# Quality 4.0 – A Quality Focused Implementation Strategy for Industry 4.0 Technologies

**Thomas Jones**
Doctoral Candidate, Department of Industrial Engineering and Management Systems
University of Central Florida
Orlando, Florida, USA
Tom.Jones@knights.ucf.edu

**Ahmad K. Elshennawy**
Professor, Department of Industrial Engineering and Management Systems
University of Central Florida
Orlando, Florida, USA
Ahmad.Elshennawy@ucf.edu

## Abstract
Industry 4.0 technologies are transforming manufacturing worldwide. Many companies struggle to successfully implement these technologies. To drive successful implementation, it is useful to understand Industry 4.0 technology applications and successful strategies. Industry 4.0 technologies utilize data and successful applications must involve data collection and management, data analytics, and automation. The value proposition of Industry 4.0 is in turning data into usable information in such a way as to improve business results. Review of case studies shows that quality applications are common cases of success for Industry 4.0 technologies. The data driven nature of Industry 4.0 lends itself to the skills of quality professionals. Taking a quality driven approach to implementation may be a successful strategy for those businesses with quality as a strategic focus for competitive success. Quality professionals already in possession of data skills and continuous improvement mindsets are well suited to drive digital transformation. A model for a Quality 4.0 implementation strategy is developed through thematic analysis of the literature on Industry 4.0 and case study analysis of successful Industry 4.0 implementations.

## Keywords
Industry 4.0, Quality 4.0, Data Analytics, Digital Transformation, Smart Factory

## 1. Introduction
Industry 4.0 is an important topic for the future of manufacturing. It can be described as the application of digital technologies to enhance our capabilities through data and information usage, and has been characterized as the fourth industrial revolution (Schwab, 2017). In spite of this shift towards digital transformation less than 30% of such transformations are reported as being successful (De la Boutetière, Montagner, & Reich, 2018). Low success rates for implementation point to an opportunity to develop strategies and guidelines for digital transformation. This opportunity is further highlighted by a limited amount of literature on Industry 4.0 implementation (Pozzi, Rossi, & Secchi, 2021).

Due to positioning within an organization along with skills in data collection and utilization, quality departments have been identified as potential drivers for Industry 4.0 implementations (Nicole M Radziwill, 2018). Quality professionals may also be strong candidates to drive Industry 4.0 efforts as many Industry 4.0 use cases are focused on quality improvement (Jacob, 2017). Early research on the topic of Industry 4.0 also shows overlap with Total Quality Management (TQM) methodology as a potential success factor in an Industry 4.0 strategy (Babatunde, 2020). The quality discipline shows potential to have major influence on digital transformations within industry and a quality centered approach to Industry 4.0 deployment is worth exploring.

### 1.1 Study Objectives

The objective of this study is to explore the existing body of knowledge on Industry 4.0 implementations and develop a high-level strategic approach for successful quality centered deployment of Industry 4.0 technologies.

## 2. Literature Review

Technology advancements in recent years have enabled Industry 4.0. The literature identifies several technologies and groupings of technologies as being Industry 4.0 enablers. Some works focus on specific technologies, highlighting technologies such as the Internet of Things (IoT), Blockchain, Cloud Computing, Big Data, and Radio Frequency Identification (RFID) (Raut, Gotmare, Narkhede, Govindarajan, & Bokade, 2020). Many works have compiled lists of specific technologies and their use cases for Industry 4.0. Other works have taken broader strokes by highlighting Industry 4.0 applications and identifying technologies that may be supporting them, such as Analytics, Data Management, Connectivity, and Scalability being Industry 4.0 technology applications (Jacob, 2017). This approach allows broader interpretation of which technologies may be utilized to implement an Industry 4.0 strategy or application. Literature about Industry 4.0 technologies can be reviewed thematically to form a model of Industry 4.0 technological applications. Reviewing the literature for technological themes leads to three types of applications that appear with great frequency:

- Data Management Technologies
- Data Analysis Technologies
- Automation Technologies

Data management technologies can be broken down into three sub-categories of data collection, data connection, and data security. Data collection technologies include IoT, RFID, Smart Sensors, and Cameras among others (Abuhasel & Khan, 2020; Bhattacharya, Chu, & Mullen, 2008; Indri, Lachello, Lazzero, Sibona, & Trapani, 2019; Massaro, Manfredonia, Galiano, & Contuzzi, 2019). Data connection is largely centered on 5g networks (Gundall et al., 2021). Data security includes blockchain as well as guidelines for managing security (Fernández-Caramés & Fraga-Lamas, 2019; Mullet, Sondi, & Ramat, 2021). Data management is foundational to Industry 4.0 as without data to feed new applications there would be no value. The data must be usable to enhance the value of an operation, and quality data can be defined though volume, velocity, variety, and veracity of the data (Saha & Srivastava, 2014). Having appropriate data sources flowing securely into well designed systems is a core tenant of Industry 4.0 applications.

