



SPEEDING ROBOTICS AUTOMATION WITH AI

Ryan Martin, Senior Research Director



EXECUTIVE SUMMARY

The US\$53 trillion manufacturing economy is undergoing a major automation paradigm shift due to Artificial Intelligence (AI). Automation projects that were once impossible or inefficient to implement are now being fast-tracked thanks to new frameworks, and robotics automation is becoming increasingly relevant to a growing number of users and scenarios.

One of the biggest advancements is the rise of closed-loop automation software. Such solutions expedite robot training, widen the aperture of tasks that robots can perform, and mitigate errors that negatively impact first-pass yield.

AI-enabled, closed-loop robotics automation is more akin to human-like interactions where functionality is learned and adapted dynamically, rather than hard-coded for specific features. This approach means that robotics automation can be better utilized and more easily implemented in arbitrary, unstructured environments and for situations where automation was previously considered not cost-viable.

CONTENTS

- EXECUTIVE SUMMARY** 1
- AI IS AN ACCELERANT FOR TRANSFORMATION, NOT A ROADBLOCK** 2
- KEY PHASES FOR CLOSED-LOOP AI SOFTWARE AUTOMATION**..... 3
 - OBSERVE 3
 - LEARN..... 3
 - REASON..... 3
 - ACT..... 3
 - FOUNDATION MODEL CHARACTERISTICS & IMPACT..... 4
- CASE STUDY: QUALITY CONTROL & INSPECTION** 5
- KEY TIMELINES** 6

But not all AI is created equal. The most innovative solutions provide a low-code approach that democratizes access from Information Technology (IT) to Operational Technology (OT) and Engineering Technology (ET) professionals, while empowering machines to operate autonomously, rather than in response to a set of predictions or recommendations.

This approach is contrasted with traditional AI/Machine Learning (ML) implementations, which require enormous amounts of data allied with cloud computing to gather, ingest, analyze, and learn. Closed-loop, AI software is different in that it relies less on cloud and vast data volumes in favor of edge-based approaches that use sensor data as a real-time input for perception and reasoning.

Certain tasks such as end-of-line quality inspections and parts sequencing/kitting have been historically difficult or impossible to automate with robotics using conventional programming techniques due to the complexity of assignments, variability of parts, and resources required. Closed-loop AI automation programming software changes the economic value equation by obfuscating a lot of complexity with algorithms that enable machines to react to changing circumstances and complete tasks without retraining or reprogramming. These AI software advances allow engineers and frontline workers to avoid dull, dirty, and dangerous jobs that can be accomplished with robotics.

AI IS AN ACCELERANT FOR TRANSFORMATION, NOT A ROADBLOCK

Traditional robotics process automation is code-heavy, expensive to deploy, and cumbersome to implement due to the inherent variability of tasks and equipment in manufacturing. Additionally, change management can be unwieldy and labor-intensive for new product introductions, requiring both retooling and significant programming time. As a result, many manufacturing processes are under-automated, and companies avoid robotics automation altogether.

AI-enabled robotics automation software challenges this old way of thinking and minimizes the chance for human error. It allows the automation of tasks previously considered uneconomical, speeds the time-to-impact for new initiatives, and better appropriates human capital for more value-added tasks.

The closed-loop component is key to facilitating robotics automation in dynamic, unstructured environments, as is the case in manufacturing. This approach feeds edge-based environmental inputs back into the AI model so that robots can adapt in real time based on the product, context, and task.

Part kitting/sequencing is one example of an area where closed-loop AI automation software is having a profound impact. The functional operation of part kitting is generally difficult to automate due to a range of variables, including the complexity and just-in-time nature of sequencing assemblies. However, if systems can sense and act in their environment like humans, automation becomes possible. Several key components to enable such implementations are detailed below.

