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Longitudinal Insights into Intelligent Manufacturing Processes: Managerial Expectations vs. Actual Adoption

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Abstract

Manufacturing enterprises often plan technological development without knowing whether their expectations can realistically be achieved, which makes long-term decisions uncertain. This study is necessary because no evidence exists comparing what quality managers expected to adopt by 2025 with what was actually implemented eight years later. We conducted a two-phase empirical study using the same 42 large manufacturing enterprises first surveyed in 2017, applying an identical research matrix of 26 processes and 14 intelligent technologies to measure changes in expected and real deployment. A follow-up rapid survey expanded the sample to 136 enterprises and examined the use of ten AI-driven technologies. The results show a clear gap between expectations and reality. Real automation exceeded expectations in logistics, maintenance, and quality activities, with processes such as manipulation, warehousing, and delivering reaching more than 50 percent adoption, and collaborative robots and autonomous vehicles exceeding expectations by 8 to 25 percentage points. In contrast, forecasting, scheduling, and process planning fell 10 to 15 percentage points below expected levels. The study's contribution is to identify which technological expectations were realistic and which were overestimated. These insights guide managers in prioritizing investments and help policymakers understand where digital transformation advances naturally and where targeted support is required.

Keywords: Industry 4.0 adoption; technological forecasting accuracy; AI integration in manufacturing; smart technologies; quality management

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1. Introduction

In 2017, we asked quality managers not only to report the actual use of intelligent technologies but also to anticipate their deployment in 2025. At that time, Industry 4.0 technologies were entering a phase of rapid development, and several reports showed that their adoption would accelerate within the following decade. Companies were making long-term investment decisions, yet many lacked data on which technologies would matter most. Capturing both the current state and the expected situation enabled us to track this shift and identify where managers saw realistic growth potential. That initial study, published by [1], mapped the future expectations of Industry 4.0 adoption and highlighted key technologies poised for growth. Intelligent manufacturing has become a central focus in industrial research because the speed and depth of technological change influence

how production systems evolve. Adoption of smart technologies depends on several interacting factors. Firms differ in their levels of digital readiness, process automation, data quality, workforce skills, and the maturity of their production systems. The structure of the industry also matters, since high-volume, highly standardized environments adopt new tools faster than sectors with irregular or low-volume operations. Investments in intelligent technologies are shaped by expected returns, supply chain stability, the availability of compatible equipment and software, and managers' ability to align technological choices with long-term development plans. For these reasons, longitudinal research is necessary. A single cross-sectional study captures only a moment in time and cannot show how expectations evolve or where actual adoption accelerates or stalls. Tracking managers' expectations and comparing them with actual use helps us understand adoption dynamics more precisely. It also helps identify which technologies move from potential to practice and which remain limited despite initial optimism.

What was considered cutting-edge or speculative in 2017 may now be either obsolete, underutilized, or surpassed by unforeseen innovations. This discrepancy raises an essential question: were quality managers' expectations about Industry 4.0 in 2017 accurate, and how closely do they align with the technological reality of 2025? This research addresses that question through a longitudinal lens, using a two-phase empirical design. The first phase re-engages the original sample of manufacturing enterprises surveyed in 2017 to assess whether the 14 smart technologies identified then were adopted as expected by 2025. Table 1 provides a schematic overview of the fourteen intelligent technologies examined. These technologies were selected in our 2017 research because they represented the most relevant and practically deployable components of Industry 4.0 within large industrial enterprises at that time. The selection relied on a detailed review of manufacturing, logistics, and quality management literature, combined with consultation with industry experts. Four groups were identified: smart devices, identification technologies, localization and navigation technologies, and information and robotics technologies. Each group contained tools that were already in use in industrial practice to some extent, were expected to develop rapidly, and had a clear link to process automation, data acquisition, and production quality. Focusing on these 14 technologies enabled us to evaluate both actual adoption and expected future deployment in a structured, comparable way across manufacturing and logistics processes.

Table 1. Overview of the fourteen intelligent technologies analyzed in the study.

Smart Devices
T1 Smart glasses—wearable displays for guided work, inspection, and documentation T2 Smart gloves—sensor-based gloves for picking, gesture input, and handling T3 Smart watches—wrist devices for alerts, monitoring, and operator support. T4 Smartphones/Tablets—mobile devices for data entry, visualization, and process control
Identification Technologies
T5 RFID technology—radio-frequency tags for object tracking and inventory accuracy T6 Barcodes—one-dimensional optical codes for product identification T7 QR codes—two-dimensional optical codes enabling richer and faster data capture
Localization and Navigation Technologies
T8 GPS tracking—position monitoring for external transport and logistics T9 Drones—unmanned aerial systems for inspection and inventory checks T10 Autonomous vehicles—self-guided transport units for internal logistics
Information and Robotics Technologies
T11 Manufacturing Execution Systems (MES)—system linking planning, control, and shop-floor data T12 3D printing—additive manufacturing for prototypes and specialized components T13 Virtual reality simulation—immersive modeling for planning, training, and system changes T14 Collaborative robots—robots designed to work safely in direct interaction with operators

In the 2017 study, quality managers identified four main expectations for technological development to be achieved by 2025. First, they expected a substantial rise in mobile and wearable support tools. Smart glasses, smart gloves, and smart watches were viewed as natural extensions of operator assistance. Managers believed these tools would improve documentation, guidance, and hands-free control. Second, managers anticipated wider use of identification technologies. RFID, barcodes, and QR codes were expected to standardize traceability across production and logistics. Third, the 2017 survey predicted that mobile devices such as smartphones and tablets would become central platforms for shop-floor communication and data entry. Fourth, managers expected only modest growth in advanced automation technologies such as collaborative robots, 3D printing, and autonomous vehicles. By 2025, these technologies exceeded expectations. By using the same set of technologies and targeting the same enterprises—wherever possible—the study ensures methodological consistency and validity. The second phase of the research expands the sample and scope, surveying a broader group of large manufacturing firms to evaluate the current and future role of AI-integrated intelligent technologies, thus capturing the evolving dynamics that were not entirely predictable in 2017. To guide the investigation, the study is structured around three research questions (RQ1–RQ3): RQ1: Is there a significant difference between the expectations of quality managers in 2017 and the actual use of intelligent technologies in 2025? RQ2: Which intelligent technologies have become essential by 2025, and which ones have proven less relevant? RQ3: Which intelligent technologies integrated with artificial intelligence are currently used or planned for use in manufacturing processes? The primary objective of this research is to determine whether there is a statistically significant difference between the technological expectations of quality managers in 2017 and the actual adoption of smart technologies in 2025. This is further broken down into four partial objectives (PO1–PO4):

- PO1: Identify the expectation–reality gap within the original 2017 sample of manufacturing enterprises.
- PO2: Evaluate the accuracy and limitations of quality managers' long-term technological forecasting.
- PO3: Define a relevant set of intelligent technologies integrated with AI based on the current literature.
- PO4: Determine the level of adoption and anticipated future use of these AI-driven technologies in manufacturing.

Figure 1 shows that the research methodology is deliberately split into two sub-studies to achieve both retrospective and forward-looking insights. The first sub-study uses a streamlined questionnaire distributed to the original participants, focusing on the same 14 technologies to ensure a valid comparison between expected and actual implementation. The second sub-study employs a rapid survey of 136 quality and production managers, who were asked to rank their current and future use of ten AI-driven technologies derived from a comprehensive literature review. This approach provides a dual perspective—verifying past expectations while capturing current trends and managerial intent in AI integration.

