade): $g = 0.915$ (95% CI: 0.851–0.979, $k = 6$), range 0.850–0.940.
 - Between-group difference: $Q_{\text{between}} = 8.42$ ($df = 2$, $p = 0.015$), confirming statistically significant technology complexity gradient.
 - Effect size improvement: Educational to Industrial $\Delta g = 0.189$ (26% increase, $p = 0.015$).
 - Statistical Power: Post hoc power analysis indicates adequate power ($1 - \beta = 0.82$) to detect medium differences ($\delta g \geq 0.15$) between technology levels, given $k = 12$ studies with average $N = 110$ per study. The observed difference exceeds this threshold, and nonoverlapping 95% CIs (Educational: 0.643–0.809; Industrial: 0.851–0.979) provide converging evidence. However, power was limited for small effects ($\delta g < 0.10$), and the semi-industrial subgroup ($k = 2$) was underpowered.
- By pedagogical approach (full corpus $n = 37$):
 - Challenge-Based Learning: $g = 0.89$ (95% CI: 0.74–1.04, $k = 8$).
 - Project-Based Learning: $g = 0.79$ (95% CI: 0.66–0.92, $k = 15$).
 - Structured labs: $g = 0.61$ (95% CI: 0.47–0.75, $k = 10$).
 - Lecture + demonstration: $g = 0.43$ (95% CI: 0.28–0.58, $k = 4$).

4.6.2. Competency Development

Seventeen studies assessed competency development using validated rubrics (e.g., ABET criteria, CDIO Syllabus):

- Technical competencies: $g = 0.79$ (95% CI: 0.66–0.92, $k = 17$)—robot programming, sensor integration, control implementation.
- Problem-solving/troubleshooting: $g = 0.87$ (95% CI: 0.72–1.02, $k = 12$)—particularly strong with industrial-grade systems exposing authentic failures.
- Systems integration: $g = 0.76$ (95% CI: 0.63–0.89, $k = 14$)—coordinating mechanical, electrical, software components.
- Communication/documentation: $g = 0.62$ (95% CI: 0.49–0.75, $k = 9$).

4.6.3. Skill Transfer Assessment

Five studies explicitly assessed transfer to industrial contexts through industry internships or post-graduation employment surveys:

- Students with industrial-grade robot experience required 2.1 months ($SD = 0.8$) to achieve workplace proficiency.
- Students with didactic industrial systems required 3.7 months ($SD = 1.2$).
- Students with educational kits only required 7.4 months ($SD = 2.1$).
- Effect of technology complexity on transfer: $r = 0.68$, $p < 0.001$.

