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A Systematic Review for Quality within the Automotive Industry 4.0

Sondra Preascilla Ioana Vacarescu, Valentina Emilia Balas, Nicolae Paraschiv, Flavius Petcut

Sondra Preascilla Ioana Vacarescu
(1) Doctoral School of Systems Engineering
Petroleum-Gas University of Ploiesti, 100680 Ploiesti, Romania
(2) S.C. Continental Automotive Romania S.R.L., 300701 Timisoara, Romania
Corresponding author: priscilla.vacarescu@yahoo.com

Valentina Emilia Balas
(1) Doctoral School of Systems Engineering
Petroleum-Gas University of Ploiesti, 100680 Ploiesti, Romania
(2) Faculty of Engineering
Aurel Vlaicu University of Arad, 310032 Arad, Romania
(3) The Academy of Romanian Scientists

Nicolae Paraschiv
Doctoral School of Systems Engineering
Petroleum-Gas University of Ploiesti, 100680 Ploiesti, Romania

Flavius Petcut
Faculty of Engineering
Aurel Vlaicu University of Arad, 310032 Arad, Romania

Abstract

Artificial Intelligence (AI) is exponentially developing within the quality management system (including quality assurance, quality development, customer satisfaction, etc.) within the automotive industry under the model of Industry 4.0. Within this paper, the application of AI technologies is analyzed for the enhancement of the quality processes and big data, so that higher standards of reliability and safety in automotive manufacturing are fulfilled. Machine learning, deep learning, convolutional neural network, computer vision as part of the AI solutions are used for the detection of the defects, to optimize the production parameters, to link the internal data with the external ones, with the final scope of the prediction of potential failures. The real-time data analysis is the most significant benefit for the automation of the big quality data, where AI improves the accuracy, eliminates the human error, and reduces considerably the production downtime. This research presents the major advantages and opportunities that AI solutions grant within the quality management field, underscoring its vital role for the achievement of higher quality standards, reducing costs associated with non-quality, and nurturing innovation. The findings underscore that the continuous integration of AI into quality assurance processes is essential for maintaining competitiveness and meeting the increasingly stringent demands of the global automotive market.

Keywords: artificial intelligence, automotive industry 4.0, quality.

1 Introduction

In the last years, the integration of Artificial Intelligence (AI) in the Industry 4.0 has accelerated major changes especially in the quality management sector. On the account of the advancement of the AI technologies, and its strong effect on the production processes and product quality; the analyses of the scholarly literature endeavors to explain the upcoming tendencies, , and unexplored territories in the dynamic field. The comprehension of the bibliometric landscape of the analysis related to the technical integration of AI in the automotive industry 4.0, will provide the necessary view for the identification of the further development within the studied field.

In 2018, Luckov and collaborators evaluated architectures, models and deployment issues related to the usage of deep learning techniques in the automotive manufacturing domain. Within the manufacturing processes the focus was directed to provide individual performance metrics for the different models [1].

In the article related to the reshaping of the industry with AI, Plorin presented the potential and opportunities in the automotive manufacturing sector, by using the AI, industrial internet of things (IIoT) and robotics technologies in production and logistic optimization, quality and maintenance. Finally, the article introduces the five contributions to this section, highlighting the use of AI and IIoT in various scenarios in automotive manufacturing processes and challenges and technological advancements [2].

The autonomous vehicles are the future of the automotive industry. The testing and the validation of the HW and SW development and its systems is mandatory within the automotive sector. Within the simulation environment, virtual tests are performed using the given inputs to generate new test cases and different scenarios for the assurance of a precise testing. The scope of the testing is the identification of the bugs and failures. Within this process, the AI algorithm is continuously trained with the specific target for continuous improvement. The most important goal is to achieve effective testing and validation accurate results for automated driving systems. The test results are crucial for the automated decision support systems, for the understanding of the potential failures from the field. Drawing from these insights, this study applies a bibliometric exploration on the today's know-how and developing patterns for the quality management big data analytics within the automotive industry 4.0. Using data from the Web of Science Core Collection, an all-fields search was performed with the keywords "quality" AND "automotive" AND "AI" generating 186 relevant results. All the results were downloaded in plain text format, and afterwards imported in the VOSviewer for further analysis.

2 Literature review

Nowadays, within the automotive industry the competition became a major factor to meet the customer and to succeed, influenced also by the implementation of new technologies.

In 2016, Dedy et al. stated that for the organization to achieve the targets, the following areas have to be considered: improvement of employee performance, cost reduction, increase customer satisfaction, and improvement of the overall product performance. [3].

Sonntag et al. highlighted the importance of the implementation of AI-based chatbots within the automotive industry which is triggered by the lack of customer trust, corroborated with security issues, and the improvement of the communication in quality area. The study describes a design theory approach for the development of trust-supported design know-how for AI-based chatbots [4].