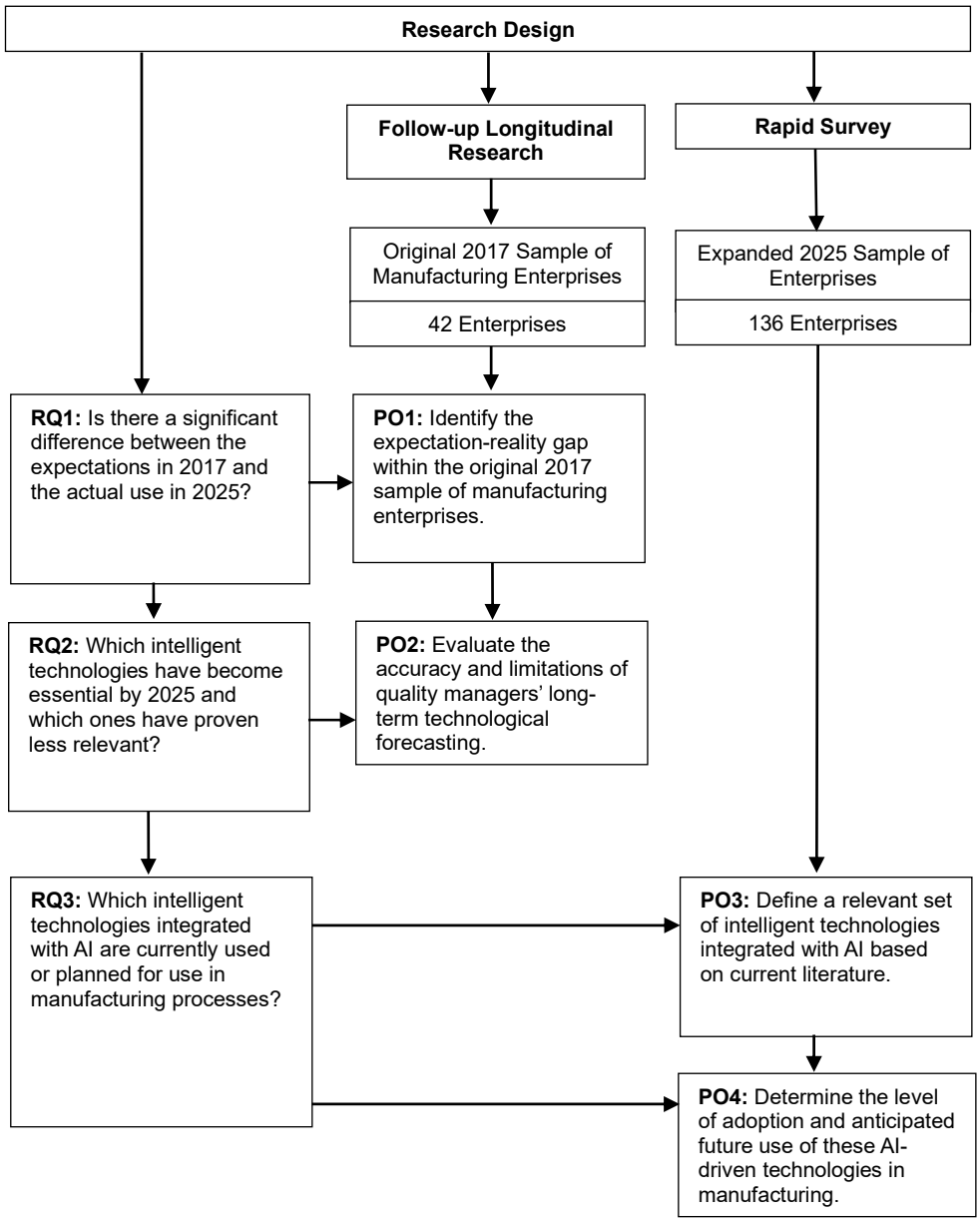


Figure 1. Research design linking the follow-up longitudinal study and rapid survey to research questions (RQ1–RQ3) and partial objectives (PO1–PO4).

2. Literature Review

This study builds on the original empirical research by [1], which serves as the basis for the first sub-study. As such, this literature review does not aim to re-analyze the evolution of Industry 4.0 or Industry 5.0. Instead, it focuses on validating and contextualizing the smart technologies evaluated in 2017, maintaining consistency in the technology set to ensure comparability. Altering the original list of technologies would compromise the validity of the longitudinal study. The literature review in this study is divided into two subsections. The first subsection summarizes the research on the 14 intelligent technologies analyzed in both 2017 and 2025. This part focuses on smart devices, identification technologies, localization and navigation tools, and information and robotics systems that formed the technological basis of the longitudinal comparison. The second subsection reviews technologies that integrate artificial intelligence. These AI-driven solutions, such as predictive analytics, machine vision, Digital Twins, and autonomous systems, represent the newer wave of digital transformation and were examined in the 2025 rapid survey.

2.1. Intelligent Technologies Involved in the Research in 2017 and 2025

Intelligent technologies form the core of Industry 4.0 and represent both technological and organizational innovation. Earlier work on organizational innovation by [2,3] shows that innovation affects not only products or equipment but also managerial practice and organizational structures. Their findings, along with the results of [4], confirm that technological and organizational innovations can improve performance even outside manufacturing. Ref. [5] further highlights the importance of measuring and assessing these innovations, which is essential when examining digital transformation in production systems. Most intelligent technologies deployed today rely on digital information, automation, and connectivity. This includes smart glasses, smart gloves, smart watches, and mobile devices, all of which support operator guidance or data capture. Several authors have demonstrated their practical use. Ref. [6] describes applications of IoT devices, VR, and cloud tools in production support. Ref. [7] shows how smart glasses can guide workers during assembly. Ref. [8] illustrates how smart watches enhance flexible planning under Kanban. Ref. [9] demonstrates the value of smartphones and tablets in complex assembly tasks. Identification and tracking technologies such as RFID, barcodes, and QR codes continue to support production and logistics, as shown by [10,11]. Autonomous vehicles, drones, and GPS systems strengthen navigation and localization, with industrial examples such as BMW's Smart Transport Robots. Information technologies such as Manufacturing Execution Systems (MESs) play a central role in integrating data flows, as described by [12,13]. Additive manufacturing has become an essential technological enabler of Industry 4.0, and its barriers have been analyzed by [14]. Virtual reality supports simulation and planning tasks, as noted by [15]. Collaborative robots, as discussed by [16,17], bring human workers and machines together in shared workspaces and represent a significant shift in industrial robotics.

2.2. AI-Driven Intelligent Technologies Involved in the Rapid Survey in 2025

Several of the technologies assessed in 2017 remain in use today, though their prominence varies. For instance, smart glasses are still used for real-time quality inspection during assembly processes [18]. Smart gloves, once seen as promising, are now less frequently implemented than wearable alternatives such as smart watches [19]. These examples show that some early expectations have not fully materialized in practice. To broaden the perspective in the second sub-study, we expanded the sample to 136 large manufacturing companies and focused on identifying AI-driven intelligent technologies. This required a selective literature review to compile the 10 most relevant technologies already in use or expected to be deployed. The integration of AI into manufacturing has been widely discussed in the academic literature. Refs. [20,21] explore the foundational role of AI in manufacturing processes. Ref. [22] further emphasizes AI's utility in process planning, resource allocation, and decision-making. Predictive maintenance is among the most cited applications of AI, in which historical and real-time data are analyzed to forecast equipment failures, reducing downtime [23,24]. AI-powered computer vision is increasingly used for defect detection, improving quality assurance [25]. Logistics optimization also benefits from AI; for example, demand forecasting and real-time adjustments to supply chain strategies enhance operational efficiency [26]. In inventory management, AI algorithms dynamically control stock levels to generate cost savings [27]. Other transformative roles include production customization, where AI enables flexible manufacturing lines tailored to consumer demands [28]. In additive manufacturing, AI supports rapid prototyping and accelerates product development cycles [29]. Nonetheless, challenges persist. AI systems require extensive data, and integrating disparate sources remains difficult [30]. Cybersecurity risks also increase as AI becomes embedded in operations [31]. Furthermore, ethical concerns

arise around workforce displacement and data privacy [32]. Robotic Process Automation (RPA) also plays a pivotal role in the digital transformation of manufacturing. Refs. [33,34] outline RPA's evolving role toward cognitive automation. Refs. [35,36] describe this transition to "intelligent automation," which handles more complex decision-making tasks. Strategic implementation challenges are highlighted by [37,38], who stress the importance of aligning RPA initiatives with business goals. While RPA can boost efficiency, it still lacks the maturity to replace human decision-making [39]. Risks include over-reliance, regulatory non-compliance, and diminished human roles [40]. These concerns are echoed in the finance and auditing sectors [41,42], where RPA enhances transparency but raises questions of accountability [43]. Digital Twin (DT) technology is also essential in understanding AI integration. Refs. [44,45] explain how DT enables the fusion of physical and digital environments, supporting predictive analytics and real-time decision-making. DT's structural components and modeling frameworks are detailed in [46], while [47] explores its benefits for maintenance and risk management. DT's predictive capabilities have matured significantly, with applications ranging from autonomous vehicles [48] and real-time diagnostics [49] to sustainable energy management [50]. Beyond manufacturing, DT is now influencing emergency response and traffic systems [51,52]. However, successful implementation depends on high investment and robust cybersecurity [53]. Interoperability and data accuracy remain significant technical barriers [54,55]. Scalability and ethical concerns, such as transparency in decision-making, are also critical issues [33,56–58]. Based on this literature review, ten AI-driven intelligent technologies were selected for the second phase of this study: Robotic Process Automation, Digital Twins, predictive maintenance systems, Computer Vision for Quality Control, collaborative robots, Supply Chain Optimization Systems, Automated Guided Vehicles, Natural Language Processing for Human–Machine Interaction, Generative Design, and Additive Manufacturing.