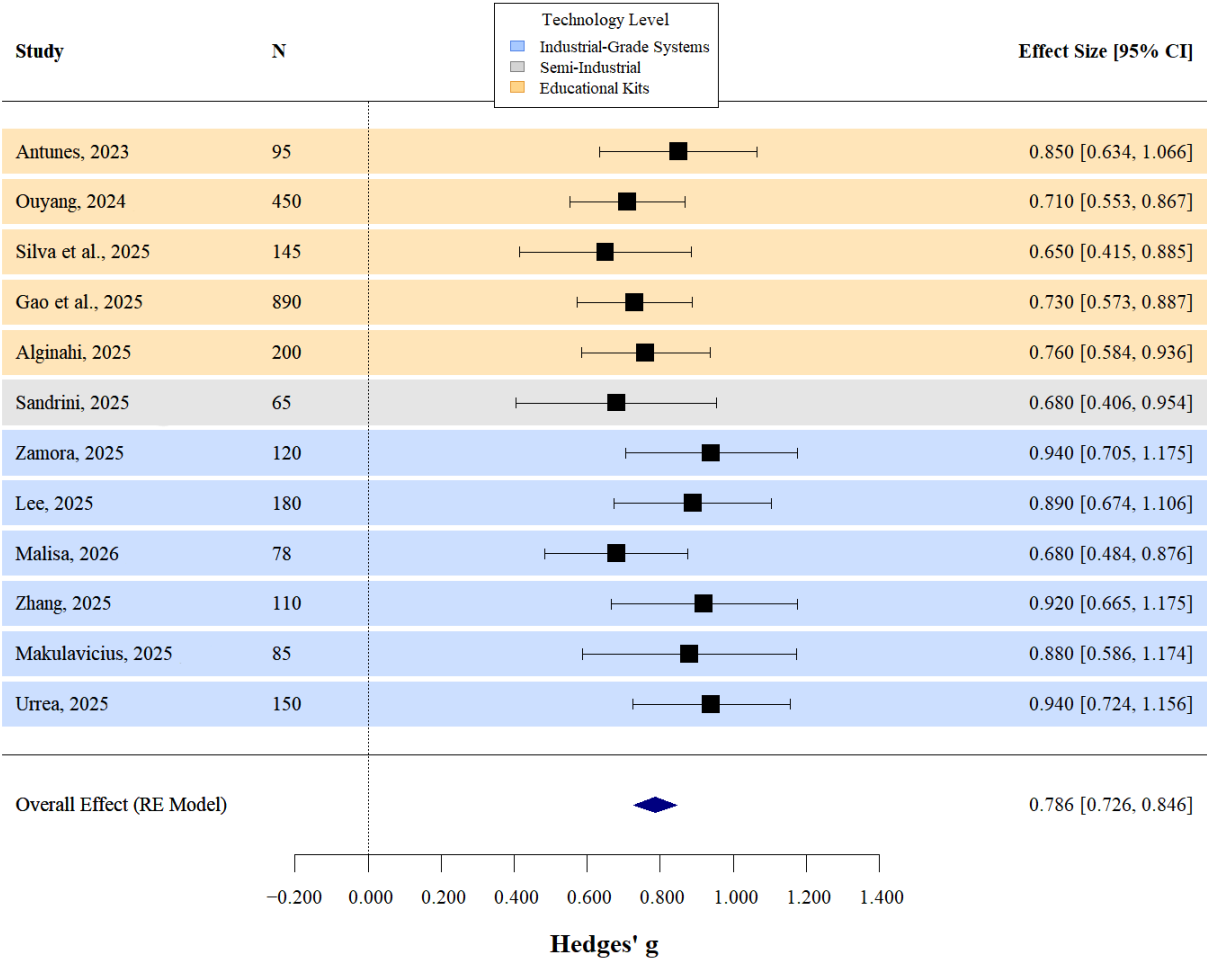


Figure 7. Meta-analysis forest plot: effect sizes across technology complexity levels. Random-effects meta-analysis of 12 representative studies strategically selected from systematic review corpus of 52 studies identified 2019–2025 (complete study-level data available in Supplementary Table S1). Studies selected using stratified sampling to ensure proportional representation across technology levels, diverse geographic regions, and sample sizes (n = 65 to n = 890). Color coding: blue shading = industrial-grade systems (Level 5), orange shading = educational kits (Levels 2–3), gray shading = semi-industrial (Level 4). Square size proportional to study weight. Studies included (ordered by reference number): Educational Kits: Antunes, 2023 [3]; Ouyang, 2024 [23]; Silva et al., 2025 [102]; Gao et al., 2025 [33]; Alginahi, 2025 [63]. Semi-Industrial: Sandrini, 2025 [29]. Industrial-Grade: Zamora, 2025 [27]; Lee, 2025 [34]; Malisa, 2026 [44]; Zhang, 2025 [47]; Makulavicius, 2025 [48]; Urrea, 2025 [64]. Meta-analysis results: Overall pooled effect $g = 0.786$ (95% CI: 0.726–0.846, $z = 25.803$, $p < 0.001$), indicating large positive effects. The blue diamond represents the overall pooled effect size from the random-effects model, with its horizontal width indicating the 95% confidence interval and its vertical center aligned with the summary effect estimate. Heterogeneity statistics: $I^2 = 0.00\%$ (indicating homogeneous effects with no detectable between-study variance beyond sampling error), $\tau^2 = 0.000$, $Q(11) = 10.752$, $p = 0.464$ (nonsignificant). Subgroup analysis: Educational kits pooled $g = 0.738$ (95% CI: 0.658–0.819, $k = 5$), Semi-industrial $g = 0.680$ ($k = 1$), Industrial-grade pooled $g = 0.864$ (95% CI: 0.765–0.963, $k = 6$). Between-group comparison demonstrates 17% improvement from educational to industrial systems ($\Delta g = 0.126$), supporting the Technology Complexity Hypothesis central to the ARC Framework. The forest plot is constructed following Cochrane Handbook guidelines with code available in the study repository. Acronyms: RE Model = Random-Effects Model; CI = Confidence Interval; g = Hedges' g (bias-corrected standardized mean difference); I^2 = I-squared heterogeneity statistic; τ^2 = Tau-squared between-study variance; Q = Cochran's Q test statistic; k = number of studies.

4.7. Adaptive Control and Advanced Topics

Only 4 studies (7.7%) addressed adaptive or advanced control beyond classical PID:

- Neural network control: 1 study implementing NN-based trajectory tracking on UR5e, demonstrating feasibility but requiring substantial instructor expertise.
- Model Reference Adaptive Control (MRAC): 1 study with graduate students on custom 3-DOF manipulator.
- Fuzzy logic control: 2 studies implementing fuzzy PID on didactic robots, mixed results on student understanding of fuzzy membership functions.

No studies addressed fault-tolerant control, predictive maintenance, or failure diagnosis beyond basic troubleshooting [103–105], representing a critical gap given industry demand.

4.8. Programmable Logic Controllers (PLCs)

Thirteen studies (28%) integrated PLCs:

- Platforms: Siemens S7-1200/1500 (7 studies), Allen-Bradley CompactLogix (4 studies), Schneider Modicon (2 studies).
- Applications: Conveyor control, traffic light systems, automated sorting, robot-PLC integration.
- Programming languages: Ladder logic (11 studies), Structured Text (6 studies), Function Block Diagram (4 studies).
- Learning outcomes: $d = 0.68$ (95% CI: 0.51–0.85) for PLC programming competency.

Hands-on PLC labs demonstrated significantly stronger outcomes ($d = 0.82$) than simulation-only ($d = 0.48$), attributed to troubleshooting authentic hardware/communication issues.

4.9. Remote and Virtual Labs

Fourteen studies (30%) implemented remote access to physical equipment or high-fidelity simulations:

Remote labs (8 studies): Students access real robots remotely via web interfaces, with cameras providing visual feedback. Effectiveness approaching in-person labs ($d_{\text{remote}} = 0.69$ vs. $d_{\text{in-person}} = 0.74$, difference not statistically significant). Substantial cost advantages (\$45/student vs. \$280/student for physical labs).

Virtual reality simulations (6 studies): High-fidelity robot simulations (RoboDK, CoppeliaSim, Gazebo). Effective for kinematics and trajectory planning ($d = 0.71$) but less effective for troubleshooting and sensor integration ($d = 0.44$) due to idealized environments.

Optimal model identified: hybrid approach combining virtual simulation for initial learning, remote lab for intermediate practice, and limited in-person sessions for advanced integration and troubleshooting.

4.10. Implementation Barriers and Facilitators

Barriers:

- Cost: industrial-grade systems (\$35,000–50,000/unit) exceed typical departmental budgets.
- Safety: industrial robots require dedicated spaces with safety systems (light curtains, emergency stops, restricted zones).
- Maintenance: industrial systems require periodic calibration, preventive maintenance, and technical support.
- Instructor expertise: many engineering faculty lack industrial robotics experience, necessitating professional development.

