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Mini Review

From Vision Language-Action Policies to Safety-Grounded Tactile World Models for Contact-Rich Robotics

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Abstract

Robotics is entering a new stage in which generalist vision-language-action policies are beginning to connect natural-language instruction, visual perception, and robot control within unified learning systems. These models are powerful because they reduce the need to train a separate policy for every task. However, contact-rich manipulation remains a major limitation. Tasks such as peg insertion, object handover, cloth folding, lid closing, and assembly require more than visual recognition and language-conditioned action generation. They require tactile feedback, force awareness, uncertainty estimation, and safety-constrained decision making. This mini review argues that the next important step in robot foundation models is the integration of vision-language-action policies with tactile world models and explicit safety layers. A proposed Safety-Grounded Tactile World Model architecture is presented, where a generalist policy proposes candidate actions, a tactile world model predicts contact outcomes, and a safety module filters risky actions before execution. This architecture may provide a practical route toward safer and more reliable contact-rich robotics.

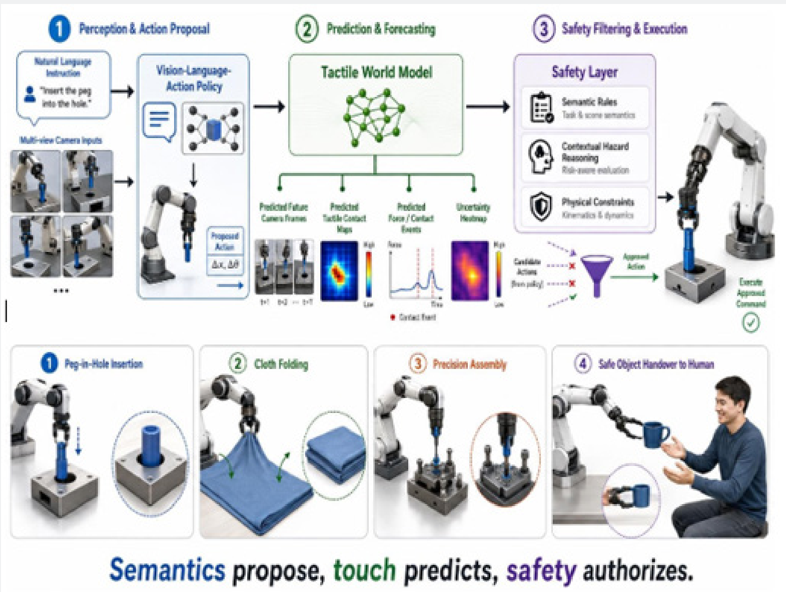

Figure 1: Safety-Grounded Tactile World Model architecture for contact-rich robotics.

Keywords: Vision-language-action model; Tactile Sensing; World Model; Robot Safety; Contact-rich Manipulation; Robot Foundation Model

Introduction

Robotics and automation have emerged as cornerstone technologies driving contemporary industrial and societal transformation. The global deployment of industrial robots has exceeded 500,000 units annually since 2020, reflecting sustained demand for flexible, intelligent manufacturing solutions [1]. Concurrently, the integration of artificial intelligence (AI) and machine learning (ML) has catalyzed a paradigm shift from pre-programmed, task-specific automation toward adaptive, learning-based robotic systems capable of operating in dynamic, unstructured environments [4-6].

The evolution from Industry 4.0 to Industry 5.0 reflects a growing emphasis on human-centric automation, where robots are designed not merely to replace human labor but to augment human capabilities through safe, intuitive collaboration [6]. This transition has accelerated research in collaborative robotics (cobots), multimodal human-robot interaction, and socially aware robotic systems [7]. Despite notable technological achievements, the rapid proliferation of automation technology has also generated significant socio-economic implications, including workforce displacement, skill mismatches, and changing organizational structures [2, 3].

This mini review provides a concise synthesis of current advances in robotics and automation technology, organized across three thematic pillars: industrial robotics and automation systems, AI-driven control and perception, and human-robot collaboration technologies. The review draws on recent peer-reviewed literature (2019-2025) and concludes with an assessment of unresolved challenges and future research trajectories.

Industrial Robotics and Automation Systems

Technological Trajectory and Recent Advances

Industrial robotics has progressed beyond traditional fixed-function manipulators toward reconfigurable, sensor-rich systems capable of multi-task operation. Urrea and Kern (2025) provide a systematic synthesis of this evolution, noting that modern industrial robots increasingly incorporate real-time process monitoring, digital twin integration, and adaptive quality control mechanisms [1]. The proliferation of collaborative robots (cobots) has further expanded the applicability of automation to small-batch, high-variability production settings where conventional industrial robots were previously uneconomical [7, 10].