2.3. Theoretical Summary: Intelligent Technologies vs. AI-Driven Technologies

The technologies examined in this study represent two distinct stages of digital transformation. The fourteen intelligent technologies evaluated in both 2017 and 2025 reflect the foundations of Industry 4.0. These include smart devices, identification tools, localization and navigation technologies, and information and robotics systems. Their primary function is to digitize processes, automate routine tasks, support traceability, and improve coordination in manufacturing and logistics. The literature on these technologies highlights their role in enabling data acquisition, real-time monitoring, and physical–digital integration, which are preconditions for more advanced digital capabilities. The 2017 expectations and 2025 reality show that the adoption of these foundational technologies has progressed unevenly. Logistics and material flow processes adopted autonomous vehicles, RFID, and collaborative robots faster than anticipated, while smart wearables and mobile solutions fell short of expectations. This confirms that technologies offering clear operational benefits and requiring less cognitive adaptation tend to diffuse more rapidly. In contrast, the AI-driven technologies surveyed in 2025 represent a second stage of development, where digitalized processes evolve toward intelligent decision-making. Technologies such as predictive maintenance systems, machine vision, Robotic Process Automation, Digital Twins, and advanced data analytics rely not only on automation but also on computational reasoning, pattern recognition, and predictive modeling. The literature positions these solutions as enablers of autonomous optimization rather than mere digitization. While the foundational Industry 4.0 technologies differ in adoption maturity, AI-driven technologies are gaining strong momentum in areas that depend on data availability and repetitive decision-making. Their high relative deployment suggests that once core technologies cre-

ate sufficient digital infrastructure, enterprises can move toward more intelligent, adaptive, and self-optimizing systems.

3. Materials and Methods

We used the same manufacturing enterprises from the 2017 study because they formed the original sample on which the technological expectations were measured. Data collection was carried out from November 2016 to March 2017. Re-engaging this identical group is essential for maintaining the validity of a longitudinal comparison. Using the same enterprises ensures that any differences between expected and actual adoption in 2025 reflect real technological developments rather than changes in the sample structure. This consistency is a core requirement of longitudinal research and allows us to assess the accuracy of the original expectations directly. The selection of enterprises in both the 2017 and 2025 studies followed predefined criteria to ensure the sample reflected the structure and conditions relevant to the adoption of intelligent technologies. Only large manufacturing enterprises were included, defined as organizations employing more than 249 employees, because these firms typically operate formalized production systems where smart technologies can be meaningfully integrated. All enterprises had to be located in the Slovak Republic and engaged in manufacturing or logistics, as the research focused on technological deployment within operational and production activities. To ensure clarity when comparing enterprises, each company was required to have a clearly identifiable product portfolio, classified according to NACE (Nomenclature of Economic Activities), a European system for classifying economic activities, enabling consistent categorization across industries. These criteria ensured that the research included firms with established production infrastructures, comparable operational environments, and sufficient technological capacity to evaluate both current and expected use of intelligent technologies. Applying the same criteria in 2017 and 2025 maintained continuity and strengthened the validity of the longitudinal comparison. This research continues the original empirical framework, grounded in a structured, methodologically rigorous approach to surveying technological expectations in the context of Industry 4.0. A total of 42 manufacturing enterprises participated in the 2025 round of the study. Two enterprises were excluded because the original quality managers were no longer employed. However, participants who had changed roles within the same organization—e.g., moving to another managerial position—were retained to ensure continuity and internal insight.

The difference in sample size (n = 42 vs. n = 44) is not statistically significant and does not affect the overall representativeness of the dataset. The sectoral distribution of the sample of 42 enterprises closely follows the expected structure based on 251 manufacturing and related enterprises. For manufacture of food products, beverages and tobacco (CA), 23 enterprises were expected and 4 were observed. For chemicals and chemical products (CE), 5 were expected and 1 was observed, while for pharmaceuticals and related products (CF), 3 were expected and 1 was observed. In rubber, plastics and other non-metallic mineral products (CG), 40 enterprises were expected and 7 were included in the sample. For basic and fabricated metal products (CH), 29 were expected and 4 were observed. In computer, electronic and optical products (CI), 11 were expected and 2 were observed, and in electrical equipment (CJ), again 29 were expected and 4 were observed. For transport equipment (CL), the largest group, 52 enterprises were expected and 9 were observed. In construction (F), 11 were expected and 2 were observed, and in transportation and storage (H), 48 were expected and 8 were observed. Overall, the observed frequencies by industry category correspond well to the expected distribution, with only minor deviations in individual sectors. The sample is representative. χ^2 is lower than the value χ^2 at the

level of statistical significance $\alpha = 0.05$ for 9 degrees of freedom (10–1). Since $2.104 < 3.32$, we can conclude that our selected set represents the basic set as in 2017.

Figure 2 shows that most industry groups maintained very similar representation in both samples. Nine out of ten industries have only minor shifts, with Δni values generally below one percentage point. This indicates stable sampling across years. The most notable change is in transport equipment (CL), which decreased by 5.84 percentage points in 2025. This sector was more strongly represented in 2017, so the reduction brings the 2025 sample closer to a balanced structure. A moderate decrease is also observed in basic metals and fabricated metal products (CH), where representation drops by 2.70 percentage points. All other industries—including food, chemicals, pharmaceuticals, plastics, electrical equipment, electronics, construction, and transportation/storage—show minimal differences, typically within ± 0.8 percentage points. This reflects consistent sample composition across both periods. Overall, the Δn_i values, calculated as the difference between ni in 2017 and ni in 2015, where ni is the frequency distribution of certain events observed in a sample, confirm that the 2025 sample remains structurally comparable to 2017, with only two sectors showing meaningful adjustments.

In both the 2017 and 2025 studies, we applied the Dillman Total Design Survey Method [59,60] to structure and administer the questionnaire. This method provides a set of principles for designing survey instruments and contact procedures so that questions are clear, response burden is minimized, and response rates are maximized. It emphasizes simple, unambiguous wording, logical ordering of questions, consistent layout, and a planned sequence of contacts with respondents. In the 2025 follow-up research, we used the same approach as in 2017. The deployment of intelligent technologies was evaluated using a research matrix that combines 26 manufacturing and logistics processes with 14 smart technologies. This matrix is presented in full in Table 2, where each row represents a specific process and each column corresponds to one of the technologies assessed in both 2017 and 2025. The table, therefore, contains all necessary details and serves as the complete framework for comparing expected and actual adoption. Each selected quality manager received a cover letter and the research matrix via email in January 2025. Ten days later, a reminder message was sent to all managers who had not yet replied. After another 10 days, we re-sent the cover letter and research matrix to those who had not responded. All communication was handled through a single dedicated email address, which was included in the cover letter so managers could ask questions or submit completed materials in a unified, controlled way.

In both studies, respondents were selected from four key managerial roles: quality managers, management representatives for quality, management representatives for integrated management systems (IMSs), and Chief Quality Officers. This structure remained stable, confirming the continuity of expertise across the longitudinal design. In 2025, quality managers again formed the largest group, representing almost half of all completed surveys, similar to 2017. The share of management representatives for quality and IMS remained proportional to the previous study, indicating that enterprises retained these functions. A new category appears in 2025, as Table 2 shows. Four respondents moved to different managerial positions within the same enterprise. Their inclusion slightly broadened the managerial profile but did not affect comparability, as they retained operational insight and organizational continuity. Overall, the respondent structure in 2025 mirrors that of 2017, with only minor internal shifts, and maintains the validity of the longitudinal comparison.