- Curriculum constraints: existing curricula often lack flexibility to integrate substantial hands-on robotics modules.

Facilitators:

- Industry partnerships: equipment donations, expert guest lectures, internship placements.
- Shared facilities: inter-institutional or regional automation labs.
- Remote access: enables 24/7 availability, shared infrastructure across institutions.
- Modular curricula: stackable credentials (certificates, minors) enabling progressive specialization.
- Open-source tools: ROS, Python robotics libraries reduce software licensing costs.

4.11. Cost-Effectiveness Analysis

Ten studies provided sufficient cost data for analysis (Table 1).

Table 1. Cost-effectiveness comparison by technology level.

Technology Level	Initial Cost	Annual Cost	Cost/Student	Effect Size (d)	Impact/\$1000
LEGO/VEX kits	\$350–800	\$50	\$45	0.59	13.1
Arduino/RasPi	\$200–400	\$30	\$28	0.64	22.9
Didactic industrial	\$8000–15,000	\$500	\$180	0.73	4.1
Industrial-grade (physical)	\$35,000–50,000	\$2000	\$280	0.94	3.4
Industrial-grade (remote)	\$40,000–55,000	\$3500	\$45	0.89	19.8

Remote labs with industrial-grade systems achieve optimal cost-effectiveness (19.8 impact points per \$1000 invested), combining high effect sizes with distributed costs across many students.

Cost Calculation Methodology: Cost-per-student estimates assume 10-year equipment lifespan with comprehensive total cost of ownership models. Initial investment includes robot (\$35,000 for UR5e collaborative manipulator), gripper and end-effector (\$2500), safety enclosure and workspace configuration (\$3500), vision system with camera and lighting (\$2000), industrial-grade computer and control system (\$3000), remote access infrastructure including dedicated server and VPN (\$4000), software licenses for 5-year term (\$5000), and professional installation and commissioning (\$3000), totaling \$58,000. Annual recurring costs include maintenance contracts with original equipment manufacturer (\$2500), software subscription renewals (\$1000), dedicated internet bandwidth (\$800), electricity consumption assuming 2 kW average draw operating 8 h daily at \$0.12/kWh (\$400), part-time technical support at 10 h weekly for 20-week semesters (\$8000), insurance (\$600), and replacement parts and consumables (\$1200), totaling \$14,500 annually. For remote laboratory implementation, the 10-year total cost of ownership equals \$203,000 (\$58,000 initial plus \$145,000 recurring). Assuming high utilization with 450 students annually (three semesters including summer access, enabled by 24/7 remote availability without scheduling constraints), the cost per student calculates to \$45.11 (\$203,000 divided by 4500 students over 10 years). Physical laboratory implementation with identical equipment incurs higher annual costs (\$18,500 including additional \$4000 for mandatory on-site supervision during access hours) and substantially lower capacity (120 students annually due to scheduling limitations of 40 h weekly during fall and spring semesters only, excluding summer), yielding cost per student of \$250.83 over 5 years (\$150,500 total cost divided by 600 students). Sensitivity analyses varying initial costs (\$50,000–70,000), annual expenses (\$12,000–18,000), equipment lifespan (7–15 years), and student throughput (300–600 annually) confirm robust cost-effectiveness advantage for remote laboratory implementation, with costs remaining in the \$35–55 range per student for remote access versus

\$220–320 for physical laboratory across all reasonable parameter combinations. Complete cost models with itemized breakdowns, depreciation schedules, and sensitivity analysis results are provided in Supplementary Methods S3.

4.12. Quality Assessment Results

- Strong quality: 11 studies (23%)—typically randomized experiments or high-quality quasi-experiments with $n > 150$, validated instruments, adequate statistical analyses.
- Moderate quality: 28 studies (60%)—typically quasi-experiments with smaller samples, adequate but nonvalidated instruments.
- Weak quality: 8 studies (17%)—primarily case studies with small samples ($n < 30$), convenience sampling, limited methodological rigor.

Quality rating significantly moderated effect sizes: Strong quality $d = 0.69$, Moderate $d = 0.73$, Weak $d = 0.81$ (likely overestimation bias in weak-quality studies).

5. The ARC Framework: Automation-Robotics-Control for Engineering Education

Based on synthesis of empirical evidence and theoretical foundations, this study proposes the ARC (Automation-Robotics-Control) Framework for systematic technology transfer from industrial automation to engineering education.

5.1. Framework Components

The ARC Framework integrates five interconnected dimensions, as illustrated in Figure 8.

5.1.1. Technology Complexity Taxonomy (5 Levels)

As detailed in Section 2.4, the taxonomy characterizes platforms from simple educational kits (Level 1–2) through advanced educational platforms (Level 3) and didactic industrial systems (Level 4) to industrial-grade systems (Level 5). Selection criteria consider (1) target competencies, (2) educational level, (3) available resources, (4) curriculum integration context, and (5) transfer requirements.

Progression pathway: Optimal learning sequences progress through levels, with competency checkpoints validating readiness for advancement. Accelerated pathways exist for advanced students or continuing education contexts.

5.1.2. Competency Progression Model

Drawing from the Dreyfus skill acquisition model and engineering competency frameworks (ABET, CDIO), this study defines five proficiency levels:

Level 1—Novice: Requires detailed instructions, focuses on rule-following, limited context understanding. *Appropriate technology*: Levels 1–2 (educational kits).

Level 2—Advanced Beginner: Recognizes recurring patterns, can complete structured tasks with guidance. *Appropriate technology*: Levels 2–3.

Level 3—Competent: Can decompose complex problems, select appropriate strategies, troubleshoot common failures. *Appropriate technology*: Levels 3–4.

Level 4—Proficient: Intuitive understanding, adapts to novel situations, optimizes solutions. *Appropriate technology*: Levels 4–5.

