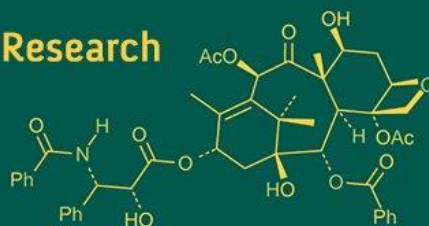


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A Meena
Assistant Professor,
Department of Statistics and
Mathematics, Professor
Jayashankar Telangana
Agricultural University
(PJTAU), Telangana, India

B Chandrasekhara Reddy
Lecturer in Statistics,
Government College
(Autonomous), Anantapur,
Andhra Pradesh, India

S Damodharan
Assistant Professor,
Department of Statistics, Sri
Venkateswara University,
Tirupati, Andhra Pradesh,
India

Sharad Bisen
Assistant Professor,
Department of Horticulture,
Jawaharlal Nehru Krishi
Vishwa Vidyalaya (JNKVV),
Jabalpur, Madhya Pradesh,
India

Bhagya Lakshmi
Research Scholar, Department
of Statistics, Sri Venkateswara
University, Tirupati, Andhra
Pradesh, India

Rajender Kumar
Associate Professor,
Department of Basic
Engineering, College of
Agricultural Engineering and
Technology, CCS Haryana
Agricultural University, Hisar,
Haryana, India

Corresponding Author:
S Damodharan
Assistant Professor,
Department of Statistics, Sri
Venkateswara University,
Tirupati, Andhra Pradesh,
India

Statistical quality control methods in modern manufacturing

A Meena, B Chandrasekhara Reddy, S Damodharan, Sharad Bisen, Bhagya Lakshmi and Rajender Kumar

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Abstract

Statistical Quality Control (SQC) underpins contemporary manufacturing excellence. SQC integrates statistical methods to monitor, control, and improve production processes. Origins in early 20th-century industrial engineering have matured into robust frameworks that leverage real-time data, process capability analysis, control charts, and design of experiments to reduce variation and defects. Modern manufacturing environments from automotive to electronics and pharmaceuticals depend on SQC strategies to ensure product conformity, elevate efficiency, and protect consumer safety. This review synthesises foundational theories, practical methodologies, case studies, emerging trends, such as Industry 4.0 integration, and implementation challenges. The article argues that advanced SQC tools, when supported by organisational commitment and data infrastructure, significantly lower costs and improve competitiveness. Future directions include adaptive control systems and machine-learning integration.

Keywords: Statistical quality control, control charts, process capability, design of experiments, industry 4.0

Introduction

Statistical Quality Control (SQC) is a set of statistical methods used to monitor, control, and improve manufacturing processes. By applying these tools, manufacturers can identify production process variations, reduce defects, and ensure the product meets required specifications (Montgomery, 2020) ^[1]. At its core, SQC aims to improve quality by preventing problems rather than correcting them after they occur. This preventive approach distinguishes SQC from traditional quality assurance (QA) methods, which often focus on inspecting finished products (Grover *et al.*, 2024) ^[2].

The evolution of SQC dates back to the early 20th century, with key contributions from pioneers such as Walter A. Shewhart, who is credited with developing the first control chart for quality improvement. Shewhart's work laid the foundation for Statistical Process Control (SPC), which is now a fundamental aspect of modern manufacturing (Hossain *et al.*, 2010) ^[3]. Later, W. Edwards Deming and other quality management experts expanded on these ideas, integrating statistical methods with broader management strategies, such as Total Quality Management (TQM) and Six Sigma (Montgomery, 2020) ^[1].

SQC has become an integral part of manufacturing operations across various industries, from automotive to electronics. Manufacturers use SQC to monitor processes, identify areas of improvement, and ensure that products meet customer requirements and regulatory standards (Grover *et al.*, 2024) ^[2]. With advances in technology and the growth of data-driven production environments, the scope of SQC has expanded to include real-time monitoring, predictive analytics, and automation, marking the onset of Industry 4.0 (Hossain *et al.*, 2010) ^[3].