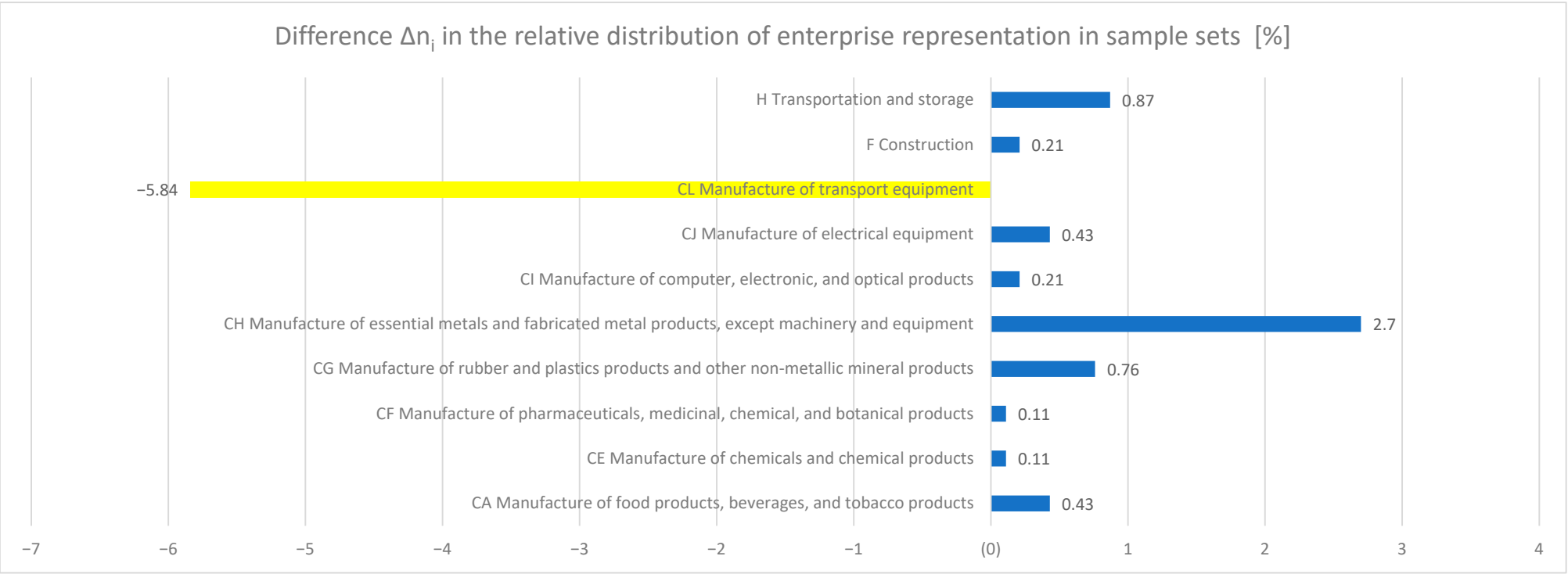


Figure 2. Difference in the relative representation of manufacturing enterprises by industry between 2017 and 2025 in the sample sets.

Table 2. Respondents' classification in 2025.

Job Position	Initial Sample	Without Reply	Second Sending	Effective Sample	Completed Surveys
Quality manager	21	2	2	19	19
Management representative for quality	13	0	0	10	10
Management representative for IMS	8	0	0	7	7
CQO	2	0	0	2	2
New job position	-	-	-	4	4
∑	44	2	2	42	42

Table 3 summarizes the methods and research stages applied in the research. It reflects the structure of the two sub-studies.

Table 3. Overview of methods and research stages.

Research Stage	Year/Sub-Study	Description of Activities	Method Applied
S1. Definition of research framework	2017 and 2025	Formulation of research questions (RQ1–RQ3) and partial objectives (PO1–PO4). Selection of 14 intelligent technologies and 26 processes for longitudinal comparison.	Conceptual framework design
S2. Sample selection based on predefined criteria	2017 and 2025	Selection of large manufacturing enterprises (>249 employees), with identifiable NACE codes and comparable production/logistics processes.	Purposeful sampling based on enterprise size and process criteria
S3. Questionnaire design	2017 and 2025	Development of a structured survey using identical variables from 2017 to maintain longitudinal validity.	Dillman Total Design Survey Method
S4. Data collection (longitudinal follow-up)	2025—Sub-study 1	Distribution of cover letter and empty research matrix (Table 4), reminder after 10 days, resend after another 10 days, all via a single dedicated email.	Mixed-mode electronic survey using the Dillman procedure
S5. Data consolidation and validation	2017 and 2025	Confirmation of respondents' roles, removal of non-responding enterprises, and retention of managers who changed positions within the same company.	Consistency validation, respondent classification
S6. Expectation vs. reality analysis	2025—Sub-study 1	Calculation of E2017_rel, R2025_rel, and ΔER for each technology. Comparison across 26 processes.	Quantitative comparative analysis
S7. Expansion of research scope	2025—Sub-study 2	Identification of 10 AI-driven technologies through a focused literature review. Expansion to 136 enterprises.	Selective literature review + sample extension
S8. Rapid survey of AI-driven technologies	2025—Sub-study 2	Managers selected five technologies they use or plan to use. Variables AI_IT_abs and AI_IT_rel calculated.	Quick survey method (indicative)
S9. Statistical evaluation of sample structure	2025	Chi-square test comparing representation across industry groups in 2017 vs. 2025.	χ^2-test for structural consistency
S10. Interpretation and discussion	2025	Identification of overestimated and underestimated technologies and changes in process-specific deployment.	Comparative and interpretive analysis

Table 4. Real intelligent technologies deployment in 2025 in the sample.

	Smart Glasses	Smart Gloves	Smart Watches	Smart Phones/Tablets	RFID Technology	Barcode	QR Code	GPS Tracking	Drones	Autonomous Vehicles	MES	3D Printing	Virtual Reality Simulation	Collaborative Robots
P1:	0.0	0.0	0.0	50.0	0.0	0.0	0.0	0.0	0.0	0.0	80.0	0.0	40.0	0.0
P2:	3.0	0.0	4.7	60.0	0.0	0.0	10.0	0.0	0.0	30.0	80.0	90.0	80.0	50.0
P3:	3.0	0.0	0.0	45.0	0.0	10.0	14.4	5.0	0.0	20.0	80.0	94.7	77.0	90.0
P4:	2.0	0.0	0.0	60.0	5.0	10.0	14.4	0.0	0.0	20.0	80.0	94.7	80.0	90.0
P5:	3.0	0.0	0.0	50.0	5.0	10.0	14.4	0.0	0.0	21.0	80.0	94.7	80.0	90.0
P6:	2.0	0.0	0.0	30.2	11.5	10.0	40.0	11.5	0.0	70.0	80.0	14.4	0.0	0.0
P7:	3.0	15.0	0.0	50.0	16.0	77.0	80.0	11.5	16.0	70.0	90.0	90.0	30.2	50.0
P8:	5.0	14.0	4.0	40.0	40.0	77.0	80.0	2.0	16.0	77.0	95.0	90.0	20.0	90.0
P9:	0.0	14.0	0.0	40.0	20.0	10.0	11.5	5.0	16.0	77.0	95.0	14.4	20.0	90.0
P10:	2.0	0.0	11.5	30.2	18.0	10.0	11.5	5.0	11.5	20.0	96.0	50.0	90.0	40.0
P11:	11.5	28.0	11.5	40.0	29.0	10.0	41.0	10.0	11.5	80.0	97.0	90.0	94.7	94.7
P12:	0.0	0.0	0.0	50.0	5.0	10.0	12.0	0.0	0.0	0.0	80.0	90.0	97.0	80.0
P13:	5.0	18.0	35.0	80.0	30.2	80.0	80.0	10.0	30.2	77.0	95.0	90.0	9.0	30.2
P14:	3.0	0.0	0.0	50.0	0.0	6.0	11.5	0.0	0.0	0.0	80.0	14.4	50.0	0.0
P15:	6.0	0.0	50.0	90.0	0.0	0.0	8.0	0.0	0.0	0.0	80.0	0.0	29.0	0.0
P16:	7.0	5.0	7.0	50.0	30.2	80.0	80.0	15.0	40.0	50.0	94.7	77.0	78.0	90.0
P17:	14.4	32.0	11.5	70.0	29.0	80.0	80.0	32.0	20.0	30.2	90.0	40.0	40.0	60.0
P18:	9.0	0.0	11.5	80.0	0.0	70.0	77.0	0.0	0.0	0.0	80.0	90.0	94.7	0.0
P19:	0.0	3.0	0.0	70.0	15.0	70.0	77.0	15.0	20.0	50.0	90.0	0.0	9.0	90.0
P20:	14.4	0.0	1.5	30.2	29.0	90.0	90.0	11.5	0.0	30.2	80.0	30.0	40.0	18.0
P21:	3.0	0.0	11.5	30.2	75.0	100	100	30.0	33.0	70.0	80.0	10.0	0.0	0.0
P22:	9.0	29.5	5.0	80.0	75.0	100	100	10.0	30.2	80.0	80.0	7.0	7.0	77.0
P23:	11.5	57.0	3.0	70.0	60.0	100	100	10.0	40.0	77.0	91.0	5.0	11.5	50.0
P24:	2.0	0.0	0.0	80.0	80.0	100	100	100	60.0	80.0	80.0	0.0	11.5	30.2
P25:	3.0	32.0	3.0	70.0	80.0	90.0	91.0	50.0	29.0	70.0	80.0	0.0	14.4	90.0
P26:	2.0	0.0	15.0	90.0	90.0	100	100	100	60.0	77.0	94.7	0.0	11.5	0.0
R2025_Trel	4.76	9.52	7.14	57.14	28.57	50	54.76	16.67	16.67	45.24	85.71	45.24	42.86	50

4. Results

The research focused on quantifying the gap between expectation and reality, using the same smart technologies and process contexts evaluated in 2017. In this first sub-research, the following research variables were defined:

- E2017_Trel: Quality managers' expectations related to the technology deployment for 2025, expressed as the arithmetic average percentage of expected deployment of each intelligent technology across the 26 manufacturing and logistic processes (results from 2017).
- E2017_Prel: Quality managers' expectations related to the process automation for 2025, expressed as the arithmetic average percentage of expected process automation across the 14 intelligent technologies (results from 2017).
- R2025_Trel: Real deployment of the same intelligent technologies in 2025, also expressed as the arithmetic average percentage across the same 26 processes (results from 2025).
- R2025_Prel: Real process automation based on intelligent technology integration in 2025, also expressed as the arithmetic average percentage across the same 14 intelligent technologies (results from 2025).
- ΔER_T: The difference between expectation and reality, calculated as the gap between E2017_Trel and R2025_Trel for each technology.
- ΔER_P: The difference between expectation and reality, calculated as the gap between E2017_Prel and R2025_Prel for each manufacturing or logistic process.