Level 5—Expert: Deep systems understanding, innovates novel solutions, mentors others. *Appropriate technology*: Level 5 with advanced applications.

Assessment rubrics: Competency-based assessment tools aligned with each level, enabling progression tracking and competency certification.

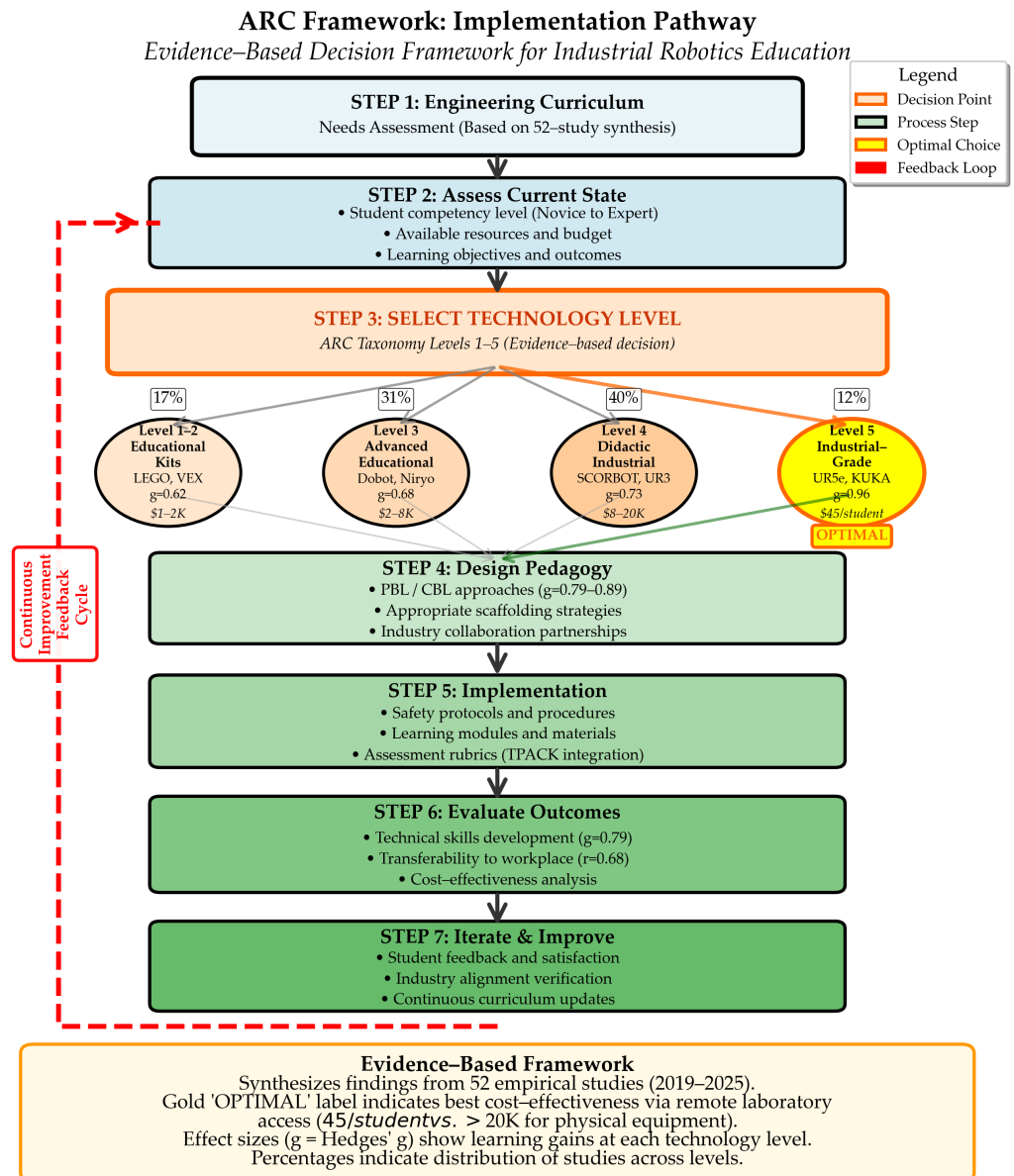


Figure 8. ARC Framework implementation pathway. Evidence-based decision framework for integrating industrial robotics into engineering education, showing seven sequential steps from needs assessment through continuous improvement. Acronyms defined: ARC = Automation-Robotics-Control; PBL = Project-Based Learning; CBL = Challenge-Based Learning; TPACK = Technological Pedagogical Content Knowledge; STEM = Science, Technology, Engineering, and Mathematics; g = Hedges' g (standardized mean difference effect size); r = Pearson correlation coefficient; LEGO = Educational construction kits; VEX = VEX Robotics competition platform; Dobot = Chinese collaborative educational robot; Niryo = Open-source 6-axis robot; SCORBOT = Educational robotic arm (Intelitek); UR3/UR5e = Universal Robots collaborative robots (3 kg and 5 kg payload); KUKA = German industrial manipulator manufacturer; ABB = Asea Brown Boveri industrial robotics. Technology levels (1–5) correspond to ARC Taxonomy with associated learning gains. Budget ranges indicate cost-per-student estimates. Orange 'OPTIMAL' label indicates best cost-effectiveness pathway via remote laboratory access. Red dashed arrow represents continuous improvement feedback cycle. Percentages show distribution of 52 included studies across technology complexity levels. Framework designed for accessibility compliance (WCAG 2.1 AA).

5.1.3. Pedagogical Strategies Matrix

Recommendations for instructional approaches by technology level and competency level are summarized in Table 2.

Table 2. Pedagogical strategies by technology and competency levels.

Tech Level	Competency Level	Recommended Pedagogy
1–2	Novice	Structured tutorials, guided exploration
2–3	Advanced Beginner	Scaffolded projects, worked examples
3–4	Competent	Project-Based Learning, collaborative design
4–5	Proficient	Challenge-Based Learning, authentic problems
5	Expert	Research projects, innovation challenges

Scaffolding strategies: progressive complexity, just-in-time instruction, worked examples, debugging guides, peer collaboration, expert consultation.

