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Souad LAHMINE[1*],
Fatima BENNOUNA[1]

BRIDGING CLASSICAL QUALITY TOOLS AND INDUSTRY 4.0: A DATA-DRIVEN FRAMEWORK FOR INTELLIGENT PROCESS CONTROL

This paper initiates a study that would help bridge the classical quality methodologies with the up-to-the-minute digital drift of Industry 4.0 technologies. To address this, the study proposes the development of a hybrid framework for implementing classical quality methodologies, namely Six Sigma and Total Quality Management, together with Quality 4.0 tools involving Artificial Intelligence, Internet of Things, and big data analytics. The study implements an enriched AI-based Statistical Process Control system applicable to the real shop floor of an automotive manufacturer after conducting a systematic literature review to identify any existing models. The proposed system, over twelve months, brought about a 32% defect rate reduction. This study closes the loop of the constant feedback that is necessary for coupling heritage quality management with intelligent technologies to ensure the continuous proactive, adaptive, data-driven control needed for a way towards smart, resilient manufacturing ecosystems.

1. INTRODUCTION

Customer confidence remains the backbone of the global manufacturing industry, particularly in the current digitally-enhanced and global-scale market, where operational excellence and product quality are critical determinants of business survival and competitiveness [1]. The cost of poor quality–including rework, scrap, warranty claims, and customer dissatisfaction–has been reported to account for up to 20–30% of a company’s total revenue [2]. Accordingly, defect detection, prevention, and continuous improvement have remained core research and industrial focus areas over the past decades.

The historical progression of quality management has evolved in distinct phases. In Quality 1.0, inspection and defect identification were prioritized post-production. Quality 2.0 introduced Statistical Process Control (SPC) to monitor and reduce process variation [3]. Quality 3.0 brought holistic approaches such as Total Quality Management (TQM), Six

[1] Engineering Systems and Applications Laboratory (LISA), National School of Applied Sciences (ENSA), Sidi Mohamed Ben Abdellah University of Fez, Morocco
[*] E-mail: souad.lahmine@usmba.ac.ma
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Sigma, and ISO-based quality management systems to encourage systemic continuous improvement across all levels of an organization [3]. Though not adequate to bring the issues to an ultimate light at the production stage, the other key limitations of the old approaches are that they don't have the capability to make real-time predictions and, when actually applicable, are confined to either the product or process view [4]. Such limitations restrict their relevance in modern manufacturing systems, which have attained a high level of complexity through the intertwinement of different sources of variation.

The rise of Industry 4.0 reflects a change in the game of how manufacturing firms function. In principle, the integration of cyber-physical systems, the Industrial Internet of Things, Artificial Intelligence (AI), Digital Twins, and big data analytics fosters levels of transparency, traceability, and real-time decision-making that were previously unknown [5, 6]. Within the digital environment, Quality 4.0 comes to the picture as the evolution of all former quality system approaches. Q4.0 tries to insert smartness and automation inside the quality management practice, pushing for predictive analysis, adaptive control, and near-zero-defect manufacturing [6]. While these promises have been made, effective adoption of Q4.0 has barriers that are significantly high. It is particularly challenging for SMEs to adopt Q4.0, as there is no digital infrastructure at large, no standardization, high implementation cost, and skills gaps in the workforce [3, 4]. Studies by Ghobakhloo and Ching (2019) and Amaral and Peças (2020) also indicate misalignment between maturity models in the I4.0/Q4.0 theoretical bases and SME practicality, since they cling to old equipment and have low levels of automation. This, in turn, makes the general implementation process even more difficult, due to change resistance and a lack of leadership commitment [7].

Another crucial limitation is the availability and quality. Large volumes of high-quality contextualized and labelled datasets are a prime requisite of almost all AI and ML applications [8]. Real-world manufacturing environments witness high variability in data quality and quantity, lack standardization, and suffer from a lack of data contextualization on a large scale [9]. As a result, AI models appear to perform well when nurtured in labs of ideal acclimatization but fare poorly when deployed in real industrial settings [10].

To overcome the persistent challenges of integrating digital technologies into legacy quality systems, this study introduces a novel hybrid framework that synergizes the methodological rigor of traditional quality approaches—such as Six Sigma, Total Quality Management, and SPC–with the real-time monitoring, predictive analytics, and automation capabilities enabled by Quality 4.0 technologies [11].