Today, SQC is not just a tool for reducing defects, but a critical element in driving continuous improvement and operational excellence. In the face of increasing global competition and customer demands for higher quality, SQC remains a vital tool for manufacturers to maintain product consistency and enhance customer satisfaction (Montgomery, 2020) ^[1].

2. Fundamentals of Statistical Quality Control

At the heart of Statistical Quality Control (SQC) lies the concept of variation. All manufacturing processes exhibit some level of variation whether it's in raw materials, machinery, or human error. Understanding and managing this variation is essential to ensuring consistent product quality (Spanos, 2019) ^[8]. In SQC, variation is classified into two types: common cause variation and special cause variation. Common cause variation is the inherent variability in a process that is always present, whereas special cause variation refers to anomalies or irregularities caused by specific, identifiable factors (Boos & Stefanski, 2013) ^[6].

2.1 Understanding Variation

Manufacturing processes are dynamic, and variation is inevitable. However, the key to quality control lies in distinguishing between acceptable levels of variation (common cause) and variation that signals a problem (special cause) (Spanos, 2019) ^[8]. Using statistical methods, manufacturers can determine whether a process is stable or requires intervention (Boos & Stefanski, 2013) ^[6].

For example, in an automotive assembly line, common-cause variation might include slight fluctuations in machine performance that are expected but generally do not affect product quality. On the other hand, special-cause variation might occur if a machine breaks down or a supplier provides defective raw materials. Identifying special-cause variation and addressing it promptly is crucial for maintaining consistent quality (Lashkari & Chenouri, 2025) ^[4].

2.2 Probability and Distributions

To quantify variation, statistical tools rely on probability theory. Probability distributions are mathematical functions that describe the likelihood of different outcomes. In SQC, the normal distribution is commonly used because it can approximate many types of process data, especially when sample sizes are large (Spanos, 2019) ^[8].

Understanding probability distributions is essential because it allows for the calculation of control limits and the assessment of process capability. For instance, in a process where the diameter of a part is critical, manufacturers might assume that variation follows a normal distribution, enabling the use of statistical tools such as control charts and process capability indices (Boos & Stefanski, 2013) ^[6].

2.3 Sampling and Statistical Inference

Full inspection of every product in a production run is impractical. Instead, manufacturers use sampling to make inferences about the entire lot based on a smaller subset of products. Statistical sampling theory provides the foundation for determining how many samples to take and how to interpret the results (Lipson, 2000) ^[7]. Key principles such as acceptance sampling and confidence intervals guide decisions on whether a batch should be accepted or rejected (Pfannkuch, 2008) ^[5].

Statistical inference, which involves drawing conclusions about a population from sample data, plays a critical role in SQC. By analysing a sample, manufacturers can estimate the characteristics of the entire production lot, assess process stability, and predict potential issues before they escalate (Lashkari & Chenouri, 2025) ^[4].

3. Control Charts and Process Monitoring

Control charts are a fundamental tool in Statistical Process

Control (SPC). They visually track the performance of a process over time, helping to distinguish between normal process variation and special cause variation. Developed by Walter A. Shewhart in the 1920s, control charts enable manufacturers to monitor processes in real-time, ensuring that any deviations from acceptable performance are detected early and addressed before they result in defective products (Staudhammer, 2004) ^[13].

3.1 Shewhart Control Charts

Shewhart control charts are the most commonly used type of control chart and form the basis for many SPC applications. A control chart consists of a time-ordered series of data points, plotted on a graph with three key components: the central line, which represents the process average; the upper control limit (UCL), which marks the highest acceptable value for the process; and the lower control limit (LCL), which indicates the lowest acceptable value (Anyaso-Samuel, 2019) ^[10].

Control charts are typically used for both variable data (e.g., dimensions, weight, temperature) and attribute data (e.g., number of defects, defective units). In a manufacturing setting, a common example would be the use of an $\bar{X}$ -R chart, where $\bar{X}$ represents the average of a sample and R represents the range of variation within that sample. This chart monitors the process mean and variability, helping to detect shifts or trends that indicate process instability (Staudhammer, 2004) ^[13].