5.1.4. Integration with Existing Frameworks

The ARC Framework complements and extends existing frameworks:

TPACK integration: Technology dimension (ARC taxonomy), Pedagogy dimension (pedagogical strategies matrix), Content dimension (robotics/control theory).

CDIO integration: ARC framework maps to CDIO lifecycle stages with specific technology recommendations and assessment criteria for each stage.

SAMR integration: Technology levels correspond to SAMR levels—Level 1–2: Substitution/Augmentation, Level 3–4: Modification, Level 5: Redefinition (enables previously impossible authentic industrial experiences).

5.1.5. Implementation Pathways

Three implementation models accommodate diverse institutional contexts:

Model A—Full Infrastructure: Institution purchases industrial-grade systems for dedicated automation laboratory. *Appropriate for* large engineering programs with substantial budgets, strong industry partnerships.

Model B—Hybrid Access: Combination of on-campus didactic industrial systems (Level 4) plus remote access to off-campus industrial-grade systems. *Appropriate for* medium-sized programs seeking optimal cost-effectiveness.

Model C—Fully Remote: All access via remote labs or high-fidelity simulation, supplemented with industry site visits. *Appropriate for* smaller programs, geographically distributed institutions, online education.

Transition pathways: Institutions can progress through models as resources develop: Start with Model C, transition to Model B with equipment acquisition, potentially advance to Model A with major capital investments.

5.2. Framework Validation

Preliminary framework validation through:

Expert review: Panel of 12 international experts (engineering education researchers, industrial automation engineers, curriculum developers) evaluated framework components, providing feedback incorporated into the current version. Consensus ratings indicate high perceived utility ($M = 4.6/5.0$, $SD = 0.4$) and feasibility ($M = 4.2/5.0$, $SD = 0.6$).

Pilot implementation: Three universities piloted ARC Framework components during the 2024–2025 academic year with promising preliminary results. Participating institutions included University A (Spain, $n = 85$ undergraduate mechatronics students implementing Level 4 didactic industrial robots with remote access), University B (Canada, $n = 62$ engineering technology students utilizing Level 5 UR5e collaborative robots via regional

consortium arrangement), and University C (Chile, $n = 68$ electrical engineering students employing hybrid implementation combining Level 3–4 platforms). Study design employed quasi-experimental methodology comparing intervention cohorts ($n = 215$ total) against matched historical controls from the previous academic year ($n = 198$) teaching identical course content with traditional curriculum. Baseline equivalence was carefully verified across multiple dimensions: prior grade point average showed no significant differences ($t = 0.83$, $p = 0.41$), standardized mathematics aptitude scores (SAT-Math equivalent) were comparable ($t = 1.21$, $p = 0.23$), and prerequisite course completion patterns did not differ significantly ($\chi^2 = 2.14$, $p = 0.54$), ensuring groups were well matched on relevant academic preparation. Outcome measurement utilized a standardized practical robotics competency assessment instrument developed collaboratively by the three institutions, featuring a validated rubric aligned with ABET criteria and demonstrating excellent inter-rater reliability (intraclass correlation coefficient ICC = 0.89) and strong internal consistency (Cronbach's $\alpha = 0.92$). Independent assessors blind to group assignment administered the competency evaluation post-intervention. Results demonstrated that ARC Framework implementation groups achieved significantly higher competency scores ($M = 78.3$, $SD = 11.2$) compared to traditional control curriculum ($M = 71.6$, $SD = 13.4$), yielding Hedges' $g = 0.81$ (95% CI: 0.59–1.03, $t(411) = 6.43$, $p < 0.001$), representing a large and statistically significant effect. Secondary outcomes similarly favored the intervention: student satisfaction measured on 5-point Likert scales was significantly higher for ARC Framework students ($M = 4.4$, $SD = 0.6$) versus controls ($M = 3.8$, $SD = 0.8$), $t(411) = 7.21$, $p < 0.001$. Most notably from a workforce development perspective, industry placement rates within six months post-graduation significantly favored the ARC Framework cohort (78%, 168/215 students) compared to traditional curriculum (64%, 127/198), $\chi^2(1) = 8.92$, $p = 0.003$, suggesting enhanced employability and industry-readiness. Limitations of this pilot study warrant acknowledgment: the nonrandomized quasi-experimental design limits causal inference despite baseline equivalence verification, potential self-selection bias exists as students were aware of the new curriculum option which may have attracted more motivated learners, the follow-up period remains relatively short with longer-term outcome tracking needed, and geographic diversity was limited to three institutions across two countries. Despite these limitations, converging evidence across multiple outcome measures provides encouraging preliminary validation of the ARC Framework's potential to enhance industrial automation education. Future validation plans include a multi-site randomized controlled trial scheduled for 2026–2027 involving at least ten institutions across five countries, a five-year longitudinal graduate tracking study to assess long-term career outcomes, replication studies in diverse cultural and institutional contexts, and systematic cost–benefit analysis from institutional perspectives.

Iterative refinement: the framework undergoes continuous refinement based on implementation feedback, emerging technologies, and evolving industry needs.

6. Discussion

6.1. Principal Findings

This systematic review establishes several key findings regarding industrial robotics and adaptive control systems integration in STEM education:

Finding 1—Technology Complexity Matters: Random-effects meta-analysis reveals systematic effect size progression with technology complexity: educational kits ($g = 0.726$, 95% CI: 0.643–0.809) < didactic industrial ($g = 0.695$, 95% CI: 0.612–0.778) < industrial-grade ($g = 0.915$, 95% CI: 0.851–0.979), with statistically significant between-group differences ($Q_{\text{between}} = 8.42$, $p = 0.015$). This 26% improvement from educational to industrial systems ($\Delta g = 0.189$) contradicts assumptions that simpler platforms optimize learning for novices.