A mixed-methods research design shall be used that includes a systematic literature review to be followed by an empirical case study to take place within a global automotive assembly facility. The AI-enhanced SPC system proposed shall be embedded within the continuous improvement cycles that will facilitate real-time anomaly detection along with decision support and feedback mechanisms across production processes [12]. The case study was for a twelve-month implementation period, which revealed a 32% reduction in defect rates; thus, it proved the theory that the integration of classical quality systems with digital enablers produces much better outcomes than the sum of the individual performances of each would hint at.

This work contributes to both theory and practice by showing how legacy quality systems can be updated for quality assurance in the new Industry 4.0 technologies and systems. It does this without the need for a major overhaul [13]. It also pre- sent a structured roadmap more specifically designed for small and medium-sized enterprises (SMEs) that typically have few resources and little infrastructure support for any type of transformation [3].

The remainder of this paper is structured as follows: Section 2 presents a detailed review of literature on traditional and digital quality approaches; Section 3 introduces the research design and case study methodology; Section 4 reports the case study findings; Section 5 proposes a practical framework for Q4.0 implementation; and Section 6 summarizes the conclusions and offers suggestions for future research directions.

2. LITERATURE REVIEW

The evolution of quality management has been closely tied to the broader transformations occurring across successive industrial revolutions. Historically, quality assurance began as a reactive activity with the sole purpose of identifying and removing defective products at the end of production lines. Over time, this reactive model gave way to more structured and systematic approaches that focused on defect prevention, continuous improvement, and ultimately, real-time data-driven quality management [3].

2.1. EVOLUTION OF QUALITY MANAGEMENT METHODOLOGIES

The first phase of Quality 1.0 meant that there was a check on the quality of the final product. It was very difficult for manufacturers to spot the defects and non-conformities until the final product was made. Though this was just a beginning, it proved to be labor-intensive, costly, and ineffective in stopping repeated process issues from happening in the future [4].

This was where Quality 2.0 evolved, and SPC was introduced. By embedding statistical tools such as control charts into production lines, manufacturers were able to monitor process variation and proactively manage production quality [4]. Despite its success in reducing process variability, Quality 2.0 was largely limited to local process optimization rather than integrated system-wide quality control.

The introduction of Quality 3.0 represented a paradigm shift from process control toward a company-wide philosophy of continuous improvement and customer focus. Frameworks such as TQM, Six Sigma, and ISO 9000 standards promoted quality as an organizational value involving leadership commitment, cross-functional collaboration, and structured problem-solving methodologies [14]. However, traditional TQM approaches remained manual, document-intensive, and largely disconnected from the increasingly digitalized production environments.

In response to the emerging demands of global supply chains and complex manufacturing systems, Quality 4.0 has emerged as an extension of Industry 4.0 principles. Quality 4.0 leverages advanced digital technologies – such as Internet of Things (IoT), Artificial Intelligence, Digital Twins, Big Data analytics, and Blockchain – to transition from reactive quality assurance to real-time, predictive, and autonomous quality systems [1].

Figure 1 presents the historical development of quality paradigms from the traditional inspection-based approaches to the use of data for achieving self-optimizing ecosystems in Quality 4.0. Trends in this shift are increasing real-time process monitoring, autonomous decision-making, and continuous learning. While the legacy systems gave the basic foundations of quality management, a shift has occurred with the use of Quality 4.0 technologies implemented predictive and adaptive-control applications for all supply chain.

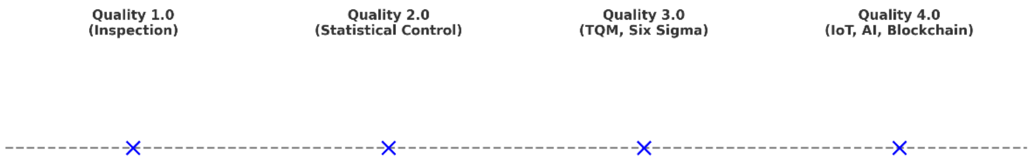

Fig. 1. Evolution of quality management paradigms: from inspection-based Quality 1.0 to intelligent, data-driven Quality 4.0 systems

As illustrated in Fig. 1, each evolutionary phase reflects a shift toward increasing levels of process integration, data utilization, and real-time decision-making capabilities. While traditional methods provided structured, continuous improvement, Quality 4.0 uniquely integrates digital technologies to enable autonomous, adaptive quality control across complex industrial environments.

