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Diploma Thesis

To Obtain A Professional Master's Degree In Quality Management

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Quality Control Methods In The Manufacturing Industry

Case Study: POLYMA Industry

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"Whoever follows a path in pursuit of knowledge, Allah will make a path to Paradise easy for him."

— Prophet Muhammad ﷺ

(Sahih Muslim)

بسم الله

الرحمان

الرحيم

Dedication

I dedicate this work:

To my beloved parents, for their endless love, sacrifices, and unwavering support. Your prayers and encouragement have been the driving force behind every step I have taken.

To my brothers and sisters, for their constant motivation and belief in me.

To my teachers, who have guided me with wisdom and patience throughout my academic journey.

To every person who believed in me, encouraged me, and stood by my side during moments of doubt.

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Abstract

This thesis investigates the effectiveness of quality control (QC) methods at POLYMA Industry, a leading plasturgy manufacturer in Tizi, Mascara, Algeria, specializing in plastic packaging for chemical and agro-food sectors. Anchored in a quantitative research approach, the study evaluates POLYMA's QC system, certified under ISO 9001:2015 and pursuing ISO 22000, through statistical analysis of defect rates, process capability indices (Cp, Cpk), and sampling effectiveness. Utilizing SPSS and Excel, the research analyzes real QC data across six methods—Functional Test, Hardness Test, Packaging Control, Raw Material Control, Visual Inspection, and Final Product Check—revealing significant performance variations. Packaging Control exhibited the lowest defect rate (0.92%) and highest stability, while Visual Inspection (3.39%) and Functional Test (2.57%) showed elevated defects and variability, indicating inefficiencies. Statistical tests (ANOVA, Tukey HSD, Kruskal-Wallis) confirmed these differences, with high variability in Hardness Test attributed to insufficient sampling. Benchmarking against Six Sigma and ISO 9001 standards highlighted gaps in achieving near-zero defects, exacerbated by reliance on manual inspections, inconsistent testing frequencies, and limited automation. The thesis proposes adopting AI-driven inspections, real-time monitoring, and standardized protocols to enhance process stability and compliance with food safety standards. Findings underscore the strategic importance of integrating traditional and modern QC methods to ensure product quality, operational efficiency, and market competitiveness, offering actionable suggestions for POLYMA and insights for SMEs navigating quality management in resource-constrained settings.

Keywords:

Quality Control, Product Quality, Manufacturing, ISO Standards, Continuous Improvement

Résumé

Cette thèse examine l'efficacité des méthodes de contrôle qualité (CQ) au sein de POLYMA Industry, un fabricant de premier plan dans le secteur de la plasturgie à Tizi, Mascara, Algérie, spécialisé dans les emballages plastiques pour les industries chimique et agroalimentaire. Basée sur une approche de recherche quantitative, l'étude évalue le système de CQ de POLYMA, certifié ISO 9001:2015 et en cours de certification ISO 22000, à travers une analyse statistique des taux de défauts, des indices de capacité de processus (Cp, Cpk) et de l'efficacité des échantillonnages. En utilisant SPSS et Excel, la recherche analyse des données réelles de CQ pour six méthodes — test fonctionnel, test de dureté, contrôle d'emballage, contrôle des matières premières, inspection visuelle et contrôle final du produit — révélant des variations significatives de performance. Le contrôle d'emballage affiche le taux de défauts le plus bas (0,92 %) et la meilleure stabilité, tandis que l'inspection visuelle (3,39 %) et le test fonctionnel (2,57 %) présentent des taux de défauts élevés et une variabilité importante, indiquant des inefficacités. Des tests statistiques (ANOVA, Tukey HSD, Kruskal-Wallis) confirment ces différences, la forte variabilité du test de dureté étant attribuée à un échantillonnage insuffisant. Une comparaison avec les normes Six Sigma et ISO 9001 met en évidence des écarts dans l'atteinte de niveaux de défauts quasi nuls, aggravés par une dépendance aux inspections manuelles, des fréquences de test incohérentes et une automatisation limitée. La thèse propose l'adoption d'inspections assistées par IA, d'un suivi en temps réel et de protocoles standardisés pour améliorer la stabilité des processus et la conformité aux normes de sécurité alimentaire. Les résultats soulignent l'importance stratégique de l'intégration des méthodes de CQ traditionnelles et modernes pour garantir la qualité des produits, l'efficacité opérationnelle et la compétitivité sur le marché, offrant des recommandations pratiques pour POLYMA et des perspectives pour les PME évoluant dans des contextes à ressources limitées.

Mots-clés :
Contrôle de la qualité, Qualité du produit, Fabrication, Normes ISO, Amélioration continue

الملخص

تتناول هذه المذكرة فعالية طرق مراقبة الجودة في شركة بوليما للصناعة، وهي شركة رائدة في مجال صناعة البلاستيك في تيزي، معسكر، الجزائر، والمتخصصة في إنتاج العبوات البلاستيكية للصناعات الكيميائية والزراعية الغذائية. بناءً على نهج والساعي للحصول على ISO 9001:2015 بحثي كمي، تقيّم الدراسة نظام مراقبة الجودة في بوليما، الحاصل على شهادة ، وفعالية أخذ العينات. (Cpk، Cp) ، من خلال تحليل إحصائي لمعدلات العيوب، ومؤشرات قدرة العمليةISO 22000 شهادة ، تحلل الدراسة بيانات مراقبة الجودة الفعلية عبر ست طرق — الاختبار الوظيفي، اختبار Excelو SPSS باستخدام برمجيات الصلابة، مراقبة التغليف، مراقبة المواد الخام، الفحص البصري، والتحقق النهائي من المنتج — مما يكشف عن تباينات كبيرة في الأداء. أظهرت مراقبة التغليف أدنى معدل عيوب (0.92%) وأعلى مستوى من الاستقرار، بينما سجل الفحص البصري (3.39%) والاختبار الوظيفي (2.57%) معدلات عيوب مرتفعة وتباينًا كبيرًا، مما يشير إلى عدم الكفاءة. أكدت الاختبارات هذه الاختلافات، مع نسبة تباين عالية في اختبار الصلابة (Kruskal-Wallis، Tukey HSD، ANOVA) الإحصائية عن فجوات في تحقيق مستويات عيوب شبه ISO 9001و Six Sigma تعزى إلى قلة العينات. كشف المقارنة مع معايير معدومة، تفاقمت بسبب الاعتماد على الفحوصات اليدوية، وتذبذب وتيرة الاختبارات، ومحدودية الأتمتة. تقترح الأطروحة اعتماد فحوصات مدعومة بالذكاء الاصطناعي، والمراقبة في الوقت الفعلي، وبروتوكولات موحدة لتحسين استقرار العمليات والامتثال لمعايير سلامة الأغذية. تؤكد النتائج على الأهمية الاستراتيجية لدمج طرق مراقبة الجودة التقليدية والحديثة لضمان جودة المنتج، والكفاءة التشغيلية، والتنافسية في السوق، مقدمة توصيات عملية لبوليما ورؤى للشركات الصغيرة والمتوسطة التي تعمل في بيئات محدودة الموارد

الكلمات المفتاحية:
التحسين المستمر،ISO مراقبة الجودة، جودة المنتج، التصنيع، المعايير

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- M: Model Summary of Regression Analysis for Non-Conformity Rate
- N: ANOVA Table for Regression
- O: Coefficients of Multiple Linear Regression Predicting Non-Conformity Rate

List of Abbreviations

AI	Artificial Intelligence
ANOVA	Analysis of Variance
ASQ	American Society for Quality
CAPA	Corrective and Preventive Action
Cp	Process Capability Index
Cpk	Process Capability Index (Centered)
DPMO	Defects Per Million Opportunities
DMAIC	Define, Measure, Analyze, Improve, Control
EMS	Environmental Management System
FSMS	Food Safety Management System
FPC	Final Product Check
FT	Functional Test
GMP	Good Manufacturing Practice
HT	Hardness Test
IML	In-Mold Labeling
IMS	Integrated Management System
IoT	Internet of Things
ISO	International Standardization Organization
JIT	Just-In-Time
MES	Manufacturing Execution System
OHSMS	Occupational Health and Safety Management System
PC	Packaging Control
PDCA	Plan, Do, Check, Act
PEBD	Low-Density Polyethylene
PEHD	High-Density Polyethylene
PEMD	Medium-Density Polyethylene
PP	Polypropylene
QFD	Quality Function Deployment
QC	Quality Control
QMS	Quality Management System
RMC	Raw Material Control
SD	Standard Deviation

SME	Small and Medium-Sized Enterprise
SPC	Statistical Process Control
SPSS	Statistical Package for the Social Sciences
TQM	Total Quality Management
VI	Visual Inspection

GENERAL INTRODUCTION

GENERAL INTRODUCTION

1) General Context

In a global industrial context marked by growing competition and strict regulatory requirements, quality control (QC) has become a key strategic lever. The manufacturing sector — particularly in plastics production in Algeria — must ensure products that are compliant, reliable, and competitive, while optimizing costs and delivery times.

At the local level, POLYMA Industry, a major player in the sector, holds approximately 94% of the national market for plastic packaging. Despite its certifications (ISO 9001:2015) and its efforts to obtain ISO 22000, certain limitations persist in its quality control methods.

2) Problem Statement

Although POLYMA has a structured quality control system, several shortcomings remain: over-reliance on manual inspections, limited sampling frequency, sometimes insufficient coordination between departments, and the absence of a formalized continuous improvement program (such as Six Sigma or PDCA).

These gaps risk leading to undetected defects, lower customer satisfaction, and challenges in maintaining high performance in line with international standards.

3) Research Objectives

- Analyze the quality control methods implemented at POLYMA Industry.
- Identify the strengths and limitations of the current system.
- Propose actionable improvement suggestions adapted to the company's constraints.

4) Hypothesis

It is assumed that excessive dependence on manual inspections and the lack of digitalization limit QC effectiveness.
Better integration of modern methods (e.g., SPC, AI) could enhance overall performance.

5) Adopted Methodology

This study adopts a case study approach, combining qualitative methods (interviews, observations, document analysis) with quantitative elements (statistical analysis, simulated data when needed).

6) Thesis Structure

This thesis is structured into three main chapters:

- **Chapter 1:** Theoretical Framework — Definitions, history, and quality control methods.
- **Chapter 2:** Organizational & Methodological Framework — Presentation of POLYMA Industry and the research methodology used.
- **Chapter 3:** Results and Discussion — Data analysis, interpretation, and recommendations.

CHAPTER 1:
LITTERATURE REVIEW

CHAPTER 01: Quality Control METHODS – LITTERATURE REVIEW

1.1. Definitions and Key Concepts of Quality Control

Quality Control (QC) in manufacturing is commonly defined as a systematic process designed to ensure that products consistently meet predefined standards of functionality, reliability, and customer satisfaction. The International Organization for Standardization (ISO, 2015) defines QC as *"a part of quality management focused on fulfilling quality requirements"* (ISO, 2015). This view is widely supported by Montgomery (2019), who describes QC as an integrated framework combining inspection, measurement, and corrective actions to maintain process stability.

Juran (1988) extends this by introducing the *"fitness for use"* concept, emphasizing that QC should address both technical specifications and practical performance in real-world applications. Similarly, Feigenbaum's (1991) *Total Quality Control* approach underlines that quality must be designed and maintained across the entire production chain, aligning technical conformance with customer expectation.

In contrast, Goetsch and Davis (2021) highlight that many small and medium-sized enterprises (SMEs) still struggle to fully apply formal QC frameworks due to high costs, training gaps, and resistance to cultural change (Goetsch & Davis, 2021). This gap between standards and real implementation is reinforced by Oakland (2018), who argues that despite advancements such as Industry 4.0 technologies, SMEs often continue to rely on manual inspections, which remain prone to human error.

This tension between best practices and practical barriers is also evident in sectors like food-safe plastic packaging, where conformance to ISO 22000 is critical yet challenging to maintain consistently. For example, in POLYMA's production of injection-molded buckets and films, maintaining wall thickness or surface finish requires robust QC processes to prevent costly non-conformities (Montgomery & Runger, 2019; Crosby, 1979).

In summary, the literature converges on the importance of robust, customer-focused QC, yet it also points to significant implementation gaps in resource-constrained contexts.

Key Concepts Integral to Quality Control

1.1.1. Conformance to Specifications

Conformance to specifications remains a foundational principle in Quality Control (QC), ensuring that manufactured products consistently adhere to predefined technical standards and tolerances. Montgomery (2019) emphasizes that robust conformance drives process consistency and

reliability, tracing its roots back to early industrial practices that relied on manual inspections to verify product dimensions and performance (Montgomery & Runger, 2019).

With the rise of international standards like ISO 9001:2015, conformance is now formalized through documented specifications and verification processes (ISO, 2015). However, as Oakland (2018) points out, while ISO frameworks standardize quality requirements, many small and medium-sized enterprises (SMEs) still depend on manual inspections, which can be error-prone and less reliable compared to modern automated methods (Oakland, 2018).

Joseph Juran's *fitness for use* concept extends conformance beyond meeting technical parameters to ensuring products perform reliably in real-world applications (Juran, 1988). In line with this, Crosby's (1979) "zero defects" philosophy argues that even minor deviations can lead to customer dissatisfaction, reinforcing the idea that conformance should aim for absolute consistency (Crosby, 1979). However, Goetsch and Davis (2021) caution that achieving zero defects remains challenging in SMEs where inspection frequency and technology adoption may be limited due to resource constraints (Goetsch & Davis, 2021).

In the plastic packaging industry, precise conformance is critical for products like injection-molded buckets and blow-molded films, where dimensional accuracy and material strength must meet regulatory and food safety standards under ISO 22000 (ISO, 2015). Studies show that advanced measurement technologies, such as coordinate measuring machines (CMMs) and automated vision systems, can significantly improve conformance rates (Montgomery & Runger, 2019; Crosby, 1979). Yet, Oakland (2018) highlights that the upfront cost and training needs often limit their use in SMEs.

1.1.2. Process Control

Process control is a cornerstone of modern Quality Control (QC), designed to minimize defects and ensure process consistency through continuous monitoring and adjustment. Walter Shewhart's early work in the 1920s pioneered Statistical Process Control (SPC) by introducing control charts that distinguish between common and special cause variations (Shewhart, 1931). Montgomery (2019) emphasizes that SPC remains a critical tool for tracking process metrics and making timely adjustments to maintain product quality (Montgomery & Runger, 2019).

Building on Shewhart's foundation, Deming (1986) argued that stable processes are essential for sustainable improvement and that operators must distinguish between inherent process variation and signs of systemic problems (Deming, 1986). Recent studies, such as Ji et al. (2023), show how the plastics manufacturing sector increasingly combines SPC with machine learning to enhance process monitoring and defect detection, highlighting its continued relevance (Ji et al., 2023).

