Root Cause Analysis in Quality 4.0: A Scoping Review of Current State and Perspectives

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Abstract **– This paper describes a subset of Industry 4.0, namely, Quality 4.0. Industry 4.0, has brought with it many changes to industry and changes that will directly impact root cause analysis. Massive amounts of data are being generated by industry 4.0 and previous quality tools and methods are no longer up to the task of handling such large amounts of data. Old root cause analysis tools and methods can still be used in Quality 4.0, but they must undergo adaptation to remain usable and high-quality professionals will need to update their skills.**

Keywords **– Quality 4.0, Root Cause Analysis, industry 4.0, big data.**

1. Introduction

The fourth industrial revolution, Industry 4.0, is now gaining more and more attention [1]. The first industrial revolution was based on mechanization, the second was based on the introduction of electrical energy, and the third industrial revolution was driven by digitalization (See Figure 1). The pace of change in industry has greatly accelerated since the beginning of Industry 3.0 with major developments in technology and changes in the global economy [2].

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The fourth industrial revolution is based on cyber-physical systems connected by the IoT (Internet of Things) [3].

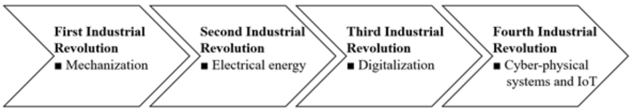

Figure 1 The four industrial revolutions

The term Industry 4.0 originated in 2011 when German manufacturing organizations, representatives from politics, and academics came together to form a working group that developed strategies to support German industry with recommendations for implementing Industry 4.0 [4]. There are four commonalities across Industry 4.0 researchers. The first is the smart factory with independently controlled and linked intelligent processes and the second is real-time communications between customers, organizations, and suppliers. The third commonality is smart products that are capable of holding information that can be analyzed. The final aspect is the ability of customers to communicate new orders and order changes in real time [5]. Industry 4.0 includes the use of digital technologies in manufacturing organizations. This increase in digitalization is leading to manufacturing processes that are networked, intelligent, and decentralized [6].

Key Industry 4.0 concepts include IoT, where machines have software that links them for real-time communication, simulation with computer models being ran in place of actual physical experiments, and IT (Information Technology) integration, both between machines in an organization and between organizations. Another key aspect of Industry 4.0 is the use of big data analytics [7].

Industry 4.0 has brought with it big data. Big data, such as the data collected by sensors, contains massive amounts of data that has complicated structures [8].

Big data can be described using the four V's consisting of the volume of the data, variety and types of data, velocity at which data is transmitted or new data is generated, and variability, which pertains to the volume, variety, and velocity being highly variable [9].

Another crucial concept in Industry 4.0 is AI (Artificial Intelligence). Artificial general intelligence is a type of AI that is comparable to human intelligence. There is also artificial narrow intelligence, which can be called machine learning, and this type of AI uses algorithms to analyze data. It is this machine learning that uses big data to make predictions [10].

A factory that has implemented Industry 4.0 methods can be viewed as a smart factory, where cyber physical systems within the factory communicate with each other though IoT [11].

Industry 4.0 has led to Quality 4.0, which is the alignment of quality management methods with Industry 4.0 and the use of technology in quality management [12]. However, implementation of Industry 4.0 in SMEs (Small and Medium Enterprises) is hindered as many SMEs are not currently capable of implementing Industry 4.0 related technologies [13].

2. Methodology

This paper uses a scoping review, which may also be called a conventional literature review or a narrative review. A scoping review is much less rigorous and detailed than a systematic review and is performed to gain an overview of a topic. To conduct the scoping review, literature sources were reviewed and conclusions were drawn from the literature that was reviewed.

3. Results

Industry 4.0 has led to Quality 4.0. Quality 4.0 must incorporate the five key Industry 4.0 concepts. The concepts are the smart factory, cyber physical systems, decentralization and self-organization, these are the new development and supply chain concepts that are more individualized, and manufacturing systems developed to fit human needs. Industry 4.0 can be viewed as a model for the interconnection of cyber physical systems through the IoT. This interconnectedness and digitalization will have a major impact on Quality 4.0, with real-time data collected by sensors on the shop floor used for diagnostics [14]. This interconnectedness will also generate massive amounts of data known as big data [15].