3.2 Advanced Control Chart Techniques

While Shewhart charts are effective for detecting large variations or shifts in a process, more advanced techniques are needed for identifying smaller shifts or variations that may still affect product quality. Methods like Cumulative Sum (CUSUM) charts and Exponentially Weighted Moving Average (EWMA) charts are often used for these purposes (Anyaso-Samuel, 2019) ^[10].

- CUSUM charts are particularly useful when monitoring small shifts in a process. These charts accumulate deviations from a target value over time, making it easier to detect subtle changes.
- EWMA charts give more weight to recent data points, making them highly sensitive to small changes in the process. These charts are ideal for environments where changes occur gradually, and early detection is critical to maintaining product quality (Staudhammer, 2004) ^[13].

Both CUSUM and EWMA charts are increasingly popular in industries where small shifts can have significant consequences, such as in pharmaceutical manufacturing, where even slight variations in production parameters can impact the efficacy of drugs (Anyaso-Samuel, 2019) ^[10].

3.3 Real-Time Monitoring and Automated SPC

With the advent of Industry 4.0 technologies, real-time data monitoring and automated SPC have become standard practices in many manufacturing environments. Sensors embedded in machinery and connected to centralised data systems can continuously monitor process variables, automatically applying control limits and alerting operators if a process goes out of control (Staudhammer, 2004) ^[13]. For instance, in an electronics manufacturing facility, automated SPC systems track variables such as temperature,

humidity, and voltage levels in real-time. When a sensor detects a deviation exceeding the predefined control limits, the system can immediately notify the operator or autonomously adjust process parameters, preventing defects (Anyaso-Samuel, 2019) ^[10].

Real-time monitoring enhances the effectiveness of SPC by reducing the time between detecting and addressing problems. This capability is particularly valuable in fast-

paced environments, where defects can accumulate quickly, resulting in high costs if not identified and corrected promptly (Staudhammer, 2004) ^[13].

As discussed previously, different types of control charts are used based on the nature of the data and the specific application. Table 1 below summarizes some of the commonly used control charts and their practical applications in manufacturing.

Table 1: Commonly Used Control Charts and Their Applications

Control Chart Type	Data Type	Application	Example
$\bar{X}$ -R Chart	Variable data (continuous)	Monitoring of process averages and ranges for subgroups of data	Monitoring diameter in a machining process
p-Chart	Attribute data (proportion defective)	Tracking the proportion of defective items in a sample	Inspection of defective items in a batch of electronics
np-Chart	Attribute data (count of defectives)	Monitoring the number of defective items in fixed sample sizes	Counting the number of defective units in a sample of cars
c-Chart	Attribute data (count of defects)	Used when counting the number of defects or nonconformities in a sample unit	Number of scratches on a product in a batch
u-Chart	Attribute data (count of defects per unit)	Monitoring defects per unit when the sample size varies	Number of defects in different lengths of fabric

Source (Montgomery, D. C. (2019); Wiley. Wheeler, D. J., & Chambers, D. S. (1992) ^[40, 41]

4. Process Capability and Performance Metrics

Process capability analysis is a key aspect of Statistical Quality Control (SQC) that assesses the ability of a manufacturing process to produce products that meet specifications consistently. Unlike control charts, which monitor a process's stability, process capability evaluates whether the process can produce acceptable quality within the given specification limits (Kane, 1986) ^[17]. By understanding process capability, manufacturers can determine whether their processes are capable of producing products that meet customer requirements and industry standards (Álvarez *et al.*, 2015) ^[15].

4.1 Capability Indices

The concept of process capability is often quantified using capability indices. These indices provide a numerical measure of how well a process fits within its specification limits. The two most commonly used capability indices are Cp and Cpk (Kane, 1986) ^[17].

- **Cp (Process Potential Index):** Cp measures the potential of a process to meet specification limits when the process is centered on the target. It is calculated by comparing the width of the process distribution to the width of the specification limits. A Cp value greater than 1 indicates that the process has the potential to meet specifications. However, Cp does not account for the centering of the process (Albing, 2006) ^[14].
- **Cpk (Process Performance Index):** Cpk accounts for both the spread of the process and the centering relative to the target. While Cp measures potential capability,

Cpk measures actual performance. A Cpk value greater than 1.33 is generally considered acceptable in most industries, although higher values are targeted in critical fields such as aerospace and medical devices (Kane, 1986) ^[17].