In the plastics industry, process control is particularly important in production methods like injection molding and extrusion-blow molding, where fluctuations in parameters such as temperature or pressure can lead to costly defects like warping, material thinning, or inconsistent film thickness. Sundaram and Zeid (2023) note that integrating smart sensors and real-time data analytics has improved defect prevention, aligning with Industry 4.0 trends (Sundaram & Zeid, 2023).

Despite these technological advancements, Goetsch and Davis (2021) and Oakland (2018) emphasize that many small and medium-sized enterprises (SMEs) in the plastics sector continue to face barriers such as limited technical expertise, high implementation costs, and resistance to adopting advanced monitoring tools (Goetsch & Davis, 2021; Oakland, 2018). These practical limitations often result in inconsistent process control, higher defect rates, and missed opportunities for continuous improvement.

Overall, the literature supports the view that robust process control — combining traditional SPC with real-time monitoring and data-driven insights — is vital for the plastics industry to reduce variability, improve product quality, and remain competitive in a rapidly evolving manufacturing landscape.

1.1.3. Customer Focus

Customer focus is widely recognized as a critical element of effective Quality Control (QC) and overall quality management. Armand Feigenbaum's *Total Quality Control* framework was among the first to emphasize that product quality must align with customer expectations at every stage — from design through production to after-sales service. Juran (1988) also reinforced this view by arguing that quality should be defined by the customer rather than the producer, encapsulated in his "fitness for use" principle (Juran, 1988).

Crosby's (1979) "zero defects" philosophy further supports a customer-centric approach, arguing that preventing defects is more cost-effective than correcting them later, ultimately leading to higher customer satisfaction (Crosby, 1979). Modern literature supports these foundational ideas but also highlights new challenges in meeting evolving customer demands, especially in highly competitive industries like plastics manufacturing.

For example, Oakland (2018) points out that while many firms recognize the importance of customer focus, small and medium-sized enterprises (SMEs) often lack systematic feedback mechanisms to identify and address customer complaints promptly (Oakland, 2018). Goetsch and Davis (2021) argue that inadequate integration of customer feedback into QC systems remains a persistent weakness in many SMEs, leading to repeated quality failures and lost trust (Goetsch & Davis, 2021).

In the plastics industry specifically, recent studies show that customer focus is increasingly linked to compliance with stringent safety and performance standards, especially for sectors like food packaging where defects can lead to significant reputational damage (Montgomery & Runger, 2019; Ji et al., 2023). However, Sundaram and Zeid (2023) note that despite the availability of advanced tools like Quality Function Deployment (QFD) and digital feedback loops, their adoption in smaller plastics manufacturers remains limited due to cost and skills gaps (Sundaram & Zeid, 2023).

Overall, the literature agrees that a strong customer focus underpins competitive advantage and sustained market trust in manufacturing. Yet, practical barriers such as resource limitations and the absence of robust customer-driven design and feedback systems remain significant challenges, especially for smaller firms in the plastics sector.

1.1.4. Continuous Improvement

Continuous improvement is widely recognized as a foundational concept in modern Quality Control (QC) and overall quality management. W. Edwards Deming's Plan-Do-Check-Act (PDCA) cycle remains one of the most influential frameworks for driving incremental improvements through systematic experimentation and feedback loops (Deming, 1986). In parallel, Kaizen — popularized by Masaaki Imai — promotes a culture of continuous small-step improvements, emphasizing the role of all employees in identifying and solving problems (Imai, M., 1986).

Pyzdek and Keller (2014) highlight that methodologies like Six Sigma have further formalized continuous improvement through the DMAIC framework (Define, Measure, Analyze, Improve, Control), setting clear defect reduction targets and using statistical tools for process optimization (Pyzdek & Keller, 2014). However, recent literature cautions that these methods can be resource-intensive and challenging to sustain, especially in small and medium-sized enterprises (SMEs). Goetsch and Davis (2021) argue that while Six Sigma is highly effective in large organizations with the necessary technical expertise, its complexity can hinder adoption in smaller firms (Goetsch & Davis, 2021).

Oakland (2018) similarly points out that continuous improvement initiatives often fail when they lack clear measurement metrics and leadership commitment, leading to superficial or short-lived gains (Oakland, 2018). In the plastics manufacturing sector, continuous improvement is particularly important for maintaining process efficiency and reducing defect rates in production lines such as injection molding and extrusion-blow molding. Ji et al. (2023) show that integrating data analytics and real-time monitoring with traditional improvement cycles can significantly enhance outcomes, but emphasize that technical and financial barriers persist for SMEs (Ji et al., 2023).

Sundaram and Zeid (2023) note that emerging Quality 4.0 tools — such as AI-driven anomaly detection and predictive analytics — can complement traditional continuous improvement frameworks by providing actionable insights more quickly. However, they stress that successful integration depends on workforce readiness and digital infrastructure, which vary widely in the plastics industry (Sundaram & Zeid, 2023).

Overall, the literature supports continuous improvement as a strategic priority in modern manufacturing but underlines that its effectiveness depends on strong leadership, employee engagement, measurable metrics, and accessible technology — all of which remain unevenly implemented, especially in the plastics sector.

1.2. Historical Development of Quality Control

Introduction to Historical Development

The historical trajectory of Quality Control in manufacturing reflects the industry's response to increasing complexity, technological advancements, and customer demands. From the pre-industrial era's reliance on individual skill to the modern era's integration of artificial intelligence (AI) and real-time data analytics, Quality Control has evolved to ensure product quality, process efficiency, and regulatory compliance. The following sections detail each phase, supported by recent references and their links, providing a thorough historical context for understanding contemporary Quality Control practices.

1.2.1. Pre-Industrial Era (Pre-1900)

In the **pre-industrial era**, quality was primarily assured through craftsmanship and the reputation of skilled artisans rather than standardized systems. Oakland and Oakland (2019) explain that medieval European guilds developed strict rules and inspection committees to enforce product standards, using unique symbols or marks to certify quality and distinguish a craftsman's work (Oakland & Oakland, 2019). These marks served as early forms of quality assurance, fostering trust between producers and customers.

Goetsch and Davis (2021) add that the guild system effectively created an early prototype of modern quality standards by relying on peer evaluation and accountability within trades (Goetsch & Davis, 2021). However, this approach lacked any objective measurement tools or process controls — meaning that consistency often depended on individual skill rather than systematic checks.

Historical overviews, like those by the American Society for Quality (ASQ, n.d.), reinforce this, showing that inspection marks were initially used to identify faulty items but evolved into trusted

symbols of craftsmanship, which laid the foundation for today's emphasis on traceability and branding (ASQ, n.d.).

Although the pre-industrial approach to quality relied heavily on manual inspection and reputation, recent authors like Goetsch and Davis (2021) highlight that the fundamental idea of *customer trust and accountability* still underpins modern Quality Control systems. For industries such as plastics manufacturing, where certification marks (e.g., ISO labels) now signal compliance and quality to customers, the legacy of these early practices remains relevant.

1.2.2. Early Industrial Era (1900–1930)

The **early industrial era (1900–1930)** marked a significant shift from artisan-based production to mass manufacturing, which demanded more systematic Quality Control (QC) practices. Frederick Taylor's principles of scientific management, published in *The Principles of Scientific Management* (1911), introduced standardized workflows and inspections to optimize efficiency and reduce waste (Taylor, 1911). Taylor's approach laid the groundwork for organized end-of-line inspections, transforming QC from informal manual checks to dedicated roles for inspectors (Montgomery & Runger, 2019).

InTouch Quality (2015) notes that this era's QC systems were largely reactive, focusing on detecting defects after production rather than preventing them (InTouch Quality, 2015). This reactive nature led to high scrap rates and wasted resources, which highlighted the limitations of relying solely on final inspections. Goetsch and Davis (2021) emphasize that while Taylor's ideas improved standardization, they did not address the root causes of process variation — a gap that would later drive the shift to Statistical Process Control (Goetsch & Davis, 2021).

Oakland (2018) also points out that during this period, workers often viewed inspections as a policing function rather than a collaborative improvement tool, which sometimes created tension between production teams and quality inspectors (Oakland, 2018). Despite these early limitations, the introduction of structured inspections during the Industrial Revolution laid the foundation for modern QC departments and quality assurance roles.

For the plastics manufacturing sector, this era's lessons highlight the continuing importance of shifting from reactive to preventive quality practices. As InTouch Quality (2015) notes, industries that fail to evolve beyond final inspections often struggle with persistent defect rates and wasted resources — issues that remain relevant for SMEs seeking to modernize their QC systems.

1.2.3. Statistical Quality Control (1930–1950)

The period between the 1930s and 1950s saw a fundamental shift in Quality Control (QC) from end-of-line inspections to proactive, data-driven process monitoring. Walter A. Shewhart is widely credited with pioneering Statistical Process Control (SPC) during this era. His seminal work,

Economic Control of Quality of Manufactured Product (1931), introduced control charts as tools to distinguish between common and special cause variation, allowing manufacturers to monitor process stability in real time (Shewhart, 1931).

Montgomery (2019) describes Shewhart's control charts — such as X-bar and R charts — as a turning point that enabled quality professionals to identify and address process deviations before they resulted in defects (Montgomery, 2019). Ji et al. (2023) confirm that SPC remains highly relevant today, especially in process-sensitive industries like plastics manufacturing, where tight control over parameters such as temperature and pressure is critical to avoid defects like warping or material thinning (Ji et al., 2023).

However, Oakland (2018) and Goetsch and Davis (2021) highlight that while SPC principles are well established, many small and medium-sized enterprises (SMEs) still struggle to implement them effectively due to limited statistical expertise, cost barriers, and cultural resistance to data-driven decision-making (Oakland, 2018; Goetsch & Davis, 2021).

Sundaram and Zeid (2023) show that the original SPC concept has evolved through its integration with Industry 4.0 technologies, including real-time data analytics and machine learning for predictive process control (Sundaram & Zeid, 2023). This evolution underscores the enduring relevance of Shewhart's work while also revealing gaps in adoption, especially for sectors like plastics where cost and skills constraints still limit full implementation.

Overall, the Statistical Quality Control era established a proactive mindset that remains foundational to modern QC systems, but the literature shows that the challenge of embedding statistical thinking and real-time monitoring in resource-constrained settings continues today.

1.2.4. Post-World War II (1950–1980)

The **Post-World War II period (1950–1980)** marked the rise of Total Quality Management (TQM) as a comprehensive approach that expanded Quality Control (QC) from isolated inspections to an organization-wide culture of continuous improvement and customer focus. W. Edwards Deming is widely credited with helping transform Japanese industry through his 14 Points for Management and the Plan-Do-Check-Act (PDCA) cycle, which emphasized process stability, statistical thinking, and leadership commitment to quality (Deming, 1986).

Joseph Juran further developed this holistic perspective through his "quality trilogy" — planning, control, and improvement — stressing that quality should be driven by customer requirements and embedded across all levels of an organization (Juran, 1988). According to Evans and Lindsay (2020), these ideas laid the foundation for what became known as TQM and significantly influenced global manufacturing competitiveness, especially in Japan, where quality circles and employee involvement became standard practices (Evans & Lindsay, 2020).

Goetsch and Davis (2021) note that while TQM frameworks spread rapidly through larger companies and multinational corporations, implementation in small and medium-sized enterprises (SMEs) has often been more superficial due to a lack of sustained leadership support, unclear measurement systems, and resource constraints (Goetsch & Davis, 2021). Oakland (2018) also cautions that, even today, some organizations interpret TQM merely as a set of tools or slogans rather than a deeply embedded organizational culture, which limits its potential to drive long-term improvement (Oakland, 2018).

Historical industry reviews (ASQ, n.d.) emphasize that the Post-WWII shift from detection to prevention still underpins modern quality management systems like ISO 9001 and methodologies such as Six Sigma and Lean. This is particularly relevant for the plastics manufacturing sector, where global competition and customer demands make continuous improvement and employee engagement essential for maintaining product quality and consistency (ASQ, n.d.).

Overall, the literature converges on the significance of the Post-War era in institutionalizing quality as a strategic, organization-wide focus rather than a purely technical function. However, it also highlights ongoing challenges in fully realizing TQM's potential in resource-constrained sectors, which continues to shape how firms adopt modern QC frameworks today.

1.2.5. Modern Era (1980–Present)

The **modern era of Quality Control (1980–Present)** is marked by the integration of advanced quality frameworks, continuous improvement methodologies, and emerging digital technologies. Pyzdek and Keller (2014) describe Six Sigma as one of the most influential approaches of this period, combining statistical tools and the Define-Measure-Analyze-Improve-Control (DMAIC) cycle to reduce process variation and target defect rates below 3.4 defects per million opportunities (Pyzdek & Keller, 2014). Motorola's initial success with Six Sigma inspired widespread adoption across industries, including high-volume sectors such as automotive and electronics.

In parallel, Lean Manufacturing — popularized by the Toyota Production System — emphasizes eliminating waste and optimizing workflows while maintaining product quality (Womack & Jones, 2003). Businessmap (2019) and Evans and Lindsay (2020) highlight how Lean and Six Sigma have been widely combined as Lean Six Sigma, offering organizations a structured, data-driven approach to improve efficiency and reduce costs (Businessmap, 2019; Evans & Lindsay, 2020).

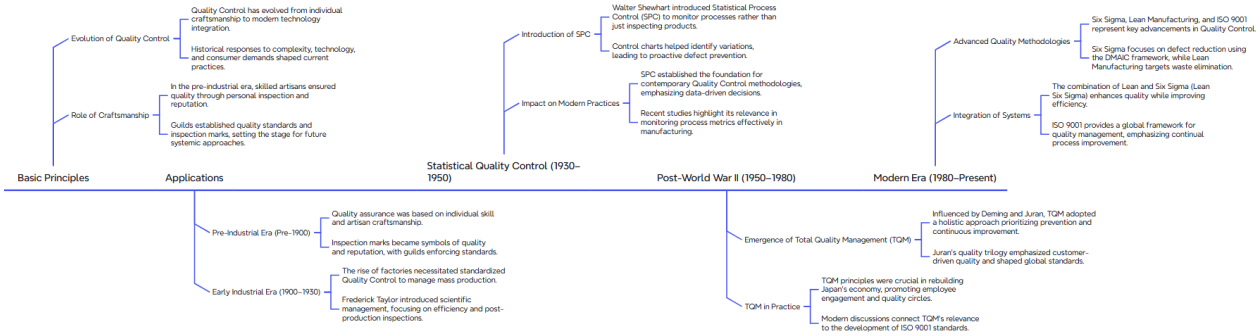
ISO 9001, first introduced in 1987 and updated most recently in 2015, formalizes these modern QC principles within a globally recognized Quality Management System (QMS) standard (ISO, 2015). Oakland (2018) argues that ISO 9001's emphasis on documented processes, risk-based thinking, and continual improvement has helped standardize quality practices worldwide (Oakland, 2018). However, Goetsch and Davis (2021) point out that achieving and maintaining certification

can be costly and administratively burdensome for SMEs, limiting its adoption in resource-constrained contexts (Goetsch & Davis, 2021).