Figure 3 presents expected levels of automation for 26 manufacturing and logistics processes.

Values represent the average planned use of 14 intelligent technologies, as estimated by quality managers in 2017. Four processes show distinctly high expectations, all above 42 percent: P24: Transportation—47.53% (highest); P26: Delivering—47.26%; P23: Dispatching—42.34%; and P22: Warehousing—42.46%. These processes involve repetitive handling, movement, and coordination tasks, making them strong candidates for digital support even in early Industry 4.0 stages. Processes with medium expected automation in 2017 ranged from 29 to 38 percent, including P11: Manufacturing, P13: Nonconformity management, P17: Quality control, P21: Purchasing, P20: Change management, and P18: Visual management. These involve semi-structured routines with growing potential for sensor data, visualization, and monitoring tools. Several processes fall below 16%, indicating limited perceived automation potential in 2017: P1: Forecasting, P9: Scheduling, P12: Converting manufacturing processes, and P14: Continuous improvement. These areas were traditionally seen as knowledge-intensive or difficult to automate with early-generation Industry 4.0 technologies.

Figure 4 presents the actual level of automation across 26 manufacturing and logistics processes in 2025, based on the average use of 14 intelligent technologies. The results show a clear shift toward higher automation in logistics-related tasks, while several administrative and planning processes remain at low levels. Five processes exceed 50%, representing the strongest technological penetration: P26: Delivering, P23: Dispatching, P24: Transportation, P22: Warehousing, and P25: Manipulation. These results confirm that logistics and material flow operations achieved the fastest and most intensive adoption of intelligent technologies by 2025. Several processes fall between 35 and 49%, indicating solid but not dominant automation: P11: Manufacturing, P13: Nonconformity management, P20: Change management, and P18: Visual management. These processes rely on structured workflows and routine decision-making, supporting moderate levels of digital integration. Many early-stage or knowledge-intensive activities remain minimally automated, with values below 15 percent: P1: Forecasting, P9: Scheduling, P12: Converting manufacturing processes, and P14: Continuous improvement. These processes typically require expert judgment or complex adaptability, limiting their automation potential in 2025.

In 2017, quality managers were optimistic about the future integration of intelligent technologies into manufacturing and logistics processes, as shown in Figure 5. Their expectations were heavily skewed toward conventional and familiar digital tools, with smartphones/tablets (85.8%), Manufacturing Execution Systems (79.5%), QR codes (50.6%), and barcodes (47.9%) leading the list. This reflects a practical outlook focused on technologies already present in the digital landscape but anticipated to expand further in functionality and reach. Interestingly, wearable technologies like smart glasses (28.8%) and smart watches (20.4%) were also expected to see notable uptake, indicating a belief in more personalized, mobile interfaces for production oversight. However, emerging and complex technologies such as collaborative robots (2.8%), 3D printing (5.2%), drones (7.5%), and virtual reality simulation (9.4%) were expected to have limited deployment, possibly due to perceived implementation complexity.

The 2025 data in Table 4 show the actual deployment of intelligent technologies in the sample (R2025_Trel). Based on these results, it is possible to determine the level of use of each defined technology. For smart glasses, the real use is very low. Adoption remains marginal because companies report limited practical benefits and difficulties integrating them into daily operations. For smart gloves, the deployment is minimal. Usage appears experimental primarily, with few enterprises applying them in routine activities. For smart watches, the actual use is minimal. Their expected role in operator communication

did not materialize in 2025. For smartphones/tablets, the adoption is moderate. These devices are used particularly in reporting, warehousing, and material handling, but not as widely as anticipated. RFID technology shows strong use, especially in warehousing, dispatching, and logistics. RFID is among the most applied smart technologies in 2025. Barcodes are one of the most widely used technologies. They remain a foundation for process identification and traceability. QR code deployment is moderate to high, higher than many other technologies. Companies use QR codes in quality control, maintenance, and material flow. GPS tracking shows high real deployment, mainly in transportation and delivery processes, reflecting strong logistics digitalization. For drones, real use is low. Although promising for inventory and inspection, adoption remains rare in 2025. For autonomous vehicles, deployment is high, especially in internal transport, manipulation, and warehousing. Actual usage exceeds original expectations. Manufacturing Execution Systems show high adoption, supporting production control, quality monitoring, and traceability. Three-dimensional printing use is moderate. It is most common in prototyping and specialized component production, but not in mass production. Virtual reality shows moderate adoption, primarily for training, planning, and visualization. Real use is higher than the 2017 forecasts. For collaborative robots, the deployment is high and increasing rapidly. Collaborative robots are used in manufacturing, quality control, and logistics, making them among the top technologies in 2025.

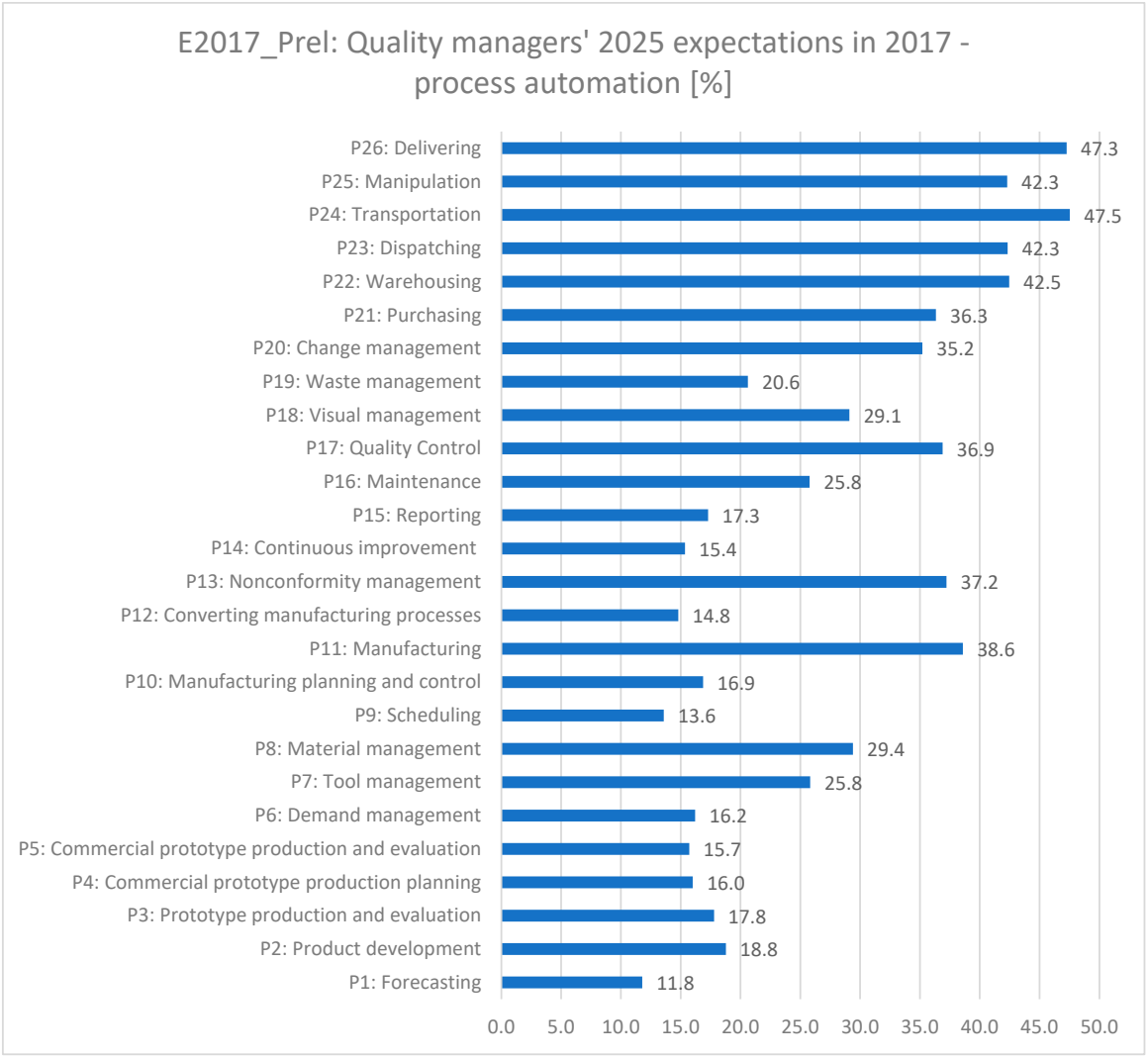


Figure 3. Quality managers' expectations related to the process automation for 2025 in 2017 [1].