For example, in an automotive manufacturing plant producing engine components, a Cp of 1.5 would suggest that the process has the potential to meet specification limits, while a Cpk of 1.2 might indicate that the process is not centered, increasing the likelihood of defects (Álvarez *et al.*, 2015) ^[15].

4.2 Process Performance Metrics

In addition to Cp and Cpk, other metrics such as Pp and Ppk are used to evaluate process performance over time. These metrics are similar to Cp and Cpk but rely on long-term process data from the entire production run (Albing, 2006) ^[14].

- **Pp (Performance Index):** Like Cp, Pp compares the spread of the process distribution to the specification limits but does not account for how well the process is centered. Pp uses complete production data, giving a broader view of variability (Álvarez *et al.*, 2015) ^[15].
- **Ppk (Performance Index with Centering Adjustment):** Ppk, like Cpk, considers both the spread and the centering of the process using actual data over time. It is widely used when evaluating long-term process capability and stability (Bais, 2008) ^[16].

Table 2: Process Capability Indices and Their Interpretation

Capability Index	Formula	Interpretation	Acceptable Value Range
Cp	$Cp = \frac{USL - LSL}{6\sigma}$	Measures the potential of the process to meet specification limits. Does not account for process centering.	$Cp > 1.33$ indicates potential capability
Cpk	$Cpk = \min \left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma} \right)$	Accounts for both process variability and centering relative to target.	$Cpk > 1.33$ indicates acceptable performance
Pp	$Pp = \frac{USL - LSL}{6\sigma_{total}}$	Measures the overall capability of a process, including both common cause and special cause variation.	$Pp > 1.33$ indicates good process capability
Ppk	$Ppk = \min \left(\frac{USL - \mu}{3\sigma_{total}}, \frac{\mu - LSL}{3\sigma_{total}} \right)$	Accounts for both the overall spread and centering of the process.	$Ppk > 1.33$ is desirable, $Ppk < 1.0$ is problematic

Sources (Douglas, C. (2006); Pyzdek, T., & Keller, P. A. (2018) ^[42, 43]

4.3 Benchmarks and Interpretation

Benchmarking involves comparing an organization's performance with industry standards or best practices. In process capability analysis, benchmarks help set target values for Cp, Cpk, Pp, and Ppk. For instance, a target Cpk value of 1.33 may be sufficient for consumer products, while more stringent targets such as 2.0 may be required for mission-critical components (Kane, 1986) ^[17].

Interpreting capability indices helps manufacturers identify opportunities for process improvement. If Cp and Cpk values are consistently low, it may indicate the need for process optimization through improved machine calibration, enhanced materials, or operator training (Álvarez *et al.*, 2015) ^[15].

5. Design of Experiments (DOE) for Quality Improvement

Design of Experiments (DOE) is a powerful statistical tool used in quality improvement that helps manufacturers optimize their processes by systematically investigating the impact of various factors on output. Unlike traditional trial-and-error methods, DOE allows manufacturers to identify the most influential factors and their interactions, enabling more efficient and effective process improvements (Vrabel'ová *et al.*, n.d.) ^[18].

5.1 Full and Fractional Factorial Designs

A full factorial design is one of the most common approaches in DOE. It involves testing all possible combinations of factors and their levels to understand how each factor affects the output. For example, if a process has three factors, each with two levels (high and low), a full factorial design would test all eight combinations of those factors. While this method provides comprehensive information, it can become time-consuming and resource-intensive when the number of factors increases.

To address this, manufacturers often use fractional factorial designs, which test only a subset of the total combinations. Fractional designs are particularly useful when there are many factors, as they allow manufacturers to obtain critical information with fewer experiments. While they are less exhaustive than full factorial designs, fractional designs can still yield valuable insights into the key factors affecting product quality (Rahmi & Mursyidin, 2024) ^[20].

For instance, in a food production line, a manufacturer might want to investigate the effects of temperature, humidity, and cooking time on the quality of a product. Using a full factorial design would involve testing all possible combinations of these factors, while a fractional factorial design could focus on the most influential factors while reducing the number of trials (Vurchio *et al.*, n.d.) ^[21].