More recently, the emergence of **Industry 4.0** — characterized by smart sensors, IoT-enabled monitoring, and AI-driven predictive analytics — has further transformed QC practices. Sundaram and Zeid (2023) and Smith et al. (2023) demonstrate how real-time defect detection and process optimization through AI have improved efficiency and reduced rework in manufacturing sectors like plastics and packaging (Sundaram & Zeid, 2023; Smith et al., 2023). Yet, they emphasize that Industry 4.0 adoption remains uneven, with significant gaps in digital readiness, skills, and capital investment, especially for small and medium-sized manufacturers.

Overall, the literature highlights that while the modern era has provided powerful frameworks and digital tools to strengthen Quality Control, the full benefits often depend on an organization's ability to integrate these practices systematically and invest in workforce capabilities — challenges that continue to shape the effectiveness of modern QC, particularly in sectors such as plastics manufacturing

Figure 1.1: Historical Development Of Quality Control In Manufacturing.



(History of Quality Control)

This table provides a concise comparative analysis of the key historical phases of Quality Control, summarizing how each era's core focus, influential figures or methods, and major contributions have shaped current quality management practices. By tracing this evolution from early craftsmanship to modern digital frameworks, the table highlights the gradual shift from reactive, inspection-based approaches to proactive, data-driven systems that underpin contemporary Quality Control, especially in dynamic manufacturing sectors such as plastics.

Table 1.1: Comparative Analysis of Historical Phases

Era	Key Focus	Key Figures/Methods	Relevance to Modern Quality Control
Pre-Industrial (Pre-1900)	Craftsmanship, personal inspection	Guilds, inspection marks	Foundation for customer trust, skilled labor
Early Industrial (1900–1930)	Standardized inspections	Frederick Taylor, end-of-line checks	Introduced structured Quality Control, reactive approach
Statistical Quality Control (1930–1950)	Process control, SPC	Walter Shewhart, control charts	Shift to proactive, data-driven control
Post-WWII (1950–1980)	TQM, continuous improvement	Deming, Juran, PDCA cycle, quality circles	Integrated employee involvement, customer focus
Modern (1980–Present)	Six Sigma, Lean, ISO 9001, AI	Motorola, Toyota, ISO standards, smart sensors	Data analytics, real-time monitoring, operational efficiency

(Oakland & Oakland, 2019, Shewhart, 1931, Deming, 1986, Juran, 1988, ISO, 2015)

This table underscores the progression from reactive to proactive, data-driven Quality Control, highlighting modern tools' role in enhancing quality consistency.

1.3. Key Quality Control Methods and Frameworks

Even though the focus is on definitions and historical context, understanding key Quality Control methods is essential to forming a theoretical foundation. Recent literature, including Montgomery (2019) and Oakland (2014), outlines several core approaches:

- **Statistical Process Control (SPC):**
  Uses tools like control charts to monitor process stability and identify deviations (Montgomery, 2019).
- **Total Quality Management (TQM):**
  A holistic strategy that embeds quality into organizational culture through employee involvement and customer focus (Oakland, 2014).
- **Six Sigma:**
  A data-driven methodology to reduce defects to 3.4 per million opportunities, following the DMAIC cycle: Define, Measure, Analyze, Improve, Control (Pyzdek & Keller, 2014).

- **Lean Manufacturing:**
  Prioritizes waste elimination while maintaining product quality, often used alongside Six Sigma for maximum efficiency (Womack & Jones, 2003).
- **ISO 9001 Standards:**
  A structured quality management system ensuring consistency and customer satisfaction. The most recent update was in 2020 (ISO, 2020).

These frameworks are widely adopted for improving process efficiency and product reliability, as supported by industry reports.

Despite their benefits, these methods may be too complex or costly for smaller firms. For instance, Six Sigma demands extensive training and statistical knowledge, potentially unrealistic for SMEs. Similarly, achieving ISO 9001 certification entails high administrative and financial costs. Additionally, these frameworks often lag in integrating Industry 4.0 technologies. ZwickRoell (2023) outlines digitalization, labor shortages, and supply chain instability as emerging issues, indicating the need for more adaptive Quality Control solutions.

1.4. Strategic importance in the manufacturing industry.

Quality Control (Quality Control) is a cornerstone of modern manufacturing, serving as a strategic imperative that drives organizational success, customer satisfaction, and market competitiveness. Far from being a mere operational function, Quality Control integrates data-driven processes, regulatory compliance, and innovation to ensure products meet stringent standards while optimizing costs and fostering long-term growth. In a globalized economy marked by fierce competition and evolving consumer expectations, Quality Control's strategic role is critical across industries such as automotive, pharmaceuticals, electronics, and food production. This section explores the strategic importance of Quality Control through five key dimensions: ensuring product quality and customer satisfaction, enhancing operational efficiency and cost reduction, ensuring regulatory compliance and risk mitigation, securing competitive advantage and market positioning, and driving continuous improvement and organizational learning.

- **Ensuring Product Quality and Customer Satisfaction**

Quality Control is fundamentally about delivering products that meet or exceed predefined quality standards, directly influencing customer satisfaction and brand loyalty. Through systematic inspections, testing, and measurements, Quality Control ensures that products—whether automotive components, pharmaceuticals, or consumer electronics—are free from defects and perform reliably. For instance, in food manufacturing, Quality Control involves chemical and microbiological testing to prevent contamination, while in electronics, stress testing and electrical measurements ensure device functionality (Investopedia, 2024). High-quality products build

customer trust, reduce returns, and enhance positive word-of-mouth, critical for maintaining market share in competitive sectors.

The strategic importance of Quality Control in this dimension lies in its ability to protect and enhance brand reputation. Consistently delivering high-quality products fosters customer loyalty, enabling manufacturers to charge premium prices and increase repeat purchases. Ferreira da Silva (2016) and Lepistö et al. (2024) emphasize that meticulous Quality Control ensures products meet customer requirements, building trust and strengthening market position (Ferreira da Silva, 2016; Lepistö et al., 2024). Moreover, Quality Control data provides insights into customer preferences, enabling manufacturers to tailor products to specific needs, further elevating satisfaction. Ji et al. (2023) highlight that SPC processes, enhanced by machine learning, generate vast datasets on raw materials, processes, and final products, which can be analyzed to inform product improvements and align with customer expectations (Ji et al., 2023). This customer-centric approach is vital in industries where quality directly impacts safety and performance, such as aerospace and medical devices.

- **Enhancing Operational Efficiency and Cost Reduction**

Quality Control significantly enhances operational efficiency by identifying and addressing quality issues early in the production process, reducing waste, rework, and scrap, which translates into substantial cost savings. In high-volume manufacturing, such as automotive or electronics, defects can lead to significant material and labor losses. Quality Control processes, such as Statistical Process Control (SPC), use control charts to monitor process variability, enabling real-time adjustments to prevent defects (Montgomery, 2019). For example, MachineMetrics (2022) notes that Quality Control in precision machining for automotive components minimizes defects, enhancing efficiency and reducing costs associated with rework (MachineMetrics, 2022).

The strategic value of Quality Control in cost reduction extends beyond immediate savings to long-term operational optimization. By collecting and analyzing quality data, manufacturers can identify inefficiencies, optimize production parameters, and streamline processes. Ji et al. (2023) underscore that SPC, enhanced by machine learning, enables early detection of defects, reducing waste and material costs, thus freeing resources for innovation and expansion (Ji et al., 2023). Additionally, Quality Control supports just-in-time (JIT) manufacturing by ensuring incoming materials meet quality standards, reducing inventory costs and production disruptions (Hertzler Systems Inc., 2023). This efficiency is critical in price-sensitive markets, where cost leadership can provide a competitive edge, allowing manufacturers to reinvest savings into research and development or market expansion.

- **Ensuring Regulatory Compliance and Risk Mitigation**

In regulated industries, Quality Control is essential for meeting stringent standards, ensuring product safety, and mitigating risks associated with non-compliance. Standards such as ISO 9001:2015 (reaffirmed 2020) and industry-specific regulations like ISO 22000 for food safety require rigorous Quality Control processes, including documentation, testing, and traceability (ISO, 2015). For example, in pharmaceuticals, Quality Control involves testing for purity and efficacy to comply with Good Manufacturing Practices (GMP), while in aerospace, Quality Control ensures components meet safety standards to prevent catastrophic failures (Investopedia, 2024). Non-compliance can result in costly recalls, legal penalties, or reputational damage, making Quality Control a critical risk management tool.

The strategic importance of Quality Control in this dimension lies in its ability to safeguard organizational viability. By ensuring compliance, Quality Control reduces the likelihood of product recalls, which can involve millions of units and significant financial losses, as seen in the 3,301 recall events across U.S. industries in 2023 (Sedgwick, 2024). Professional Resource Partners (2024) emphasizes that rigorous Quality Control is critical to identifying defects in high-risk products like medical devices, preventing life-threatening flaws before they reach consumers (Professional Resource Partners, 2024). Furthermore, Quality Control enhances transparency and accountability, as digital Quality Control systems provide auditable records to meet stringent regulatory requirements in global markets (Compliance & Risks, 2024). This risk mitigation strengthens a manufacturer's credibility, facilitating access to international markets where regulatory adherence is a prerequisite.

- **Securing Competitive Advantage and Market Positioning**

Quality Control is a strategic differentiator in competitive manufacturing landscapes, enabling companies to deliver superior products that stand out in the market. High-quality products command premium prices, increase market share, and enhance brand loyalty, positioning manufacturers as industry leaders. PTC (2024) notes that best-in-class Quality Control processes ensure products meet customer expectations, essential for maintaining competitiveness and complying with industry standards (PTC, 2024). For instance, in automotive manufacturing, Quality Control ensures vehicles are defect-free, enhancing brand reputation and customer trust, as seen with Toyota's leadership in quality management (PARSEC, 2024).

Beyond product quality, Quality Control supports innovation by providing data on performance and customer needs, informing the development of new products or processes. For example, Quality Control data can guide the creation of sustainable materials, such as biodegradable packaging, aligning with environmental trends and opening new market opportunities (Advantive, 2023**)**. WoodWing (2024) highlights that fierce competition compels manufacturers to prioritize Quality Control to protect brand reputation and ensure compliance, particularly in sectors like pharmaceuticals and aerospace (WoodWing, 2024). By integrating Quality Control into strategic

planning, manufacturers can leverage quality as a competitive weapon, differentiating themselves in global markets and attracting discerning customers who value reliability and innovation.

- **Driving Continuous Improvement and Organizational Learning**

Quality Control is a catalyst for continuous improvement, aligning with methodologies like Total Quality Management (TQM), Six Sigma, and Lean Manufacturing, which use quality data to enhance processes and reduce waste. TQM fosters a culture of quality by involving all employees in identifying and solving quality issues, often through quality circles and the Plan-Do-Check-Act (PDCA) cycle (Evans & Lindsay, 2020). Six Sigma's DMAIC framework targets defect reduction, aiming for near-zero defects, while Lean eliminates non-value-adding activities, optimizing efficiency (Pyzdek & Keller, 2018). These approaches rely on Quality Control data to drive iterative improvements, ensuring processes evolve with market demands.

The strategic importance of Quality Control in this dimension extends to organizational learning, where insights from Quality Control processes are shared across departments to enhance product design, supply chain management, and operational strategies. MachineMetrics (2022) notes that continuous Quality Control monitoring identifies process gaps, enabling proactive improvements that enhance efficiency and reduce defects (MachineMetrics, 2022). Digital Quality Control systems, integrated with AI and IoT, further amplify this by providing real-time analytics and predictive insights, as seen in Industry 4.0 applications (Sundaram & Zeid, 2023). For example, posts on X highlight automated Quality Control systems that monitor quality in real-time, reducing defects and waste, reflecting current industry trends toward data-driven improvement. This learning culture ensures manufacturers remain adaptable, innovative, and resilient in dynamic markets.

This Table presents a comparative analysis of the key strategic dimensions of Quality Control within the manufacturing industry. By summarizing the distinct impacts, practical examples, and strategic outcomes associated with each dimension, the table illustrates how Quality Control contributes holistically to product reliability, operational efficiency, regulatory compliance, competitive positioning, and continuous improvement. This overview reinforces the argument that Quality Control is not merely an operational function but a vital strategic driver for sustainable success across diverse manufacturing sectors.

Table 2.1: Comparative Analysis of Strategic Dimensions

Dimension	**Key Impact**	**Example in Manufacturing**	**Strategic Outcome**
Product Quality & Customer Satisfaction	Enhances reliability, builds trust	Testing electronics for functionality	Increases loyalty, enables premium pricing

Operational Efficiency & Cost Reduction	Reduces waste, optimizes processes	SPC in automotive machining	Improves profitability, allows reinvestment
Regulatory Compliance & Risk Mitigation	Ensures safety, reduces legal risks	GMP testing in pharmaceuticals	Avoids recalls, enhances market access
Competitive Advantage & Market Positioning	Differentiates products, gains market share	Quality Control for sustainable packaging	Strengthens brand, opens new markets
Continuous Improvement & Organizational Learning	Drives efficiency, fosters innovation	TQM in consumer goods production	Enhances adaptability, promotes long-term sustainability

(Investopedia, 2024, Ferreira da Silva, 2016; Lepistö et al., 2024, Montgomery, 2019., MachineMetrics, 2022, ISO, 2015, Investopedia, 2024, Evans & Lindsay, 2020, Pyzdek & Keller, 2018., MachineMetrics, 2022, Sundaram & Zeid, 2023)

This table underscores Quality Control's multifaceted role, highlighting its strategic contributions to manufacturing success.

1.5. Methods Applied in the Manufacturing Industry

Introduction to Quality Control Methods

In the manufacturing industry, ensuring product quality and process efficiency is essential to meet customer expectations and comply with regulatory standards. Quality Control (Quality Control) involves various techniques—from traditional methods like visual inspections to cutting-edge solutions such as Artificial Intelligence (AI) and smart sensors. These methods play a crucial role in detecting defects, optimizing operations, and maintaining competitiveness, particularly for small to medium-sized enterprises (SMEs). This section outlines key Quality Control methods, their applications, benefits, and challenges, emphasizing their strategic relevance in modern manufacturing.

