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A PANORAMA OF THE ROLE OF CLASSICAL QUALITY TOOLS IN INDUSTRY 4.0 THROUGH BIBLIOMETRIC INDICATORS

Um panorama do papel das ferramentas clássicas da qualidade na indústria 4.0 por meio de indicadores bibliométricos

Un panorama del papel de las herramientas clásicas de calidad en la Industria 4.0 través de indicadores bibliométricos

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ABSTRACT

With the transition to Quality Management 4.0, questions arise regarding the role played by classical quality tools, which have been used since the twentieth century. To investigate this issue, a bibliometric analysis study was conducted using articles published in the Web of Science database that presented applications of classical quality tools in conjunction with the pillars of Industry 4.0. With the support of the VOSviewer software, bibliometric indicators were generated and analyzed. The results showed that stratification, histograms, and control charts were mainly used in combination with big data, simulation, and robotics. It was concluded that, in practice, these quality tools are used by Industry 4.0 organizations in environments characterized by large data flows, gaining new applications beyond process monitoring and being employed in other non-traditional industrial applications. Thus, this study indicates that there are still research gaps to be explored to ensure the effective integration of quality tools with the technological environment, especially regarding the Pareto diagram, the cause-and-effect diagram, and the scatter diagram.

RESUMO

Com a transição para a Gestão da Qualidade 4.0, surge o questionamento sobre papel desempenhado das ferramentas clássicas da qualidade, utilizadas desde o século XX. Para verificar essa indagação, foi realizado um estudo de análise bibliométrica com artigos que apresentavam aplicações das ferramentas clássicas da qualidade em conjunto com os pilares da Indústria 4.0, publicados na base Web of Science. Com o auxílio do software VOSviewer, foram gerados indicadores bibliométricos, onde foram alisados. Os resultados demonstraram que a estratificação, os histogramas e as cartas de controle foram utilizados principalmente em conjunto com big data, simulação e robótica. Concluiu-se que, na prática, estas ferramentas da qualidade são utilizadas pelas Indústrias 4.0 em meio a um grande fluxo de dados, adquirindo novas aplicações além do monitoramento de processos e sendo empregadas em outras aplicações industriais não tradicionais. Assim, este estudo indica que ainda existem lacunas de pesquisa a serem exploradas para garantir a integração efetiva das ferramentas da qualidade com o ambiente tecnológico, principalmente com as ferramentas de digrama de Pareto, diagrama de causa e efeito e o diagrama de dispersão.

RESUMEN

Con la transición hacia la Gestión de la Calidad 4.0, surge el cuestionamiento sobre el papel desempeñado por las herramientas clásicas de la calidad, utilizadas desde el siglo XX. Para verificar esta cuestión, se realizó un estudio de análisis bibliométrico con artículos que presentaban aplicaciones de las herramientas clásicas de la calidad en conjunto con los pilares de la Industria 4.0, publicados en la base Web of Science. Con el apoyo del software VOSviewer, se generaron indicadores bibliométricos que fueron analizados. Los resultados demostraron que la estratificación, los histogramas y las cartas de control se utilizaron principalmente en conjunto con big data, simulación y robótica. Se concluyó que, en la práctica, estas herramientas de la calidad son empleadas por las industrias 4.0 en entornos caracterizados por un gran flujo de datos, adquiriendo nuevas aplicaciones más allá del monitoreo de procesos y siendo utilizadas también en otras aplicaciones industriales no tradicionales. Así, este estudio indica que aún existen lagunas de investigación por explorar para garantizar la integración efectiva de las herramientas de la calidad con el entorno tecnológico, especialmente en el caso del diagrama de Pareto, el diagrama de causa y efecto y el diagrama de dispersión.

INTRODUCTION

According to Kumar and Kumar (2020), the fourth evolution of industry has been gradually transforming the landscape of production systems. There is a long history leading up to Industry 4.0. Since the 18th century, the world has experienced significant advancements in productive technologies, beginning with the first revolution, or Industry 1.0, in 1784, when steam engines replaced manual production systems in the textile industry. Industry 2.0 evolved from 1870 with the introduction of production lines and mass production utilizing electric motors. In 1969, Industry 3.0 began with the use of automation through electrical and computational systems. Currently, Industry 4.0, known as the fourth industrial revolution, is in its consolidation phase. This concept originated in Germany in 2011, referring to the digitalization of the industrial value chain, where products communicate with machines to specify production steps. Among the main expected benefits are increased efficiency, flexibility, quality, and customization.

It is worth noting that with the consolidation of Industry 4.0, discussions are already underway regarding the characterization of the fifth industrial revolution, known as Industry 5.0.

All these historical revolutions in industrial production have also impacted subfields of production engineering, which have adapted to historical contexts, and quality engineering is no exception. According to Zonnenshain and Kenett (2020), quality is essential for products and processes and is a requirement in the competitive global market. Quality engineering models and practices have undergone various evolutionary stages throughout history, from inspection to quality control, moving through quality assurance, quality management, and design for quality. Despite this, it has been observed that in recent years there has been stagnation in the evolution of quality models and techniques, and Industry 4.0 presents an opportunity for the development of these models and techniques, leveraging the technological framework supporting the fourth industrial revolution. The application of quality engineering in the context of Industry 4.0 is termed Quality 4.0, which is still in development, thus becoming a fertile area for research and practice for quality professionals.

Throughout the evolutionary history of industry, managers or decision-makers have begun to use techniques and tools to detect problems, identify causes, plan and develop corrective and preventive actions, and monitor solutions, improving communication and understanding of the process (Castello et al., 2019). One way to gather knowledge for solving quality problems is the use of the seven basic quality control tools. The seven quality tools consist of a set of simple, effective, statistical, and graphical tools for data analysis (Engelhardt, 2000).

Thus, as we are witnessing the implementation of Industry 4.0, will incorporate the technological pillars of the fourth industrial revolution, and knowing that classic quality tools have historically played a significant role in yielding positive results for quality engineering processes, the existing gap in the need to solidify and affirm Quality 4.0 methods and techniques justifies the objectives of this study.

This scenario, therefore, served as motivation and justification for conducting this study. Considering the historical context in which the classic quality tools have been used since the first industrial generation, it naturally raises the question of whether these tools are still being applied within the context of Industry 4.0 and how they have evolved over time in line with current technological advancements. Another point that justifies this study is the fact that these seven quality tools are well established in quality engineering and have consistently produced positive results; however, a stagnation in the evolution of their models and techniques can currently be observed, especially within the Quality 4.0 environment, contrasting with the rapid development of industrial technologies. Thus, doubts also arise regarding how these tools are being integrated with contemporary technological pillars.

Therefore, through bibliometric indicators, it becomes possible to quantify the published studies, observing and analyzing the evolution and integration of the classic quality tools into Industry 4.0, including a brief examination of practical examples, as well as identifying research gaps.

The main objective of this study is to analyze the role of classic quality tools within the industry 4.0 context and assess their contribution to Quality 4.0 through bibliometric indicators. The secondary objectives are to examine the number of scientific publications related to each of the seven classic quality tools in the context of the pillars of Industry 4.0, analyze the generated bibliometric indicators, and explore possibilities that encourage the use of basic quality tools in Industry 4.0.