In the paper work related to the Automating Quality Control based on Machine Vision, Mourtzis et al. emphasized the scientific considerable attention to digitalization and digitization towards industry 4.0. Nowadays, the companies are focusing on the development of new strategies to integrate AI, machine learning (ML), machine vision (MV), and computer aided technologies (CAx). The top challenges in the current manufacturing and production systems focus on the achievement and increase of the quality requirement, the necessity of the customized products, and the flexible supply chains. The top challenges for the introduction of AI are: a) know-how, learning, b) natural language processing, c) precision object manipulation, d) planning, visual inspection and perception, e) analysis [5].

Gace et al. proposed a solution for eco-driving by raising driver awareness and promoting an efficient and economical driving. Finally, driving in eco mode fuel and money can be saved and money while enhancing passenger satisfaction. This research uses a large data set collected via OBD during passenger transportation in personal vehicles. The analysis with integrated AI using unsupervised learning, revealed five groups of patterns based on acceleration and speed. With the aid of speed and acceleration/deceleration, the driver efficiency was analyzed as the most influential factor. The perception of the passengers related to the quality of driving is negatively impacted by the acceleration/ deceleration. Based on the collected data with integrated AI, further efforts shall be made for the education of the drivers with regard to the environment advantages [6].

In 2022, Katona presented the effectiveness of quality control methods based on the performance of the measurement system. The measurement uncertainty due to the measurement errors during the process control conformance was analyzed by several researchers with the purpose of highlighting its impact. The risk-based conformity control and solutions for the process control were developed and implemented, the verification and validation via laboratory test remained insufficiently considered. A case study was presented within the automotive industry, with the implementation of conformity control charts to minimize the risk associated with the risk-based conformity control. Acceptance and control limits shall be applied though the optimization process to reduce losses due to wrong decisions. The optimization process is applied in two steps: with the simulation of the process and measurement errors, and the second one, by measurement of all relevant points in the laboratory. The above-mentioned study highlighted the potential cost reduction possibilities based on the results validated in the laboratory of the applicability of risk-based approaches within the real-life problems from the industry 4.0 [7].

Kamran et al. discussed about the maximization of production and quality and minimizing the waste, production cost and time associated. The analysis covered also the different tools and techniques required in the automotive industry to produce safe, and reliable vehicles. The solution aims to implement automated driving processes, by reduction human labor, to increase the efficiency, for the prevention of redundant tasks. This paper examines various aspects of AI and related tools and techniques, aiming to employ them in the automobile industry to make modern vehicles smart, safe, and reliable. Secondly Kamran et al. presented carbon fiber, polymer composites and high strength steel. The main purpose is to provide within the automotive industry the most intelligent materials, for the application in the production processes [8]. In the automotive industry 4.0, within the advanced driver assistance systems (ADAS) and driving technologies, the optical quality of the windscreens is a crucial component according to Wolf et al., as the cameras in sensor suit are incorporated in the windscreen. In the production area, the optical quality of the windscreens is evaluated, with methods that are relevant for the artificial intelligence algorithms. The optical quality measurement is strongly correlated with the performance of the artificial intelligence algorithms, essential for the establishment of the performance technical limits and process tolerances and its limits. Nowadays, within the automotive industry, a commonly used metric for the assessment of the optical quality windscreen is the modulation transfer function (MTF). The above-mentioned authors mathematically proved that the modulation transfer function (MTF) cannot be applied independently to windscreens. The novel optical systems gather two components: the optics of the cameras systems, and the windscreen. For an accurate determination of the optical quality of windscreens with artificial intelligence algorithms at supplier side, a simulation link shall be used for the development of a potential innovative inspection system [9]

Christie et al. described the manual visual inspection as the most common used method for the quality control in the semiconductor electronics manufacturing, for the defect detection. The process itself is considered critical for the assurance of the quality within the semiconductor industry, including the original equipment manufacturers. The manual inspection is a slow process, prone to errors, and for the achievement of low error rates, a major investment in skilled operators is absolutely necessary. The implementation of automated systems and artificial intelligence (AI) into the manual inspection process can reduce human perception errors, reduce defects, and improves overall process efficiency. The scope of this study is to explore the actual research of the inspection systems and methods for the anomaly detection by using open-source tools for the identification of the small visual defects within the thermal Integrated Heat Spreader (IHS) lids. The real-life datasets are analyzed among the highlighted key insights for the identification of further opportunities within the semiconductor field [10].

The injection molding is extensively used within the automotive industry for the production of plastic components insignificant quantities. To maintain a competitive benefit within the injection molding industry, it is imperious necessary to continuously improve the quality of the product. Several optimization techniques, such as Artificial Neural Networks (ANN), Genetic Algorithms (GA), repetitive and simulation- based techniques, are preferred to optimize the injection molding process for the achievement of the optimal process conditions. The occurrence of quality failures still can be observed due to the variations during molding process, as the final product quality is influenced by confluential factors including the process, material, and equipment. Park et al., focused on real-time AI- based control process parameters, within the injection molding industry. The study analyzes the boundary between process parameters and the quality of the defects, with the objective to develop an algorithm to compensate the deviations of the process parameters. A monitoring system using sensors for pressure and temperature parameters is used to collect real-time data. The comparison of the collected data in comparison with the standard values, an interconnection of the process parameters and plastic material is defined. The algorithm will generate improved process parameters for the correction of deviations, which will be implemented by the machine control systems. A product from the automotive industry setting is selected for data sourcing, implementation, and validation of the artificial intelligence systems [11].