5.2 Interaction Effects

One of the key advantages of DOE is its ability to detect interaction effects when the effect of one factor depends on the level of another factor. These interactions are often critical to understanding complex processes, as they reveal how factors work together to affect the output.

For example, in a chemical manufacturing process, the interaction between temperature and pressure may significantly impact the yield of a reaction. A DOE experiment might reveal that increasing the temperature increases yield at low pressure, but decreases yield at high pressure. By detecting these interactions, manufacturers can

fine-tune their processes to achieve optimal performance (Vrabel'ová *et al.*, n.d.) ^[18].

5.3 Taguchi Methods and Robust Design

The Taguchi method, developed by Genichi Taguchi, is a variation of DOE that focuses on creating robust designs processes that maintain consistent performance despite variations in external factors (e.g., environmental conditions, raw material quality). Taguchi's approach emphasises minimising the impact of "noise" uncontrollable factors that can influence process outcomes.

The key concept in Taguchi's approach is the Signal-to-Noise (S/N) ratio, which measures process stability under varying conditions. By maximising the S/N ratio, manufacturers can identify process settings that deliver the best quality with the least variability (Lin *et al.*, 2025) ^[19]. For example, in a manufacturing process where temperature is the primary factor affecting product quality, the Taguchi method would guide process settings to minimise the impact of temperature fluctuations.

In practice, Taguchi's methods are widely used in industries such as automotive manufacturing, where small changes in component dimensions can lead to significant performance differences. By using robust design principles, manufacturers can ensure that their products perform reliably even under varying conditions (Rahmi & Mursyidin, 2024) ^[20].

5.4 Practical Examples of DOE in Manufacturing

One of the most significant applications of DOE is in optimising the performance of complex systems. For example, in a semiconductor manufacturing plant, DOE can be used to determine the optimal settings for the deposition process in order to maximise wafer yield. By adjusting factors such as temperature, pressure, and gas flow rate, engineers can identify the conditions that yield the highest-quality product with the fewest defects (Lin *et al.*, 2025) ^[19]. Similarly, in the automotive industry, DOE has been used to improve assembly line processes. By studying the impact of factors like torque, fastening speed, and material properties on the strength of joints, manufacturers can improve the quality of assembled components and reduce rework (Vrabel'ová *et al.*, n.d.) ^[18].

6. Case Studies in Modern Manufacturing

Case studies provide practical insights into how Statistical Quality Control (SQC) methodologies are implemented in real-world manufacturing settings. These case studies highlight the challenges faced by manufacturers, the SQC tools they used, and the improvements they achieved. Examining real-life examples of SQC applications across different industries can help manufacturers understand the practical benefits and potential pitfalls of these methods (Sütőová *et al.*, n.d.) ^[23].

6.1 Automotive Industry

The automotive industry has long been a leader in adopting Statistical Quality Control (SQC) techniques, with a strong focus on reducing defects and improving production efficiency. For example, a major global automobile manufacturer implemented a comprehensive SPC system to monitor and control the production of critical engine components. Using $\bar{X}$ -R and p-charts, the company tracked key parameters like machining tolerances, material defects,

and assembly precision. The application of control charts allowed the company to identify out-of-control conditions in real-time and make adjustments before defects were produced (Gomaa, 2025) ^[25].

One notable result of this implementation was a significant reduction in scrap rates by more than 20% in the first year alone. Furthermore, the company was able to achieve a higher Cpk index, indicating that its processes were capable of consistently producing parts within specification limits. As a result, the company improved product reliability, reduced costs associated with rework, and strengthened its reputation for quality (Vrabel'ová *et al.*, n.d.) ^[18].

6.2 Electronics and Semiconductor Manufacturing

The electronics and semiconductor industries are particularly sensitive to small variations, where even minor deviations can result in significant performance issues or product failure. In these industries, manufacturers often use advanced SQC methods, such as CUSUM and EWMA charts, to detect small shifts in critical process variables. For example, a semiconductor manufacturer applied these tools to monitor the thin film deposition process, which is crucial for determining the electrical properties of semiconductors (Gomaa, 2025) ^[25].