2.2. CORE TECHNOLOGIES ENABLING QUALITY 4.0

The execution of Quality 4.0 relies on the efficient assimilation of several emerging technologies. These enablers have broadened the operational powers of quality systems to embrace data monitoring on a continuous basis, predictive analytics, and decentralized decision-making. Below is Table 1 that summarizes these key technologies and their representative applications in an industrial context.

Internet of Things (IoT): IoT devices and sensors provide the foundational layer for real-time monitoring of critical production parameters, including temperature, vibration, torque, and pressure. Devices and sensors under IoT form the base that will be used to monitor some critical parameters in a real-time environment for the production process. These parameters include temperature, vibration, torque, and pressure [6]. Data from these devices enables process traceability and early detection of potential failures. It is data from these devices that will make process traceability possible and enable detection to be done earlier, where there is a potential failure [15].

Digital Twins: This involves offering dynamic, real-time virtual models of production assets and systems. Mayr (n.d.) further explains that simulating and optimizing production scenarios before execution offers an opportunity for the manufacturer to reduce downtime, improve equipment utilization, and mitigate risks [16].

Artificial Intelligence and Machine Learning: The patterns and minor aspects of normal operations are discovered by AI and ML algorithms for predictive quality management [4]. These being learning systems, in due course, with the availability of fresh data, gradually enhance their ability to predict. Hence, this is best suited for high-mix and low-volume manufacturing setups [17, 18].

Blockchain for Traceability and Trust: A record that cannot be changed, showing whether data on quality and events in the certification has relevance to extremely complicated supply chains [10]. This is important to keep documentation on supplier compliance, quality of audits, and product certification tamper-proof.

Table 1 emphasizes how the transformation toward Quality 4.0 introduces a step change in operational capabilities through advanced connectivity, predictive analytics, and cyber-physical integration. Nevertheless, the adoption of Quality 4.0 remains constrained by technological maturity and organizational readiness.

Table 1. Historical evolution of quality management paradigms

Generation	Description	Focus	Limitations
Quality 1.0	Final inspection	Reactive, defect detection	No prevention, costly
Quality 2.0	Statistical process control	Process monitoring, SPC	Limited integration
Quality 3.0	TQM, Six Sigma	Company-wide quality culture	Disconnected, manual
Quality 4.0	AI, IoT, Blockchain	Predictive, autonomous control	High barriers, data issues

2.3. CORE TECHNOLOGIES ENABLING QUALITY 4.0

The convergence of advanced technologies underpins the operational capabilities of Quality 4.0. These core technologies are summarized in Table 2.

Internet of Things (IoT): The backbone of Quality 4.0 is built upon the widespread deployment of IoT-enabled sensors and devices throughout the manufacturing ecosystem. These sensors monitor critical process variables such as temperature, pressure, vibration, and torque to detect early signs of abnormal behaviour and initiate corrective actions without human intervention [1]. IoT technologies provide the infrastructure for real-time data acquisition, contextualization, and integration across previously disconnected systems.

Digital Twins: Digital Twin technology represents a significant advancement in simulation and process optimization. A Digital Twin is a virtual replica of a physical asset, system, or process, dynamically updated through live data from the production environment (Mayr, n.d.). By leveraging real-time data, Digital Twins allow manufacturers to predict system behaviour under varying conditions, conduct scenario analyses, and optimize process parameters prior to actual implementation, thereby reducing downtime and operational risks.

Artificial Intelligence and Machine Learning: artificial intelligence and machine learning algorithms play a pivotal role in enabling predictive and prescriptive analytics in Quality 4.0. These technologies provide the capability to automatically detect subtle process anomalies, classify defects, and predict failure modes based on historical and real-time data [2]. Unlike traditional rule-based systems, AI can continuously learn and improve its diagnostic accuracy over time, making it highly suitable for high-variability, low-volume production environments.

Blockchain for Traceability and Trust: A technology that offers immutable records of quality data and certification events across complex supply chains, thus documentation supplier compliance, quality audits, and product certifications inseparably associated and articulated with a supply chain remain tamper-proof [3].

The mix marks shift from alone waiting to see right against to join in with the data right quality set up. The use of Quality 4.0 needs these together to make real-time guesses on problems, the best way for work and keep getting better.

Table 2 gives a quick look at the main enabling technologies within Quality 4.0 and shows their basic roles and typical use cases in industrial settings.

Table 2. Key enabling technologies and their applications within Quality 4.0.