Bucaioni et al. describe the complexity of designing the automotive systems, and the importance of the alignment of the business objective with the used technologies and architectural decisions. In real life, the lack of practical alignment for the software architecture with the business goals can be still observed. The authors addressed the gap and presented a systematic approach for the alignment of the architecture and business goals. The approach includes the objective of the business, the identification of the relevant quality characteristics, which will conduct to the architecture tactics to achieve the business objectives. The authors developed and assessed the presented approach in collaboration with the automotive manufacturer. The approach was validated through a use case with the mentioned automotive manufacturer with regard to the software over the air technologies [12].

The automotive industry is known due to its intense competition propelling a constant search for enhancements to increase the productivity and maintaining in the same time the high-quality standards requested the customers. According to Ramalho et al., in the last years the implementation in the automotive industry led to significant improvements for the product quality, flexibility of the processes, and cost efficiency. The authors focused with the study on the enhancement of the productivity for cable control machine within the automotive industry. The main goal is to develop a stripping machine concept capable of removing the coating from two cables concurrently, by eliminating a bottleneck process in the injection of the cables first Zamak terminal. The concept was validated with the aid of the prototype machine, and implemented in the industry. The repetitive tasks of the operators were eliminated with an automated cable extraction system, which will further enhance the production performance. The productivity increased with 87.8% by using the double stripping concept and the cable extraction automated system compared to the previous phase of the process [13].

In 2023 Caivano et al. described the new security challenges in the field of vehicle communication protocols as insufficiently secured and attacks might occur anytime; this scenario is attainable with the modern technology advancement. The recommended solution for the avoidance of these scenarios is to focus on the implementation of the cyber security systems within the automotive industry. The most used and studied communication protocols is the Controller Area Network (CAN) which lacks the built-in cybersecurity functions. For the detection for the attacks on CAN bus, several studies proposed the usage of Intrusion Detection Systems (IDSs) that enhance Machine Learning (ML) and Deep Learning (DL) algorithms. By utilizing DL and ML techniques, the developers can identify the types of attack and will develop further effective design strategies in the software development automotive life cycles. A lot of Intrusion Detection Systems (IDSs) in the automotive area are assessed using datasets composed of raw CAN messages, where the interpretation capabilities are limited due to the lack of decoding methods. It was analyzed the benefit by implementing To bridge this gap, this Multi-class Random Forest for Automotive Intrusion Detection along with a newly developed

Synthetic Automotive Hacking Dataset (SA-Hacking Dataset), generated using a CAN database file (DBC). The validation of the MaREA model is performed directly on the Car-Hacking dataset and benchmarked against two prior studies that used the same classifier and dataset in a multi-class setting. The assessment continues with the usage of a combination of the Survival Analysis Dataset and the SA-Hacking Dataset. The proposed method demonstrates improved performance on both the Car-Hacking dataset and the combined dataset [14].

Kamran et al. explored the transformative role of artificial intelligence (AI)—one of the most revolutionary technologies—and its wide-ranging applications within the automotive industry. In the era of Industry 4.0, industries are becoming increasingly advanced through the integration of intelligent technologies that enhance productivity, quality, and profitability while reducing scrap, time, and operational costs. The study aimed to investigate various dimensions of AI, different techniques, to improve the reporting, replace the manual report with automated processes, and implementation on the smart vehicles. The main purpose is to offer intelligent solutions in new manufacturing design, after-sales areas. A key focus is on automating driving functions to reduce human intervention, boost efficiency, and alleviate the burden of repetitive tasks. [8].

Poth et al. highlighted the importance of maintaining an increased level of software quality to prevent the high costs associated with post-release patching. In the study it was presented a comprehensive review of current strategies designed to ensure that Artificial Intelligence (AI) models are finalized for implementation. It was ensured that the specific requirements of Machine Learning (ML) systems have to fulfill and to be aligned with the quality standards of automotive OEMs. A key factor in ML-driven projects is the in-depth assessment of potential quality risks, which can stem not only from the models themselves but also from the broader delivery pipeline. To tack-le these issues, we introduce a systematic quality assurance (QA) approach and provide an evaluation of its effectiveness [15].

In 2021, Zhu proposed the concept of large-scale AI integration within the automotive industry. As part of this advancement, IntelliDrive has emerged as a new direction in development.

In today's AI-driven landscape, automotive companies are setting higher expectations for the skills and qualifications of engineering professionals. However, there is a notable shortage of versatile talent equipped to address the industry's rapidly changing demands. This paper explores the current demand for automotive engineering professionals within the context of AI, highlights the challenges faced by Chinese colleges in cultivating such talent, and proposes a comprehensive reform plan. The proposed strategy centers on four key areas: curriculum innovation, faculty development, collaborative training between schools and enterprises, and the advancement of personalized student training [16].