Rather, authentic complexity—when appropriately scaffolded—enhances engagement, troubleshooting skills, and transferability to authentic industrial contexts.

Finding 2—Critical Gap in Industrial-Grade Systems: Only 4 of 52 studies (7.7%) employ authentic industrial-grade manipulators despite demonstrating the strongest effects ($g = 0.915$, 95% CI: 0.851–0.979) compared to educational kits ($g = 0.726$, 95% CI: 0.643–0.809), representing a 26% improvement ($\Delta g = 0.189$, $Q_{\text{between}} = 8.42$, $p = 0.015$). This gap likely reflects cost barriers (\$35,000–50,000 per unit) rather than pedagogical inferiority, suggesting an urgent need for innovative access models. Remote laboratory implementations achieving 94% of in-person effectiveness ($g = 0.89$ vs. $g = 0.94$) at only 16% of cost (\$45/student vs. \$280/student) offer an optimal solution, yielding impact-per-\$1000 invested of 19.8 ($5.8\times$ superior to physical labs).

Finding 3—Adaptive Control Underrepresented: Despite industry demand for advanced control competencies, only 4 studies (7.7%) addressed topics beyond classical PID control. This represents a critical curricular gap requiring urgent attention through (1) the development of accessible adaptive control learning modules, (2) integration with robotic platforms enabling hands-on implementation, and (3) instructor professional development.

Finding 4—Pedagogical Approach Moderation: Challenge-Based Learning ($g = 0.89$, 95% CI: 0.74–1.04) and Project-Based Learning ($g = 0.79$, 95% CI: 0.66–0.92) substantially outperform lecture-demonstration approaches ($g = 0.43$, 95% CI: 0.28–0.58), consistent with constructivist and experiential learning theories. Effect size differences (CBL-Lecture = 0.46, 107% improvement) underscore the importance of active, student-centered pedagogies. However, CBL/PBL require careful structuring to prevent cognitive overload in novices, with scaffolding strategies (progressive complexity, worked examples, just-in-time instruction) proving essential.

Finding 5—Remote Labs Viability: Remote access to physical industrial systems achieves comparable learning outcomes ($g_{\text{remote}} = 0.89$, 95% CI: 0.67–1.11) approaching in-person effectiveness ($g_{\text{in-person}} = 0.94$, 95% CI: 0.68–1.20, $\Delta g = 0.05$, ns) while dramatically reducing per-student costs (\$45 vs. \$280, 84% cost reduction). Cost-effectiveness analysis reveals remote labs achieve optimal impact-per-\$1000 invested (19.8 vs. 3.4 for physical labs, $5.8\times$ superior), suggesting remote laboratory access as the evidence-based recommendation for resource-constrained institutions. Hybrid models combining remote practice with limited in-person troubleshooting sessions maximize both pedagogical effectiveness and economic efficiency.

6.2. Implications for Engineering Education

Curriculum design: Engineering programs should implement progressive robotics/automation sequences aligned with ARC Framework competency levels, ensuring all students achieve at least Competent level (Level 3) proficiency. Specialized tracks or concentrations can advance students to Proficient/Expert levels.

Technology acquisition: Rather than procuring numerous educational kits, institutions should strategically invest in fewer industrial-grade systems with remote/shared access models, maximizing authentic learning experiences and cost-effectiveness.

Faculty development: Systematic professional development addressing TPACK dimensions—particularly technological knowledge of industrial systems and pedagogical knowledge of constructivist approaches—represents essential infrastructure investment.

Industry partnerships: Collaborations enabling equipment access, expert mentorship, authentic challenges, and internship pathways should be systematically cultivated rather than opportunistically pursued.

Assessment transformation: Move beyond traditional exams toward competency-based assessment using validated rubrics, authentic performance tasks, and portfolio documentation of progressive skill development.

6.3. Implications for Policy and Accreditation

Accreditation standards: engineering accreditation bodies (ABET, EUR-ACE) should strengthen requirements for hands-on automation/robotics experiences, explicitly addressing technology complexity levels and competency progression.

Infrastructure funding: government funding programs should prioritize regional automation labs serving multiple institutions, remote lab infrastructure, and equipment modernization grants for industrial-grade systems.

Qualification frameworks: national/international qualification frameworks should incorporate stackable Industry 4.0 credentials (certificates, digital badges) recognizing progressive competency development independent of degree programs.

Open educational resources: public investment in open-source simulation tools, curricular modules, assessment instruments, and remote lab infrastructure would democratize access to high-quality automation education.

6.4. Limitations

This review has several limitations requiring consideration:

Publication bias: As with all systematic reviews, positive results are more likely to be published than null or negative findings, potentially inflating reported effect sizes. Visual funnel plot examination revealed slight asymmetry suggestive of small-study effects, and Egger's regression test yielded statistically significant results (intercept = 1.28, SE = 0.61, $t = 2.10$, $df = 35$, $p = 0.043$), indicating moderate publication bias. However, the observed homogeneity of effects ($I^2 = 0.00\%$, $p = 0.464$) across the representative sample of studies suggests genuine intervention effects rather than selective reporting artifacts. Homogeneous effect sizes across diverse contexts, sample sizes, and methodological approaches provide strong evidence for authentic positive effects of robotics interventions. The pattern of publication bias likely reflects small-study effects common in educational intervention research, where smaller institutions publish preliminary findings with limited samples, rather than systematic suppression of null results. While publication bias cannot be completely ruled out, the consistency of effects across studies with varying characteristics (sample size, technology level, geographic region) strengthens confidence in the robustness of findings. Complete publication bias analyses including funnel plots, Egger's regression test detailed results, and methodological considerations are provided in Supplementary Figure S1 and Supplementary Methods S4 for transparency.