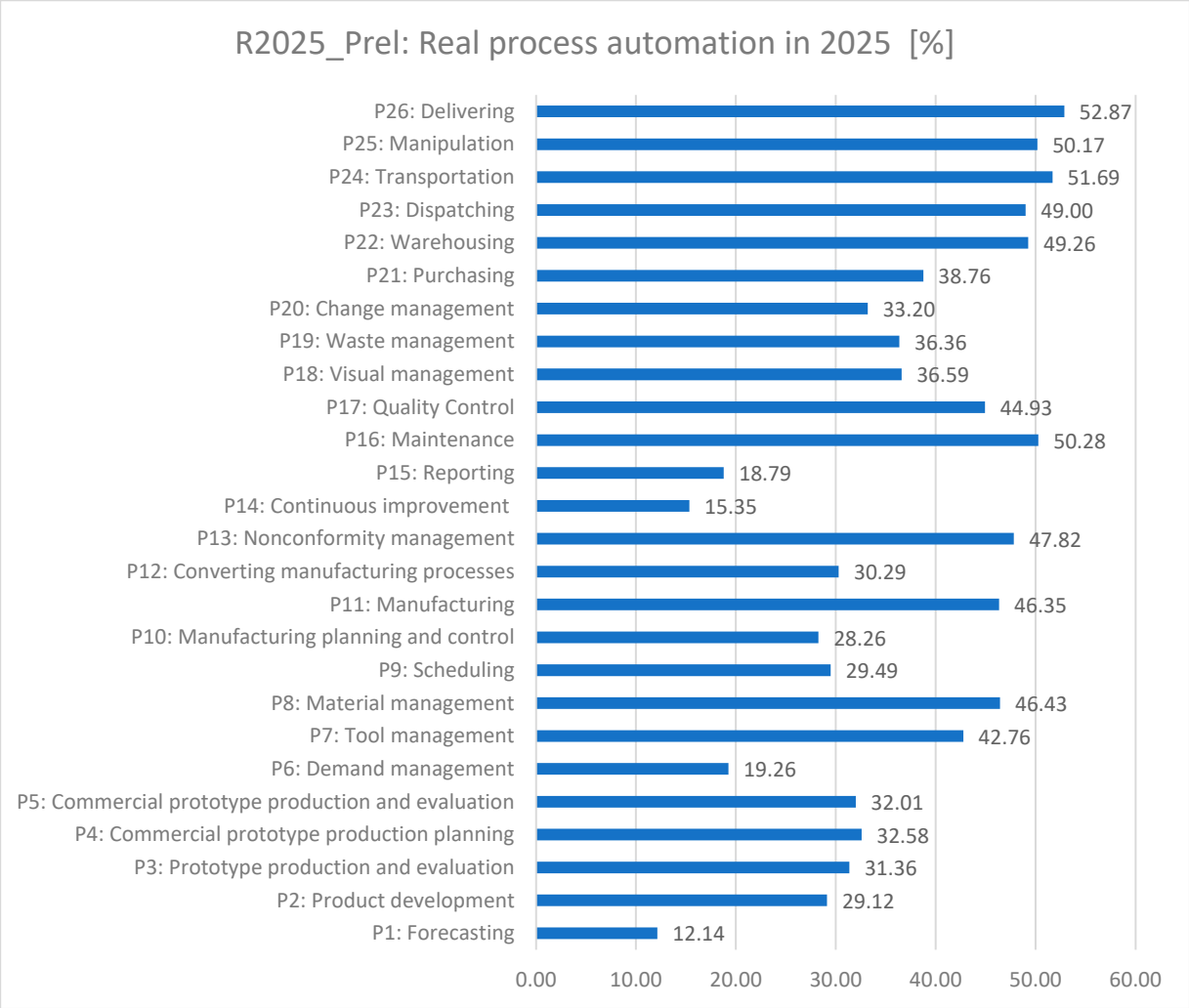


Figure 4. Real process automation based on the integration of intelligent technologies in 2025.

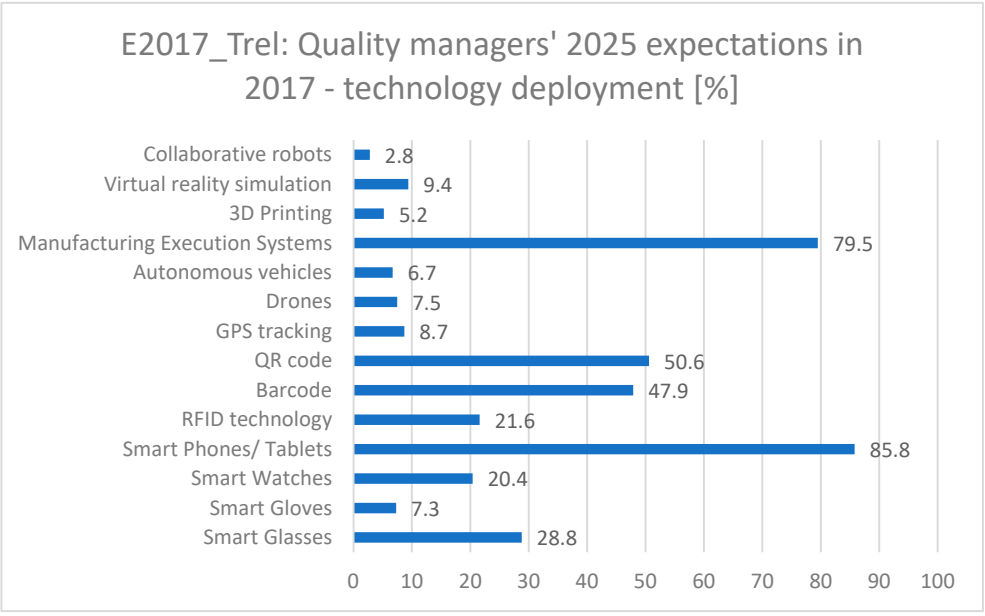


Figure 5. Quality managers' expectations in 2017 for how the intelligent technologies will be deployed in 2025 [1].

Given the integration of artificial intelligence into manufacturing and logistics processes, we conducted a rapid survey of managers' perceptions of these technologies. The main objective of our quick survey was to quantify the perceptions of how intelligent technologies with integrated artificial intelligence are used or will be used in manufacturing processes. The respondents included 97 quality managers and 39 production managers. The survey results are only indicative. Based on a literature review, we defined a set of intelligent technologies that can integrate artificial intelligence: RPA = Robotic Process Automation; DT = Digital Twins; PMS = predictive maintenance system; CVQC = Computer Vision for Quality Control; CR = collaborative robots (Cobots); SCOS = Supply Chain Optimization Systems; AGV = Automated Guided Vehicles (AGVs); NLP = Natural Language Processing for Human–Machine Interaction; GD = Generative Design and 3DP = Additive Manufacturing (3D printing). Respondents were asked to select five intelligent technologies integrated with artificial intelligence that they use or plan to use in manufacturing and logistics processes in the indefinite future. The survey was conducted in January and February 2025. Although 10 technologies with integrated artificial intelligence were defined, we wanted to determine respondents' preferences. Therefore, they could select only five technologies. We determined these variables for the survey:

- AI_IT_abs = absolute number of managers from manufacturing enterprises where an AI-driven manufacturing technology is used or planned to be used;
- AI_IT_rel = percentage of managers from manufacturing enterprises where an AI-driven manufacturing technology is used or planned to be used.