1. Statistical Process Control (SPC)

- **Definition and Explanation:**

SPC is a statistical method used to monitor and control manufacturing processes. Tools like control charts, run charts, and process capability analysis help detect process variations, distinguish between common and special causes, and guide corrective actions. Originating from Walter Shewhart's work, SPC has evolved with real-time analytics and Industry 4.0 integration (Montgomery, 2019).

- **Application in Manufacturing:**

SPC is widely used to track parameters such as dimensions or defect rates in real-time, allowing proactive adjustments before defects occur. It's especially critical in high-precision sectors like automotive and electronics (Quality-One, 2024).

- **Benefits and Challenges:**

It minimizes waste, reduces defects, and boosts efficiency. However, SPC requires statistical knowledge and implementation resources, which can be challenging for SMEs. Modular SPC tools are emerging as cost-effective options (ASQ, n.d.).

The following table presents a comparative summary of the key advantages and limitations of Statistical Process Control (SPC)

Table 3.1: Advantages and Limitations of Statistical Process Control (SPC)

Advantages	**Limitations**
Early Detection and Prevention of Problems	**Requires Statistical Expertise** – Not all teams are trained in statistical methods.
Reduction in Time and Costs – Less rework and scrap leads to savings.	**Resource-Intensive** – Needs investment in training, data systems, and maintenance.
Improved Process Stability and Capability – Ensures consistent output.	**Complexity in Data Analysis** – Interpreting SPC tools may be difficult without proper skills.
Data-Driven Decision Making – Supports informed and objective choices.	**Initial Setup Time** – Establishing control charts takes time and preparation.
Facilitates Continuous Improvement – Helps reduce variability long-term.	**Dependency on Accurate Data** – Flawed data collection undermines the system.
Provides Competitive Advantage – Enhances customer satisfaction and efficiency.	**May Not Address All Quality Issues** – Limited impact on design/material flaws.

(ASQ, n.d.)

2. Quality Audits

- **Definition and Explanation:**

Quality audits are systematic evaluations of a QMS or specific processes to ensure compliance with standards such as ISO 9001. These audits can be internal or external and aim to assess conformance, identify improvement areas, and validate process capabilities (ISO, 2015).

- **Application in Manufacturing:**

Audits assess internal processes, supplier performance, and regulatory compliance. Digital tools now assist in streamlining audit documentation and reporting (Goaudits, 2024).

- **Benefits and Challenges:**

Audits enhance consistency and mitigate risk, but they can be expensive and time-consuming. For SMEs like POLYMA, digital platforms offer a way to automate and reduce audit-related burdens (ComplianceQuest, 2024).

This Table summarizes the main advantages and limitations of conducting Quality Audits, based on recent literature.

Table 4.1: Advantages and Limitations of Quality Audits

Advantages	Limitations
Ensures Compliance with Standards – Aligns operations with ISO, internal, and legal standards.	**Time-Consuming** – Comprehensive audits can take significant time.
Identifies Non-Conformances – Detects deviations for corrective/preventive actions (CAPA).	**Resource-Intensive** – Requires trained personnel, preparation, and sometimes external auditors.
Improves Process Efficiency – Pinpoints inefficiencies to streamline operations.	**Potential for Disruption** – May interrupt normal operations during audit activities.
Enhances Product Quality – Verifies conformance to specs and customer expectations.	**May Not Catch All Issues** – Some problems may go unnoticed if audits are infrequent or shallow.
Facilitates Continuous Improvement – Drives ongoing enhancements in quality systems.	**Dependency on Auditor Expertise** – Quality of audit depends on auditor skill and diligence.

Builds Customer Confidence – Demonstrates commitment to consistent, high-quality output.	**Cost of Compliance** – Maintaining certifications can be financially burdensome for SMEs.

(ComplianceQuest, 2024)

3. Visual Inspections

- **Definition and Explanation:**

Visual inspection involves manually examining products or components to detect surface-level defects. It is a non-destructive, basic Quality Control method often supported by tools like magnifiers or cameras (IBM, 2022).

- **Application in Manufacturing:**

Common in assembly lines, visual inspections are increasingly supported by AI and machine vision to enhance accuracy. For example, automated systems inspect soldering on PCBs in electronics (Kriticalsolutions, 2024).

- **Benefits and Challenges:**

This method is low-cost and fast but prone to human error. AI-based enhancements improve precision but require technology investments that may challenge SMEs (IBM, 2022).

This Table summarizes the main advantages and limitations of conducting Visual Inspections, based on recent literature.

Table 5.1: Advantages and Limitations of Visual Inspections

Advantages	Limitations
Cost-Effective – Low-cost method suitable for SMEs.	**Prone to Human Error** – Subject to fatigue, oversight, and bias.
Quick and Simple – Easy to implement and fast in detecting obvious flaws.	**Limited to Surface-Level Issues** – Cannot detect hidden/internal defects.
Non-Destructive – Does not damage the product during inspection.	**Dependency on Inspector Expertise** – Results vary based on inspector's skill and experience.
Versatile – Can be adapted for various products, industries, and defect types.	**Time-Consuming for Large-Scale Production** – Not ideal for high-volume inspections.
Provides Real-Time Feedback – Enables immediate response to detected defects.	**Inconsistent Standards** – Lack of clear criteria can lead to subjective and unreliable results.

Enhances Safety – Helps detect hazards early, contributing to workplace safety.	**Not Suitable for All Defects** – Some defects require advanced methods (e.g., X-rays, ultrasonic).

(IBM, 2022)

4. Artificial Intelligence (AI) in Quality Control

- **Definition and Explanation:**

AI enables data-driven automation in Quality Control, using techniques like machine learning and computer vision for defect detection, predictive maintenance, and process optimization. These tools analyze large datasets to generate real-time insights (Sundaram & Zeid, 2023).

- **Application in Manufacturing:**

AI is deployed for real-time defect detection through smart cameras and sensors and for predictive maintenance based on historical trends. Automotive industries notably use AI for assembly line quality checks (Engineering.com, 2025; HSO, 2024).

- **Benefits and Challenges:**

AI improves precision and efficiency, but implementation involves significant infrastructure and training costs. Tailored AI solutions are increasingly available for SMEs with limited resources (Capgemini, 2024).

This Table summarizes the main advantages and limitations of conducting Artificial Intelligence (AI) in Quality Control, based on recent literature.

Table 6.1: Advantages and Limitations of Artificial Intelligence (AI) in Quality Control

Advantages	Limitations
High Accuracy and Speed – AI detects defects with precision and speed, especially complex ones.	**High Initial Investment** – Requires significant upfront investment in technology and training.
Real-Time Monitoring – Enables immediate detection and correction of production issues.	**Complexity in Integration** – Integrating AI into existing systems may require significant workflow changes.
Consistency – Provides uniform inspection results, eliminating human variability.	**Dependency on Data Quality** – Requires high-quality data; poor data can lead to inaccurate results.

Scalability – Handles large volumes of data and inspects at high speeds, ideal for large-scale operations.	**Lack of Expertise** – Skilled personnel are required for development and maintenance.
Predictive Maintenance and Analytics – Allows for proactive identification of issues and maintenance needs.	**Potential for Over-Reliance** – Over-reliance on AI may miss defects or issues outside its programming.
Cost Reduction – Leads to long-term savings by improving efficiency and reducing defects.	**Ethical and Privacy Concerns** – Potential ethical issues regarding data privacy, especially with personal data.

(Capgemini, 2024)

1. Smart Sensors

- **Definition and Explanation:**

Smart sensors are IoT-enabled devices that measure physical parameters and transmit data for real-time process control. They are vital for predictive maintenance and quality assurance (Smart Sensors., 2014).

- **Application in Manufacturing:**

These sensors track variables like temperature and vibration to detect equipment wear and ensure process consistency. Industry 4.0 integrations enhance automation and analytics capabilities (RAKwireless, 2024; Advanced Technology Services, 2024).

- **Benefits and Challenges:**

Smart sensors boost operational reliability and minimize downtime. However, they require robust IoT infrastructure, which can be costly for SMEs. Modular and scalable sensor systems are viable alternatives for smaller firms (MachineMetrics, 2022).

Table 7.1: Advantages and Limitations of Smart Sensors

Advantages	Limitations
Real-Time Monitoring – Provides immediate data on critical parameters like temperature and pressure.	**High Initial Costs** – Requires significant investment in hardware, software, and system integration.
Improved Efficiency – Optimizes processes and reduces downtime, enhancing overall efficiency.	**Complexity in Integration** – Can be complex to integrate into existing systems, requiring expertise.

Data-Driven Decision Making – Generates vast amounts of data for process improvement and quality enhancement.	**Maintenance and Repair** – Requires regular maintenance and can fail if not properly maintained.
Automation and Control – Enables real-time process adjustments, ensuring consistency and quality.	**Data Overload** – Large volumes of data generated, requiring advanced analytics to process effectively.
Cost Reduction – Prevents equipment failures and optimizes energy use, leading to cost savings.	**Dependency on Connectivity** – Relies on stable connectivity for transmitting data.
Enhanced Safety – Detects hazardous conditions, improving workplace safety.	

(MachineMetrics, 2022)

This Table provides a comparative overview of key Quality Control methods, highlighting their type, primary applications, main benefits, and practical challenges as discussed in the literature. This comparison illustrates how different approaches meet diverse manufacturing needs, especially for firms balancing cost, complexity, and quality requirements.

Table 8.1: Comparative Analysis of Quality Control Methods

Method	Type	Primary Application	Key Benefit	Main Challenge
Statistical Process Control	Modern	Process monitoring and variation control	Reduces defects, improves efficiency	Requires statistical expertise
Quality Audits	Quality Management	Compliance and process evaluation	Ensures regulatory adherence	Costly and time-consuming
Visual Inspections	Traditional	Surface defect detection	Cost-effective and quick	Human error risk
Artificial Intelligence (AI)	Modern	Automated inspections and maintenance	High accuracy, continuous learning	High initial investment
Smart Sensors	Modern	Real-time monitoring and optimization	Enhances efficiency, reduces downtime	Infrastructure and data management costs

(Quality-One, 2024, ASQ, n.d., Montgomery, 2019, ISO, 2015; GoAudits, 2024, ComplianceQuest, 2024, IBM, 2022; KriticalSolutions, 2024, Engineering.com, 2025; HSO, 2024, Capgemini, 2024; Sundaram & Zeid, 2023, Smart Sensors, 2014; RAKwireless, 2024; ATS, 2024, MachineMetrics, 2022)

This comparison illustrates the diversity of Quality Control approaches, highlighting how each method serves specific manufacturing needs. For SMEs like POLYMA, strategic selection and gradual implementation of suitable methods are essential.

1.6. Integration into quality management systems (QMS/IMS).

Introduction to QMS and IMS

In the manufacturing sector, ensuring consistent product quality and operational efficiency is critical for meeting customer expectations and regulatory requirements. A Quality Management System (QMS) is a structured framework that defines and documents an organization's processes, procedures, and responsibilities for achieving quality policies, practices, and objectives. It aims to reduce waste, increase efficiency, and improve customer satisfaction, often formalized through standards like ISO 9001 (ASQ - Quality Management System).

For SMEs, implementing a QMS is essential for gaining customer trust and ensuring compliance.

An Integrated Management System (IMS) extends this by combining QMS with other management systems, such as Environmental Management Systems (EMS) and Occupational Health and Safety Management Systems (OHSMS), into a single, cohesive framework. For **POLYMA Industry**, an IMS would integrate Quality Control methods into a broader system that also addresses environmental and safety concerns, ensuring alignment across all operational aspects.

➢ Integration of Quality Control Methods into QMS

Quality Control methods are integral components of a QMS, contributing to the "control," "assurance," and "improvement" phases of quality management. Below is a detailed explanation of how each method is integrated, with practical implications for SMEs.

Statistical Process Control (SPC)

- **Role in QMS**: SPC is a data-driven methodology that uses statistical techniques to monitor and control manufacturing processes, ensuring they operate within specified limits. It is part of the "control" phase, where data from processes is collected and analyzed to detect variations (Montgomery, 2019).
- **Integration**:
    1. Define critical quality characteristics for each process (e.g., product dimensions, defect rates).
    2. Use control charts to track process performance over time, identifying deviations.
    3. Implement software tools for real-time data collection, integrated with ERP or MES systems.

4. Trigger corrective actions when processes deviate from acceptable limits, documented within the QMS.

- **For SMEs**: Industries can start with basic SPC tools, such as control charts for key processes, and gradually integrate digital tools as resources allow. SPC data should be documented within the QMS to support continuous improvement.

Quality Audits

- **Role in QMS**: Quality audits are systematic and independent examinations of the QMS to determine if it conforms to standards and identifies areas for improvement. They are part of the "assurance" phase, ensuring that quality processes are effective (ISO, 2015).
- **Integration**:
  1. Schedule audits regularly (internal quarterly, external annually for ISO 9001 certification).
  2. Assess compliance with quality policies, documenting findings and corrective actions.
  3. Use digital audit tools for streamlining data collection and reporting.
- **For SMEs**: Industries can conduct internal audits using checklists aligned with their QMS and seek external audits for certification, enhancing credibility with customers. The process should focus on resource-efficiency and critical areas.

Visual Inspections

- **Role in QMS**: Visual inspections involve examining products for surface defects or non-conformities, often using the naked eye or simple tools. These inspections are part of the "control" phase, ensuring products meet quality standards before reaching customers **(Inspectle, 2024)**.
- **Integration**:
  1. Plan inspections as part of production workflows with clear criteria and checklists.
  2. Automate with machine vision systems for consistency and reduce human error.
  3. Document inspection results to track recurring issues, supporting continuous improvement.
- **For SMEs**: Industries can start with manual inspections using standardized checklists and gradually adopt digital tools or AI-powered visual inspection systems as technology becomes more accessible.

Artificial Intelligence (AI)

- **Role in QMS**: AI enhances Quality Control through predictive maintenance, real-time defect detection, and process optimization. It is part of the "improvement" phase, where data analytics is used to identify patterns and anomalies (Sundaram & Zeid., 2023).

- **Integration**:
    1. Use AI for advanced analytics (predicting quality issues based on historical data).
    2. Incorporate AI into visual inspection systems to automate defect detection.
    3. Link AI to SPC for real-time process monitoring and adjustment, enhancing data-driven decision-making.
    4. Validate and document outputs within the QMS for compliance with quality standards.
- **For SMEs**: Industries can explore AI for specific applications like defect detection and ensure that AI systems are validated and their outputs documented within the QMS. Starting with modular AI solutions can help manage costs.