By using CUSUM charts to track small changes in key parameters such as temperature, pressure, and gas flow rates, the company was able to detect deviations that traditional control charts might miss. This early detection allowed the company to make adjustments before defects occurred, resulting in a significant reduction in product defects and an improvement in yield. Over time, the company's implementation of advanced SPC techniques helped them reduce variation, improve product consistency, and maintain a competitive edge in a highly competitive market (Sütöová *et al.*, n.d.) ^[23].

6.3 Pharmaceutical and Medical Devices

In the pharmaceutical industry, where product quality is directly linked to safety and efficacy, SQC plays a critical role in ensuring compliance with stringent regulatory standards. For example, a pharmaceutical company used p-charts and $\bar{X}$ -R charts to monitor the weight and dosage of tablets produced on its high-speed tablet press. By tracking these variables, the company was able to identify variations that could lead to dosage inaccuracies (Vrabel'ová *et al.*, n.d.) ^[18].

Through the application of process capability analysis, the company found that its production process had a low Cpk value due to slight shifts in temperature during production. By adjusting process parameters and implementing stricter controls on raw materials, the company increased the Cpk value to above 1.33, ensuring that the process consistently met regulatory standards. This resulted in fewer batch rejections, reduced costs, and improved product quality, all while maintaining patient safety and satisfaction (Sütöová *et al.*, n.d.) ^[23].

In the medical device industry, SQC is also crucial for maintaining stringent quality standards. (Magrey, A. H., & Belagalla, N.). For instance, a manufacturer of implantable devices used DOE techniques to optimize the molding process of plastic components. By examining the effects of factors like temperature, pressure, and injection speed, the manufacturer was able to significantly reduce defects and

ensure that the final product met the high-quality standards required for medical devices (Vurchio *et al.*, n.d.) ^[21].

7. SQC in the Era of Industry 4.0

The rise of Industry 4.0 has revolutionized the field of Statistical Quality Control (SQC), blending traditional manufacturing practices with cutting-edge digital technologies. As industries move toward more interconnected, automated, and data-driven production environments, the scope of SQC has expanded dramatically. (Amarhetti, K.) New technologies like the Internet of Things (IoT), real-time analytics, and artificial intelligence (AI) are transforming how manufacturers monitor, control, and improve their processes.

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7.1 Real-Time Monitoring and Data Analytics

One of the most significant advancements in SQC brought about by Industry 4.0 is the ability to monitor manufacturing processes in real-time. Through the integration of IoT sensors into production equipment, manufacturers can collect vast amounts of data on variables such as temperature, pressure, speed, and humidity. These sensors continuously feed data into centralized systems, where sophisticated algorithms analyze it in real-time to detect potential issues before they lead to defects (Ramírez-Montoya *et al.*, 2023) ^[30].

For example, a high-speed packaging line in the food industry might be equipped with IoT sensors that monitor variables such as sealing temperature and pressure. The real-time data allows operators to adjust the settings immediately if they begin to deviate from optimal values, ensuring that the packaging remains secure and the product stays fresh. This level of monitoring significantly reduces downtime and enhances product quality (Belgrave, 2022) ^[29].

Furthermore, real-time analytics enable manufacturers to implement predictive maintenance, a key benefit of Industry 4.0. By continuously analyzing data from sensors, manufacturers can predict when equipment is likely to fail, allowing them to perform maintenance proactively rather than reactively. This predictive capability reduces unexpected downtime and ensures a smoother, more efficient production process (Ramírez-Montoya *et al.*, 2023) ^[30].

7.2 AI and Machine Learning Integration

As manufacturing processes become more complex, the integration of artificial intelligence (AI) and machine learning (ML) into SQC offers manufacturers the ability to improve quality control beyond traditional statistical methods. AI and ML algorithms can analyze large datasets, identify patterns, and make predictions based on historical data, enabling faster and more accurate decision-making (Durugbo *et al.*, 2020) ^[27].

In the context of SQC, AI can enhance traditional tools like control charts by incorporating real-time data from multiple sources, identifying trends, and suggesting adjustments. (Bhamini, K. 2025) ^[32]. For example, in a semiconductor manufacturing plant, AI can predict potential yield issues by analyzing historical production data alongside real-time sensor data. If the AI system detects a potential problem, it can alert operators or even trigger automatic adjustments to process variables, ensuring that production remains within acceptable limits (Belgrave, 2022) ^[29].