Data analysis technologies focus heavily on Artificial Intelligence (AI) applications, but also include the field of business intelligence as well as cloud and edge computing (Aazam, Zeadally, & Harras, 2018; Bordeleau, Mosconi, & de Santa-Eulalia, 2020; Peres et al., 2020). AI applications have been growing in capability and in many cases can outperform humans at certain tasks centered around identification or classification. This advantage has utility when developed into a business system with value in mind. Cloud and edge computing are methods of performing data processing either offsite where skills and software may be more readily available, or locally to where the data is collected to simply the movement of data by moving smaller amounts of data already processed into higher value formats. Data analytics is a second tenant of Industry 4.0, as data must be converted into a usable form of information to drive value-adding action, non-action, or decisions.

Automation technologies can take many forms. Automation can range from a human operator giving commands to be explicitly followed by a computer driven system to a system analyzing data and selecting courses of action with various forms of human management or awareness (N. M. Radziwill, 2020, pp. 13-14). Many forms of automation are mechanical such as robotics applications and autonomous vehicles for logistics (Barbosa et al., 2020; Sell, Rassolkin, Wang, & Otto, 2019). Automation may also be information based, such data analysis being executed within a system and actionable information flowing to the appropriate user of the system when action may be merited. Automation is a third tenant of an Industry 4.0 application; the automation step typically yields the practical value of the application.

## 3. Methods

The study method is as follows:

1. Identification of successful Industry 4.0 use cases through case study literature review
2. Thematic analysis of case studies to highlight common themes

    a. Technological themes
    b. Contextualizing themes
    c. Success themes
3. Categorical analysis of themes from case studies
4. Model development for industry 4.0 implementation
5. Model evaluation for business case

The goal of this methodology is to highlight factors associated with successful use cases of Industry 4.0 technologies in order to develop a practical model for development of an Industry 4.0 application. The output of this study is a high-level model and not a specific roadmap to implementation, as the body of literature and case analysis is limited.

## 4. Data Collection

Case studies were identified from the literature to formulate the data for this study. Categories of themes identified from cases included:

- Technologies used
    - Data management
    - Data analytics
    - Automation
- Business case / problem being addressed
- Value proposition

A summary of cases identified with their themes can be found in table 1:

Table 1 - Industry 4.0 Case Studies

| Case | Technology | Problem | Value |
|---|---|---|---|
| (Marino et al., 2021) | Machine Learning, Sensors, Edge Computing | Time required to perform visual inspection | Machine learning model detects defects faster than human inspection with 100% visual inspection |
| (Massaro et al., 2019) | Machine Learning, Sensors, IoT | Time required to perform visual inspection | Machine learning model identified defects in tires faster and more accurately than human inspection |
| (Ahmed, Rahaman, Rahman, & Kashem, 2019) | Sensors, Machine Learning | Water quality not suitable for fish farming | Prediction model with high accuracy of water quality |
| (Ozdemir & Koc, 2019) | Sensors, Machine Learning | Parts not being sorted quickly or accurately enough | Machine learning model identified parts faster and just as accurately as an operator |
| (Pittino, Puggl, Moldaschl, & Hirschl, 2020) | IoT, Machine Learning, Sensors | High rate of defects in wafer production when machines required maintenance | Machine learning model predicted maintenance needs prior to wafers going out of spec, optimized maintenance operation |
| (Logvin, Kulikov, Shurpo, & Yvarova, 2020) | Simulation, Digital Twin | Operational parameters during coating process are challenging to identify resulting in poor coating quality | Simulation model able to develop quality recipes for parameters with reduced defects during actual production |
| (Villalba-Diez et al., 2019) | Machine Learning, Sensors, IoT | Inspection of printed sheets is time consuming and costly | Machine learning model identified defects faster and with greater accuracy than human operators |

| | | | |
|---|---|---|---|
| (Kulkov, Korytov, Popov, & Larionov, 2019) | Sensors, Edge Computing | Coating thickness measurement accuracy not adequate | Accuracy of detection of out of tolerance coating thickness |

The cases highlight different individual applications of Industry 4.0 technologies with realized business cases beyond theoretical applications. The next step in this analysis is a categorical analysis of themes present in this sample of successful use cases. Themes are compiled through pareto analysis in figures 1-3. Cases may present multiple themes.