Smart Sensors

- **Role in QMS**: Smart sensors provide real-time data on critical parameters (temperature, pressure, vibration) to maintain process stability and product quality. These sensors are part of the "control" phase, enabling proactive monitoring **(Jones et al., 2021)**.
- **Integration**:
    1. Deploy sensors at key production points to collect continuous data.
    2. Use sensors to trigger alerts or automatic adjustments when parameters deviate from norms.
    3. Integrate sensor data into the QMS for analysis, supporting SPC and predictive maintenance.
- **For SMEs**: Industries can start by installing smart sensors for critical processes (e.g., temperature monitoring in molding) and expand their use over time as part of a digital transformation strategy.

➢ Integration into IMS

If POLYMA Industry adopts an IMS, integrating Quality Control methods into a broader IMS framework would include:

- **Data Sharing**: Data from smart sensors used for Quality Control can also be used for environmental monitoring or safety assessments, ensuring alignment with EMS and OHSMS goals.
- **Unified Audits**: Quality audits can be conducted alongside environmental or safety audits to ensure comprehensive compliance, documented within the IMS.
- **Holistic Improvement**: Improvements from Quality Control methods (e.g., reducing waste via SPC) can also benefit environmental goals, aligning with the IMS's sustainability and safety objectives.

➢ Best Practices for SMEs

For SMEs, integrating Quality Control methods into QMS/IMS requires a tailored approach:

1. **Start Small**: Focus on high-impact areas (SPC for critical processes or visual inspections for key products) to manage initial costs.
2. **Leverage Affordable Tools**: Use cloud-based QMS software or basic digital tools for documentation, audits, and data analysis.
3. **Train Staff**: Ensure all employees understand their roles in Quality Control and engage in regular training.
4. **Gradual Digitalization**: Introduce AI and smart sensors incrementally, focusing on the most beneficial applications.
5. **Seek Certification**: Pursue ISO 9001 certification to formalize the QMS and improve customer trust.
6. **Continuous Improvement**: Regularly review QMS effectiveness through audits and metrics, using data from SPC, AI, and sensors to drive improvements.

➢ Case Studies and Examples

- **AI in Visual Inspections**: Samsung uses AI-powered systems to detect defects in printed circuit boards (PCBs), reducing reliance on human inspectors (Quality Magazine - AI in Manufacturing).
- **Smart Sensors in Process Control**: Manufacturers use smart sensors for real-time production monitoring, integrating data into their QMS for process optimization (Gupta, D., Tyagi, A. K., García-Díaz, V., & Dhiman, G. (Eds.)., 2024).
- **SPC in SMEs**: Small manufacturers use SPC software to monitor key processes, documenting results for compliance and improvement (MachineMetrics - Quality Control in Manufacturing).

For **POLYMA Industry**, starting with basic SPC and visual inspections while planning for future integration of AI and smart sensors can provide a scalable path to a robust QMS.

This Table summarizes how key Quality Control methods can be integrated into a Quality Management System (QMS), outlining their role, typical implementation approaches, common challenges for small and medium-sized enterprises (SMEs), and best practice suggestions drawn from the reviewed literature.

Table 9.1: Comparative Analysis of Integration

Method	Role in QMS	Integration Approach	Challenges for SMEs	Best Practices for SMEs

Statistical Process Control (SPC)	Monitors process stability using statistical techniques	Use control charts and real-time data; document results within QMS	Requires statistical expertise and data analysis tools	Start with basic SPC tools; use affordable or open-source software
Quality Audits	Verifies compliance with QMS and identifies improvement areas	Schedule regular audits; document findings digitally; align with ISO standards	Can be time-consuming and resource-intensive	Conduct internal audits; use templates; seek certification gradually
Visual Inspections	Detects visible surface defects prior to shipment	Standardize visual checklists; automate with machine vision; document defects	Human error; limited to surface defects	Use checklists; later adopt AI/machine vision for consistency
Artificial Intelligence (AI)	Predicts defects and optimizes processes using data analytics	Use AI in predictive maintenance and defect detection; validate outputs within QMS	High setup costs; requires technical expertise	Start with modular AI tools for high-impact applications (e.g., visual inspection)
Smart Sensors	Enables real-time monitoring of critical process parameters	Install in key stages; integrate with IoT systems and QMS for analysis	Complex implementation; data volume handling	Begin with critical control points; scale with affordable cloud-based integration tools

(Montgomery, 2019, MachineMetrics, ISO, 2015, Inspectle, 2024, Sundaram & Zeid, 2023, Quality Magazine, Jones et al., 2021, Gupta et al., 2024)

CHAPTER 02: METHODOLOGICAL & ORGANIZATIONAL FRAMEWORK

2. CHAPTER 02: METHODOLOGICAL & ORGANIZATIONAL FRAMEWORK

2.1. Company Profile of POLYMA Industry

Overview

POLYMA Industry, officially known as Sarl POLYMA Industry, is a privately-owned, mixed-capital economic enterprise specializing in plasturgy, with a focus on the design, creation, and manufacturing of industrial plastic packaging. Established in 1999, the company is headquartered in the industrial zone of Tizi, Mascara, Algeria, and operates on a sprawling 22,678 m² facility. Employing 213 workers, including 116 technical staff and 71 administrative personnel, POLYMA has grown from a small family business into a leading player in Algeria's plasturgy sector, holding a significant market share and serving prominent clients in the chemical and agro-food industries. (POLYMA Industry)

2.1.1. Historical Background

The origins of POLYMA Industry trace back to 1987, when the founding family launched a venture focused on producing carbonated beverages and importing raw materials for industrial use. In 1989, the company pivoted to plastic packaging production, starting with a dedicated unit for manufacturing plastic films and bags. This initial venture gained momentum over the next decade, leading to the formal establishment of POLYMA Industry in 1999. The company specialized in producing high-quality plastic packaging tailored for industrial applications, particularly in the chemical and agro-food sectors. Over the years, POLYMA has invested heavily in modern production technologies and biodegradable packaging solutions, consolidating its presence in the national market through innovation and quality excellence. (POLYMA Industry)

2.1.2. Core Operations and Facilities

POLYMA Industry's primary activity is the transformation of plastic materials into a diverse range of packaging products using advanced manufacturing processes. The company operates four main production workshops: injection molding, extrusion-blow molding, shaping (façonnage), and printing. These workshops enable POLYMA to produce a wide array of products, including:

- ✓ **Injection Molding:** Buckets (3.8L to 20L), pots (0.25L to 3L), lids, handles, crates, and preforms for water bottles.
- ✓ **Extrusion-Blow Molding:** Plastic films, packaging bags, and industrial sacks, with capabilities for micro-perforation and corona treatment.

- ✓ **Shaping:** Conversion of extruded films into bags through thermo-cutting and thermo-welding, producing simple or complex designs (e.g., three-sided welds).
- ✓ **Printing:** High-quality offset and serigraphic printing on plastic products, using UV inks for vibrant, durable designs, critical for brand differentiation.

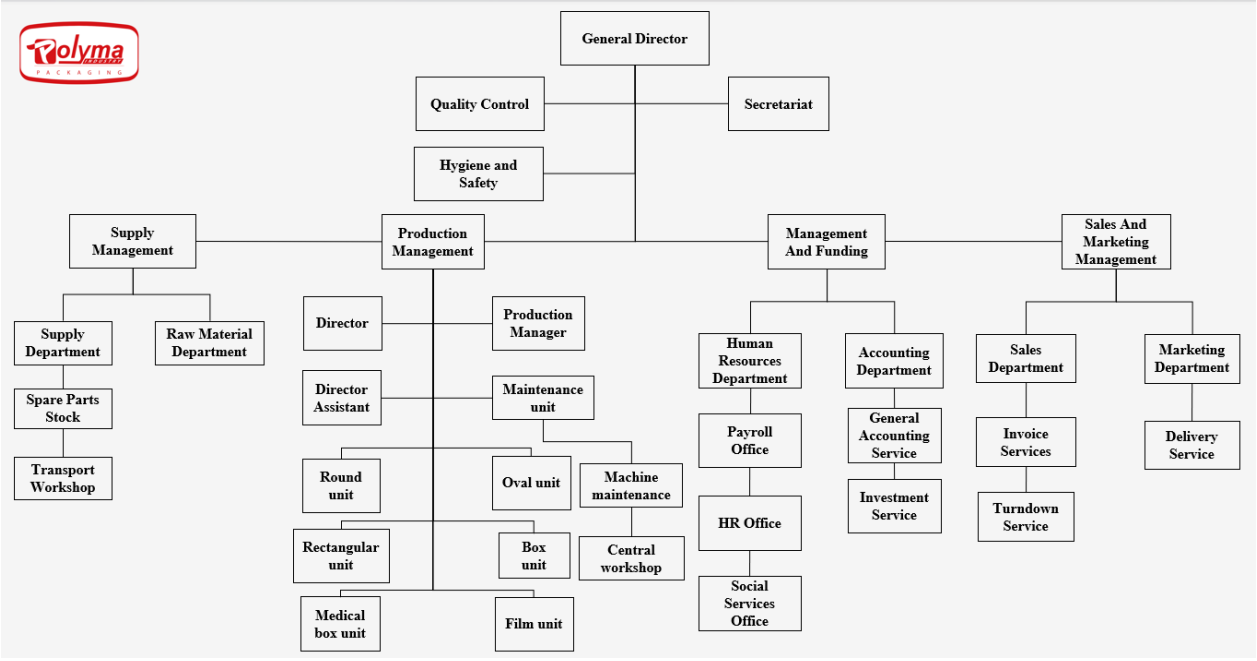
The company's state-of-the-art production lines, characterized by speed and precision, enable high output and adherence to quality standards. POLYMA's commitment to innovation is evident in its adoption of In-Mold Labeling (IML) technology and biodegradable packaging, aligning with environmental trends and regulatory requirements.

2.1.3. Organizational Structure

POLYMA Industry is led by President Director General Mr. Meslem Djamel and operates a well-defined internal structure comprising multiple departments to ensure efficient operations. Key departments include:

- ✓ **Maintenance:** Oversees equipment upkeep and process optimization.
- ✓ **Production:** Manages manufacturing across the four workshops.
- ✓ **Quality Control:** Ensures product conformance through rigorous testing and inspections.
- ✓ **Supply Chain and Procurement:** Handles raw material sourcing and inventory management.
- ✓ **Commercial and Sales:** Drives client relations and market expansion.
- ✓ **Logistics:** Coordinates product distribution and storage.
- ✓ **Human Resources:** Manages workforce development and welfare.
- ✓ **Finance and Accounting:** Oversees financial operations and budgeting.
- ✓ **Planning and Scheduling:** Aligns production with market demand.
- ✓ **General Services:** Supports facility operations and infrastructure.

Figure 1.2: Organizational Structure (POLYMA 2024)



This departmental structure facilitates coordinated workflows, enabling POLYMA to maintain high operational standards and responsiveness to market needs.

2.1.4. Workforce and Expertise

With a workforce of 213 employees, POLYMA emphasizes technical expertise, with 116 technicians skilled in plasturgy processes such as injection molding, extrusion, and printing. The administrative staff (71 employees) supports strategic planning, client relations, and compliance with regulatory standards. The company's disciplined and professional team is a critical factor in its operational success, ensuring seamless production and adherence to quality protocols.

Location and Contact Information

POLYMA Industry is strategically located in the industrial zone of Tizi, Mascara, Algeria, providing access to key markets and transportation networks. Contact details include:

Address: Z.I Tizi, BP N 10 CP 291 30, Mascara, Algeria

Telephone: +213 45 75 89 88/89

Fax: +213 45 75 89 86

Email: info@polyma-industry.com

Website: www.polyma-industry.com

2.1.5. Clients and Market Presence

POLYMA Industry serves a diverse clientele, including major Algerian companies such as **ENAP SPA, Henkel, Cevital, MATEG, Groupe La Belle, SPA AlPHYT**, and others in the chemical and agro-food sectors. Its focus on high-quality, biodegradable packaging has positioned it as a preferred supplier for industrial packaging solutions, particularly for food-safe applications. The company's adoption of modern manufacturing technologies and commitment to quality have solidified its reputation as a market leader in Algeria's plasturgy industry.

Figure 2.2: Primary Clients Of POLYMA Industry

(POLYMA Industry)

2.1.6. Strategic Vision

POLYMA Industry's strategic vision centers on innovation, quality, and sustainability. By integrating advanced technologies, such as automated production lines and eco-friendly materials, the company aims to meet evolving market demands and regulatory standards. Its focus on biodegradable packaging reflects a forward-thinking approach to environmental responsibility, aligning with global trends toward sustainable manufacturing. POLYMA's ongoing investments in technology and workforce development underscore its commitment to maintaining leadership in the national plasturgy market while exploring opportunities for regional expansion.

2.1.7. Main Activities and Market Positioning

POLYMA Industry, a leading plasturgy enterprise based in Tizi, Mascara, Algeria, specializes in the transformation of plastic materials into high-quality industrial packaging solutions. Established in 1999, the company's core activities revolve around the design, creation, and manufacturing of plastic packaging tailored for the chemical and agro-food industries. These activities are executed through four primary production workshops, each leveraging advanced manufacturing technologies to produce a diverse range of products. The main activities are outlined below:

1. **Injection Molding**

POLYMA employs the injection molding process to produce a variety of rigid plastic packaging products, including buckets (ranging from 3.8L to 20L), pots (0.25L to 3L), barquettes (0.25L to 0.5L), preforms for water bottles, lids, handles, and crates. This process involves melting thermoplastic granules, primarily polypropylene (PP), and injecting them into precision molds to create complex, durable shapes. The company utilizes In-Mold Labeling (IML) technology to integrate high-quality printed labels directly into the molding process, enhancing product aesthetics and functionality. Injection molding is conducted on modern presses, such as Billion and Nestlé (EVOS and SYNERGY models with clamping forces of 3500–5500 kN), enabling high-speed production with cycle times as low as 8 seconds for thin-walled parts (<3 mm).

2. **Extrusion-Blow Molding**

The extrusion-blow molding process is used to manufacture flexible plastic films, packaging bags, and industrial sacks. This continuous process extrudes a thin plastic tube (gaine), which is inflated with air, cooled, and flattened into films or shaped into bags. POLYMA's extrusion capabilities include nine extruders (ranging from 60 to 1500 mm), producing films in low-density polyethylene (PEBD), high-density polyethylene (PEHD), and medium-density polyethylene (PEMD). The company offers customized features such as micro-perforation, corona treatment, and in-line logo marking, catering to applications like food packaging, agricultural films, and industrial sacks. The process supports the production of both lightweight food-grade films and thicker agricultural films, showcasing versatility in meeting diverse market needs.