As Figure 6 shows, the most dominant intelligent technologies are Robotic Process Automation (69.12%), Additive Manufacturing (63.97%), Digital Twins (61.03%), collaborative robots (52.21%), and predictive maintenance systems (47.06%). These results also answer the question in RQ3—which intelligent technologies with integrated artificial intelligence are used or will be used in manufacturing processes?

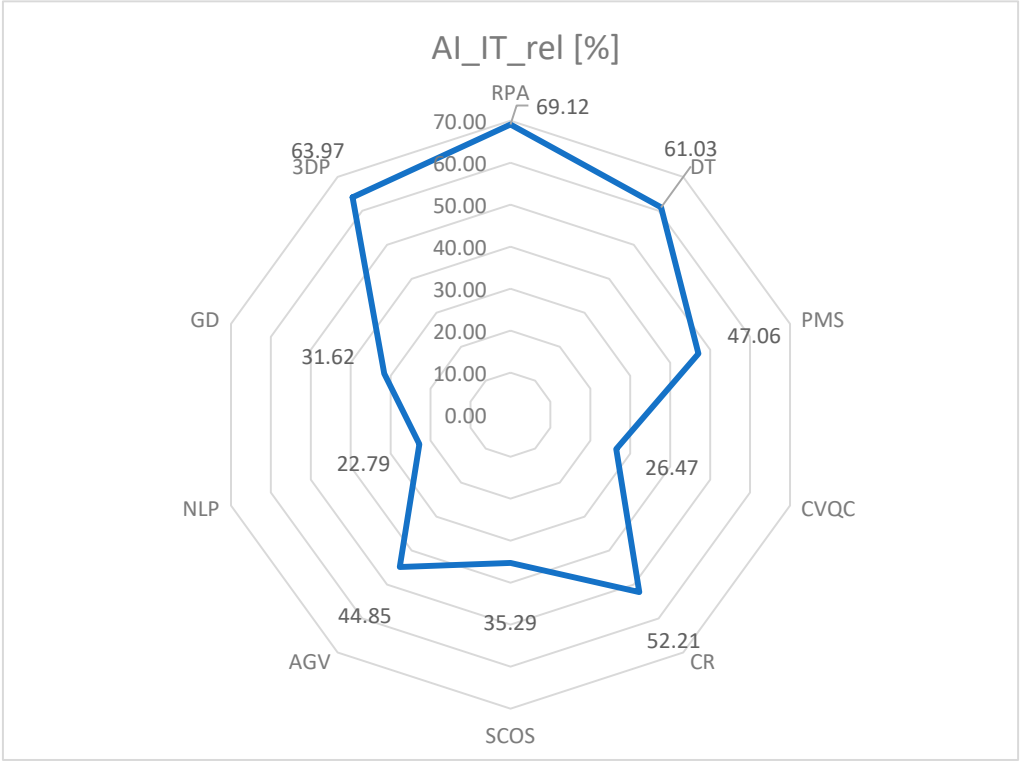


Figure 6. Managers' perceptions of AI-driven technologies in manufacturing processes.

5. Discussion

Figure 7 shows significant discrepancies between expected and actual adoption of smart technologies in manufacturing and logistics processes. The most crucial positive gap was observed for collaborative robots (+47.20%), followed by 3D printing (+40.04%), autonomous vehicles (+38.54%), and virtual reality simulation (+33.46%). These results indicate that technologies previously considered peripheral or experimental became far more relevant than anticipated. The most significant negative gap appeared with smartphones/tablets (−28.66%) and smart glasses (−24.04%), suggesting that while initially viewed as central to digital transformation, their relevance plateaued or was supplanted by more advanced or integrated solutions. Smart watches (−13.26%) also underperformed against expectations, reinforcing the broader trend of overestimating wearable technologies.

Technologies such as RFID, barcodes, QR codes, and Manufacturing Execution Systems showed only minor deviations, indicating more accurate forecasting in areas that were already maturing in 2017. The comparative analysis of expectations from 2017 and the actual deployment of smart technologies in 2025 reveals a clear trend: on average, real-world implementation exceeded original forecasts by +9.4%. While quality managers in 2017 anticipated an average deployment rate of 27.3%, the realized adoption across processes and technologies reached 36.7%. This gap signals significant progress in smart technology integration—though not uniformly across all areas.

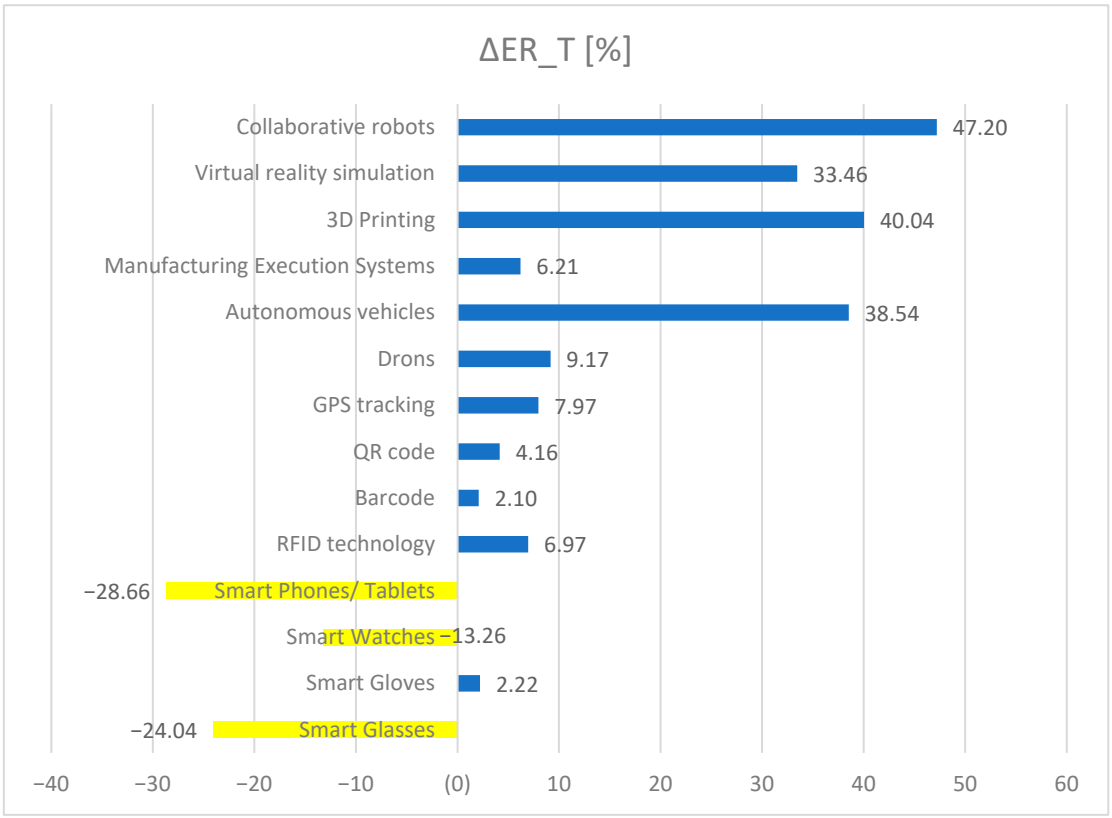


Figure 7. The difference ΔER_T between expectation in 2017 and reality in 2025 for each technology.

Figure 8 shows how much the real level of process automation in 2025 differed from what quality managers expected in 2017. A positive value indicates real automation is higher than expected, and a negative value means it is lower than expected. The most significant positive gaps appear in logistics and maintenance, confirming that these areas developed faster than managers anticipated: P16: Maintenance; P18: Waste management; P11: Manufacturing; P25: Manipulation; P17: Quality control; P22: Warehousing; P23:

Dispatching; P26: Delivering. These results show that logistics (P22–P26) and supporting activities (maintenance, waste, quality control) achieved more automation than expected. Processes where automation was lower than expected (negative ΔER_P) show a negative difference, meaning expectations were overly optimistic: P14: Continuous improvement and P20: Change management. These typically represent planning, analytical or cognitive processes, where automation proved more difficult than anticipated. Logistics, manufacturing execution, and support activities automated faster than expected. Planning, forecasting, scheduling, and process analysis were automated more slowly than expected. The most significant positive deviation occurs in Maintenance (P16), a process that experienced strong digitalization. The most underestimated area overall is logistics. The most overestimated processes are those requiring complex decisions rather than routine physical operations.