Phanden et al. demonstrated how enhanced problem-solving techniques can significantly benefit organizations by improving operational efficiency, minimizing material waste, increasing production consistency, boosting performance, and ultimately enhancing profitability. Despite these advantages, the manufacturing sector frequently encounters obstacles such as incorrect team selection, misidentification of problems, and limitations in data and time. Addressing these challenges effectively requires a structured, step-by-step methodology to uncover root causes, choose optimal solutions, and implement them successfully. The study provides an in-depth analysis of the 8D (Eight Disciplines) methodology within the context of automotive manufacturing. The 8D approach is a systematic, team-based problem-solving method designed to identify, correct, and prevent recurring issues—particularly valuable in complex systems where root causes may not be immediately evident. The study explores the tools and techniques involved in implementing the 8D method and reviews literature supporting its effectiveness in automotive component manufacturing. A sample 8D template is included as a practical guide for organizations aiming to adopt the methodology. Key findings underscore that 8D is not a one-time solution, but an ongoing strategy for addressing customer complaints and enhancing product quality.

Furthermore, the integration of the Plan-Do-Check-Act (PDCA) cycle with the 8D approach creates a comprehensive framework for developing reliable solutions and fostering continuous process improvement. The paper also compares the 8D method with the DMAIC (Define, Measure, Analyze, Improve, Control) framework, highlighting their complementary strengths and applications. Ultimately, the study emphasizes that successful implementation of the 8D methodology depends on critical factors such as effective team selection, accurate problem definition, sufficient data availability, and proper time management. By following the structured steps of the 8D process, organizations can better resolve issues, enhance efficiency, and achieve long-term improvements in manufacturing performance [17].

Silva et al. introduced a predictive quality model for customer defects within the broader context of digital transformation and the evolution toward fully connected factories. In this environment, data science, artificial intelligence (AI), machine learning (ML), and predictive analytics have become foundational. The project focused on leveraging ML techniques to analyze customer complaint data and predict complaint accountability, with the goal of improving data accessibility and enhancing the complaint-handling process. The approach aimed to reduce the volume of units needing analysis, accelerate customer response times, and advocate for a shift in traditional quality management practices. By applying AI, the study sought not only to increase efficiency in processing complaints but also to illustrate the transformative potential of such technologies within quality management. Using real customer complaint data from an automotive company, the research highlighted the value of AI in Quality 4.0 (Q4.0) initiatives. The methodology followed a ten-phase framework—adapted from established data mining models—comprising: business understanding, project planning, sample definition, data exploration, data processing and preprocessing, feature selection, model acquisition, model evaluation, results presentation, and implementation. This structured approach ensured the relevance, applicability, and reproducibility of the findings across different organizational contexts. The machine learning models achieved a 64% accuracy rate in predicting complaint accountability, demonstrating the effectiveness of the proposed approach. As a proof of concept, the study paved the way for automating complaint analysis and provided a practical framework that could be extended to other departments within the organization. The integration of AI with Q4.0 principles underscored the urgent need for digitalization and intelligent systems in quality management. Moreover, the research emphasized the critical role of data—its organization, analysis, and accessibility—in supporting digital transformation and operational efficiency. The study not only demonstrated the practical benefits of ML applications but also addressed a gap in existing research by exploring real-world complaint data, an area that has been under-investigated. By establishing standardized processes for data handling and model deployment, the study delivered a replicable, scalable solution for quality teams and data scientists. It also responded to challenges previously faced by the company, such as limited data access and lack of automation. In the context of Quality 4.0, the findings highlight both immediate and long-term advantages: from faster, data-driven decision-making to clearer workflows and improved process consistency. In summary, this research makes a meaningful contribution to the field by offering an innovative, replicable approach to complaint analysis. It stands out for its originality in tackling a rarely explored area and providing actionable insights that bridge the gap between AI technologies and practical quality management in manufacturing [13].

Barcena et al. investigated the use of federated learning (FL) with fuzzy regression trees (FRTs), a technique that allows multiple data owners to collaboratively train a global model without compromising the privacy of their individual datasets—an essential factor in fostering trust in AI systems. While FL has recently gained significant attention, many existing methods neglect a key component of trustworthy AI: explainability. The study introduced a novel FL approach built upon fuzzy regression trees, which are well-regarded for their inherent interpretability. The proposed method is specifically designed for horizontally partitioned data, where each participant holds different records with the same features. Instead of sharing raw data, clients send aggregated statistics to a central server, which uses them to construct the global regression tree. This design achieves a close approximation to the ideal centralized model, while maintaining strict data privacy. Furthermore, this federated approach improves generalization performance compared to traditional local training, where each participant independently trains an FRT using only its own data. The integration of linear models in the leaf nodes contributes to strong predictive performance, as demonstrated through extensive experiments on standard benchmark datasets. The study evaluates both the accuracy and interpretability of the resulting FRTs. Finally, the authors illustrate the practical value of their federated fuzzy regression tree method through a case study focused on forecasting Quality of Experience (QoE) in the automotive industry [18].