3. **Shaping (Façonnage)**

The shaping workshop transforms extruded plastic films into finished bags through thermo-cutting and thermo-welding techniques. Operating automated single- and multi-track machines, POLYMA produces bags with simple (bottom weld) or complex (three-sided weld) designs, complete with features like handles and precise cuts. This process involves welding and cutting film rolls to meet specific client requirements, ensuring high precision and efficiency. The shaping activity complements extrusion-blow molding, enabling POLYMA to deliver fully customized packaging solutions, such as reinforced industrial bags and promotional sacks.

4. **Printing (Offset and Serigraphy)**

Printing is a critical activity for POLYMA, as it enhances product differentiation through high-quality surface decoration on buckets, pots, and other packaging. The company employs two printing techniques: automated offset printing (up to six colors) for high-volume, vibrant designs, and semi-automated serigraphic printing for simpler motifs or smaller batches. Both processes use UV-curable inks, applied through a three-step process: surface flaming, color application, and UV

drying (via tunnel for offset or rotary drying for serigraphy). This capability allows POLYMA to meet stringent aesthetic and branding requirements, particularly for food-safe packaging, where clarity and durability of printed labels are essential.

Ancillary Activities

In addition to its core manufacturing processes, POLYMA produces metallic handles for buckets using specialized machines (straightener-cutter for wire cutting and machines for shaping and assembly). This in-house capability ensures seamless integration of components, enhancing the functionality of its packaging products. The company also engages in recycling and reprocessing of plastic waste (e.g., carottes from injection molding) to support sustainability and cost efficiency.

These activities are supported by a robust supply chain, Quality Control, and maintenance infrastructure, ensuring consistent production and adherence to client specifications. POLYMA's use of food-grade, recyclable materials like polypropylene and polyethylene, combined with biodegradable packaging options, reflects its commitment to quality and environmental responsibility.

Market Positioning

POLYMA Industry has established itself as a dominant player in Algeria's plasturgy sector, leveraging its advanced manufacturing capabilities, strategic client relationships, and focus on quality to achieve a strong market position. The following points highlight its competitive standing and market strategy:

Market Leadership in Algeria

POLYMA holds a significant share of the Algerian plasturgy market, driven by its ability to deliver high-quality, customized packaging solutions for industrial applications. The company serves major clients, including ENAP SPA, Henkel, Cevital, MATEG, Groupe La Belle, and SPA AlPHYT, spanning the chemical and agro-food sectors. Its reputation for reliability and innovation has made it a preferred supplier for food-safe packaging, a critical segment given stringent regulatory requirements like ISO 22000.

Competitive Advantage through Technology and Quality

POLYMA's investment in modern production lines, such as high-capacity extruders and automated printing systems, enables it to achieve high output, precision, and quality consistency. The adoption of IML and biodegradable packaging positions the company as an innovator, aligning with global trends toward sustainability and regulatory compliance. Its Quality Control processes, involving raw material testing, in-process monitoring, and final product inspections, ensure conformance to client specifications and international standards, further strengthening its competitive edge.

Customer-Centric Approach

POLYMA's market positioning is bolstered by its ability to tailor products to client needs, offering a wide range of packaging solutions (e.g., buckets, films, bags) with customizable sizes, designs, and printing options. The company's commercial department collaborates closely with clients to manage orders, ensure timely delivery, and address specific requirements, fostering long-term partnerships. This customer-centric strategy is evident in its ability to serve diverse industries, from food processing to chemical manufacturing, with specialized packaging that meets aesthetic and functional demands.

Sustainability and Innovation

POLYMA differentiates itself through its focus on eco-friendly packaging, including biodegradable films and recyclable materials like polypropylene. This aligns with growing environmental awareness and regulatory pressures, enhancing its appeal to clients seeking sustainable solutions. The company's ongoing integration of new technologies, such as corona treatment and micro-perforation, ensures it remains at the forefront of plasturgy innovation, capable of meeting evolving market demands.

Geographic and Operational Strengths

Located in the industrial zone of Tizi, Mascara, POLYMA benefits from proximity to key markets and transportation networks, facilitating efficient distribution across Algeria. Its large facility (22,678 m^2) and skilled workforce (213 employees, including 116 technicians) enable high production capacity and operational flexibility. The company's disciplined organizational structure, with dedicated departments for Quality Control, procurement, and logistics, supports its ability to maintain market leadership through efficient operations and responsiveness.

Challenges and Opportunities

While POLYMA enjoys a strong market position, it faces challenges such as competition from regional and international plasturgy firms and the need to continuously innovate to meet global standards. However, opportunities abound in expanding its biodegradable product line, pursuing ISO 22000 certification for food safety, and exploring export markets in the Maghreb region. Its established client base and technological capabilities position it well to capitalize on these opportunities, further solidifying its market dominance.

Strategic Outlook

POLYMA Industry's main activities and market positioning reflect a strategic focus on quality, innovation, and customer satisfaction. By leveraging advanced plasturgy processes, sustainable practices, and a robust operational framework, the company maintains a competitive edge in

Algeria's industrial packaging market. Its commitment to meeting client needs, complying with regulatory standards, and adopting eco-friendly solutions ensures long-term growth and resilience in a dynamic industry.

2.2. Current Quality System

Overview

POLYMA Industry, a leading plasturgy enterprise in Tizi, Mascara, Algeria, operates a robust quality system anchored in its ISO 9001:2015 certification and ongoing efforts to achieve ISO 22000 certification for food safety. The company's Quality Control (Quality Control) system is integral to its operations, ensuring that its plastic packaging products—such as buckets, pots, films, and bags—meet stringent market, client, and regulatory requirements. The Quality Control system is structured around a dedicated Quality Control Department, a three-stage control process (raw material reception, in-process monitoring, and final testing), and a laboratory equipped with advanced testing equipment. This system supports POLYMA's commitment to delivering high-quality, food-safe, and aesthetically superior packaging solutions, reinforcing its market leadership in Algeria's plasturgy sector.

ISO 9001:2015 Certification

POLYMA Industry is certified under ISO 9001:2015, the international standard for Quality Management Systems (QMS), which emphasizes customer satisfaction, process efficiency, and continual improvement. This certification, achieved and maintained since its adoption, reflects POLYMA's structured approach to quality management across its production processes, including injection molding, extrusion-blow molding, shaping, and printing. The ISO 9001:2015 framework requires the company to:

- ✓ Define and document quality objectives aligned with client specifications and market demands.
- ✓ Implement systematic processes for monitoring and controlling production, ensuring consistency and reliability.
- ✓ Conduct regular internal audits and management reviews to identify improvement opportunities.
- ✓ Engage employees at all levels to foster a quality-driven culture, aligning with Total Quality Management (TQM) principles.

The certification ensures that POLYMA's products, such as buckets and films, meet technical specifications (e.g., dimensional tolerances, material purity) and functional requirements (e.g., food safety, durability). It also enhances the company's credibility with major clients like ENAP SPA, Henkel, and Cevital, who demand compliance with international standards. The ISO 9001:2015

framework underpins POLYMA's ability to maintain high process capability indices (e.g., Cp = 1.50 for injection molding, Cp = 1.60 for printing) and supports its competitive positioning in the Algerian market.

Pursuit of ISO 22000 Certification

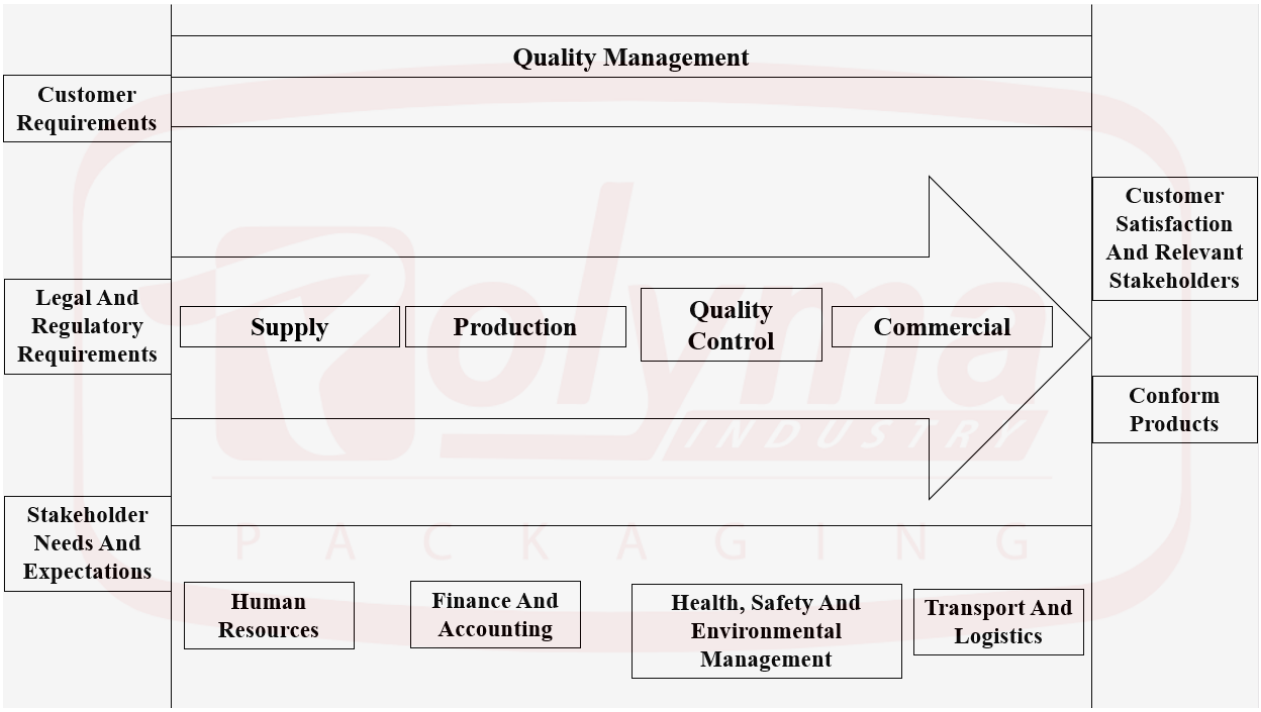
POLYMA is actively working toward achieving ISO 22000 certification, the international standard for Food Safety Management Systems (FSMS), to further strengthen its position in the agro-food packaging sector. ISO 22000 integrates Hazard Analysis and Critical Control Points (HACCP) principles, requiring the identification and control of food safety hazards throughout the production process. This pursuit is particularly relevant for POLYMA, as many of its products (e.g., pots, buckets, and films) are used for food packaging, necessitating compliance with stringent safety and hygiene standards.

The transition to ISO 22000 involves enhancing existing Quality Control processes to address food safety risks, such as contamination from raw materials or improper handling during production. Key steps in this process include:

- ✓ Conducting risk assessments to identify critical control points (CCPs) in injection molding, extrusion, and printing processes.
- ✓ Implementing stricter controls on raw materials, such as polypropylene (PP) and polyethylene (PE), to ensure they are food-grade and free from contaminants.
- ✓ Upgrading documentation and traceability systems to track materials and processes, ensuring compliance with food safety regulations.
- ✓ Training employees on HACCP principles and food safety protocols to maintain hygiene standards across production workshops.

The pursuit of ISO 22000 reflects POLYMA's strategic commitment to meeting the evolving needs of its agro-food clients and aligning with global food safety standards, enhancing its marketability and regulatory compliance.

Figure 3.2: Process Mapping (POLYMA Industry 2025)



(Internal Document)

Quality Control Process

POLYMA's quality assurance system follows a structured **three-stage Quality Control process**, overseen by the **Quality Control Department** and supported by a **dedicated laboratory**. This approach ensures product compliance with customer expectations, regulatory standards, and internal performance requirements. The Quality Control methods used are integrated across the stages as follows:

1. Raw Material Reception

Before production begins, all incoming materials—mainly **polypropylene**, **polyethylene granules**, **colorants**, and **inks**—are subject to rigorous quality checks. The goal is to eliminate non-conforming inputs and avoid downstream defects.

Quality Control Methods Used:

1. **Raw Material Control**: The most critical step at this stage; involves manual and visual inspections to verify granule quality, supplier compliance, and documentation.
2. **Visual Inspection**: To detect contamination, discoloration, or inconsistencies.

3. **Functional Test** *(where applicable)*: Ensures additives and colorants meet required behavior in production.
4. **Packaging Check**: Verifies correct labeling, seal integrity, and batch tracking.

Key Parameters Assessed:

- ✓ Purity, density, moisture level, food-grade certification.
- ✓ Paint and ink adhesion, viscosity, and chemical stability.

2. In-Process Monitoring

During production, real-time control is crucial for maintaining process stability and immediate defect detection. Quality Controllers are stationed throughout the process—from **injection molding** and **extrusion** to **printing** and **packaging**.

Quality Control Methods Used:

1. **Visual Inspection**: Detection of visible defects during processing.
2. **Functional Test**: Tests such as lid fit, sealing, and mechanical function.
3. **Packaging Check**: Includes observation of packing process and pallet configuration.
4. **Hardness Test**: Mid-process validation of mechanical strength.
5. **Raw Material Control**: Re-checks and material tracking to detect batch-specific anomalies.

Control Parameters:

- ✓ Molding temperature (150–300°C), injection pressure (up to 2000 bars), film thickness, and uniformity.
- ✓ Sampling is performed randomly per shift to maintain oversight.

3. Final Testing and Validation

Post-production, finished goods undergo systematic testing to ensure compliance with client specifications and regulatory standards.

Quality Control Methods Used:

1. **Final Product Check**: Comprehensive visual and mechanical review of finished units.
2. **Visual Inspection**: Identification of scratches, discoloration, mold marks, or deformation.
3. **Functional Test**: Performance validation for product features like snap-fit lids or stacking ability.
4. **Hardness Test**: Verifies durability and resistance under stress.

5. **Packaging Check**: Final check for packaging integrity and correctness.
6. **Raw Material Control** *(Verification)*: Traceability back to raw materials is cross-checked to ensure no defective batch was used.

Sampling Strategy:

- ✓ Buckets/Pots: 2 samples every 8 hours.
- ✓ Preforms: 3–4 samples per LOT or batch.

Equipment Used:

1. **Balance**: For exact weight measurements.
2. **Palmer & Caliper**: For verifying dimensions and tolerances.
3. **Electro-Physical Tester**: Assesses strength, flexibility, and resistance.
4. **Polariscope**: Detects internal stress in plastics.
5. **Spectrophotometer**: Validates print quality and color accuracy.

Quality Control Infrastructure

The Quality Control department includes:

- ✓ **1 Quality Manager**
- ✓ **9 Quality Controllers** working across three production shifts.