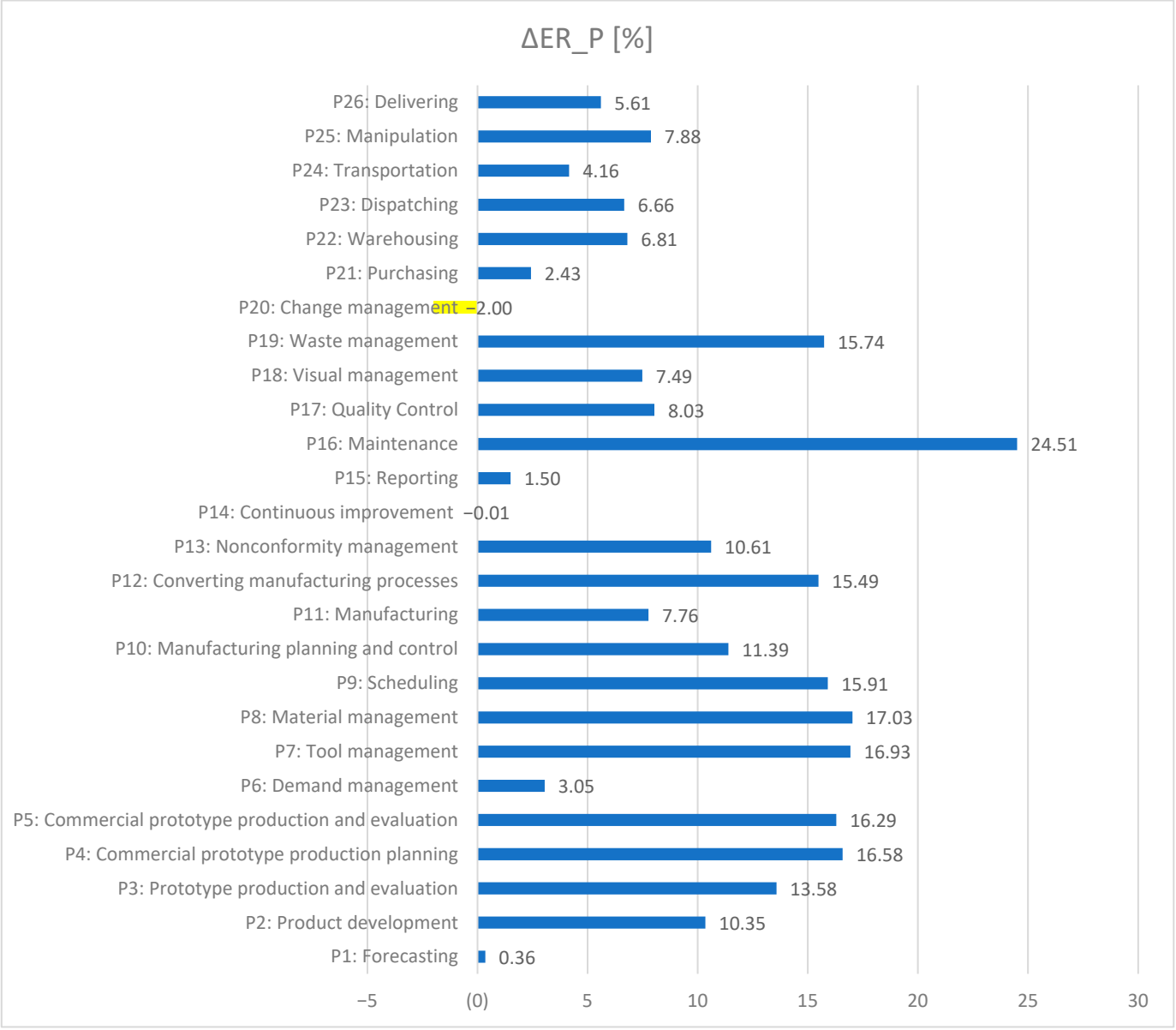


Figure 8. The difference ΔER_P between expectation in 2017 and reality in 2025 is related to the process automation.

Based on the results of both research and survey, we can conclude that the expectations of quality managers were statistically significantly unfulfilled. The average difference was

9.4% across all 14 original intelligent technologies. These findings need to be analyzed. However, they were wrong only in three smart technologies. All other technologies met expectations or showed a slight increase. So, the managers were not significantly wrong when evaluating expectations regarding the number of deployed intelligent technologies. The only significant difference was with wearable innovative technologies. Comparing expected and actual automation levels provides several insights for managers and policymakers. The positive values of ΔER_P and ΔER_T in logistics, maintenance, and quality-related processes show that these areas advanced faster than expected. For managers, this indicates that technologies such as autonomous vehicles, RFID, collaborative robots, and QR-based identification are becoming standard operational tools. Enterprises that still rely on manual procedures in warehousing, dispatching, or internal transport risk falling behind in efficiency and traceability. Managerial planning should therefore prioritize these processes when designing modernization roadmaps, including training programs and requalification of workers who now cooperate more directly with intelligent systems. Negative ΔER_P values in forecasting, scheduling, and process planning highlight that cognitive and analytical tasks remain far more difficult to automate than anticipated. Policymakers should view this as a signal to support investments in data quality, interoperability, and AI-related analytical capacities. Without reliable data and strong digital foundations, automation cannot progress evenly across the production system. Public support could help firms implement advanced planning tools, strengthen digital infrastructure, and prepare workforce upskilling programs focused on AI-driven decision support. The results from the second part of the 2025 research (AI_IT_rel) show that enterprises are increasingly adopting AI technologies such as predictive analytics, machine vision, and AI-enhanced maintenance. Their growing use suggests that the next stage of digitalization will be shaped by AI integration rather than the expansion of basic Industry 4.0 tools. Future research should therefore focus on measuring how AI changes organizational structures, worker competencies, and the interaction between processes. Longitudinal studies will be essential to understand how AI-driven technologies evolve and which capabilities help firms convert experimentation into sustained performance improvements.

Research limitations and barriers can also be identified within the two sub-studies. From the perspective of smart technology development, examining the same set of 14 technologies appears to pose a research barrier. However, to ensure the research was valid, we had to ask managers about the same set of technologies as in 2017. The sample of large enterprises consisted of the same enterprises, but two managers did not respond to the invitation to participate in the research. Therefore, there are 42 enterprises in the sample for this research, but this difference is not statistically significant. The last research barrier of the first sub-research is that some former quality managers were enterprise employees in the sample. Still, they already worked in a different job position. They had the same company email but were already managers for other processes. Despite this, they responded. This approach is consistent with the requirements for research validity, namely that the same managers react to the same questions. The quick survey also had three fundamental research barriers that could be removed. It should be emphasized that this second sub-research is complementary and indicative. It indicates managers' perceptions of the deployment of AI-driven intelligent technologies. The use of AI-driven technology could already be in place or planned for the future; therefore, the time limit is the limit. This is only an indicative, quick survey that will be developed as a separate scientific study. The expanded sample of respondents included quality managers and production managers. However, we followed the basic rule for selecting enterprises: only large manufacturing enterprises were selected. The last research barrier was that we did not verify the represen-

tativeness of the expanded sample. Since this is indicative research that will continue, this is acceptable.

6. Conclusions

This study provides the first longitudinal evidence on how accurately quality managers predicted the adoption of intelligent technologies over an eight-year horizon. By revisiting the same set of 14 technologies and re-engaging the same manufacturing enterprises surveyed in 2017, the research confirms a statistically significant expectation–reality gap. On average, actual deployment in 2025 exceeded the anticipated level by 9.4 percentage points, though this difference was uneven across technologies and processes. Manufacturing and logistics processes primarily benefited from higher-than-expected automation: collaborative robots, 3D printing, autonomous vehicles, and virtual reality recorded the most significant positive deviations, in several cases exceeding expectations by more than 40 percentage points. These findings indicate that technologies initially perceived as peripheral matured quickly and delivered tangible operational benefits. Conversely, the most substantial underestimations were associated with wearable technologies—smart glasses, smart watches, and smartphone/tablet applications—suggesting that their practical relevance was overestimated in 2017. The second study confirms that the technological landscape has shifted toward AI-integrated systems. Robotic Process Automation (69.12%), Additive Manufacturing (63.97%), Digital Twins (61.03%), collaborative robots (52.21%), and predictive maintenance systems (47.06%) emerged as the most dominant AI-driven technologies, reflecting managers' strategic alignment with data-driven process optimization and automation. These results have clear implications for manufacturing enterprises. First, long-term forecasting requires continuous recalibration, as technologies perceived as marginal may become transformative within a single investment cycle. Second, enterprises should prioritize systems that enhance automation, traceability, and predictive capabilities, as these areas have demonstrated the strongest real-world adoption. Third, expectations regarding wearable and mobile devices should be reassessed, as their role in production environments appears limited. Future research should examine how process characteristics (complexity, variability, workforce structure) influence deviations between expected and actual adoption, and how AI-driven technologies reshape decision-making roles and competencies within manufacturing enterprises.

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