Recent analyses emphasize the convergence of robotics with complementary technologies such as the Internet of Things (IoT), 5G connectivity, and edge computing, enabling distributed, low-latency automation architectures [4, 8]. Rahman et al. (2025) highlight that edge AI deployment allows machine learning inference to occur directly on robotic hardware, reducing dependence on cloud infrastructure and improving response times for safety-critical operations [8].

Challenges in Industrial Deployment

Despite technological maturity in laboratory settings, several barriers impede widespread industrial adoption. Urrea and Kern (2025) identify a persistent gap between academic demonstrations and real-world deployment, citing concerns regarding long-term reliability, maintenance costs, and regulatory compliance [1]. Additionally, small and medium-sized enterprises (SMEs) often lack the capital investment and technical expertise required for comprehensive automation integration [4].

The integration of heterogeneous robotic platforms within existing manufacturing ecosystems presents further complexity. Standardization efforts remain fragmented across communication protocols, data formats, and safety certification procedures, limiting interoperability between multi-vendor automation solutions [4, 8].

AI-Driven Control and Perception

Machine Learning for Robotic Automation

The integration of AI and ML into robotic systems has fundamentally expanded autonomous capabilities across perception, planning, and control domains. Rahman et al. (2025) reviewed the application of supervised, unsupervised, and reinforcement learning techniques to industrial automation, identifying key trends including the use of computer vision for defect detection, predictive maintenance algorithms based on time-series sensor data, and multi-agent coordination in warehouse logistics [8].

Digital twin technology has emerged as a particularly impactful approach, enabling high-fidelity simulation of robotic systems for training, testing, and optimization before physical deployment [8,9]. Simulation-to-reality (sim-to-real) pipelines allow reinforcement learning agents to acquire complex manipulation and navigation policies in virtual environments, subsequently transferring learned behaviors to physical robots with appropriate domain adaptation [9,10].

Reinforcement Learning and Adaptive Control

Reinforcement learning (RL) has demonstrated considerable promise for adaptive robotic control in dynamic manufacturing environments. Tarapder (2025) proposed an AI-driven framework utilizing policy gradient methods-such as Proximal Policy Optimization (PPO)-for real-time adaptation of robotic manipulation strategies under varying workpiece conditions and environmental disturbances [9].

Bio-inspired control strategies, including evolutionary algorithms and neural network controllers modeled after biological motor systems, represent an emerging research direction that complements conventional model-based approaches [6]. Urrea (2025) systematically reviewed AI-driven and bio-inspired control methods, noting their particular utility for systems with complex, nonlinear dynamics where analytical modeling is infeasible [6]. However, RL-based controllers face ongoing challenges regarding sample efficiency, safety verification, and interpretability in safety-critical applications [9,10].

Edge AI and Real-Time Decision Making

The deployment of AI models on edge computing platforms addresses latency constraints inherent in cloud-dependent architectures. Rahman et al. (2025) identified model compression techniques-including quantization, pruning, and knowledge distillation-as essential enablers for deploying deep neural networks on resource-constrained robotic controllers [8]. These techniques reduce inference latency to millisecond scales while maintaining acceptable accuracy levels for real-time object recognition, anomaly detection, and trajectory adjustment tasks [8,10].

Human-Robot Interaction and Collaboration

Collaborative Robotics (Cobots)

The development of collaborative robots has redefined human-robot interaction paradigms by enabling safe physical coexistence in shared workspaces. Rodriguez-Guerra et al. (2021) characterized the technological foundations of modern cobots, including compliant actuation, force/torque sensing, and real-time collision detection systems that allow robots to operate alongside human workers without physical safety barriers [7].

Cobot applications span assembly, welding, quality inspection, and material handling in manufacturing, as well as surgical assistance, rehabilitation therapy, and eldercare in service sectors [1, 5]. The declining cost and improving performance of cobot platforms have democratized automation access for SMEs, although programming complexity and task-specific customization remain barriers to broader adoption [7, 10].

Interaction Modalities and Natural Interfaces

Effective human-robot collaboration depends on robust interaction interfaces that accommodate both physical coexistence and cognitive coordination. Multimodal communication techniques-encompassing gesture recognition, voice commands, augmented reality visualization, and haptic feedback-have been investigated as means to reduce the cognitive load on human operators during collaborative tasks [5, 7, 10].