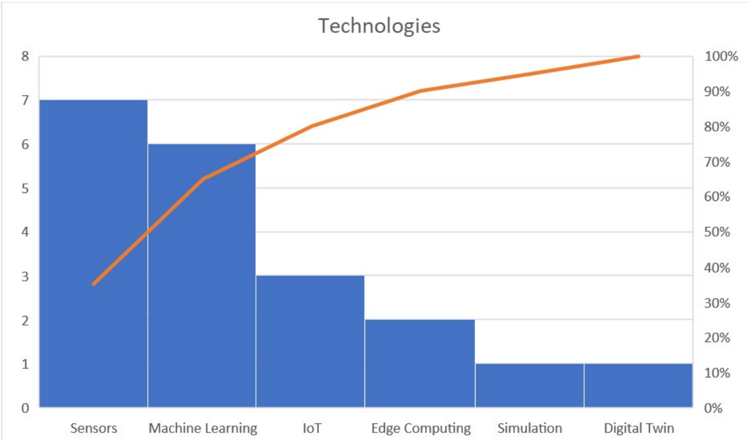


Figure 1 - Technologies Themes

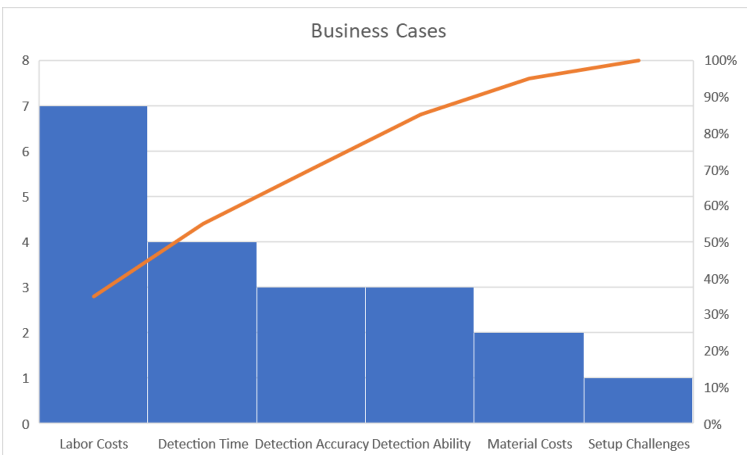


Figure 2 - Business Case Themes

 

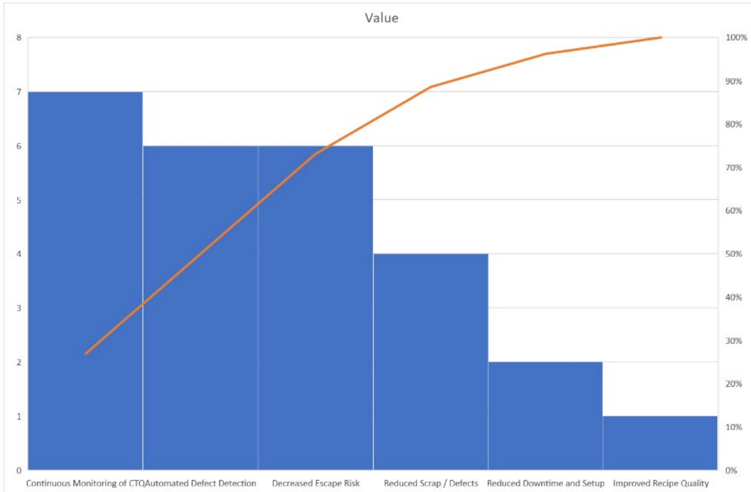


Figure 3 - Value Propositions

Common themes that emerge include:

- Technologies
  - Sensors
  - Machine Learning
  - IoT
  - Edge Computing
- Business Cases
  - Labor Costs
  - Detection Time
  - Detection Accuracy
  - Detection Ability
- Value Proposition
  - Continuous Monitoring
  - Automatic Defect Detection
  - Reduced Customer Escapes
  - Reduced Defect Rates

The business cases and value propositions tend to mirror each other thematically, which is logically sound and serves as a validation of the identified themes. Generally, the successful use cases identified enhance system capabilities by improving the speed and accuracy of decision making, relieving the operators' responsibilities to continuously process data and generate actionable information from it.

## 5. Results and Discussion

The thematic analysis of successful use cases highlights strengths of Industry 4.0 technologies when applied correctly. These technologies are well suited to augment human ability to operate complex systems through continuous monitoring and analysis of data points, coupled with the ability to autonomously convert that data into usable applications. These strengths are well aligned with the quality discipline as it exists within the manufacturing sector. Quality departments generally serve as administrators over the collection and management of manufacturing data, even if they delegate the data collection and usage tasks to other departments. As all Industry 4.0 applications depend on the flow and use of data, quality professionals are well positioned within organizations to identify areas where data management technologies would be beneficial to be applied to fill gaps or improve organizational competencies. Quality professionals are already versed in key data points and sources which may be worth systematizing.