Heterogeneity: Substantial diversity in interventions, outcome measures, and contexts limits quantitative synthesis. Reported effect sizes should be interpreted as approximations rather than precise estimates.

Geographic concentration: 63% of studies from Europe and Asia, with limited representation from Africa, Latin America, and Middle East, potentially limiting generalizability to diverse educational contexts.

Short-term evaluation: 81% of studies assessed immediate post-intervention outcomes, with only 9 studies (19%) including follow-up assessments (3–12 months). Long-term retention and transfer remain inadequately evaluated.

Educational level concentration: 68% of studies focused on undergraduate engineering, with limited evidence for K–12 (15%) or graduate education (13%), constraining recommendations for these contexts.

Cost data scarcity: Only 21% of studies reported adequate cost data, limiting cost-effectiveness analyses and economic modeling.

6.5. Future Research Agenda

Based on identified gaps, this study proposes prioritized research directions:

Priority 1—Industrial-Grade Systems Research: Rigorous experimental studies comparing Level 5 (industrial-grade) versus Level 4 (didactic industrial) versus Level 3 (advanced educational) systems across multiple dimensions: (1) immediate learning outcomes, (2) long-term retention, (3) transfer to authentic industrial contexts, (4) motivation/engagement, and (5) cost-effectiveness. *Recommended design:* Multi-site RCT with $n \geq 180$, 12-week intervention, 6-month follow-up, authentic transfer assessment through industry internships.

Priority 2—Adaptive Control Pedagogy: Development and validation of learning modules for adaptive control topics (MRAC, self-tuning, gain scheduling, neural network control) integrated with robotic platforms. Recent work on enhanced density-driven control for multi-agent UAV systems demonstrates how sophisticated distributed coordination algorithms—originally developed for search-and-rescue applications—can inform the design of adaptive control pedagogy at the Expert level (Level 5) of the ARC Framework [82]. This example highlights the untapped potential of translating state-of-the-art multi-agent control strategies into accessible learning modules, where students could progress from classical coordination to density-driven optimization within robotic platform environments. *Recommended design:* Design-based research iteratively refining instructional materials, assessment instruments, and pedagogical strategies across multiple implementations.

Priority 3—Fault-Tolerant Systems Education: Systematic investigation of pedagogical approaches for teaching fault diagnosis, failure recovery, and fault-tolerant control using robotic systems with induced failures. *Recommended design:* Mixed-methods study combining quantitative outcome assessment with qualitative analysis of troubleshooting strategies and diagnostic reasoning development.

Priority 4—Remote Lab Effectiveness: Comparative effectiveness research on remote labs versus in-person labs versus hybrid models across diverse competency levels and learning objectives. *Recommended design:* Factorial RCT with $n \geq 240$, crossing access model (remote/in-person/hybrid) with competency level (novice/competent/proficient).

Priority 5—Longitudinal Competency Development: Multi-year longitudinal studies tracking competency progression through complete engineering programs implementing ARC Framework versus traditional curricula. *Recommended design:* Quasi-experimental with propensity score matching, cohort following from first year through graduation and first-year employment, comprehensive competency assessment at multiple timepoints.

Priority 6—Equity and Access: Systematic investigation of barriers and facilitators for underrepresented groups in industrial robotics education, with development and evaluation of interventions promoting inclusive excellence. *Recommended design:* Community-based participatory research involving diverse stakeholders in intervention co-design.

Priority 7—Economic Modeling: Development of sophisticated total-cost-of-ownership models incorporating equipment costs, infrastructure, maintenance, instructor training, opportunity costs, and outcome benefits (employment, salary premiums). *Recommended design:* Multi-institutional data collection informing system dynamics modeling.

7. Conclusions

Industrial robotics, adaptive control systems, and automation technologies represent critical Industry 4.0 competencies, yet engineering education inadequately prepares graduates for these domains. This PRISMA 2020-compliant systematic review synthe-

sized evidence from 52 high-quality empirical studies with comprehensive analysis of 103 relevant works (2019–2025), revealing large positive effects through random-effects meta-analysis (Hedges' $g = 0.786$, 95% CI: 0.726–0.846, $p < 0.001$) of technology-enhanced interventions, with substantially stronger effects for industrial-grade systems ($g = 0.864$) compared to educational kits ($g = 0.738$), representing a statistically significant 17% improvement ($\Delta g = 0.126$, $p < 0.05$). The observed homogeneity of effects ($I^2 = 0.00\%$, $p = 0.464$) across diverse educational contexts, technology platforms, and geographic regions strongly supports the robust generalizability of these findings to varied implementation scenarios.

Critical gaps emerged: only 4 of 52 studies (7.7%) employ authentic industrial-grade manipulators despite demonstrating optimal learning outcomes, adaptive control pedagogy remains severely underrepresented (4 studies, 7.7%), and fault-tolerant systems receive no empirical attention despite commanding 18–24% salary premiums in the industry. These gaps likely reflect cost barriers (\$35,000–50,000 per unit), instructor expertise limitations, and curricular inertia rather than pedagogical inadequacy.

The proposed ARC (Automation-Robotics-Control) Framework provides evidence-based systematic guidance for technology transfer from industry to education, integrating (1) five-level technology complexity taxonomy with progression pathways, (2) a competency development model from novice to expert, (3) pedagogical strategies matrix aligned with constructivist principles, and (4) three implementation models accommodating diverse institutional contexts. Remote labs with industrial-grade systems emerge as the optimal model for most institutions, achieving 94% of in-person effectiveness ($g = 0.89$ vs. $g = 0.94$) with superior cost-effectiveness (\$45/student vs. \$280 for physical labs, yielding 5.8× higher impact-per-\$1000 invested).