Pandy et al. (2025) highlighted that natural language processing and intent recognition systems enable non-expert users to command robots through conversational interfaces, lowering the technical skills required for robot operation [10]. However, performance degradation in noisy industrial environments and challenges in disambiguating contextual intent remain active research areas [5, 7].

Safety and Trust Considerations

Safety assurance remains a critical prerequisite for human-robot collaboration. Rodriguez-Guerra et al. (2021) identified three complementary safety mechanisms: (1) inherent safety through compliant mechanical design, (2) active safety through sensor-based collision detection and avoidance, and (3) predictive safety through human motion tracking and behavioral anticipation [7].

Beyond physical safety, psychological and cognitive dimensions of trust influence the effectiveness of human-robot teams. Operators must develop appropriate mental models of robot capabilities and limitations to calibrate their reliance on autonomous systems [5, 10]. Over-trust in automated systems can lead to complacency and reduced vigilance, while under-trust results in excessive monitoring and reduced productivity [3, 5].

Challenges and Future Directions

Technical Challenges

Several unresolved technical challenges constrain the next generation of robotic automation systems. First, the sim-to-real gap-the discrepancy between simulated training environments and physical deployment conditions-limits the effectiveness of learning-based control policies [9, 10]. Domain randomization and meta-learning approaches offer partial solutions but require further refinement for safety-critical applications.

Second, the computational demands of deep learning models conflict with the real-time, low-power requirements of embedded robotic controllers [8]. Advances in neuromorphic computing, specialized AI accelerators, and algorithmic efficiency may help reconcile these competing constraints. Third, ensuring robustness and generalizability across diverse operating conditions remains an open challenge. Most current systems exhibit narrow task specificity and performance degradation when confronted with novel object geometries, environmental disturbances, or sensor failures [4, 6].

Socio-Economic and Ethical Dimensions

The widespread deployment of robotics and automation carries significant implications for workforce composition, labor markets, and organizational structures. Wang and Siau (2019) conducted a comprehensive analysis of AI and automation impact on employment, identifying high-risk occupations characterized by routine, predictable tasks alongside emerging demand for robot maintenance, programming, and system integration expertise [2].

Dumlao Jr et al. (2024) reviewed the socio-economic consequences of automation, emphasizing the need for proactive reskilling programs, educational reform, and social safety net policies to mitigate workforce displacement effects [3]. The equitable distribution of automation benefits-avoiding concentration of economic gains among technology owners while displaced workers bear transitional costs-represents a critical policy challenge [2, 3]. Ethical considerations extend to data privacy, algorithmic transparency, and accountability in autonomous decision-making processes. As robots increasingly collect and process personal data in healthcare, eldercare, and domestic service contexts, robust governance frameworks must accompany technological development [5, 10].

Toward Industry 5.0

The emerging Industry 5.0 paradigm envisions a collaborative future where robots augment rather than replace human workers, emphasizing sustainability, resilience, and human-centric design [6]. Key research directions supporting this vision include:

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(1) Explainable AI for Robotics: Developing interpretable decision-making processes that enable human operators to understand and trust autonomous system behaviors [5, 9].

(2) Sustainable Automation: Designing energy-efficient robotic systems with recyclable materials and circular economy principles, reducing the environmental footprint of manufacturing automation [1, 6].

(3) Human-Robot Team Intelligence: Investigating emergent collaborative intelligence arising from effective human-robot teams, including shared planning, mutual adaptation, and distributed problem-solving [5, 7, 10].

Conclusion

Robotics and automation technology has undergone transformative evolution, progressing from rigid, pre-programmed industrial manipulators to adaptive, AI-driven systems capable of safe collaboration with humans in diverse environments. Recent advances in machine learning, edge computing, and collaborative robot design have substantially expanded both the technical capabilities and application domains of robotic automation.

Nevertheless, significant challenges impede the full realization of intelligent, human-centric automation. Technical barriers-including sim-to-real transfer, computational efficiency, and generalization robustness-require sustained research investment. Socio-economic challenges encompass workforce transformation, equitable benefit distribution, and ethical governance frameworks that must evolve alongside technological capability.

The transition toward Industry 5.0 presents both an aspirational vision and a research agenda that centers human wellbeing, sustainability, and collaborative intelligence. Achieving this vision demands interdisciplinary collaboration spanning robotics engineering, artificial intelligence, ergonomics, economics, and ethics to develop automation systems that are not only technically sophisticated but also socially responsible and economically equitable.

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Conflict of interest

No conflict of interest.

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