Background

Barsalou (2023) states that there are several ways to classify which tools are considered the seven quality tools, and that this classification varies depending on the author used as a reference. Therefore, in this study, for instructional purposes and to guide the research, the classification proposed by Tarí and Sabater (2004) has been selected. According to this classification, the classic quality tools are comprised of the cause-and-effect diagram, check sheet, control chart, histogram, Pareto diagram, stratification, and scatter diagram.

The Seven Classify Quality Tools

The Ishikawa diagram or the fishbone diagram (due to its shape) it is a graphical method used to represent influencing factors (causes) on a specific effect (outcome), identifying the problem to be explored and its potential causes. After constructing the diagram, the true causes and their corrections are analyzed to alleviate or resolve the identified problem (Miguel, 2001). Pramusinta et al. (2025) explain the use of the cause-and-effect diagram; A “fishbone-shaped” diagram is created, and the problem to be analyzed is identified at the “head of the fish.” The causes of this problem are usually gathered through a survey or meeting and organized along the “bones of the fish,” being classified into categories such as method, material, environment, people, measurement, and facilities. After the diagram is constructed, it is analyzed to identify the root cause of the problem.

A check sheet is a form used to systematically, orderly, and uniformly collect and record a set of data, allowing for a rapid interpretation of the results (Miguel, 2001). Nadiyah and Dewi (2022) demonstrate how the check sheet is constructed; The data are collected with information on the most frequent types of defects, organized in tabular form, and based on this completed checklist, data on the type and quantity of product defects are obtained. These data can then be analyzed using other control tools.

A control chart is a graphical method used to monitor a process over time, indicating whether the process is under control or not. The goal is to assess if the process exhibits variability and whether there are any special causes affecting it (Miguel, 2001). Tayalati et al. (2024) state that, to construct a control chart, continuous data are required to enable process monitoring and control. In summary, a control chart consists of a central line (the process mean) and upper and lower control limits, which are obtained through statistical formulas. A process is considered inconsistent when the chart consistently shifts toward the upper or lower control limit, or when it oscillates between the limits (Matorera, 2024).

Histogram is a statistical tool consisting of a bar chart that displays the variation in the frequency distribution of a set of data over a specific range. If the process is under statistical control, it follows a pattern known as a distribution. If this distribution remains stable over time, the process is considered predictable; otherwise, the process is deemed unpredictable (Cesar, 2011). Therefore, a histogram consists of bar charts that display the distribution or pattern of observations grouped into convenient class intervals and can be constructed with the aid of software (Matorera, 2024).

The Pareto analysis is a bar chart that classifies causes in descending order of frequency, which are defects or nonconformities. There is a tendency for 80 to 90% of problems to be the result of 20% of the causes. Therefore, it is important to identify and address the primary causes, as they represent the most significant problems to be solved and typically have simpler, more manageable resolutions (Miguel, 2001). The Pareto diagram is used to identify which types of defects should be addressed immediately (Nadiyah & Dewi, 2022).

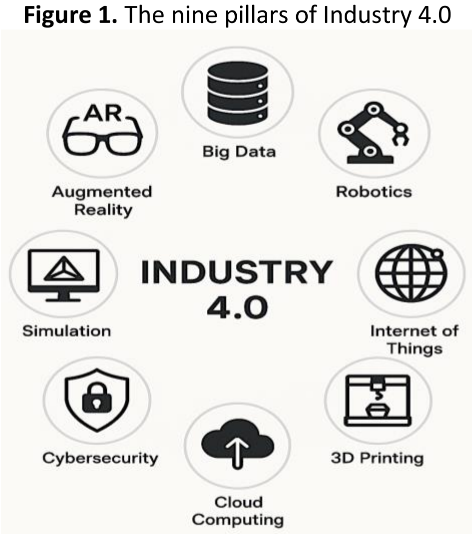
Stratification divides groups of data into subgroups based on appropriate factors, known as stratification factors, such as inputs, people, month, year, etc. These data groupings are made from various perspectives with the aim of taking action (Cesar, 2011). By separating parts of a dataset, it becomes possible to use them to identify, analyze, and solve quality-related problems (Filho et al., 2023).

Correlation diagram or the scatter diagram examines the potential correlation between two variables, one as an input and the other as an output (cause-effect). Once the correlation chart is constructed, linear regression or other types of regression can be applied to determine prediction models (Miguel, 2001). Based on the constructed relationship diagram, it is possible to analyze the quality of a process in the context of relationships that enhance, neutralize, or compromise it, considering the elements that may contribute to the improvement or deterioration of the assessed quality (Matorera, 2024).

THE PILLARS OF INDUSTRY 4.0

The 4th Industrial Revolution initiated many technologies into production processes, resulting in increased productivity and improved quality of the products produced. Industry 4.0 represents the current vision defining the future of many industries, creating new business models through what are known as cyber-physical systems. Thus, it is essential to understand its dimensions to achieve the proposed business efficiency (Erboz, 2017) (Figure 1).

Figure 1. The nine pillars of Industry 4.0



Source: Authors (2024).

Kumar and Kumar (2020) discuss and explain that the technologies comprising the pillars of Industry 4.0 are robotics, simulation, system integration, the Internet of Things, cybersecurity, cloud computing, 3D printing, augmented reality, and big data.

With the use of robotics, production systems are increasingly becoming autonomous, acquiring human-like skills. The aim of using robotics is to achieve more efficient and cost-effective production outcomes compared to traditional manufacturing systems. Robots on the production line have the added capability of monitoring and transmitting data with greater accuracy. For Soori et al. (2024), integrated advanced robotics lead to a more efficient and responsive manufacturing processes in the context of Industry 4.0.

Used to virtually represent the real world, simulation relies on real-time data. It can use this real-time data to conduct more efficient tests, allowing processes and configurations to be refined and optimized even before production begins. Thus, De Paula Ferreira et al. (2020) emphasize that this technology can aid companies to evaluate costs, risks, impacts on operational performance, implementation barriers and be a roadmap for Industry 4.0.

Information systems across different areas of production systems can be integrated, exchanging information and fostering connection and interaction between distinct areas. One of the frameworks existing in the literature, proposed by Huber et al. (2024), shows that the Information systems have primary capabilities (connect and store, understand and act, and predict and self-optimization), and Support Capabilities (strategy, technology and human resource). This is important to explore the full potential of such systems in manufacturing companies.

The Internet of Things (IoT) is a system of digitally connected physical objects, such as sensors and actuators, that can detect, compute, monitor, and interact within an industry as well as across various industries and their supply chains, or as Kalsoom et al. (2021) stated, this technology can also improve services like transportation or road traffic, healthcare and customer services. By connecting sensors and actuators to machines and other physical objects, manufacturers can obtain real-time data to enhance productivity and efficiency. The IoT implements autonomous, secure and robust connections and the exchange of data between many devices, integrating a machine-to-machine interconnectivity and communication, also making devices “intelligent” (Lampropoulos et al., 2019).