Machine learning models can also be used to identify subtle variations that might otherwise go unnoticed by traditional statistical methods. For instance, ML algorithms can detect shifts in process parameters that indicate the onset of defects, allowing for early intervention before quality issues escalate (Ramírez-Montoya *et al.*, 2023) ^[30].

7.3 Predictive Quality and Adaptive Control

Predictive quality is a concept that relies heavily on AI and machine learning to forecast product quality before it is even produced. By analyzing data from across the production process, manufacturers can predict the likelihood that a product will meet quality standards, even before it reaches the final inspection stage. This predictive capability allows manufacturers to adjust processes dynamically, reducing the risk of defects and improving overall product quality (Durugbo *et al.*, 2020) ^[27].

For example, a manufacturer of medical devices might use predictive quality models to forecast the performance of a product based on variables such as raw material properties, machine settings, and environmental conditions. By integrating real-time data with predictive models, manufacturers can make adjustments before defects occur, ensuring that products meet strict regulatory and quality standards (Belgrave, 2022) ^[29].

In addition, adaptive control systems are emerging as an important development in the era of Industry 4.0. These systems use real-time data to automatically adjust process parameters and maintain product quality, even in the face of varying environmental conditions and other external factors. This autonomous adjustment of processes is a significant advancement over traditional SQC methods, allowing for higher levels of precision and efficiency (Hassan, 2017) ^[28].

8. Implementation Challenges and Best Practices

While Statistical Quality Control (SQC) offers substantial benefits in terms of process improvement and defect reduction, implementing SQC systems in modern manufacturing environments can present several challenges. These challenges are not just technical but also organizational, cultural, and human. Overcoming these obstacles requires a systematic approach, strong leadership, and commitment from all levels of the organization (Vrabelová *et al.*, n.d.) ^[18].

8.1 Organizational and Cultural Barriers

One of the primary challenges manufacturers face when implementing SQC is overcoming organizational resistance. Resistance to change is common in any organization, and manufacturing environments are no exception. Employees may be skeptical about the value of SQC or may fear that it will disrupt established workflows. This resistance can manifest in reluctance to adopt new practices or even sabotage of quality control efforts (Sütöová *et al.*, n.d.) ^[23].

In order to overcome these challenges, it is crucial to foster a culture that values continuous improvement and quality excellence. Leaders must create an environment where employees at all levels are engaged in quality initiatives and feel empowered to contribute to process improvements. This requires clear communication, ongoing training, and demonstrating the tangible benefits of SQC in terms of product quality, cost savings, and customer satisfaction (Gomaa, 2025) ^[25].

One approach to overcoming cultural resistance is to establish cross-functional teams that include representatives from production, quality, engineering, and management. By involving employees from different departments in the SQC process, manufacturers can ensure buy-in across the organization and encourage collaboration. These teams can also identify potential barriers to implementation and work together to develop effective solutions (Ganji, 2022) ^[37].

8.2 Training and Skill Development

Another critical challenge is ensuring that employees have the necessary skills and knowledge to effectively use SQC tools and techniques. Statistical methods such as control charts, capability analysis, and Design of Experiments (DOE) require specialized knowledge and expertise. Without proper training, employees may struggle to understand how to apply these tools, leading to incorrect interpretations and suboptimal decisions (Lin *et al.*, 2025) ^[19].

To address this challenge, manufacturers must invest in training programs that teach employees how to use SQC tools and interpret their results. These programs should be designed for different levels of expertise, from introductory training to advanced analytical courses. Additionally, ongoing education is essential so that employees stay updated on the latest quality methodologies, Industry 4.0 technologies, and digital tools relevant to SQC (Gomaa, 2025) ^[25].

8.3 Data Integrity and Measurement Systems

A fundamental prerequisite for the success of any SQC initiative is reliable data. If the data collected from manufacturing processes is inaccurate or inconsistent, the conclusions drawn from statistical analyses will be flawed. Ensuring high data integrity is therefore crucial (Aldmour, 2024) ^[39].