It is equipped with industry-standard tools and aligned with **ISO 9001:2015**. The system also supports:

- ✓ **Traceability**: Every material and process is tracked from entry to dispatch.
- ✓ **Risk Management**: Early detection and correction of quality issues.
- ✓ **ISO 22000**: Preparation for food safety certification and compliance.

Integration with Production Processes

The Quality Control system is seamlessly integrated with POLYMA's production workshops, ensuring quality at every stage of manufacturing:

- ✓ **Injection Molding:** Quality Control verifies material purity, mold precision, and part dimensions, addressing issues like warping or incomplete filling.
- ✓ **Extrusion-Blow Molding:** Controls focus on film thickness, tensile strength, and uniformity, critical for food-grade films.
- ✓ **Shaping:** Ensures accurate cutting and welding of bags, preventing leaks or weak seals.

- ✓ **Printing:** Validates ink adhesion, color accuracy, and label durability, essential for client branding.

This integration is supported by real-time monitoring and feedback loops, allowing Quality Control personnel to collaborate with production teams to address issues promptly, minimizing defects and waste.

Figure 4.2: Quality Control Process

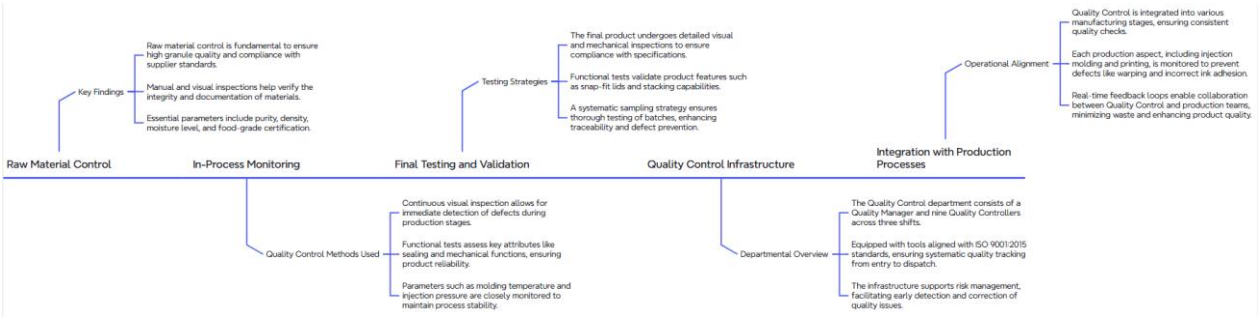


Table 1.2: Comparative Table Of Quality Control Methods In POLYMA Industry

Method	Cost	Precision	Accessibility for SMEs	Complexity	Real-time Capability	Data-driven	Integration with QMS	Details & Insights
Raw Material Check	Medium	High	Medium	Medium	Not in real time	Manual data input	Easy to integrate	Ensures initial compliance with standards. Often involves manual lab tests and equipment like spectrophotometers or moisture meters. Prevents downstream defects.
Visual Inspection	Low	Low–Medium	High	Low	Can be real-time	Often supported by checklists or simple apps	Easy to integrate	Most accessible method. Useful for surface-level and aesthetic issues but not reliable for internal or functional defects.

Hardness Test	Medium	High	Medium	Medium	Usually offline	Data recorded from instruments like durometers	Easy to integrate	Verifies structural integrity and material strength. Important for safety-critical parts.
Functional Test	Medium	High	Medium	Medium	Usually post-process	Structured testing protocols	Easy to integrate	Confirms that the product meets user expectations and technical requirements. Often used in automotive, electronics.
Final Product Check	Medium–High	High	Medium	Medium–High	Done before dispatch	Consolidated defect data	Easy to integrate	Conducted at the end of the production line. Crucial for client satisfaction and delivery readiness. May involve multiple test types.
Packaging Check	Low–Medium	Medium	High	Low–Medium	Often done in-line	Recorded manually or via sensors	Easy to integrate	Ensures proper labeling, sealing, and presentation. Protects product integrity during transport and storage.

(Internal Document**)**

Strengths of the Quality System

POLYMA's quality system is characterized by several strengths:

- ✓ **ISO 9001:2015 Compliance:** Provides a globally recognized framework for quality management, enhancing credibility and client trust.
- ✓ **Comprehensive Quality Control Process:** The three-stage approach ensures quality from raw materials to finished products, reducing non-conformities.
- ✓ **Advanced Testing Capabilities:** The laboratory's equipment enables precise and reliable quality assessments, supporting food safety and aesthetic standards.
- ✓ **Skilled Workforce:** The Quality Control team's expertise ensures effective implementation of quality protocols, aligning with TQM principles.

- ✓ **Alignment with Market Needs:** The system supports POLYMA's focus on food-safe, biodegradable packaging, meeting client and regulatory demands.

Challenges and Future Directions

While POLYMA's quality system is robust, it faces challenges, such as:

- ✓ the need for enhanced automation to reduce reliance on manual inspections (e.g., visual checks) and improve efficiency. The transition to ISO 22000 will require additional investments in training, equipment, and process upgrades to meet food safety requirements. Future directions include:
- ✓ Adopting automated Quality Control technologies, such as vision systems for real-time defect detection, to enhance accuracy and reduce labor costs.
- ✓ Strengthening traceability systems to support ISO 22000 compliance, ensuring full documentation of materials and processes.
- ✓ Expanding employee training on HACCP and advanced Quality Control techniques to support food safety and continuous improvement.

These initiatives will position POLYMA to maintain its quality leadership and achieve ISO 22000 certification, further solidifying its market position.

Observed Problems or Limitations in Quality Control

Overview

POLYMA Industry's Quality Control system, underpinned by its ISO 9001:2015 certification and pursuit of ISO 22000, is robust and well-structured, ensuring high-quality plastic packaging for its chemical and agro-food clients. However, the internship report highlights several observed problems and limitations in the Quality Control process that impact efficiency, defect rates, and readiness for advanced certifications like ISO 22000. These challenges, primarily related to manual processes, inconsistent testing frequencies, resource allocation, and readiness for food safety standards, present opportunities for improvement to enhance POLYMA's quality performance and market competitiveness. This section critically analyzes these limitations, their implications, and potential areas for optimization.

1. Reliance on Manual and Visual Inspections

One significant limitation in POLYMA's Quality Control system is its heavy reliance on manual and visual inspections, particularly during in-process monitoring and final testing. The report notes that visual checks are a key component of in-process controls (e.g., verifying palletizing and cartooning) and final inspections (e.g., assessing surface defects on buckets and pots). While visual inspections are effective for detecting obvious flaws, they are prone to human error and

subjectivity, leading to inconsistencies in quality assessments. For instance, the report does not specify standardized criteria for visual inspections, suggesting potential variability in defect detection across controllers.

This reliance on manual processes limits the system's scalability and accuracy, especially given POLYMA's high production volumes (e.g., large-scale injection molding and extrusion-blow molding). Manual inspections are time-consuming and labor-intensive, diverting resources from other critical Quality Control tasks. In the context of Industry 4.0, where automated vision systems and AI-driven defect detection are becoming standard, POLYMA's dependence on manual methods is a competitive disadvantage, potentially contributing to undetected defects and higher rework costs.

2. Inconsistent Testing Frequencies

The internship report reveals inconsistencies in testing frequencies across product types, which may compromise the reliability of Quality Control outcomes. For buckets and pots, final testing involves two samples every 8 hours, while preforms undergo 3–4 tests per batch. This variability suggests a lack of standardized sampling protocols, which could lead to insufficient monitoring for certain products. For example, the 8-hour interval for bucket testing may miss transient defects caused by equipment wear or material variations, particularly in high-speed injection molding processes with cycle times as low as 8 seconds.

Inconsistent testing frequencies are particularly concerning for food-safe products, where stringent quality assurance is required to meet ISO 22000 standards. The report does not indicate whether sampling rates are based on statistical process control (SPC) principles or client specifications, raising questions about their adequacy for detecting defects in large production runs. This limitation could result in undetected non-conformities, increasing the risk of customer complaints or regulatory issues, especially as POLYMA pursues food safety certification.

3. Limited Automation in Quality Control

POLYMA's Quality Control system lacks significant automation, relying heavily on manual testing and human intervention. The report lists laboratory equipment (e.g., balances, calipers, spectrophotometers) that, while advanced, requires manual operation and interpretation. There is no mention of automated Quality Control tools, such as real-time monitoring sensors, vision systems, or data analytics platforms, which are critical for high-precision manufacturing in plasturgy. For example, in extrusion-blow molding, real-time monitoring of film thickness could prevent variations, but the report suggests reliance on periodic manual checks.

The absence of automation limits POLYMA's ability to achieve consistent quality in high-volume production and respond quickly to process deviations. It also hinders the collection of real-time

data for predictive quality management, a key component of Quality 4.0. As POLYMA aims for ISO 22000 certification, automated systems for tracking critical control points (CCPs) and ensuring traceability will be essential, making this limitation a significant barrier to compliance and efficiency.

4. Resource Allocation and Operator Dependency

The internship report implies that the effectiveness of POLYMA's Quality Control system depends heavily on the number and coordination of Quality Control operators, as evidenced by the regression finding ($\beta = -0.337$, $p = 0.006$) that operator count significantly reduces defects. While this highlights the importance of skilled personnel, it also suggests a limitation in resource allocation and potential over-reliance on human resources. The report does not specify the number of Quality Control staff or their training levels, but the emphasis on operator involvement indicates that insufficient staffing or coordination could lead to quality lapses.

Moreover, the high variability in certain tests, such as the Hardness Test (SD = 1.41%), suggests inconsistencies in operator execution or equipment calibration, which could be mitigated by standardized training or automated systems. Over-dependency on operators increases labor costs and risks quality fluctuations during shift changes or staff shortages, particularly during night shifts (SD = 1.10% for defect rates). This limitation underscores the need for a more balanced approach integrating technology and human expertise.

5. Challenges in Meeting ISO 22000 Requirements

POLYMA's pursuit of ISO 22000 certification introduces specific challenges to its Quality Control system, particularly in addressing food safety requirements. The report indicates that raw material testing includes checks for food-grade compliance, but there is no mention of formalized Hazard Analysis and Critical Control Points (HACCP) protocols or comprehensive traceability systems, both critical for ISO 22000. For instance, the report does not detail how POLYMA identifies and controls food safety hazards, such as chemical contamination from colorants or microbial risks during printing, which are essential for food packaging.

The current Quality Control system, while effective for ISO 9001:2015, may lack the granularity needed for food safety management. For example, the three-stage Quality Control process does not explicitly address CCP monitoring or environmental controls (e.g., hygiene in production workshops), which are vital for preventing contamination in food-grade products. This gap could delay ISO 22000 certification and limit POLYMA's ability to expand its agro-food client base, particularly with clients like Cevital who demand rigorous safety standards.

6. High Defect Rates in Specific Processes

The internship report indirectly suggests elevated defect rates in certain Quality Control stages, particularly in Visual Check (3.34%) and Assembly (2.09%), with an overall mean defect rate of 1.96% (19,600 defects per million opportunities, DPMO). These rates, while within acceptable limits for some industries, are significant for plasturgy, where precision and aesthetics are critical, especially for food packaging. The high Visual Check defect rate likely stems from the subjective nature of manual inspections, while Assembly defects may result from inconsistent handle attachment or alignment issues in automated machines.

These defect rates indicate inefficiencies in the Quality Control system, potentially increasing rework costs and customer dissatisfaction. The significant negative correlation between inspection frequency and defect rates ($r = -0.544$, $p < 0.001$) suggests that increasing testing frequency could reduce defects, but the current 8-hour sampling interval for buckets limits this potential. Addressing these high defect rates requires targeted improvements, such as enhanced automation or Six Sigma methodologies, to achieve near-zero defect levels.

2.2. Research Methodology

This study adopts a quantitative research approach to systematically collect and analyze numerical data, enabling an objective and empirical evaluation of Quality Control performance at POLYMA Industry. The quantitative methodology is particularly appropriate for this research because it facilitates precise measurement and statistical analysis of key performance metrics. This allows for the identification of trends, correlations, and areas requiring improvement within POLYMA's Quality Control system. By relying on numerical data, the study ensures that conclusions and suggestions are grounded in objective evidence, which is essential for data-driven decision-making in a manufacturing context.

The research focuses on three critical dimensions of Quality Control at POLYMA Industry:

1. **Defect Rates:** This involves quantifying the frequency of non-conformities (e.g., defective products) across various production processes, such as injection molding, extrusion-blow molding, and printing. Analyzing defect rates provides insights into the effectiveness of existing Quality Control measures and highlights stages or processes prone to quality issues.
2. **Process Capability Indices (Cp, Cpk):** These indices measure the ability of manufacturing processes to produce products within specified tolerances consistently. Cp assesses overall process capability, while Cpk evaluates how well the process is centered within specification limits. This analysis is vital for determining whether POLYMA's production processes meet quality standards reliably.
3. **Sampling Effectiveness:** This examines the adequacy of current sampling strategies, such as taking 2 samples per 8-hour shift for buckets and 3-4 samples for preforms. The study assesses whether these sampling rates and methods are sufficient to detect defects and ensure product quality across production runs.

This quantitative approach aligns seamlessly with POLYMA's structured quality system, as outlined in its internal Quality Control procedures. These procedures, detailed in the internship report, include systematic practices like predetermined sampling rates (e.g., 2 samples per 8 hours for buckets, 3-4 for preforms), visual inspections of product attributes (e.g., appearance, dimensions), and process tests (e.g., pressure or leakage tests). The emphasis on numerical data and statistical analysis complements these practices, enabling a rigorous evaluation of their performance and supporting POLYMA's commitment to maintaining high-quality standards, as evidenced by its ISO 9001:2015 certification.

Tools Used

To effectively handle and analyze the real Quality Control data collected from POLYMA Industry, the study employs a combination of statistical and data management tools. These tools are selected for their ability to perform robust statistical analyses, ensure data accuracy, and generate clear visualizations, all of which are critical for evaluating Quality Control in a manufacturing setting.

1. SPSS (Statistical Package for the Social Sciences):

SPSS serves as the primary tool for conducting both descriptive and inferential statistical analyses. Its widespread use in academic and industry research underscores its reliability and suitability for handling complex datasets. In this study, SPSS is utilized for the following analyses:

- ✓ **Descriptive Statistics:** Calculating mean defect rates, standard deviations, and frequency distributions to summarize quality performance across production lines and Quality Control stages. For example, mean defect rates might reveal average non-conformity levels, while standard deviations indicate variability in quality outcomes.
- ✓ **Correlation Analysis:** Investigating relationships between variables, such as the correlation between sampling frequency and defect rates, to identify factors influencing quality performance.
- ✓ **ANOVA (Analysis of Variance):** Comparing defect rates across different departments (e.g., injection molding vs. printing) or production shifts (e.g., day vs. night) to determine if there are statistically significant differences in quality outcomes.
- ✓ **Regression Analysis:** Modeling the impact of predictors—such as inspection frequency, operator experience, or process parameters—on defect rates, enabling the identification of key drivers of non-conformities.