Quality 4.0 includes the big data aspects descriptive analytics for displaying information such as in dashboards, diagnostic analytics for identifying causes, predictive analytics for the prognosis of future states, and prescriptive analytics, but there is more overlap in the traditional quality methods.

Descriptive analytics include dashboards and score cards, diagnostic analytics includes DoE and RCA (Root Cause Analysis), predictive analytics include regression analysis and SPC (Statistical Process Control), and prescriptive analytics include optimization techniques [16].

However, new technical competencies will be need for qualifiedprofessionals to analyze large amounts of data, but standard quality methods will not disappear in Industry 4.0. But, they will need to be integrated into Industry 4.0 [17] and Quality 4.0. The field of quality must adapt to the many changes that are happening and qualified quality professionals will need to learn to cope in dealing with big data and failure analysis based on statistics [18]. The implementation of Quality 4.0 in an organization can reduce quality costs, while improving product quality and customer satisfaction, resulting in a competitive advantage [19].

However, an organization must have the necessary infrastructure to support Quality 4.0. This means systematizing thinking supported by machine learning and AI, PLC (Programmable Logic Controllers) and adaptive feedback loops, automated processes with robots, automated material transfer, and automated information collection using sensor networks [20].

Traditional quality methods must be integrated with information technologies when implementing Quality 4.0 in an organization [21]. For example, traditional SPC (Statistical Process Control) process control only monitors one characteristic. Data from big data will require multivariate monitoring [22]. Yet many quality tools remain relatively unchanged across decades. Some, such as the Ishikawa diagram, were developed over half a century ago.

Quality 4.0 influenced changes have been coming to the field of quality over the years. For example, statistical software packages have had an influence on Six Sigma, increased data on customer complaints makes it possible to respond quicker, and statistical software packages can now assist in failure investigations and performance improvement [23].

Broday expects quality methods to change, but not be replaced, with Quality 4.0 leading to quicker results from combining big data and AI with more traditional quality methods [24]. Industry 4.0 also reduces the need for labor and organizations will need to ensure their employees are able to gain new skills [25] as new competencies are needed in Quality 4.0 [26].

Skills such as analysis, critical thinking, and problem solving will be essential in Quality 4.0 [27]. Massive amounts of data can be collected through the IoT [28] and performing RCA can be enhanced by using large data sets to gain traceability data containing details such as the settings on a machine when the material was produced [29].

4. Discussion

An organization should implement IoT and use big data methods to analyze the data. But, basic quality tools still have a place: for example. An artificial intelligence system may indicate that there are eight problems with various associated costs. Engineers can still use a Pareto to prioritize the improvement of the problems. In Quality 4.0, control charts can be created for large amounts of data, but an investigation is still needed when an out of control data point is detected.

A 2019 survey of 221 companies by BCG (Boston Consulting Group), ASQ (American Society for Quality), and DGQ (Deutsche Gesellschaft für Qualität) found that 20% were planning to implement Quality 4.0 and only 16% of organizations had started to implant Quality 4.0 and none had completed the transformation [30]. The study data was assessed using Chi-square goodness of fit table (see Table 1) to determine if there was a statistically significant difference between the number of organizations that have no plan or decision to implement Quality 4.0 and the number of organizations that have started implementing Quality 4.0 or are planning to implement Quality 4.0. The Chi-square goodness of fit P-value was less than the critical value of 0.05, indicating a statistically significant difference exists. This means most organizations either have mode made a decision on Quality 4.0, or have no plan for implementing Quality 4.0.

Table 1 Chi-square goodness of fit table

Category	Observed	Test proportion	Expected	Contribution to Chi-Square	N	DF	Chi-Sq	P-Value
No decision or plan	141	0.5	110.5	8.41855	221	1	16.837	0.000
Planning or implementing	80	0.5	110.5	8.41855				

The skills of a data scientist will be needed in Quality 4.0 [31] and qualiied professionals already have some skills that will be necessary for Quality 4.0; for example, systems oriented thinking and decisions based on data as well as continuous improvement and an understanding of processes. There are also critical questions, such as which problems matter and who is affected by the problem, which must be asked before analyzing data and these can't be asked or answered by an algorithm in an AI.

The use of DoE may change to the use of simulations in software, but DoEs will still require planning as a poorly planned experiment may result in unusable results [32]. Somebody must identify the response variable, experimental design to use, factors for the DoE, and the levels for the factors [33].