In the cybersecurity pillar, as connectivity increases, so does the number of cyberattacks, which can potentially damage various business areas, from the supply chain to operations (Lezzi et al., 2018). It is essential for industry to protect its information systems and production lines against cyber threats with dedicated information security technologies. Corallo et al. (2022) highlight that the companies attacked have significant economic damage to restore normal working conditions and face a loss of competitiveness in the relevant market.

With the desired interconnection between various areas of industry, cloud computing technology enables access to company resources from anywhere via the internet. The high availability of data and access from different devices provides flexibility to the manufacturing environment (Velásquez et al., 2018).

Additive manufacturing, or 3D printing, is increasingly used in the industrial sector for unit production and prototyping. This technology enables industries to achieve high performance in the production of small quantities or batches of customized products, facilitating the implementation of decentralized production systems, reducing transportation costs, and simplifying inventory management. It also enables the production of these small batches at a lower level of cost in development, shorter lead-times, less energy consumption and material waste (Prashar et al., 2023).

Augmented reality enables digital content to be viewed in the real world through electronic devices such as tablets, smartphones, and glasses. It provides industry operators with real-time information, allowing for faster and more efficient decision-making and improving work processes. This technology accelerates the integration of big data existing in the Cyber-Physical Production Systems (CPPS) into human experience in real time, allowing a radical paradigm shifting in the era of Industry 4.0 (Morales Méndez & del Cerro Velázquez, 2024).

With Industry 4.0, a vast amount of data is generated, and big data offers the capability to analyze this data, thereby enabling energy savings, production quality optimization, and service improvement. Big Data deals with a vast amount of data, seeking to manage it quickly and efficiently, even in a constantly growing database. This technology aims to analyze and separate useful information, enabling the optimization of processes and improvement of customer services, for example (Janík et al., 2022).

MATERIAL AND METHODS

This research is exploratory, as it consists of a bibliometric analysis with the primary objective of selecting relevant articles that may contribute to the research question: What is the role and contribution of classical quality tools in Industry 4.0?

Bibliometric analysis is a quantitative and statistical technique that allows for the measurement of publication quantity and the dissemination of knowledge. Through a database, it is possible to count the number of publications on a topic, identify the most cited authors, classify the most frequently used terms, and determine the dates or years with the highest number of publications, among other bibliometric indicators that can be created and utilized (Lopes et al., 2012; Coates et al., 2001).

Cauchick-Miguel (2019) describes the stages that constitute a bibliometric analysis and, drawing on this framework, the research method used in this study was developed. The stages of the bibliometric analysis are outlined in Figure 2 and are subsequently detailed.

Figure 2. Workflow applied in this research

Source: Authors (2024).

Phase 1. Select Research Database: This initial stage involves selecting the research database for conducting searches for the desired bibliographic publications. In this study, the chosen research database was the Web of Science (WoS);

Phase 2. Collect Data: At this stage, the details of the search, selection, and exclusion of articles are considered. The search criteria involve the use of full articles written in English, without temporal restrictions and open access, to facilitate the complete reading of the articles when necessary. For each of the seven tools, a search was conducted according to the respective keywords or search strings presented in Table 1. The search terms were applied to any field within the articles (title, abstract, and keywords). No temporal cutoff was applied during the searches, as it was desired to obtain a historical understanding that allows for the analysis of the evolution of the applications of classic quality tools in the evolving context of industrial technologies, given that these tools have been used long before the concepts of Industry 4.0. The research includes articles published up to August 24, 2024. Each of these searches was exported, thus generating seven ".ris" files format. The selection criteria were for empirical or theoretical studies that encompass the use of some classic quality tool in one of the pillars of Industry 4.0. The exclusion criteria were scientific articles outside the scope described in this study;

Phase 3. Create Analysis Database: With the search results from the WoS platform, the obtained data were exported and saved in ".ris" file format, allowing for processing in bibliometric analysis software. The following information was exported for constructing the bibliographic research databases: title, keywords, and abstract;

Phase 4. Execute the Analysis: This phase involves processing the analysis database using specific software that assists with bibliometric analysis. For this research, VOSviewer 1.6.20 was chosen for constructing and visualizing co-authorship networks. For the creation of the seven maps based on bibliographic data extracted from the bibliographic database files, the following parameters were adopted in VOSviewer: co-authorship analysis, using author keywords as the unit of analysis and applying the full counting method. Only articles with at least one author were included. Additionally, each generated map was limited to a maximum of 10 authors to facilitate visualization;

Phase 5. Describe the Analysis: The information gathered from the bibliometric research database is analyzed and described. Some data and bibliometric indicators may also be directly obtained from the search platform.

Table 1. Search strings used in the searches

Quality tool	Search strings
Cause-and-effect diagram	(quality) AND (("Cause-and-effect diagram") OR ("Fishbone diagram") OR ("Ishikawa diagram")) AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))
Check sheet	(quality) AND (("Check sheet") OR (Checklist)) AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))
Control chart	(quality) AND (("Control chart") OR ("Shewhart Charts") OR ("Statistical Process Control Charts")) AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))
Histogram	(quality) AND ((Histogram) OR ("Frequency distribution graph")) AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))
Pareto diagram	(quality) AND ("Pareto chart") AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))
Stratification	(quality) AND (Stratification) AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))
Scatter diagram	(quality) AND (("Scatter Diagram") OR ("Scatter plots") OR ("Correlation diagram")) AND ((Robotics) OR (Simulation) OR ("System Integration") OR ("Internet of Things") OR ("Cloud Computing") OR ("3D Printing") OR ("Augmented Reality") OR ("Big Data") OR (Cybersecurity))

Source: Authors (2024).

RESULTS AND DATA ANALYSIS

After conducting searches on the WoS platform regarding quality tools in the context of Industry 4.0, seven datasets were created for bibliometric analysis, which will serve as research material throughout the study. The first indicator analyzed was the number of articles on basic quality tools (Table 2). It is important to note that the research captured articles up to August 24, 2024.

Table 2. Distribution of the number of articles among the basic quality tools

Basic quality tools	Number of articles
Cause-and-effect diagram	7
Check sheet	200
Control chart	220
Histogram	243
Pareto diagram	3
Stratification	379
Scatter diagram	15

Source: Authors (2024).

The number of articles resulting from the bibliographic research on the topic under study. A predominance of the use of stratification, histograms, and control charts can already be observed.

Cause-and-Effect Diagram

The use of the cause-and-effect diagram within the context of the pillars of Industry 4.0 will be analyzed exclusively. Initially, a chart was created to assess the number of articles published over the years, according to the WoS platform. By examining the number of articles published over time, it is observed that the highest number of publications related to this quality tool occurred in 2021, with three articles published. The years 2023, 2022, 2017, and 2014 each had only one article published, respectively. Thus, the next step was to identify the three most cited articles among the search results (Table 3).