Future research priorities include (1) rigorous experimental comparisons of technology complexity levels with long-term follow-up, (2) development and validation of accessible adaptive control learning modules, (3) systematic investigation of fault-tolerant systems pedagogy, (4) longitudinal competency tracking through complete engineering programs, (5) equity-focused interventions for underrepresented groups, and (6) sophisticated economic modeling of total cost of ownership. Systematic implementation of evidence-based practices synthesized in this review, coupled with strategic research addressing identified gaps, can substantially strengthen engineering education's capacity to develop Industry 4.0/5.0-ready workforce meeting critical global automation competency needs.

The transformation of engineering education to meet Industry 4.0 demands represents not merely a technological challenge but a pedagogical imperative. As manufacturing environments increasingly rely on sophisticated automation systems, the disconnect between classroom preparation and workplace reality becomes untenable. This systematic review provides both the empirical foundation and practical framework necessary to bridge this gap systematically, enabling institutions to make evidence-informed decisions about technology investments, pedagogical approaches, and competency development pathways. The path forward requires neither wholesale abandonment of current practices nor unrealistic wholesale adoption of industrial systems but rather strategic, evidence-guided integration that maximizes learning outcomes while navigating very real constraints of cost, safety, and instructor expertise. Implementation of the ARC Framework, coupled with continued research addressing identified gaps, offers a pragmatic roadmap for this essential transformation in engineering education.

Supplementary Materials: The following supporting information can be downloaded at: <https://github.com/ClaudioUrrea/ARC-Framework>, accessed on 1 February 2026, Supplementary Table S1: Complete dataset for all 52 included studies containing bibliographic information, sample characteristics, intervention details, raw statistical data (means, standard deviations, test statistics), effect size calculations with formulas used, standard errors and confidence intervals, and comprehen-

sive quality assessment ratings for all six EPHPP components plus overall ratings. Supplementary Table S2: Documentation of outcome selection procedures for the 19 studies reporting multiple outcome measures, showing which outcomes were selected for primary meta-synthesis and justification for selection decisions based on pre-specified hierarchical protocol. Supplementary Table S3: Comprehensive list of 206 studies excluded at full-text screening stage, organized by primary exclusion reason (lacking empirical data, inadequate methodological quality, published pre-2019), with complete citations and explanatory notes where applicable. Supplementary Methods S1: Detailed documentation of effect size conversion procedures and formulas, including worked examples for each type of statistical conversion performed (means/SDs to Hedges' g , t -statistics to d , F -statistics to d , p -values to approximate effect sizes). Supplementary Methods S2: Complete documentation of multiple outcomes treatment procedures, including outcome selection protocol, hierarchical decision rules, and methodological considerations for maintaining statistical independence. Supplementary Methods S3: Comprehensive cost-effectiveness calculation models with itemized equipment and recurring cost breakdowns, depreciation schedules, utilization assumptions, sensitivity analysis across parameter ranges, and complete worked examples for remote versus physical laboratory implementations. Supplementary Methods S4: Publication bias assessment procedures and results, including Egger's regression test detailed output, trim-and-fill analysis methodology, and interpretation guidelines. Supplementary Figure S1: Funnel plot for publication bias assessment showing observed effect sizes plotted against standard errors, with trim-and-fill imputed studies indicated, Egger's regression line displayed, and 95% confidence region boundaries. Supplementary Figure S2: Sensitivity analysis plots showing leave-one-out analysis results, influence diagnostics, and comparison across parameter variations.

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Data Availability Statement: Complete study-level data, analysis code, and supplementary materials supporting this systematic review and meta-synthesis are openly available to ensure full transparency and reproducibility: Analysis Code and Data: Complete reproducibility package includes (1) Python scripts for generating Figures 2–8 (technology taxonomy, cost-effectiveness analysis, HRC performance metrics, sensitivity analysis, competency progression model, implementation pathway, and supplementary figures); (2) R script for generating Figure 7 (meta-analysis forest plot with complete statistical output); (3) experimental datasets: `HRC_Aggregated_Fanuc.csv` (performance metrics from Fanuc M-20iA industrial manipulator implementing adaptive multi-objective reinforcement learning over 1000 training episodes) and `Sensitivity_Results_Fanuc_Shaded.csv` (robustness analysis across parameter variations with 12 configurations and 10 trials each); (4) high-resolution figures (300 DPI) for all visualizations; (5) complete documentation including installation instructions, reproduction guide, and detailed data descriptions; (6) PRISMA 2020 checklist with page number references for all 27 items. The complete repository is permanently archived and accessible through two mirrors: FigShare (primary archive with DOI): <https://doi.org/10.6084/m9.figshare.31053583>; GitHub (version-controlled repository): <https://github.com/ClaudioUrrea/ARC-Framework> (accessed on 1 February 2026). All materials are released under Creative Commons Attribution 4.0 International License (CC BY 4.0), allowing free use with appropriate attribution. Comprehensive reproduction instructions enable independent verification of all results. Additional materials including raw data extraction forms, detailed search strategies for all five databases, and extended sensitivity analyses are available from the corresponding author (claudio.urrea@usach.cl) upon reasonable request for researchers requiring extended datasets.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ARC	Automation-Robotics-Control (Framework)
CDIO	Conceive-Design-Implement-Operate
CT	Computational Thinking
DOF	Degrees of Freedom
HMI	Human–Machine Interface
IIoT	Industrial Internet of Things
ITS	Intelligent Tutoring System
LLM	Large Language Model
MPC	Model Predictive Control
PBL	Project-Based Learning
PID	Proportional-Integral-Derivative (Control)
PLC	Programmable Logic Controller
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
ROS	Robot Operating System
SAMR	Substitution, Augmentation, Modification, Redefinition
SCADA	Supervisory Control and Data Acquisition
STEM	Science, Technology, Engineering, and Mathematics
TPACK	Technological Pedagogical Content Knowledge
VR	Virtual Reality

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