Measurement systems must be regularly calibrated and maintained to ensure that they produce accurate and consistent results. Furthermore, manufacturers must ensure standardized data collection across departments and production lines. Inconsistent data collection methods or poor record-keeping can lead to errors and unreliable conclusions (Sütöová *et al.*, n.d.) ^[23].

A robust data governance framework is necessary to ensure data quality and reliability. This includes implementing processes for data validation, using automated data-collection systems to reduce human error, and ensuring that all process data is stored in a centralized, secure, and accessible digital platform (Aldmour, 2024) ^[39].

8.4 Resistance to Technological Integration

The integration of advanced technologies, such as real-time monitoring systems and Industry 4.0 infrastructures, into existing manufacturing environments presents another major challenge. Many companies struggle with compatibility

issues between new digital systems and older legacy equipment, leading to delays and complications in the adoption of SQC practices (Ganji, 2022) ^[37].

To overcome these challenges, manufacturers should adopt a phased and strategic approach to technology integration. This allows for incremental upgrades, reduced disruptions, and smoother transitions. Collaborating with technology providers is also essential to ensure that new systems are scalable, interoperable, and aligned with the company's existing technological ecosystem (Gomaa, 2025) ^[25].

8.5 Best Practices for Successful Implementation

To ensure the successful implementation of SQC, manufacturers should follow several best practices:

- **Leadership Commitment:** Senior management must be committed to quality and continuous improvement. Their active support is essential for overcoming resistance and driving SQC initiatives across the organization (Ganji, 2022) ^[37].
- **Clear Objectives:** Establishing clear and measurable quality goals that align with organizational objectives helps focus improvement efforts and enhances accountability (Vrabelová *et al.*, n.d.) ^[18].
- **Ongoing Monitoring and Evaluation:** Continuous evaluation of SQC processes allows manufacturers to refine strategies, identify emerging issues, and maintain long-term effectiveness (Sütöová *et al.*, n.d.) ^[23].
- **Employee Involvement:** Engaging employees at all levels in quality improvement efforts ensures broad participation and fosters a culture of shared responsibility for product quality (Lin *et al.*, 2025) ^[19].

By following these best practices, manufacturers can ensure that SQC implementation is successful, leading to sustained improvements in product quality, efficiency, and customer satisfaction.

Reference

9. Conclusion

Statistical Quality Control (SQC) has long been a cornerstone of modern manufacturing, enabling companies to ensure product quality, reduce defects, and improve process efficiency. As manufacturing environments evolve and become increasingly data-driven, SQC methods continue to play a crucial role in driving operational excellence. From traditional tools like control charts and process capability analysis to modern innovations in Industry 4.0, SQC methods provide manufacturers with the means to meet customer demands, enhance competitiveness, and reduce operational costs.

The integration of advanced technologies, such as real-time monitoring, artificial intelligence, and machine learning, is transforming the landscape of quality control. These innovations have expanded the scope of SQC, enabling manufacturers to predict defects, optimize processes in real-time, and continuously improve product quality with greater precision. The shift from reactive quality control to predictive and preventive measures marks a significant evolution in how manufacturers approach quality assurance. However, the successful implementation of SQC systems requires overcoming various challenges. Organizational resistance, the need for specialized training, ensuring data integrity, and integrating new technologies are all obstacles that manufacturers must address. Despite these challenges,

the benefits of SQC far outweigh the difficulties. By fostering a culture of continuous improvement, investing in employee training, and embracing technological advancements, manufacturers can unlock the full potential of SQC.

Looking forward, the future of SQC will be shaped by ongoing advancements in automation, data analytics, and artificial intelligence. As manufacturing processes become more complex, the demand for real-time data analysis and adaptive control systems will increase. Manufacturers will need to adopt more sophisticated tools and integrate them into their operations to stay competitive in a globalized market.

The continuous evolution of SQC tools, alongside the rapid advancements in manufacturing technologies, ensures that SQC will remain a vital part of manufacturing strategy for years to come. By leveraging these tools effectively, companies can maintain high product quality, increase efficiency, and secure a competitive advantage in the marketplace. The ongoing commitment to quality and process improvement will be essential in driving success in an increasingly complex and fast-paced industrial environment.

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