Table 3. Most cited articles - cause-and-effect diagram

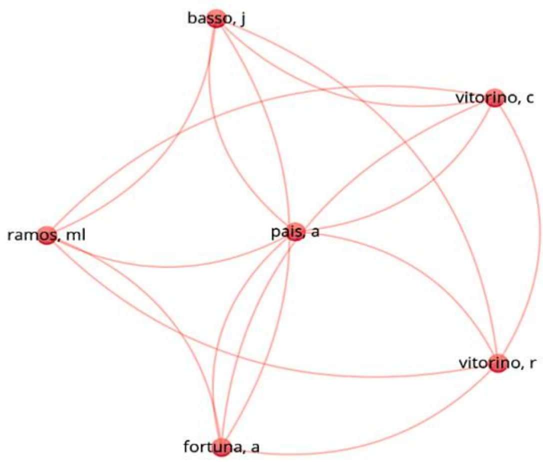
Article title	Citations	Author(s)
Unit operation optimization for the manufacturing of botanical injections using a design space approach: a case study of water precipitation	13	Gong, X., Chen, H., Chen, T., & Qu, H. (2014)
Expediting disulfiram assays through a systematic analytical quality by design approach	7	Basso, J., Ramos, M. L., Pais, A., Vitorino, R., Fortuna, A., & Vitorino, C. (2021)
Network model analysis of quality control factors of prefabricated buildings based on the complex network theory	6	Yang, S., Hou, Z., & Chen, H. (2022)

Source: Authors (2024).

The study by Gong et al. (2014) used the Ishikawa diagram to determine the critical parameters of a pharmaceutical process, and a Monte Carlo simulation was applied to assess the probability of process acceptance, conducted in China. Basso et al. (2021) performed an analysis of pharmaceutical processes using the cause-and-effect diagram for risk assessment, identifying the critical parameters of a production method. Monte Carlo simulations were used to evaluate the probability of failures in Portugal. Yang et al. (2022) describe a Chinese case study on quality in civil construction. They used the fishbone diagram to examine the advantages of the quality method under study, and simulations were employed to assess the quality factors derived from this quality control method for building construction.

The co-authorship network map for the cause-and-effect diagram is shown. This map reveals six authors with the highest number of connections out of a total of twenty-four authors. Each of these authors in the cluster has at least one article in the bibliometric research database. This network of connections includes the work of Basso et al. (2021), which was later analyzed among the most cited (Figure 3).

Figure 3. Co-authorship relationship map related to the cause-and-effect diagram

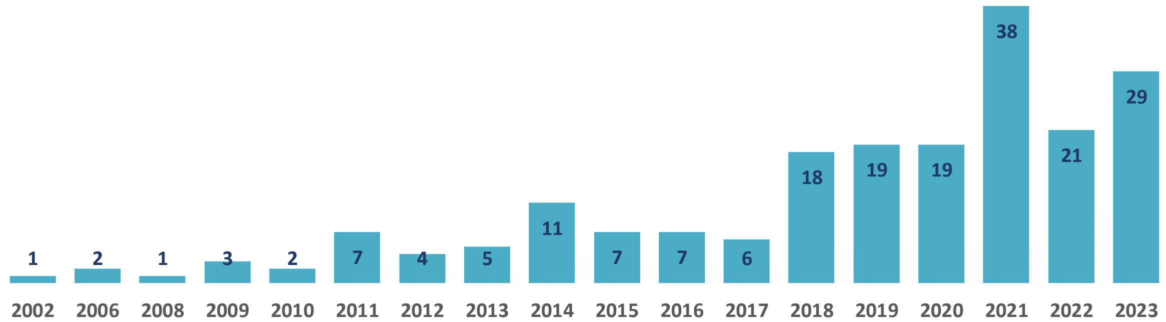


Source: Authors (2024).

Check Sheet

When analyzing the use of the check sheet in the pillars of Industry 4.0, the indicator of the number of articles published over time was examined. Based on this observation, a chart was created to illustrate this bibliometric indicator (Figure 4).

Figure 4. Annual production of articles related to the check sheet



Source: Designed from WoS (2024).

The first publication using the check sheet tool in any pillar of Industry 4.0 occurred in 2002. In 2021, there is a noticeable peak in the number of published articles on this topic, with significant quantities starting from 2018 (Table 4).

Table 4. Most cited articles - check sheet

Article title	Citations	Author(s)
Simulation-based trial of surgical-crisis checklists	373	Arriaga, A., Bader, A., Wong, J., Lipsitz, S., Berry, W., Ziewacz, J., Hepner, D., Boorman, D., Pozner, C., Smink, D., & Gawande, A. (2013)
Mastery learning of advanced cardiac life support skills by internal medicine residents using simulation technology and deliberate practice	249	Wayne, D. B., Butter, J., Siddall, V. J., Fudala, M. J., Wade, L. D., Feinglass, J., & McGaghie, W. C. (2006)
Reporting guidelines for health care simulation research extensions to the CONSORT and STROBE statements	233	Cheng, A., Kessler, D., Mackinnon, R., Chang, T., Nadkarni, V., Hunt, E., Duval-Arnould, J., Lin, Y., Cook, D., Pusic, M., Hui, J., Moher, D., Egger, M., Auerbach, M., & Int Network Simulation-Based Pedia. (2016)

Source: Authors (2024).

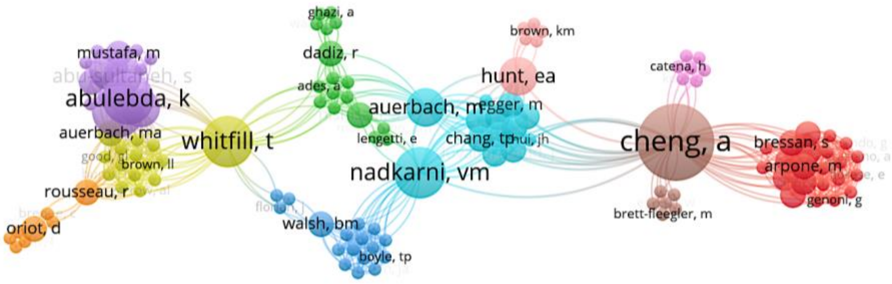
The article by Arriaga et al. (2013), published by the Massachusetts Medical Society, is a study in the field of medicine where operating room teams from three institutions participated in simulated surgical crisis scenarios. Each team managed half of the scenarios using crisis checklists and the other half based solely on memory, leading to a discussion on the utility and relevance of checklists, and demonstrating an improvement in crisis management in surgical rooms through their use.

The second most cited study, by Wayne et al. (2006), reports work done in the medicine department of a university in Chicago. This study aimed to use a simulator to assess the initial proficiency of second-year residency graduates in advanced cardiac life support scenarios, evaluating the impact of an educational intervention based on deliberate practice on skill development to achieve mastery standards, using checklists to measure various aspects, including residents' assessments of the quality of the developed program.

Finally, the third most cited article, by Cheng et al. (2016), is another health-related study conducted in the United States that proposes reporting guidelines for simulation-based health research to improve the quality of reports in simulation research, utilizing a checklist for support.