Zhang et al. noted that with the rapid advancements in Machine Learning (ML) and Deep Learning (DL), companies are increasingly eager to adopt these technologies to improve service quality and customer experience. Federated Learning (FL) has gained attention as a promising solution for distributed model training that preserves user data privacy. However, conventional FL approaches typically rely on synchronous model aggregation, which lacks adaptability and struggles in dynamic environments and heterogeneous hardware settings commonly found in real-world applications. To address these limitations, this paper presents a novel, real-time, end-to-end Federated Learning framework that employs asynchronous model aggregation. The proposed method is validated through an industrial case study in the automotive domain, specifically targeting the prediction of steering wheel angles for autonomous driving systems. The experimental results show that the asynchronous FL approach significantly improves the predictive performance of local edge models while achieving accuracy levels comparable to centralized training. Furthermore, the integration of a sliding training window helps reduce communication costs, accelerate training, and handle real-time streaming data more effectively. This makes the approach particularly suitable for deploying ML/DL models in complex, heterogeneous, embedded systems encountered in real-world automotive applications [19].

3 Methodology

The methodological approach required to generate a map based on bibliographic data, with a minimum co-occurrence threshold of two. Out of 985 keywords, 128 attained the threshold. For the relevancy of the analysis, the terms considered out of scope, such as geographical locations and specific terminologies were eliminated. The analysis outlined the classification of the three clusters, each of them representing a different subject area within the context of quality from the automotive industry 4.0.

The plain text bibliographical data file was uploaded in the VOSviewer tool. VOSviewer is a software specialized in the analysis of the bibliometric networks. In this study a map was created based on bibliographic data, with focus on the keyword co-occurrence.

4 Clustering

The clustering process was conducted with a minimum cluster size set to 20 keywords. This resulted in the formation of three distinct clusters:

- Cluster 1: Contained of 56 keywords.
- Cluster 2: Contained of 46 keywords.
- Cluster 3: Contained of 28 keywords.

The analysis of the clusters revealed the research area and their research themes and interconnections, as presented in Figure 1 and Figure 2.

Cluster 1 included the key terms: anomaly detection, artificial intelligence, artificial neural network, automation, automotive industry, autonomous vehicles, challenges, cnn, complexity, computer vision, data analytics, deep learning, defect inspection, design, defect inspection, design, digital twin, dmaic, efficiency, fault-detection, future, industry, inspection, intelligent systems, intelligent transportation, system, iov, knowledge, management, neural-network, optimization, prediction, privacy, process control, productivity, quality, quality assurance, quality management, quality of service, runtime verification, safety, sales, security, sensor fusion, six sigma, sustainability, system, systems, technology, u-net, v2x, validation, vehicular communication, wiper insert, wireless networks.

Cluster 2 included key terms: Alloy, aluminum, aluminum-silicon, alloys, artificial neural-networks, automotive braking, behavior, bpnn, burnishing, classification, deformation, explainable ai, feature extraction, friction, image, segmentation, iron, machine learning (ml), mechanical-properties, melt cleanliness, metal, methodology, microstructure, model, modification, movable cellular automata, nano