A common application seen in the analyzed cases was 100% inspection being carried out by a system. This is a valuable application for Industry 4.0 technologies as these systems don't suffer from real human inspection issues such as mental and physical fatigue. Performing a 100% inspection task is very repetitive, and repetitive work is the most appropriate to automate. Machine Learning has allowed computer-based systems to perform visual inspections with accuracy rivaling human operators. Quality 4.0 applications may capitalize on 100% inspection opportunities which would free human resources up to perform tasks of greater complexity. The quality professional is likely the most appropriate individual to lead the effort of implementation of autonomous inspection systems due to their visibility to both the technical aspect of products and the operations aspect of manufacturing. A proposed initial model for Quality 4.0 implementation is shown in figure 4:

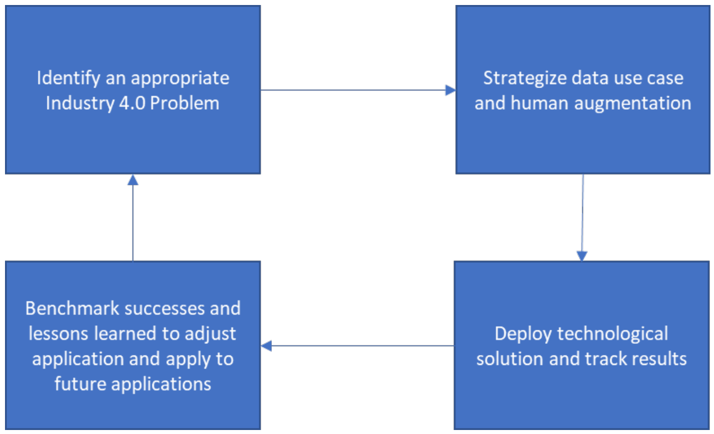


Figure 4 - Quality 4.0 Implementation Model

This model suits the quality professional as it mirrors the traditional Plan-Do-Check-Act (PDCA) cycle of continuous improvement. Quality skills are likely to be critical across all steps of the implementation process. During the problem identification phase, it is critical to identify an appropriate problem. An appropriate problem in this model is one in which there exists the potential for data collection and application in such a way that the usage of this data will directly influence the outcome of the process. Problems in which useful data cannot be conceptualized or collected in a way that isn't significantly cost prohibitive to the effort are not appropriate. Problems which are not standard or repeatable enough for data to be modeled consistently are also not appropriate. Conceptualizing the data use case and strategizing how to augment the human system, phases one and two in the model, are tasks appropriate for quality departments already versed in data skills with data driven mindsets. The third and fourth phases in the model are broader and will require diverse skill sets. For the implementation and lessons learned portions of the process, the quality department may engage with a team including production, IT, engineering, and other groups, however as the goal of these implementations is centered on improving business performance through data usage it is likely that quality professionals may still be the most appropriate owners of this process.

## 6. Conclusion

Industry 4.0 is affecting the entire global business landscape. It goes well beyond quality departments or the quality profession. Due to the data centered nature of Industry 4.0 and the established data skills and focus of the quality profession, Quality 4.0 may be an appropriate strategic approach to the implementation of Industry 4.0 technologies for the purpose of improved business performance. The context of the business and its core competencies and market strategies are relevant in determining how to initiate a digital transformation and Quality 4.0 is not the only appropriate approach to Industry 4.0 technology deployment. Quality professionals are well positioned within organizations to enhance digital transformation strategies, and quality driven digital transformation should be considered by companies with quality as a key business focus.

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## Biography

**Thomas Jones** is a Doctoral Candidate in the Industrial and Systems Engineering department at the University of Central Florida. His research focus is on Quality 4.0 strategies and implementation with an emphasis in manufacturing settings. Thomas received both his Bachelor of Science and Master of Science in Industrial Engineering from Wichita State University. He has a background in quality engineering and lean manufacturing.

**Ahmad K. Elshennawy,** Ph.D. is Professor and Executive Director of The UCF Quality Institute in the Department of Industrial Engineering and Management Systems at the University of Central Florida (UCF). Dr. Elshennawy combines over 30 years of international experience with exemplary academic record in the areas of quality management and strategic improvement, as a researcher, academician and a consultant in the United States and different parts of the world. Elshennawy received a BS and MS degrees in Production Engineering from Alexandria University and M.Eng. & Ph.D. degrees in Industrial Engineering from Penn State University. He is a Fellow of the American Society for Quality (ASQ), Senior Member of the Institute of Industrial Engineers (IIE), and the Society of Manufacturing Engineers (SME). He is an ASQ Certified Quality Engineer (CQE) and a Certified Reliability Engineer (CRE) and is a Certified Lean Six Sigma Master Black Belt. Dr. Elshennawy has served on the Editorial Review Board of ASQ Quality Press and currently serves on the Technical Review Board of Quality Progress.