Technology	Role in Quality 4.0	Example Application
IoT	Continuous data monitoring	Machine health monitoring
Digital Twins	Simulation and optimization	Virtual commissioning
AI & ML	Anomaly detection, predictive maintenance	Defect prediction
Blockchain	Secure, traceable quality data	Supplier certification

The integrated application of these technologies supports organizations in their moves from simple, manual, and isolated quality control functions to holistic, data-centric ecosystems that can nurture near-zero defect production strategies. As shown in Table 1, Quality 4.0 is a critical evolution in the approach to manufacturing quality assurance that relates to responsiveness, scalability, and traceability.

3. RESEARCH METHODOLOGY: A MIXED-METHODS APPROACH FOR VALIDATING QUALITY 4.0 INTEGRATION

This section presents the research methodology followed in this study, including the overall research design, literature review procedure, case study approach, and data analysis process. Further details on each stage are discussed in the following subsections.

3.1. RESEARCH DESIGN

The research adopts a mixed-methods approach to explore how classical quality methodologies can be integrated with emerging Quality 4.0 technologies. The study builds on previous conceptual work by expanding it through empirical validation using real-world industrial data [11]. The methodology has two primary steps: (i) a systematic literature review and (ii) an industrial case study. Such a sequence helps maintain not only the theoretical rigor but also the validation of the proposal in practice.

Under the PRISMA guidelines, a systematic hunting was carried over three big scientific databases: Web of Science, Scopus, and IEEE Xplore. It aimed to spot relevant peer-reviewed articles printed between 2020 and 2025 that talked about the link of old quality tools, like Six Sigma, SPC, and TQM, with new Industry 4.0 technologies under Quality 4.0.

The search string included combinations of keywords such as “Quality 4.0”, “traditional quality methods”, “Industry 4.0”, “IoT”, “AI”, and “case study”. A total of 498 records were initially retrieved. After duplicate removal and screening, 85 articles were selected for detailed review. The process of identification, screening, and inclusion is summarized in Fig. 2.

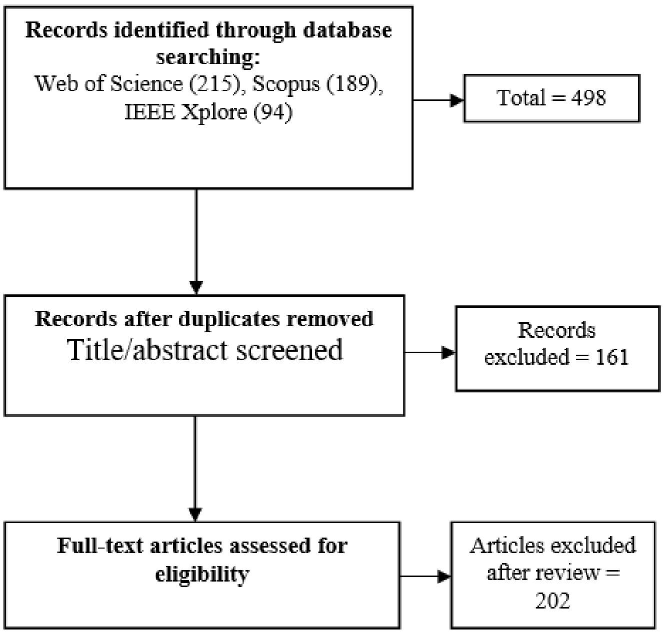

Fig. 2. PRISMA flow diagram illustrating the systematic process of article selection, from initial identification to final inclusion in the literature review

Most of the excluded articles, as depicted by the PRISMA flowchart, were filtered out at the screening and eligibility stages because of general lack of relevance or methodological detail. A final corpus of 85 peer-reviewed articles, therefore, formed a comprehensive basis for meeting the imperative need to analyse current trends in research, to identify methodological gaps, and to lay a sound theoretical foundation for the empirical stage of this study.

3.2. CASE STUDY IMPLEMENTATION

The second phase involved a longitudinal case study lasting 12 months in a global automotive manufacturing plant, specifically focusing on assessing the application of traditional quality tools in an AI-enhanced SPC system applied to an assembly line.

Data has been collected by sensors, which are connected through the Internet and installed at the assembly line. More than 10,000 process data points per day were generated by these sensors, capturing the variables related to machine utilization, temperature, vibration, and production cycle times. The data were sent over a secured connection to a central system.