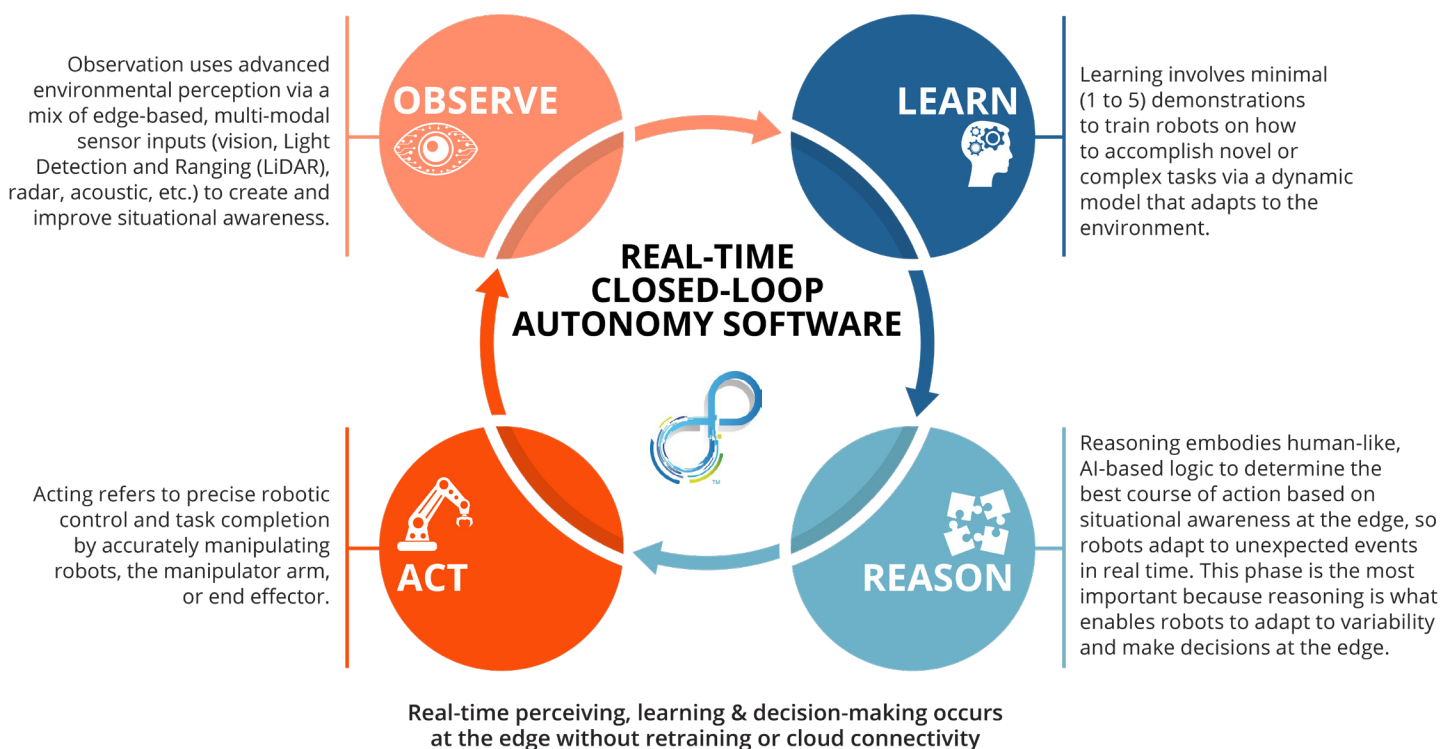
KEY PHASES FOR CLOSED-LOOP AI SOFTWARE AUTOMATION

Full-stack, closed-loop automation leverages vision systems and sensors for real-time, edge-based data inputs, executable hardware (robotics) to make real-world changes, and holistic software to connect and enable the execution of variable tasks.

Until recently, most solutions addressed one aspect—just vision, or just hardware—but fell short in their ability to close the feedback loop that supports true autonomy. Closed-loop AI software was the missing link—to connect sensor inputs and executable hardware so robots can perform tasks autonomously.