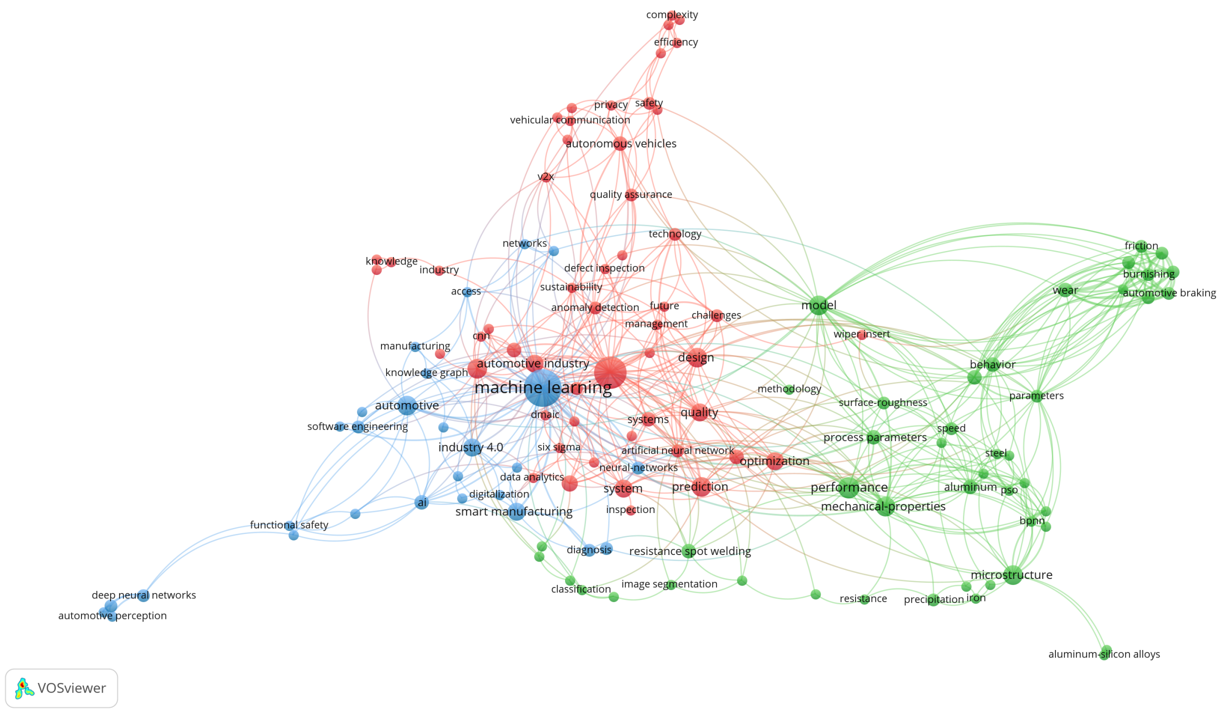

Figure 1: Bibliometric analysis – connectivity

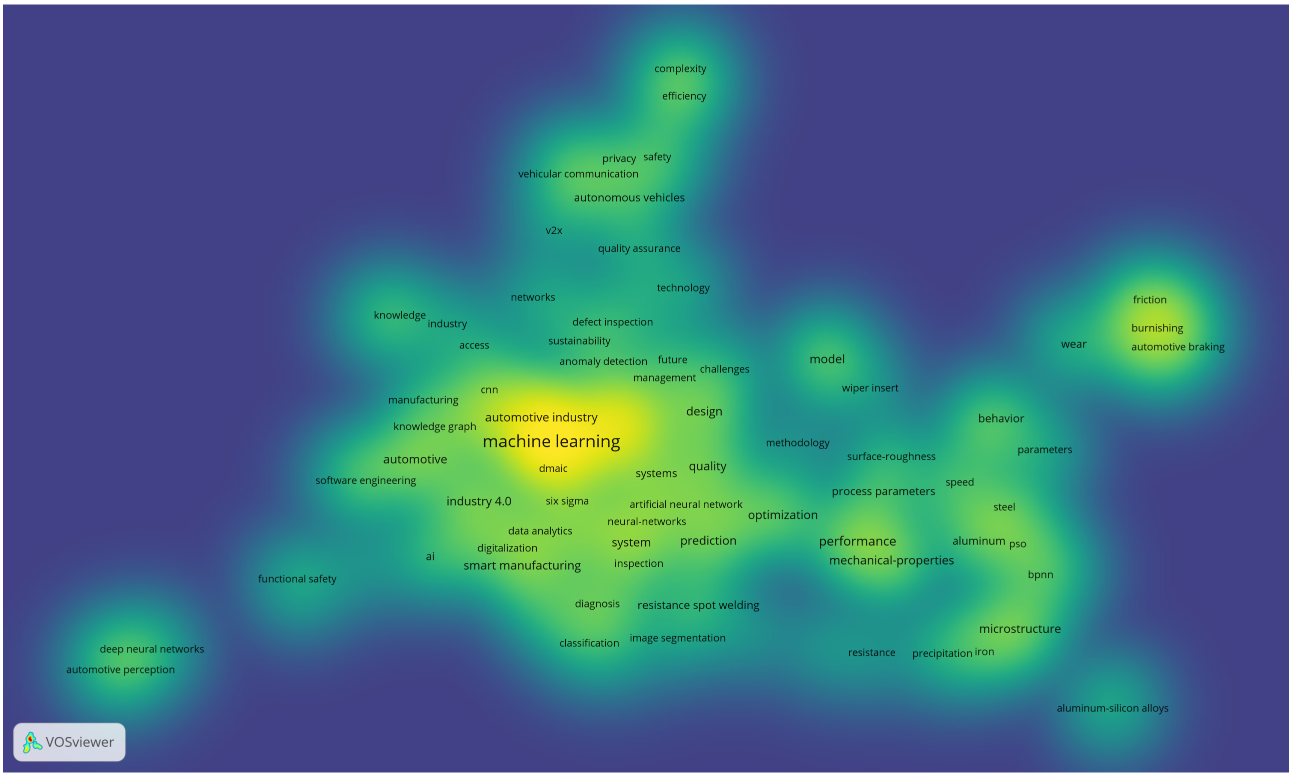

Figure 2: Bibliometric analysis – density

structuring, nondestructive evaluation, numerical modeling, parameters, performance, porosity, precipitation, process parameters, pso, resistance, resistance spot welding, shear instability, simulation, speed, spot welding, stainless-steel, steel, surface-roughness, Taguchi, tensile, time series, wear

Cluster 3 included the key terms: access, ai, automotive, automotive perception, deep neural networks, detection system, diagnosis, digitalization, federated learning, functional safety, iiot, industry 4.0, knowledge graph, knowledge, graphs, machine learning, manufacturing, models, networks, neural-networks, out-of-distribution, predictive maintenance, quality control, reliability, robustness, semantic web, smart manufacturing, software engineering, vehicles.