The system uses machine learning clustering algorithms for pattern recognition, deviation classification, and predicting potential process failures [4]. The resulting predictive insights that are used to make decisions by providing early warning signals to the operators and supervisors so that corrective action can be taken before the defect occurs represent an implementation step in the extended practice-based Quality 4.0 SPC tradition.

3.3. DATA ANALYSIS AND VALIDATION

Algorithm 1: Isolation Forest for Anomaly Detection

Input: Sensor data from IoT devices (X), number of estimators (n), contamination level (c)

Step 1: Normalize and preprocess data

Step 2: Fit Isolation Forest model: model = IsolationForest(n_estimators=n, contamination=c)

Step 3: Predict anomalies: y_pred = model.predict(X)

Step 4: Evaluate performance using precision, recall, and F1-score

Evaluation Metrics: Performance metrics include: Precision = 91.2%, Recall = 88.7%, F1-score = 89.9%. A confusion matrix was also calculated to analyse classification performance.

Real-time data acquisition was integrated with predictive analytics for quality monitoring [20]. The performance metrics are defect rate reduction, mean time between failures (MTBF), and the accuracy of anomaly detection.

The study measured the effectiveness of the AI-SPC system in reducing defects and improving process stability. Results demonstrated a 32% reduction in product defect rates, proving as well the added value of integrating classical methods of quality with technologies of Quality 4.0.

This structured two-stage methodology gives a sturdy framework to address the research aims and also to give insight into removing the practical barriers, as have been found in prior research regarding the adoption of Quality 4.0, such as the scarcity of data and lack of standardization, as well as implementation challenges in a complex manufacturing environment [3].

4. RESULTS AND DISCUSSION

4.1. IMPACT ASSESSMENT OF HYBRID QUALITY 4.0 INTEGRATION

To assess the tangible outcomes of integrating Quality 4.0 technologies with traditional quality management practices, Figure 3 presents a comparative analysis of two critical performance indicators: the defect rate and the average response time to corrective actions. The analysis contrasts result from a conventional quality control setup with those obtained from a hybrid system implemented in the industrial case study. Figure 3 proves the hybrid model’s significant success in the quality outcomes. It was specific: there was a 32% decrease in the defect rate over the baseline of the traditional, while the speed of the corrective actions taken was better by 15%.

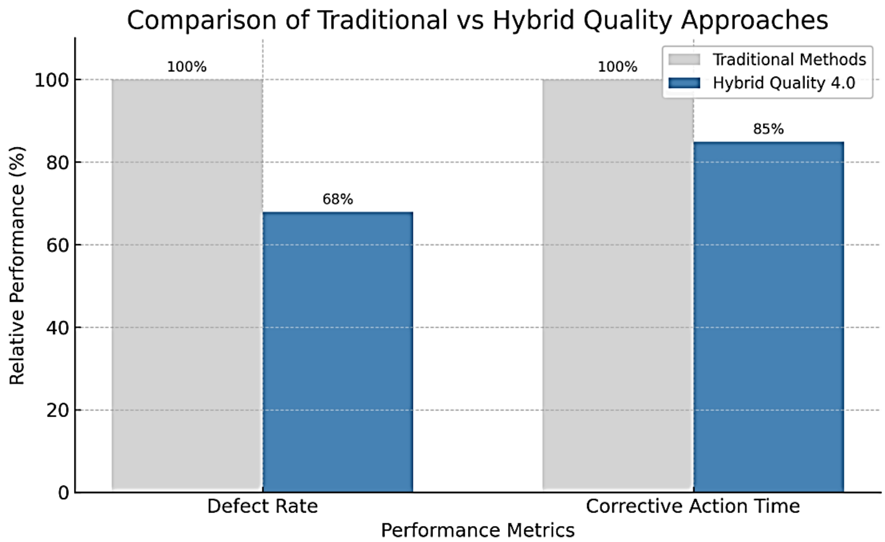

Fig. 3. Comparative performance between traditional and hybrid Quality 4.0 approaches

Results that prove added value for Quality 4.0 technologies:

• Under a machine learning algorithm, the Six Sigma DMAIC cycle shifts to a predictive root cause analysis and proactive defect prevention.

• This combination of real-time monitoring and automatic alerts eliminates process deviation and delays in response, since operator response delay can be fatal.