Best-of-breed AI software facilitates this exchange of information and execution in a closed-loop fashion via four interrelated phases.

Figure 1: Closed-Loop AI Software Automation
(Source: ABI Research)



Full-stack, closed-loop systems are essential to true autonomy. The four phases work in a circular fashion, feeding new inputs back into the model so robots can perceive, learn, and reason—enabling them to make decisions at the edge (e.g., adapting to variability in an object’s position or orientation) without retraining or cloud connectivity.

FOUNDATION MODEL CHARACTERISTICS & IMPACT

Some approaches that look to accomplish similar objectives regarding automation utilize what are called Foundation Models (FMs). FMs are large deep learning neural networks trained on massive datasets to give data scientists a better starting point for ML model development. In practice, FMs are less than ideal because of various qualities that could be improved, as detailed in Table 1. Better approaches leverage edge AI alongside low-code architectures that are lightweight and adaptable, so automation is more cost-effective and accessible to more users and tasks.

Important attributes to look for in evaluating closed-loop AI software automation include the use of edge versus cloud, because edge-based applications are generally lower cost and lower latency; the amount of time it takes to complete training requirements, which are directly related to achieving an attractive time-to-value; and the applicability of AI software to robotics, given the need to implement reasoning to achieve action in dynamic, real-world environments.

Table 1: Foundation Model Characteristics & Impact
(Source: ABI Research)

Quality	Foundational Model for Robotics	Desired Approach
Model Size	Large	Compact
Training Data	Massive, diverse “generalist” datasets with high compute requirements	Smaller, domain-specific datasets with moderate compute requirements due to Central Processing Units (CPUs)/Graphics Processing Units (GPUs) at the edge versus requiring cloud
Cost	High cost with persistent cloud connection, latency, and parameters for model training; long time-to-value	Low cost with no cloud connection requirement & low-code, motion-specific training at the edge; faster time-to-value
Applicability to Robotics	Limited due to lack of robotic training data in favor of general-purpose tasks	Aligned to robotics-specific and dynamic use cases

CASE STUDY: QUALITY CONTROL & INSPECTION

The US\$4.97 trillion electronics industry is home to companies that manufacture high-precision, high-complexity products at every range of scale. Additionally, suppliers are under constant pressure to innovate rapidly with new products that accommodate a diversity of customer preferences and locales.

Many products, such as phones, laptops, and server equipment, endure stringent Final Quality Checks (FQCs) to ensure compliance within manufacturing tolerances for high levels of customer satisfaction. Historically, these FQCs have been done manually without automation, requiring workers to visually inspect and document more than 100 FQCs for approval in the case of a server rack.

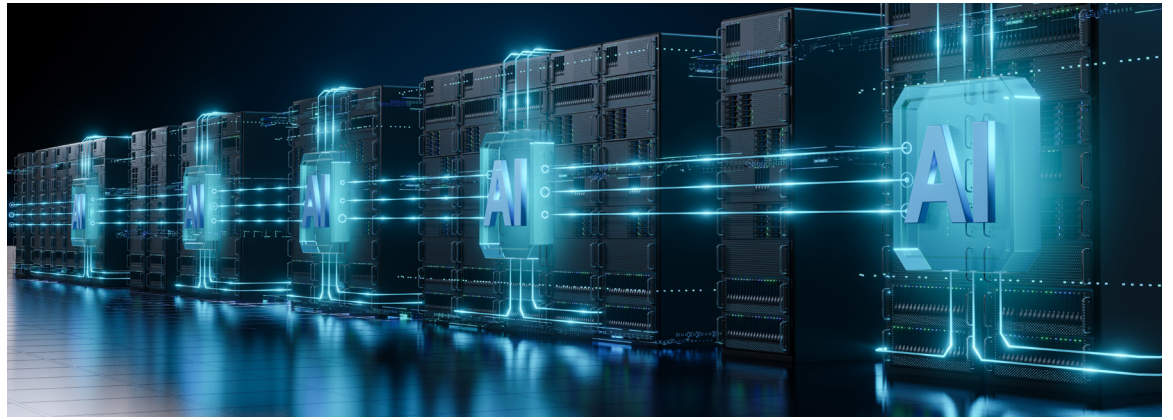
Server equipment is a good example because, like many products, there are multiple variations for each server model, resulting in thousands of FQCs that are unique across Stock Keeping Units (SKUs). These activities are challenging, if not impossible to automate effectively using conventional robotics programming techniques, requiring extensive human quality checks. This is a problem because the tasks can be tiresome for workers and issues are quickly compounded in the event of error or delays, at an estimated cost of more than US\$1 million per hour of downtime.