Quality 4.0 can enhance the use of 8D reports.

An 8D report is a problem solving process and report that has 8 steps [34]. Some automation of the steps should be possible: for example, the fifth step is the planning of corrective actions [35]. Once implemented and validated as effective, these actions are to be carried over to comparable products that could have the same problem as part of the seventh step, where lessons learned are also documented [36]. Automation can be used to ensure every comparable product or system receive a notification that a failure has happened elsewhere and the solution needs to be implemented to prevent the same failure happening at the other part or process.

Graphical methods are often used in RCA [37] and EDA (Exploratory Data Analysis), which is an approach that uses graphical methods to generate new ideas, in contrast with CDA (Confirmatory Data Analysis), which is performed to provide confirmation such as through the use of statistical methods [38]. New explanatory hypotheses can be generated using EDA based on statistical outliers, patters, or gaps in data [39] and here is where big data generated by sensors in cyber-physical systems can be processed by machine learning to identify features of interest in the data, that could then be analyzed by qualified professionals.

For example, run charts are used to display data in time order [40] (see Figure 2) and machine learning can be used to highlight the interesting aspects in the data. These aspects could then be further analyzed, either through other machine learning methods, or more traditional quality analysis methods.

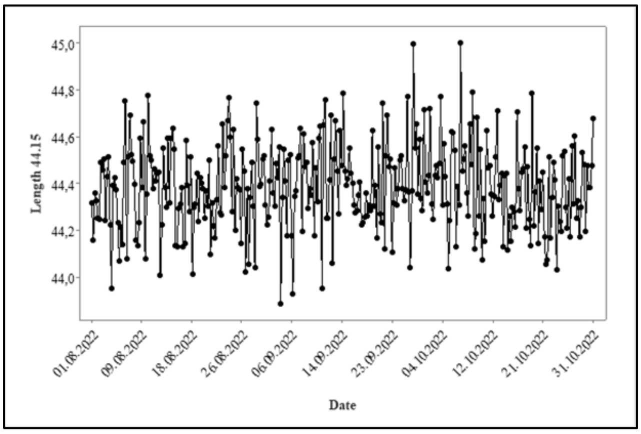

Figure 2 Run chart

Some quality tools have started the transition to Quality 4.0. For example, the formerly paper-based check sheet, which is used for collecting data that could then be analyzed [41], has started the transition to Quality 4.0, with scanners gathering information and entering it straight into databases and laser-based and optical measuring devises automatically checking parts and storing data.

A variation on the check sheet uses a graphical depiction of an object with marks identifying were failures have happened [42] (see Figure 3). This could be especially useful when visual systems are being used to check quality, such as when a camera observes parts and software looks for the profile of a failure, as such data can be analyzed with machine learning to seek out patters that is where the greatest concentration of failures happen.

Figure 3. Graphical check sheet

Another quality concept undergoing changes though the use of technology is the FMEA (Failure Modes and Effects Analysis), which has been mostly unchanged since being originally released in 1949 [43]. An FMEA lists the reason a failure happened, the failure, and the effect of the failure as well as actions to prevent and detect failures [44]. Traditionally, FMEAs have been done in a spreadsheet, although some organizations have started using software programs. The use of FMEA software is even mandated by a large automotive company. This is to ensure lessons learned are transferred using templates linked togeather in FMEA software. [45]. This mean that if one location experiences a new type of failure, all locations will receive an update to prevent an occurrence at the other locations using a connectivity that was previously unavailable in early Quality 3.0.

One of the most commonly used quality tools is the Ishikawa diagram [46] (see Figure 4). An Ishikawa diagram lists hypotheses, which could explain the cause of a problem [47]. However, a survey found 75% of organizations used only brainstorming and feelings with an Ishikawa diagram when solving problems [48]. Only using an Ishikawa diagram is a critical mistake, as the cause of a problem can only be found though an analysis [49].