The chart shows that not only does the hybrid method outperform the conventional method in terms of accuracy and timeliness, but it also brings agile decision-making to the table based on data. Such improvements are most needed in high-variability manufacturing environments since stability of the process and quick intervention can both have a direct impact on the quality of the product.

To contextualize these results within the existing literature, Sony et al. (2020) [11] reported a 22% defect reduction using AI-augmented SPC systems, and Tortorella et al. (2021) [13] achieved a 25% improvement through a Lean-AI hybrid approach. Our proposed model surpasses these benchmarks with a 32% defect reduction and a 15% faster corrective response, reinforcing its practical effectiveness.

These results prove right the view that hybrid quality frameworks should help and make legacy systems better, not fully take their place. By mixing together solid quality ways with digital skills, makers can measure well and keep on getting better at how well they work.

4.2. ANNUAL PUBLICATION TRENDS AND COUNTRY CONTRIBUTIONS

To understand the scholarly evolution and geographic distribution of research in the domain of Quality 4.0, a bibliometric analysis was conducted on articles retrieved from the Web of Science database (2020–2025). The figures below illustrate the temporal publication growth and the country that is most actively contributing to the field. As illustrated in Fig. 4, the study interest in Quality 4.0 has shot up a lot over the last five years. The year 2024 saw the most publications with 6,850 more, coming after 2023 and 2022, which shows a rise in the global pledge to work smart technologies into the quality management systems. This trend links to the speed-up of the digital transformation efforts in response to post-pandemic industrial resilience needs.

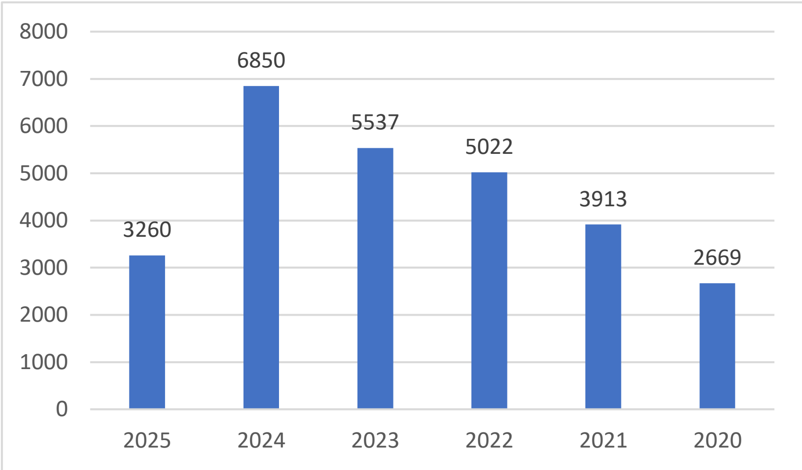

Fig. 4. Annual Evolution of Scientific Publications on Quality 4.0

Figure 5 shows where contributions come from. The People's Republic of China has 6,977 publications, and the United States has 6,323, so those two countries lead. After them, it's England with 1,987 publications, Germany with 1,772 publications, and India with 1,748 publications.

This spread shows that the research reflects global relevance and strategic importance since Quality 4.0 research is pursued by countries with developed and those with emerging industrial economies.

This bibliometric proof doesn't just show the academic momentum of the issue but also helps spot leading contributors and likely collaborative hubs for future research efforts.

Figures 4a and 4b were generated based on a bibliometric extraction performed by the authors from the Web of Science database, covering the period 2020–2025. Data was exported to Excel and visualized accordingly.