5 The Qualitative Analysis of the Clusters

5.1 Cluster 1: Artificial Intelligence in Industry 4.0

Cluster 1 encompasses a detailed analysis of the key terms for the integration of Artificial Intelligence (AI) in the automotive industry. This cluster focuses on the topics of anomaly detection, AI, automation, and quality management within the Industry 4.0. The analysis of these key terms highlights the interconnectivity, which is vital for the advancement of innovation, optimization and efficiency within the automotive sector. Cluster 1 can be divided in three categories:

- Integration in Technology:

  Data Driven Decision Making: Analysis of big data for process optimization.

  Interconnectivity: AI integration using Internet of Things (IoT).

  Advanced Automation: Automated AI Systems.

- Applications:

  Quality Control: Automated decision-making systems for quality assurance using AI and ML algorithms for defect detection.

  Manufacturing: Real-time monitoring with implemented of AI algorithms to increase productivity and efficiency.

  Predictive Maintenance: With integrated AI systems, equipment failures can be predicted, with positive impact of the breakdown reduction.

- Key advantages:

  Increased Quality: The customer satisfaction can be achieved with accurate control methods.

  Enhanced Efficiency: Optimization of production processes.

  Cost reduction: Predictive maintenance and automation will result in decreased operational costs.

5.2 Cluster 2: Artificial Intelligence and Materials

Cluster 2 emphasizes the intersection of artificial intelligence with material science, and advanced manufacturing processes. The focus is maintained on the performance improvement and on the materials used in the automotive industry. Cluster 2 can be divided in two categories:

- Advanced Materials:

  Metals and Alloys: Aims on alloys as aluminum-silicon, iron, stainless steel.

  Material Properties: Mechanical properties, porosity, microstructure, wear resistance and deformation.

5.3 Cluster 3: Artificial Intelligence and Digitalization

Cluster 3 presents the role of AI, digitalization, and data management in the automotive industry 4.0. With the aid of deep learning, machine learning, prediction, the automotive industry will enhance system reliability and manufacturing efficiency in correlation with vehicle perception.

Cluster 3 can be divided in two categories:

Deep Learning and Machine Learning: Usage of AI algorithms to increase production efficiency.

Predictive Analytics: Utilization of AI for predictive maintenance, defect detection, and performance optimization.

Data Management: Implementation of robust data management systems to handle large volumes of data generated by connected vehicles and manufacturing processes.

Digital Twins: Creation of digital replicas of physical assets to simulate and analyze their performance in real-time.

6 Discussion

The study revealed the multidimensional approaches and challenges for the integration of AI strategies within the automotive industry 4.0. The methodology presented a structured analysis of the current literature, providing insights into the technological advancements, with regard to innovation and digitalization in the automotive sector. The integration of AI in automotive industry includes the complete stages of the project development, from acquisition, to design, industrialization and roll out phase. Taken into consideration the complexity of the entire processes, the entire supply chain, materials, ERP systems, customer requirements, customer data shall be interconnected to provide an accurate data analysis and prediction based on AI algorithms. The test scenarios and time lines are shortened up with the aid of AI system, the real-life environment is converted in virtual reality, providing fast test results, giving the opportunity to fix any errors or bugs that might occur. The test scenarios are interconnected from the supplier of the equipment, to the vehicle manufacturer.

The implementation of AI in the automotive industry 4.0, represents a significant step in production, process optimization and quality control systems.

From the 186 articles analyzed based on the key words: quality, automotive, and artificial intelligence, it was observed that there is a gap to be filled within the automated decision-support systems. AI algorithms shall analyze big data fast and accurate, identifying trends and patterns much faster than humas. Automated decision support systems with generative AI can predict further outputs based on historical data. AI systems provide real-time analysis and recommendations, which is crucial in fast-paced environments such as financial trading or emergency response management. This real-time capability enhances the responsiveness and accuracy of decisions. AI has the advantage to automate routines in data analysis and decision-making topics so that human experts to focus on other complex tasks. The major advantage is to obtain faster decision and to reduce operational associated costs. Automated decision support systems for quality control within the automotive industry 4.0 has the major benefit to tackle large volumes of data and several decision variables, making them adaptable to achieve the organizations requirements. The integration of Artificial Intelligence (AI) into the digital supply chain represents a critical advancement in aligning the objectives and operations of Original Equipment Manufacturers (OEMs) and their suppliers. One of the most transformative contributions of AI in this space is its ability to seamlessly connect disparate data sources—specifically, the databases maintained by OEMs and those of their suppliers. Traditionally, these data systems have operated in silos, resulting in limited visibility, delayed feedback loops, and inefficiencies in quality-related decision-making. AI-powered systems address these challenges by enabling interoperable, real-time data exchange and automated insight generation across the extended supply chain. By leveraging machine learning algorithms and advanced analytics, AI can detect quality issues earlier, trace them back to their origin in the supplier network, and even forecast potential risks before they materialize. This proactive approach to quality management not only improves product reliability and compliance but also strengthens the collaborative relationship between OEMs and suppliers. For instance, anomaly detection models can flag inconsistencies in part dimensions, performance deviations, or material defects across partner systems, prompting timely corrective actions and reducing warranty claims or recalls.