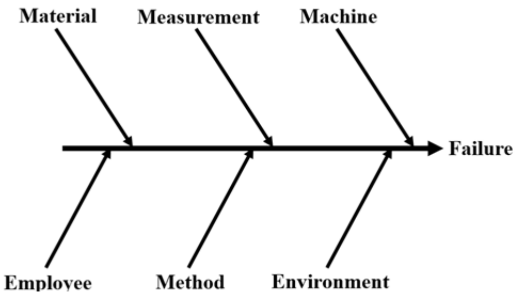

Figure 4. Ishikawa diagram

The Ishikawa diagram has been around since the 1940s [50] and remains relatively unchanged. Traditionally, problem solving team members work gather to brainstorm ideas for an Ishikawa diagram; however, insights from big data analysis and cyber-physical systems can be used to replace feelings in identifying explanatory hypotheses listed in an Ishikawa diagram.

Another quality tool which could use an update in Quality 4.0 is the affinity diagram. An affinity diagram supports brainstorming by organizing comparable concepts when generating ideas. The ideas are listed on note cards and then alike ideas are clustered together under main ideas [51]. Such a quality tool may still be useful in Quality 4.0 when people must generate ideas; however, such a quality method should move from paper note cards to software.

A smart factory will be able to detect many failures before they happen and machine learning, drawing on big data, can be useful for analyzing data if failures do still happen. However, there will still be a need for quality professionals to make decisions when things happen outside the parameters in a software program's coding.

For example, the author once investigated the failure of a retuned part and the root case was found to be an insect, which had blocked a metal tube that connected to the customer's system. Having happened only once and outside of the production facility, this information would not be in the data contained within a smart factory and the only way to find the root cause would be an analysis of the returned part. Therefore, old quality methods will retain relevance in Quality 4.0; however, they must be supplemented by new methods for the qualified professional to remain relevant.

Automated analysis systems can analyze data and present conclusions, yet a skilled investigator is still needed. Consider the analysis of damage to bombers during the Second World War. The objective was to find where the planes were sustaining the most damage to armor those areas, but a statistician concluded that those were the areas were where bomber could be damaged and still return to base. The undamaged areas were areas that would cause planes to crash if heavily damaged. This phenomenon is known as survivorship bias [52] and may not be identified by a statistical software package; therefore, a knowledgeable human is still needed.

Watson warns that qualified professionals must adapt with new roles and responsibilities to the changes coming due to new technology [53].

Watson believes that the roles of data scientist and qualified professional will be superseded by "'collaborative analytics,'" (see Figure 5) which "will merge all continual improvement activities into an integrated, cross-functional, organization wide method driven by a structured, scientific approach to problem investigation, diagnosis and remediation" [54].

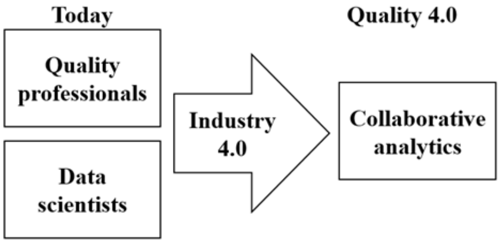

Figure 5. Transformation of quality professionals and data scientists

Data scientists are capable of collecting, preparing, and analyzing data using statistical methods with programing languages such as Python [55]. An alternative program language is R [56], which has a packages specifically intended for use in the field of quality such as R-Bar, [57], QCR, qualityTools, QCC, SixSigma, or IQCC [58]. Fortunately, there already is some overlap between a data scientist and a qualified professional. For example, the quality engineer body of knowledge includes statistical methods [59].

5. Conclusion

This paper consolidates information pertaining to Quality 4.0 and provides guidance on what updates organizations must implement to successfully perform RCA in a networked and data intensive Quality 4.0 environment.

Industry 4.0 has brought with it Quality 4.0. Organizations are becoming more networked with smart machines in place and this will have an impact on qualified professionals. Industry 4.0 is dominated by technology and, when performing the RCA, qualified professionals in Quality 4.0 will need to adapt to be able to analyze the massive amounts of data generated by Industry 4.0 technology.

As shown by the statistical analysis of the BCG/ASQ/DGQ Quality 4.0 study, the majority of organizations currently have not reached a decision to implement Quality 4.0 or have no plan for implementing Quality 4.0.

Although qualified professionals should have the necessary statistical knowledge, much additional learning in this area may still be needed to handle massive amounts of data generated by processes and to do the necessary coding in a statistical programming language such as R or Python.

Qualified professionals should already be skilled problem solvers; therefore, they just need to adapt their current skills, gain some new skills, and adapt their tools to survive the transition from Quality 3.0 to Quality 4.0. However, organizations must start planning for the transition to Quality 4.0.

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