The co-authorship map (Figure 5) is the result of synthesizing data from 1,226 authors present in the research database. Of these, 126 authors were selected due to their connections with each other, forming 12 clusters of interest. Regarding the number of connections, notable researchers include Cheng, A. with 6 article contributions and 49 connections with other authors, followed by Nadkarni, V. M. with 4 articles and 32 connections, and Whitfill, T. with 4 articles and 37 connections. Among the three most prominent researchers, it is evident that all are involved with checklists in the healthcare field, using simulations.

Figure 5. Co-authorship relationship map related to the check sheet

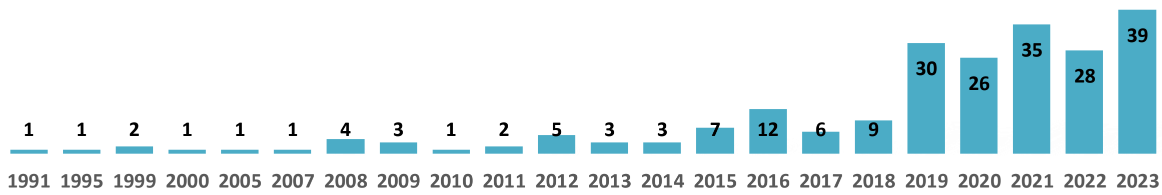


Source: Authors (2024).

Control Chart

This section examines the key inputs of control charts to Industry 4.0. The study begins with an analysis of the indicator showing the number of articles published over time (Figure 6).

Figure 6. Annual production of articles related to the control chart



Source: Designed from WoS (2024).

The first article was published in 1991, and the highest number of publications occurred in 2023, with 39 articles, followed by 35 articles in 2021 and 30 articles in 2019. Thus, there was a noticeable trend in the number of articles published between 2019 and 2023, a period that concentrated most of the publications resulting from the research (Table 5).

Table 5. Most cited articles - control chart

Article title	Citations	Author(s)
Data quality for data science, predictive analytics, and big data in supply chain management: an introduction to the problem and suggestions for research and applications	482	Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014)
Using profile monitoring techniques for a data-rich environment with huge sample size	105	Wang, K. & Tsung, F. (2005)
Monitoring process mean level using auxiliary information	103	Riaz, M. (2008)

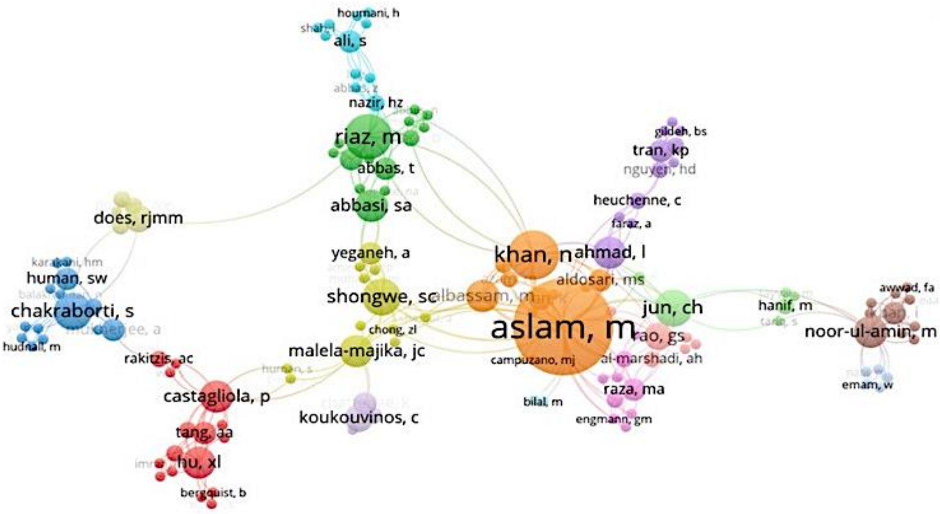
Source: Authors (2024).

The study of Hazen et al. (2014) focuses on the study of data quality for data science, predictive analytics, and big data in supply chain management. The control chart tool was employed for monitoring and controlling the quality of data originating from the supply chain. This article was produced in the United States.

Similarly, Wang and Tsung (2005) conducted a study on profile monitoring techniques for data-rich environments with large sample sizes, combining statistical process control techniques and control charts. They also used simulations to analyze patterns of change in large samples. The researchers note that in-process sensors with large sample sizes are becoming popular in modern manufacturing industries, generating large amounts of data. This study was carried out at a Chinese university, and it integrates control charts with big data and simulation.

Completely, Riaz (2008) utilized simulation and control charts to enhance the monitoring of a quality characteristic of interest and was conducted at a university in Pakistan. Thus, based on the co-authorship indicator, a co-authorship relationship map was created (Figure 7).

Figure 7. Co-authorship relationship map related to the control chart



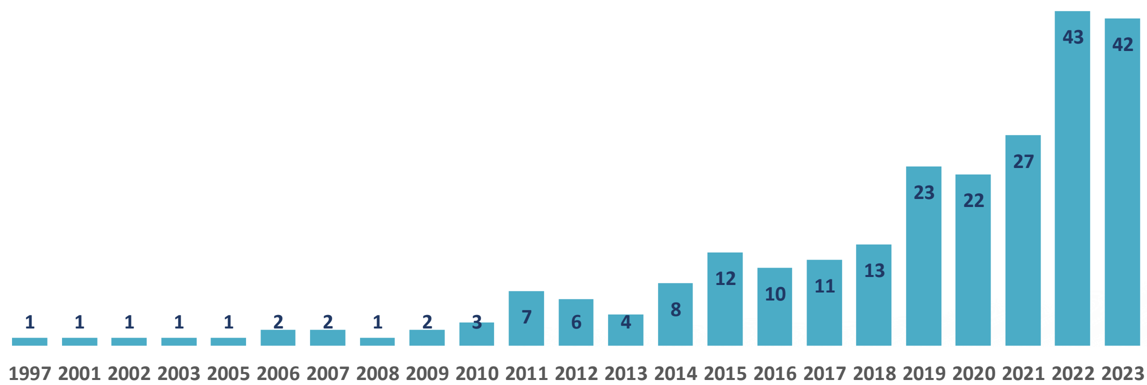
Source: Authors (2024).

The co-authorship relationship map for articles that use control charts in one of the pillars of Industry 4.0 and the bibliometric research database consists of 575 authors. From this total, 137 authors were selected based on their connections, forming 16 clusters. Aslam has the highest number of articles in the analysis, with 23 articles and 36 connections between authors, followed by Khan with 9 and 13 connections and Riaz with 8 and 19 collaborative connections. Examining these prominent researchers, it is noted that they have conducted studies on control charts using the EWMA technique, which allows for monitoring small changes in processes over time. Additionally, Riaz has published studies on process monitoring and its feasibility with the support of control charts. Some of these publications used simulations and processed large amounts of data.

HISTOGRAMS

From the annual publication indicators graph (Figure 8) it can be observed that the first article on the use of histograms in applications within the pillars of Industry 4.0 was published in 1997. Since, the number of published articles has increased significantly over time and the highest number occurred in 2022, with 45 articles. Also, Table 6 presents the articles with the highest number of citations.

Figure 8. Annual production of articles related to the histograms



Source: Designed from WoS (2024).