AI-enabled, closed-loop automation software changes the game by making robotics automation the logical choice, rather than impossible.

Palladyne AI’s closed-loop, Palladyne IQ software is the first legitimate solution to solve such challenges. In the case of server equipment manufacturing, the software empowers Collaborative Robots (cobots) to perform server inspections at the end of the manufacturing line, as well as points throughout assembly using a closed-loop system where robots observe, learn, reason, and act at the edge. This edge-based, closed-loop system makes it possible to identify the server rack model and capture images to complete the FQC sequence.

Improving quality levels is the #1 operational challenge facing manufacturing professionals.

(Source: ABI Research’s 2025 Industrial & Manufacturing Survey).



Closed-loop AI software for such an application can shorten the inspection process significantly (>8X), free up human resources, and minimize downtime thanks to better consistency and fewer delays. Also, because it is a closed-loop system with reasoning at the edge, the solution adapts to different product models with minimal retraining, fostering an uncanny flexibility to meet changing manufacturing requirements.

KEY TIMELINES

Low-code, closed-loop robotics software will become a more common part of the automation workflow as more companies become aware of its ease of implementation and efficacy. Initial implementations will likely use a human-in-the-loop approach to ensure and verify actions. In the medium term, users and beneficiaries will gain confidence in the implementation, so they may go from regular verification-in-the-loop to more of a monitoring role—which can be thought of as an on-the-loop relationship across the four phases of observe, learn, reason, and act.

Table 2 outlines key milestones on various time scales for a practical construct of next steps.

Table 2: Key Milestones to Implement & Scale Closed-Loop AI Software Automation
(Source: ABI Research)

Short Term (Weeks)	Medium Term (Months)	Long Term (1 Year)
Pilot new robotics automation scenarios with a small number of core users. These are internal advocates for new capabilities and essential to test and prove implementations, while planning for scale.	Expand the number of applications and scenarios where robotics automation plays. Introduce new users and locations to no-code robotics automation opportunities as an embedded part of the company process to scale existing use cases.	Extend proven use cases to all cohorts who would benefit from automating tasks with robotics. Provide safeguards to scale implementations from in-the-loop to on-the-loop operations.



Published March 2025
157 Columbus Avenue
New York, NY 10023
Tel: +1 516-624-2500
www.abiresearch.com

We Empower Technology Innovation and Strategic Implementation.

ABI Research is uniquely positioned at the intersection of end-market companies and technology solution providers, serving as the bridge that seamlessly connects these two segments by driving successful technology implementations and delivering strategies that are proven to attract and retain customers.

©2025 ABI Research. Used by permission. Disclaimer: Permission granted to reference, reprint or reissue ABI products is expressly not an endorsement of any kind for any company, product, or strategy. ABI Research is an independent producer of market analysis and insight and this ABI Research product is the result of objective research by ABI Research staff at the time of data collection. ABI Research was not compensated in any way to produce this information and the opinions of ABI Research or its analysts on any subject are continually revised based on the most current data available. The information contained herein has been obtained from sources believed to be reliable. ABI Research disclaims all warranties, express or implied, with respect to this research, including any warranties of merchantability or fitness for a particular purpose.