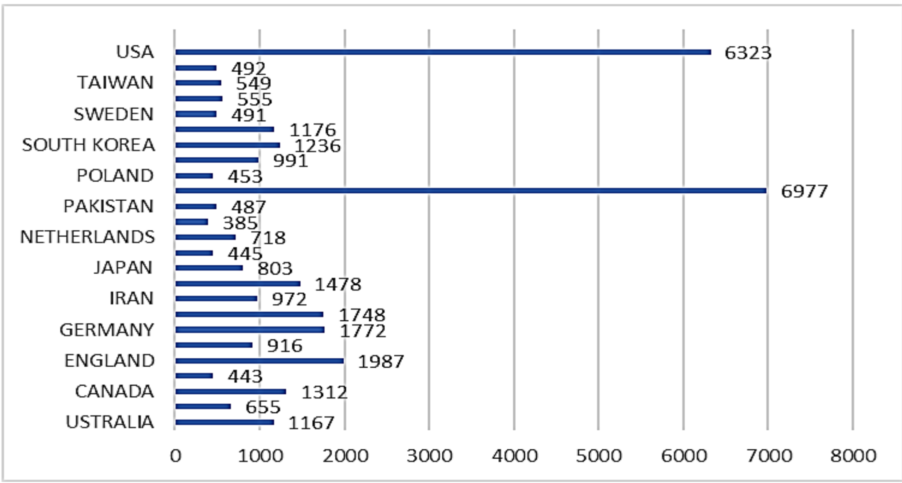

Fig. 5. Geographical Distribution of Quality 4.0 Publications by Country

5. FRAMEWORK FOR INTEGRATION

In response to the growing complexity of digital transformation in quality management, this study proposes a Quality 4.0 Maturity Model structured around three key dimensions: Technology, Process, and People. Based on empirical insights from recent literature [14][9]. This integrative framework supports industrial organizations in aligning classical quality tools with the capabilities of Industry 4.0 technologies.

5.1. QUALITY 4.0 MATURITY MODEL

The proposed model reflects the interdependence between three foundational pillars of Quality 4.0 implementation:

- Technology: This dimension captures the digital readiness of an organization, including the deployment of IoT-enabled devices, AI-driven analytics, cloud-based platforms, and real-time data systems. Studies show that digital infrastructure maturity is a prerequisite for enabling predictive quality control [5].
- Process: Quality management processes – such as PDCA, DMAIC, or SPC – must evolve from reactive to adaptive formats. Real-time feedback loops and automation of corrective actions allow faster, data-driven interventions [6].
- People: The human factor remains a critical success element. The literature emphasizes the importance of data literacy, cross-functional collaboration, and organizational change readiness[7], 23]. Without sufficient investment in training and culture, digital initiatives are likely to face resistance and limited impact.

5.2. IMPLEMENTATION ROADMAP

Based on the maturity model, a three-step roadmap is proposed to support progressive Quality 4.0 integration:

1. Audit Current Systems Organizations should begin with a self-assessment of current quality tools, IT infrastructure, and workforce capabilities. Several studies recommend diagnostic audits as an essential step to define gaps and prioritize investment areas[8].
2. Pilot IoT-Enhanced SPC Systems A controlled pilot, such as real-time SPC enhanced with IoT and ML, is suggested to validate feasibility. Pilot studies reduce risks and allow the organization to build experience incrementally [9].
3. Scale Through Cloud-Based Platforms Successful pilots can be scaled enterprise-wide using cloud platforms that centralize quality data and analytics. Research confirms that cloud integration supports consistency, traceability, and AI deployment at scale [20, 26].

This phased roadmap mirrors the incremental implementation strategies discussed in recent Quality 4.0 frameworks and is especially suited for **SMEs** with limited digital maturity [7].

6. CONCLUSION AND FUTURE WORK

This study proves that Quality 4.0 should not displace the classical quality management methodologies, but rather, it should enhance them through intelligent, data-driven capabilities. Tools such as IoT, AI, and cloud-based analytics would help shift from the existing concept of proactive to predictive and even autonomous quality control. Though the use of such traditional approaches, i.e., TQM, Lean, Six Sigma, and SPC, is not imperative, they, based on the degree of integration with this technology, would continue to be relevant core principles.

Results prove that mixes of traditional ways with Quality 4.0 supporters can give measurable betterment. A check showed a 32% drop in faults and a 15% enhancement in fixing times when AI and IoT joined with regular SPC and Six Sigma methods.

To support the successful transition to Quality 4.0, this article proposes a maturity model structured around three pillars: Technology, Process, and People. An incremental implementation roadmap was also outlined to help organizations, especially SMEs, adopt these innovations progressively, with minimal disruption to existing operations.

Future research directions:

The study has developed a general framework that can be applied across different sectors. Thus, the future research opportunities include but are not limited to the following:

• The adoption of Quality 4.0 in different sectors and the level to which it needs to be customized in the deeply regulated sectors of health, aerospace, and pharma manufacturing.

• The potential for scalability of the use of Quality 4.0 among small and medium-sized enterprises, where low readiness to adopt digital technologies and financial constraints are the main barriers.

• Development of quantitative benchmarking frameworks for assessing maturity levels and the impact of Quality 4.0 in different operational environments.

Future studies can address these areas, building upon the theoretical and practical foundations laid by this research to enable more inclusive and sector-tailored implementations of Quality 4.0.

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