Table 6. Most cited articles - histograms

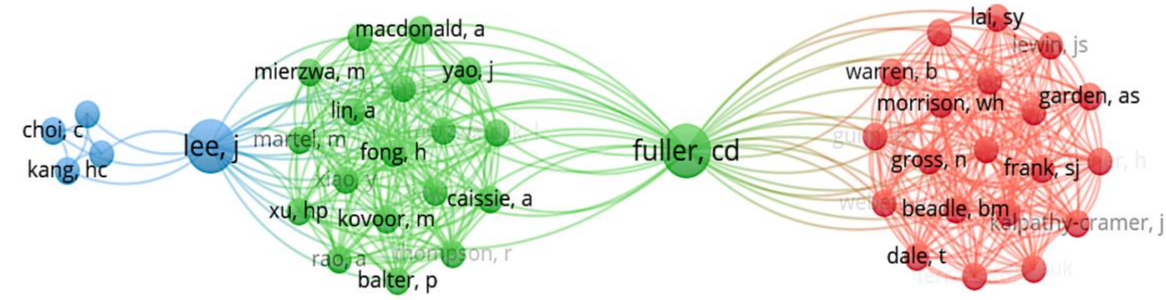
Article title	Citations	Author(s)
Learning a no-reference quality assessment model of enhanced images with big data	270	Gu, K., Tao, D., Qiao, J.-F., & Lin, W. (2018)
Robust reversible audio watermarking scheme for telemedicine and privacy protection	144	Zhang, X., Sun, X., Sun, X., Sun, W., & Kumar Jha, S. (2022)
Robust point cloud registration framework based on deep graph matching	142	Fu, K., Luo, J., Luo, X., Liu, S., Zhang, C., & Wang, M. (2022)

Source: Authors (2024).

Gu et al. (2018) conducted research to assess image quality through machine learning in a big data environment, also using histograms to iteratively adjust the brightness and contrast of images to an appropriate level. This study involved researchers from China, Singapore, and Australia. In the study by Zhang et al. (2022), Chinese and Polish researchers in information technology developed a technology to prevent audio data leakage in telemedicine. They used histograms to evaluate audio and simulations to verify the functionality of this new feature. And Fu et al. (2022) addressed a problem with 3D point cloud registration, which is relevant to robotics and computer vision. However, this study did not involve the application of histograms, one of the seven quality tools.

The co-authorship map (Figure 9) displays 44 authors who collaborated on articles included in the bibliometric analysis database out of a total of 1,202 researchers. This map reveals three major clusters and highlights the authors Lee and Fuller, each with two articles present in the database. The other researchers have only one article published in the research database.

Figure 9. Co-authorship relationship map related to the histograms



Source: Authors (2024).

Analyzing the works of the highlighted researchers mentioned here, it is concluded that Lee utilized the histogram in his research on computed tomography imaging within the simulation pillar. He also published an article in the field of radiology, employing histogram in the context of big data. In turn, Fuller conducted a study using histogram to analyze the effects of radiology with the support of a data set, and his second publication was a collaboration with Lee, focusing on big data and radiology, as previously mentioned.

Pareto Diagram

The articles search, to add in the bibliometric database, about Pareto Diagram related to any of 9 pillars of Industry 4.0 resulted two published in 2023 and one in 2020 (Table 7).

Table 7. Most cited articles - Pareto Diagram

Article title	Citations	Author(s)
Assembly line anomaly detection and root cause analysis using machine learning	22	Abdelrahman, O. & Keikhosrokiani, P. (2020)
Study and characterization of polyvinyl alcohol-based formulations for 3D printlets obtained via fused deposition modeling	4	Ilieva, S., Georgieva, D., Petkova, V., & Dimitrov, M. (2023)
A study of transverse bowing defect in cold roll-forming asymmetric corrugated channels	2	Xu, C.-T., Chen, J.-C., Wei, Y.-F., Han, H., Zong, X., & Yuan, Y. (2023)

Source: Authors (2024).

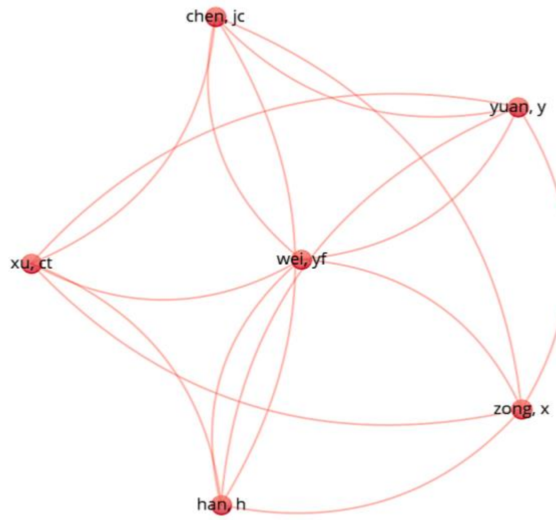
Abdelrahman and Keikhosrokiani (2020), conducted in Malaysia, proposed detecting and identifying the root causes of anomalies in the assembly line using machine learning. They employed the Pareto chart to visualize the frequency of potential causes and their cumulative occurrence within a centralized big data environment, with data generated by assembly machines through cameras for compliance inspection.

Ilieva et al. (2023) highlights that 3D printing has emerged as a new technique for producing pharmaceutical forms and personalized medical devices. 3D printers connected to a health database enable the production of small batches or even individual medications. The Pareto chart was used to analyze data from a statistical software package to verify the dissolution rate of these medications. This study was conducted in Bulgaria.

Xu et al. (2023) studied the cold rolling production process and used simulation and data from statistical software to construct a Pareto chart for optimizing compliance parameters.

Upon reviewing also, it can be observed that 6 authors have emerged as the most prominent in terms of co-authorship of the articles. The bibliometric research database comprises a total of 12 authors. It was likewise noted that this cluster relates to the article by Xu et al. (2023), which was previously discussed among the most cited works on this topic (Figure 10).

Figure 10. Co-authorship relationship map related to the Pareto diagram

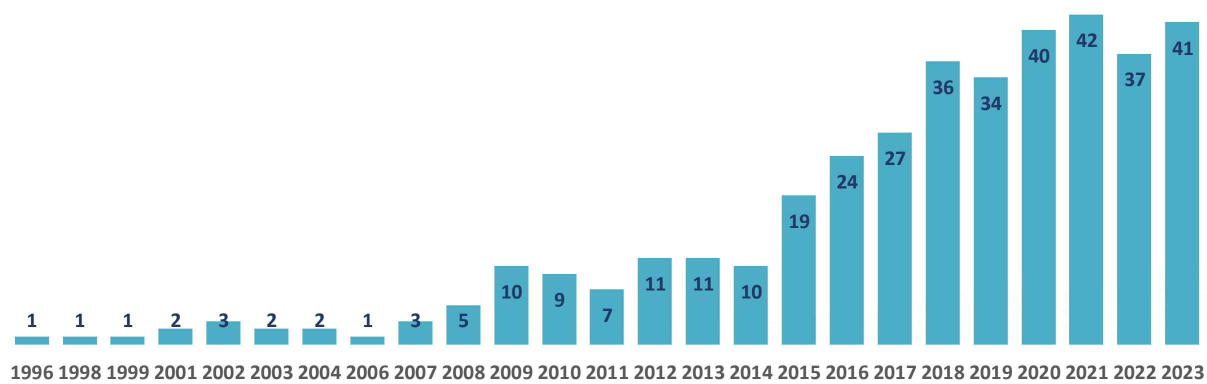


Source: Authors (2024).