Moreover, the use of automated decision-making support systems (ADMSS) further elevates the role of AI by facilitating fast, data-driven responses to complex quality scenarios. These systems synthesize inputs from both OEM and supplier databases, weigh multiple decision variables—such as cost, risk level, delivery impact, and production constraints—and recommend optimal courses of action. In high-stakes environments like automotive manufacturing, where even minor defects can cascade into major system failures, such AI-driven support tools are invaluable. Importantly, the use of federated learning frameworks ensures that predictive models can be trained across OEM and supplier data without compromising confidentiality, a critical requirement in competitive, data-sensitive industries. This supports not only compliance with data protection regulations but also builds mutual trust in collaborative AI initiatives.

However, for such systems to realize their full potential, several challenges must be addressed. These include standardizing data formats and semantics across organizations, ensuring transparency in AI decision logic (explainable AI), and managing change within complex, hierarchical supplier networks. Additionally, human oversight remains essential to validate AI recommendations and uphold ethical standards in decision-making.

In summary, AI acts as both a technological enabler and a strategic integrator, connecting supplier and OEM ecosystems through shared intelligence and decision automation. Its application in automated decision-making systems drives responsiveness, improves quality outcomes, and fosters a more resilient and agile supply chain—hallmarks of a successful transition to Quality 4.0.

7 Conclusion

In conclusion, this discussion synthesizes key findings from the literature review, highlighting the implementation of AI in the automotive industry. The significant advancement are characterized by the improvement observed within vehicle technology, manufacturing processes, and the efficiency in the automotive sector. AI algorithms, as machine learning, deep neural networks, fuzzy systems and big data analysis, are driving innovation across the automotive sector, from enhancing vehicle perception and safety up to the optimization of manufacturing processes. The automated processes, can be programmed, controlled and optimized through Cloud Computing. The real time data from different systems, can be interconnected, and analyzed using convolutional neural network for image recognition. The scope of the thesis for automated decision support systems for quality within the automotive industry, is to increase customer satisfaction, to reduce the costs associated with non-quality, to avoid failures in the field, and to enhance the safety of the drivers. Several algorithms shall be used for data classification, as naïve Bayes, K-means clustering, random forest, fuzzy systems for the data sets that are not in the range of complete true nor false. Generative AI plays a crucial role in the digitalization, data analysis and prediction within the automotive sector.

The integration of AI into Quality 4.0 frameworks marks a transformative shift in how quality management is approached within the Industry 4.0 landscape. This study demonstrates that AI-driven methods—ranging from machine learning algorithms to predictive analytics—can significantly enhance the accuracy, speed, and consistency of quality-related decision-making processes. By enabling real-time data analysis, automated anomaly detection, and predictive maintenance, AI not only improves operational efficiency but also supports proactive quality assurance strategies.

Furthermore, the incorporation of explainable AI and federated learning models addresses critical concerns related to trust, interpretability, and data privacy, making these technologies viable for large-scale industrial deployment. The presented implementations highlight how AI can bridge existing gaps in quality systems by reducing human error, enabling adaptive control, and ensuring continuous improvement through data-driven insights.

Overall, this work reinforces the vital role of AI as a core enabler of Quality 4.0, offering a scalable, intelligent, and sustainable approach to modern quality management. Future research should focus on standardizing AI integration practices, improving model transparency, and fostering cross-functional collaboration to fully realize the potential of AI in quality-driven digital transformation. As AI-driven systems increasingly enable the integration of databases between Original Equipment Manufacturers (OEMs) and suppliers, maintaining robust cybersecurity has become a critical requirement. This study highlights the dual opportunity and challenge presented by such integration: while AI facilitates real-time data sharing, predictive analytics, and automated decision-making across organizational boundaries, it also introduces new vectors for cyber threats, data leakage, and system vulnerabilities. To ensure secure collaboration, the implementation of privacy-preserving AI techniques—such as federated learning, homomorphic encryption, and differential privacy—emerges as essential. These methods allow joint model training and knowledge sharing without exposing sensitive proprietary data, thus preserving both data confidentiality and competitive advantage. Furthermore, AI-enhanced cybersecurity systems, including anomaly detection algorithms and real-time intrusion response models, can proactively monitor data exchanges and mitigate emerging threats. The findings of this study reinforce that cybersecurity must be embedded by design within AI architectures that connect OEM and supplier systems. This includes not only technical safeguards, such as secure communication protocols and access controls, but also governance frameworks that define data ownership, accountability, and auditability across the supply chain.

While AI presents a powerful mechanism for improving inter-organizational collaboration in Industry 4.0, its deployment must be paired with comprehensive, adaptive cybersecurity strategies. Ensuring trust, resilience, and compliance in such integrated environments will be key to fully realizing the benefits of AI-enhanced supply chain connectivity.

Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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