STRATIFICATION

The first article on stratification applied to any of the pillars of Industry 4.0 was published in 1996, with a significant increase in publications starting from the year 2000. The highest number of publications occurred in 2021, with 42 articles (Figure 11 and Table 8).

Figure 11. Annual production of articles related to the stratification



Source: Designed from WoS (2024).

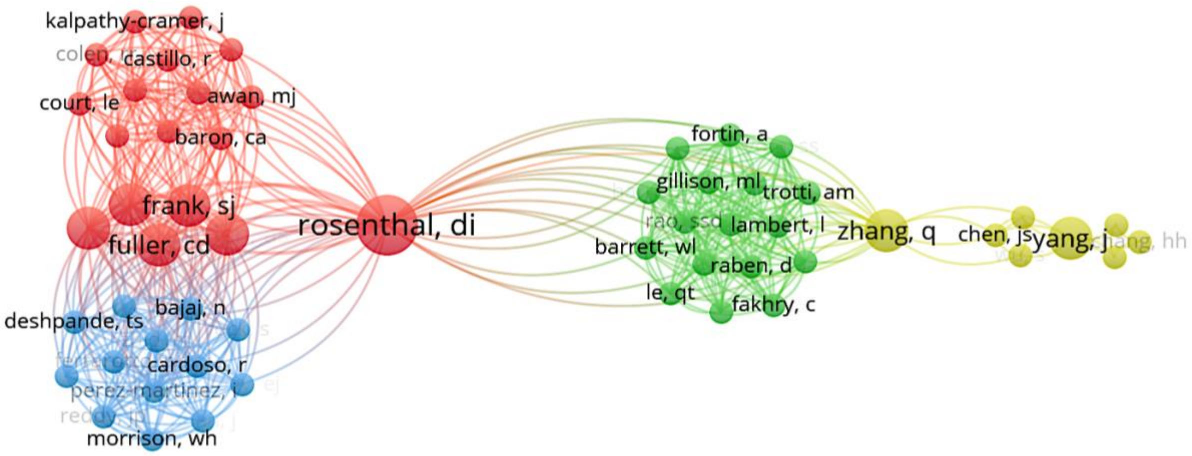
Table 8. Most cited articles - stratification

Article title	Citations	Author(s)
Towards global empirical upscaling of FLUXNET eddy covariance observations: validation of a model tree ensemble approach using a biosphere model	533	Jung, M., Reichstein, M., & Bondeau, A. (2009)
KDIGO clinical practice guideline on the evaluation and care of living kidney donors	376	Lentine, K. L., Kasiske, B. L., Levey, A. S., Adams, P. L., Alberú, J., Bakr, M. A., Gallon, L., Garvey, C. A., Guleria, S., Li, P. K.-T., Segev, D. L., Taler, S. J., Tanabe, K., Wright, L., Zeier, M. G., Cheung, M., & Garg, A. X. (2017)
Heterogeneity in healthy aging	290	Lowsky, D. J., Olshansky, S. J., Bhattacharya, J., & Goldman, D. P. (2014)

Source: Authors (2024).

Jung, Reichstein and Bondeau (2009) is a climatic study that developed processes using simulation and data stratification. Lentine et al. (2017) conducted a study on organ donation, utilizing stratification to draw conclusions from a large volume of data. Lowsky et al. (2014) led a study in the health field that used stratification to obtain information about a study group from extensive databases. Thus, Figure 12 presents the co-authorship indicator, showing how the authors of the articles in the bibliometric research database are interconnected in their studies.

Figure 12. Co-authorship relationship map related to the stratification



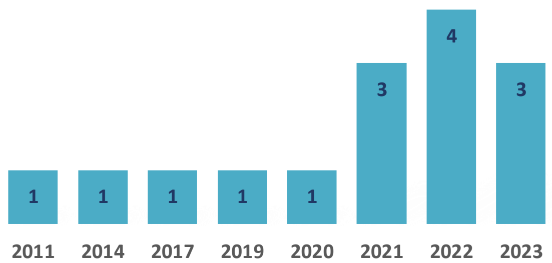
Source: Authors (2024).

Created based on a total of 1,881 authors, from which 56 were selected for their connections in the research, forming the co-authorship relationship map distributed across four clusters. Among the other researchers, Rosenthal stands out with a total of three published articles and 48 connections with other authors. In Rosenthal's, stratification is used to divide the study population into subgroups in his health-related research, particularly in radiology.

Scatter diagram

It is observed that the first publication on the scatter diagram occurred in 2011. Over time, the number of publications was dispersed, with the years 2021, 2022 and 2023 showing the highest number of publications, with 3 and 4 articles (Figure 13 and Table 9).

Figure 13. Annual production of articles related to the scatter diagram



Source: Designed from WoS (2024).

Table 9. Most cited articles - scatter diagram

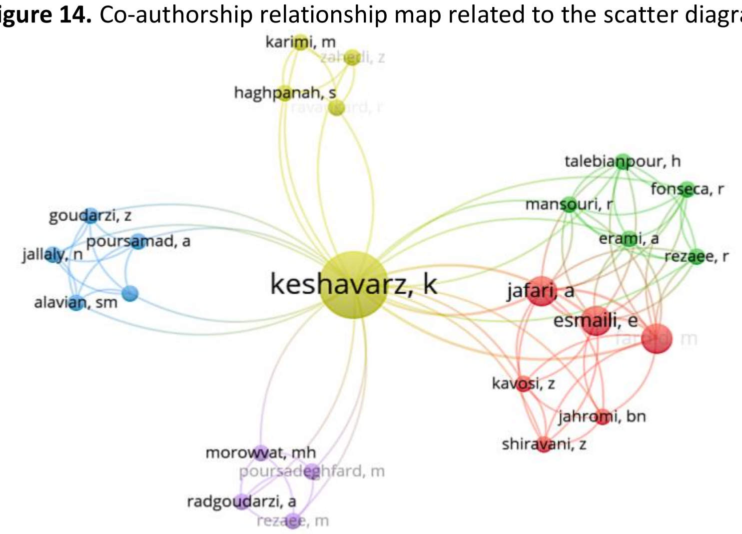
Article title	Citations	Author(s)
Material separation in x-ray CT with energy resolved photon-counting detectors	171	Wang, X., Meier, D., Taguchi, K., Wagenaar, D. J., Patt, B. E., & Frey, E. C. (2011)
Detection and classification of power quality disturbances in distribution networks based on VMD and DFA	30	Xu, Y. C., Wang, L. F., Yuan, X. F., & Zhao, Z. (2019)
Modeling stage-discharge-sediment using support vector machine and artificial neural network coupled with wavelet transform	28	Kumar, M., Kumar, P., Kumar, A., Elbeltagi, A., & Kuriqi, A. (2022)

Source: Authors (2024).

Wang et al. (2011) conducted a study in Norway in the field of medical radiology, utilizing scatter diagrams and simulation with photon count data from a computed tomography (CT) scanner to mitigate X-ray emission. Xu et al. (2019) proposed a study in electrical engineering focused on developing an algorithm for detecting and classifying power quality disturbances in the public electrical distribution network. Scatter diagrams were employed to differentiate disturbances under various operating conditions. Simulations indicated that the algorithm is effective, providing a real-time online detection approach for integrated embedded systems. And Kumar et al. (2022) published a study with researchers from Egypt, India, and Portugal in the environmental field, investigating water issues using scatter diagrams to simulate processes in environmental engineering.

Also, it is noted that there are 65 authors in the bibliometric analysis database, of which 25 were selected for having at least one connection with other researchers in these clusters. Five groups were formed, with the researcher Keshavarz standing out, having 5 articles and establishing 24 connections, distinguished from the others. The author used stratification to analyze health-related data and some of the studies were identified as employing simulations (Figure 14).

Figure 14. Co-authorship relationship map related to the scatter diagram



Source: Authors (2024).

CONCLUSIONS

With the evolution of Industry 4.0, new resources, mainly technological, have emerged, which companies have begun to incorporate into their production processes. In this context, the classic quality tools have not been forgotten. They have continued to be applied in this new industrial era, and this assertion was the main contribution of this study. The search terms linking the pillars of Industry 4.0 to the classical quality tools were used to ensure thematic accuracy and relevance, verifying the specific use of these tools. This allowed us to conclude that they continue to be applied, through this bibliometric study, where the analysis of co-authorship maps was sufficient to achieve the objective of this study: to verify the role of classical quality tools in the transition to Quality Management 4.0.

Initially, published works helped quantify the most explored quality tools in the Industry 4.0 scenario. The Pareto diagram and cause-and-effect diagram were the least explored, respectively. Likewise, stratification, histogram, and control chart were the most used.

For the cause-and-effect diagram, the articles indicated successful application in statistical control processes in the pharmaceutical industry, process engineering concerning failure probability studies, and quality control in construction. These studies highlighted the use of the cause-and-effect diagram together with simulation.

Regarding the check sheet, the articles showed its application in medicine, primarily to assess the quality of simulated scenarios.

The articles also illustrated the use of the control chart in Industry 4.0. They demonstrated its relevance in big data applications, using data science mainly for predictive analysis, and its use with simulation was also identified. The primary goal was to monitor quality characteristics and analyze small changes in process behavior, with the help of the EWMA method cited in some articles.

The articles also contributed to understanding the histogram tool, revealing its use in simulation and big data pillars. It was applied outside production processes but in product development to improve image quality in information technology and audio file technology. It was also applied in medical equipment such as CT scans and radiology.

The Pareto diagram was explicitly applied in the pillars of simulation, big data, and 3D printing. Its use in the pharmaceutical industry and medical equipment, as well as in industrial production processes, was highlighted.

Regarding stratification, the articles affirmed that this quality tool was mainly used in big data, simulation, and robotics, with data collection for statistical analyses. It was applied in climatology, radiology, and healthcare studies.

As for the scatter diagram, the conclusion was that it was used in simulation and big data pillars, and indirectly in robotics. The articles that contributed to understanding this tool originated from engineering and healthcare studies.

In terms of theoretical implications, this study identifies the role played by the seven classic quality tools within some technological pillars of Industry 4.0. It can be said that these classic quality tools were used alongside simulations, big data, robotic equipment, 3D printing, and indirectly integrated into systems utilizing other resources such as cloud computing, the Internet of Things, and systems with an implicit level of security. This is relevant because it reinforces that these quality tools have not been forgotten over time, but continue to play important roles, particularly in quality management in an Industry 4.0 reality. Additionally, this study ranks the tools that have been applied in an Industry 4.0 context, constructing a bibliographic reference that allows for quick reading and conclusions about the application of classic quality tools within the pillars of Industry 4.0.

The practical implications of this study suggest that the seven basic quality tools play a role in Industry 4.0, with practical implications such as interpreting large volumes of data to ensure product and process quality, optimizations, equipment improvement, supporting the development of new products, and even aiding in environmental impact management. Again, the study provides an overview that allows us to affirm that the classic quality tools generate practical results in Industry 4.0 industries.

Another contribution of this research was to conclude that the quality tools in question did not play a significant role only in production processes, but, in an Industry 4.0 environment, they also helped in the development of new products. As we have seen, they supported the development of a system to verify the authorship of an audio file or helped in optimizing and understanding environmental phenomena. Also, in the healthcare sector, which uses some Industry 4.0 pillars in its processes, the classic quality tools supported the organization and interpretation of large volumes of data to assist decision-making. Even to ensure that data generated by robotic equipment or processes are reliable, the classic quality tools were important. Therefore, it can be said that, just as Industry 4.0 is being gradually implemented, the seven quality tools still have much to contribute to these industries, and thus, this work contributes to knowledge by clarifying the importance of using these tools in increasingly technological industries.

Considering the entire scenario developed, it can be analytically stated, based on the specific verification of classical quality tools in the transition to Quality 4.0, that these tools have been predominantly applied in a data-oriented manner, using data generated by the pillars of Industry 4.0. This suggests that classical quality tools have not been replaced, but rather integrated into a technological environment that generates vast amounts of data, which are then leveraged for the application of quality tools. This also indicates that the transition to Quality Management 4.0 is characterized by the coexistence of traditional quality tools with advanced technologies.

From a practical perspective, the results of this bibliometric analysis demonstrated that classical quality tools continue to play an important role in decision-making within Industry 4.0 environments, where the visualization and interpretation of large volumes of data generated by technologies such as big data analytics, simulation, and robotics are essential. In this sense, quality tools assume a cognitive role between technological systems and managerial decision-making. Moreover, this study showed that the seven quality tools are important not only for process control, but also for the development of products and services, whether in industrial or non-industrial contexts.

Thus, from a scientific perspective, the fragmented co-authorship networks identified in this study suggest the existence of an important research gap, indicating that there are numerous opportunities to investigate the role and barriers of classical quality tools in the context of Industry 4.0. This highlights the need to integrate these classical quality tools into next-generation industrial architectures, enabling their integration and automated application, as well as allowing for new applications and objectives for these tools.

In addition to these gaps, future research is suggested to focus on the exclusive analysis of each of the seven classical quality tools, with the aim of examining their technological integration with the pillars of Industry 4.0, analyzing barriers and new applications in decision-making as well as in Quality Management 4.0. Particular attention should be given to the less explored tools in the context studied here, namely the cause-and-effect diagram, the Pareto diagram, and the scatter diagram.

As this is an initial study, it is important to note that the results and analyses presented do not exhaust the topic. The limitations of the study are related to the application of bibliometric indicators themselves, which may lead to the exclusion or underestimation of more recent studies that could be highly relevant to the field of knowledge.

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