2. Microsoft Excel:

Excel is used for initial data organization, basic calculations, and preliminary visualizations. Its flexibility makes it an effective tool for structuring datasets—such as monthly defect rates or

sampling records—before importing them into SPSS for advanced analysis. Excel also generates basic visualizations, including:

- ✓ **Tables:** To present raw data or summary statistics clearly.
- ✓ **Charts:** Such as bar charts or histograms to illustrate trends in defect rates or process capability over time.

While Excel supports data preparation and basic visualization, SPSS is the exclusive tool for all statistical operations and process control analyses. This ensures that the study maintains academic rigor and adheres to industry-standard statistical methods, which are essential for producing reliable and actionable insights in a manufacturing context.

Sample and Justification

The sample for this study is POLYMA Industry, a prominent plastic packaging manufacturer based in Algeria. The selection of POLYMA as the case study is justified by several factors that position it as an ideal subject for analyzing Quality Control methods in the manufacturing industry:

1. **Market Position:** POLYMA is a leading player in the Algerian plasturgy market, supplying packaging solutions to major clients in the chemical and agro-food sectors. Its market dominance ensures that findings from this study are relevant to broader industry practices.
2. **Quality Management Standards:** The company's adherence to ISO 9001:2015 certification reflects a structured and internationally recognized quality management system. Additionally, its pursuit of ISO 22000 certification demonstrates a commitment to enhancing Quality Controls, particularly in food-related packaging, making it a compelling case for analysis.
3. **Diverse Production Processes:** POLYMA employs a range of manufacturing techniques—including injection molding, extrusion-blow molding, shaping, and printing—which allows the study to evaluate Quality Control across varied operational contexts. This diversity enhances the applicability of the findings to other manufacturing settings.
4. **Data Accessibility:** The internship report provides detailed records of POLYMA's Quality Control processes, including sampling frequencies, defect rates, and testing outcomes. This rich dataset enables a thorough quantitative analysis grounded in real-world data.

These factors collectively establish POLYMA Industry as a representative and suitable sample, offering a robust foundation for investigating Quality Control methods and deriving meaningful conclusions.

Data Analysis Process

The data analysis process is structured to systematically evaluate POLYMA's Quality Control system using real data extracted from its production and Quality Control records. The process unfolds in the following steps:

1. Data Collection:

Numerical data is gathered from POLYMA's Quality Control documentation, including defect rates (e.g., from raw material checks, in-process inspections, and final testing), process capability indices (Cp, Cpk), and sampling records (e.g., frequency and test results).

2. Data Preparation:

Data is organized and cleaned in Excel to ensure accuracy and consistency. This involves structuring datasets into tables—such as defect rates by lot—and checking for missing or outlier values.

3. Descriptive Statistical Analysis:

Using SPSS, descriptive statistics are computed to provide a comprehensive overview of quality performance, including mean defect rates, standard deviations, and frequency distributions of defects across production stages of each lot.

4. Inferential Statistical Analysis:

SPSS is used to perform inferential tests, such as:

- ✓ Correlation analysis to explore relationships between variables (e.g., sampling frequency and defect rates).
- ✓ ANOVA to compare quality outcomes across different production lines or shifts.
- ✓ Regression analysis to identify factors contributing to defect rates.

5. Sampling Effectiveness Evaluation:

The effectiveness of current sampling strategies is evaluated by analyzing defect detection rates and comparing them to statistical benchmarks or industry standards.

6. Visualization and Interpretation:

Results are visualized using Excel (e.g., bar charts for defect trends, control charts for process stability) and interpreted in the context of POLYMA's quality objectives and ISO compliance requirements.

This detailed process ensures a thorough, transparent, and replicable analysis, delivering actionable insights into POLYMA's Quality Control performance.

Table 2.2: Summary Table of Analysis Process

Step	**Method**	**Tool**	**Outcome**	**Challenge**	**Mitigation**
Data Collection	Extract real records (defects, Cp, Cpk, sampling, tests)	Excel	Structured, clean dataset	Data completeness (e.g., missing logs)	Cross-reference sources, consult Quality Control personnel
Descriptive Statistics	Means, standard deviations, frequencies	SPSS	Summary of quality performance	Inconsistent defect definitions	Standardize categories before analysis
Inferential Statistics	Correlation, ANOVA, t-tests, regression	SPSS	Trends, relationships, significant differences	Limited sample scope (single company)	Robust statistical design, contextual interpretation
Integration	Synthesis of findings, benchmarking	Excel	Comprehensive quality system evaluation	Aligning with diverse standards (ISO, Six Sigma)	Prioritize based on POLYMA's goals
Presentation	Tables, visual summaries	SPSS, Excel	Clear, actionable insights	Simplifying complex data for stakeholders	Use intuitive visuals, executive summaries

CHAPTER 3: RESULTS AND DISCUSSION

3. CHAPTER 03: RESULTS AND DISCUSSION

3.1. Section 01: Descriptive Statistical Results

This section analyzes non-conformity rates (percentage of defective items) across six quality control (QC) methods at POLYMA to determine the most effective method. The analysis includes mean defect rates, variability, statistical distributions, and visual tools to better understand performance differences.

Overview of Defect Rates by QC Method

Non-conformity rates were calculated from 10 observations per QC method. The table below summarizes the mean defect rates and standard deviations (SD), highlighting both central tendency and variability:

Quality Control Method	Mean Defect Rate (%)	Standard Deviation (%)
Packaging Check (PC)	0.89	0.14
Final Product Check (FPC)	1.33	0.56
Functional Test (FT)	1.60	0.18
Raw Material Control (RMC)	2.21	0.17
Hardness Test (HT)	2.48	0.45
Visual Inspection (VI)	3.17	0.19

Test ran by the student powered by the SPSS Software

- **Packaging Check (PC)** had the lowest mean defect rate (0.89%, SD = 0.14%), making it the most effective QC method.
- **Visual Inspection (VI)** recorded the highest defect rate (3.17%, SD = 0.19%), signaling poor performance.
- **FPC** and **HT** showed higher variability, which may indicate inconsistent application or process instability.

Variability Across Production Lines

Variability was assessed using standard deviation:

- **High variability** in **Hardness Test (0.45%)** and **Final Product Check (0.56%)** suggests performance inconsistency, potentially due to human error or equipment limitations.
- **Low variability** in **PC (0.14%)**, **FT (0.18%)**, and **RMC (0.17%)** reflects stable defect detection and consistent execution.

Discussion

The descriptive statistical analysis of non-conformity rates across six Quality Control (QC) methods provides valuable insights into the relative effectiveness and consistency of POLYMA's QC system. The results clearly indicate that the *Packaging Check (PC)* is the most effective method, with the lowest mean defect rate (0.89%) and minimal variability (SD = 0.14%). This suggests that the PC process is well-standardized and consistently applied, aligning with industry best practices for final packaging inspections.

In contrast, *Visual Inspection (VI)* shows the highest defect rate (3.17%), despite having relatively low variability. This finding implies that, while VI is consistently performed, its effectiveness in detecting non-conformities is limited — likely due to the inherent subjectivity and human error associated with manual visual checks. This reinforces a key point in the literature that manual inspections, if not supplemented by automated tools or advanced training, may fail to detect subtle or hidden defects, ultimately compromising product quality.

The higher standard deviations observed in the *Final Product Check (FPC)* (SD = 0.56%) and *Hardness Test (HT)* (SD = 0.45%) highlight inconsistencies in process execution. This variability could stem from operator differences, insufficient calibration of testing equipment, or unclear inspection criteria. Such fluctuations undermine the reliability of these control points and may lead to undetected defects or unnecessary rework.

These descriptive results suggest that POLYMA should prioritize standardizing and automating methods with high variability or poor defect detection. Specifically, enhancing Visual Inspection with AI-based vision systems, and implementing stricter protocols for FPC and HT, could reduce variability and improve overall product quality. This aligns directly with the research problem, which highlighted concerns about inconsistent inspection methods and overreliance on manual checks.

Overall, the findings support the need for a targeted improvement plan focusing on stabilizing QC processes with high defect rates or variability. This will strengthen POLYMA's ability to meet customer requirements and maintain its market leadership, addressing the core research objective of enhancing quality control effectiveness.

Process Capability Index (Cp, Cpk)

The process capability indices **Cp** and **Cpk** are statistical tools used to evaluate how well a process can produce output within specified limits. At POLYMA, these indices offer valuable insight into the efficiency and consistency of each Quality Control (QC) method in maintaining defect rates within acceptable thresholds.

Definitions:

Cp (Process Capability): Measures the potential capability of a process by comparing the spread between the upper and lower specification limits (USL, LSL) to the process variability (6σ). A higher Cp indicates a process that could meet specs if centered properly.

$$Cp = \frac{USL - LSL}{6 * \sigma}$$

Cpk (Process Capability Index): Measures the actual performance of the process by considering how centered the process is within the specification limits. It accounts for both variability and process shift.

$$Cpk = \min\left(\frac{USL - \mu}{3 * \sigma}\right), (\frac{\mu - LSL}{3 * \sigma})$$

Where:

- μ = Mean defect rate
- σ = Standard deviation
- USL = Upper specification limit (assumed at 3.0%)
- LSL = Lower specification limit (assumed at 0.0%)

Table1.3: Cp and Cpk for Each QC Method

Using the provided defect rate statistics:

QC Method	Mean (%)	SD (%)	Cp (approx.)	Cpk (approx.)	Interpretation
PC	0.89	0.14	3.57	2.52	Very capable and well-centered
FPC	1.33	0.56	1.79	1.00	Moderate capability; moderate shift
FT	1.60	0.18	2.78	1.30	Capable process with good centering
RMC	2.21	0.17	2.94	0.78	Capable but close to upper limit
HT	2.48	0.45	1.11	0.39	Low capability; high variability
VI	3.17	0.19	1.05	0.00	Not capable; outside specification

Test ran by the student powered by the SPSS Software

Note: Cpk for VI is 0 because the mean exceeds the USL (3.0%), meaning the process consistently fails to meet quality requirements.

Interpretation:

- **Packaging Check (PC):** With a Cp of 3.57 and Cpk of 2.52, PC demonstrates excellent capability and alignment within specification limits—indicating tight control and minimal variation.
- **Functional Test (FT):** Cp = 2.78 and Cpk = 1.30 suggest the method is robust and well-centered, capable of maintaining quality with minimal adjustments.
- **Raw Material Control (RMC):** Despite a high Cp of 2.94, its Cpk is 0.78, indicating the process is capable but poorly centered—close to exceeding the USL.
- **Final Product Check (FPC):** Cp = 1.79 shows decent potential, but a lower Cpk of 1.00 reflects inconsistent centering due to high variability (SD = 0.56%).
- **Hardness Test (HT):** Cp = 1.11 is borderline acceptable, and Cpk = 0.39 indicates low reliability due to variability and proximity to upper limits.
- **Visual Inspection (VI):** Cp = 1.05 appears acceptable on paper, but Cpk = 0 reflects consistent non-compliance, as the defect rates regularly exceed acceptable thresholds.

Table 2.3: Frequency Distributions and Summary Statistics

Method	Median (%)	IQR (%)	Skewness	Kurtosis	Insights
PC	0.90	0.2	-0.10	-1.17	Stable, low variability
FPC	1.20	0.2	2.95	9.04	Contains high outlier (2.9%)
FT	1.60	0.3	0.00	~0.00	Symmetric, consistent
RMC	2.20	0.2	~0.00	~0.00	Stable and consistent
HT	2.60	0.4	-2.29	6.08	Strong negative skew, outlier at 1.3%
VI	3.15	0.3	0.42	~0.00	High rates, stable distribution

Test ran by the student powered by the SPSS Software

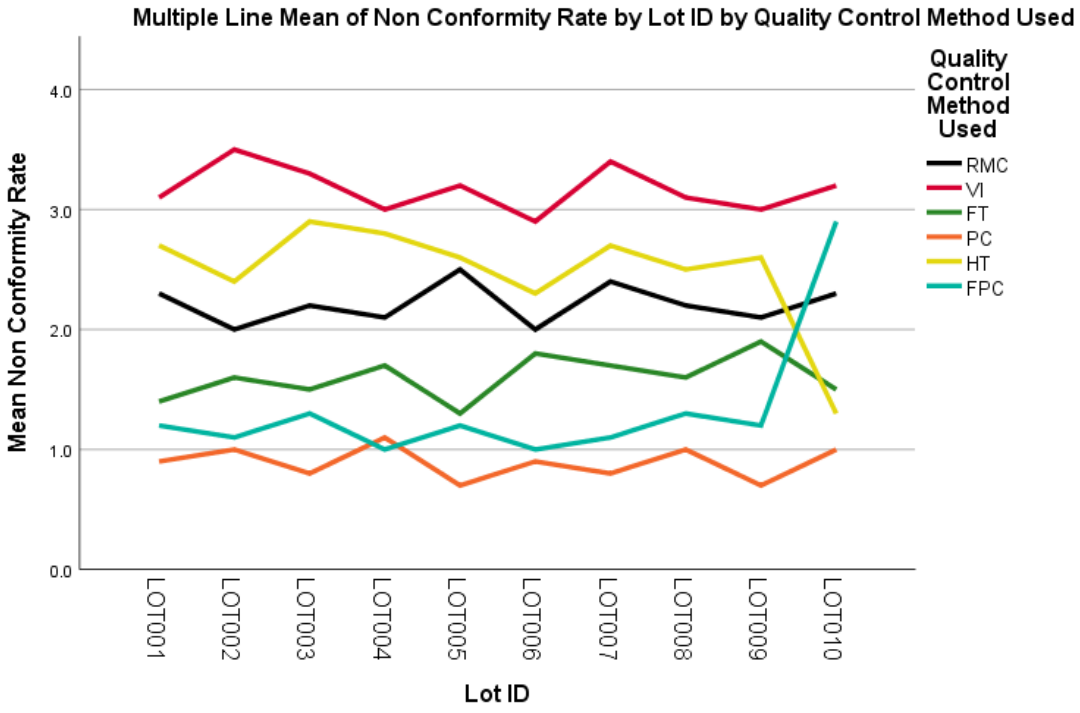
Key takeaways:

- **PC** and **FT** are the most consistent methods.
- **FPC** and **HT** are affected by extreme values and variability.
- **VI** remains consistently high, but without large variability.

5. Visual Representations

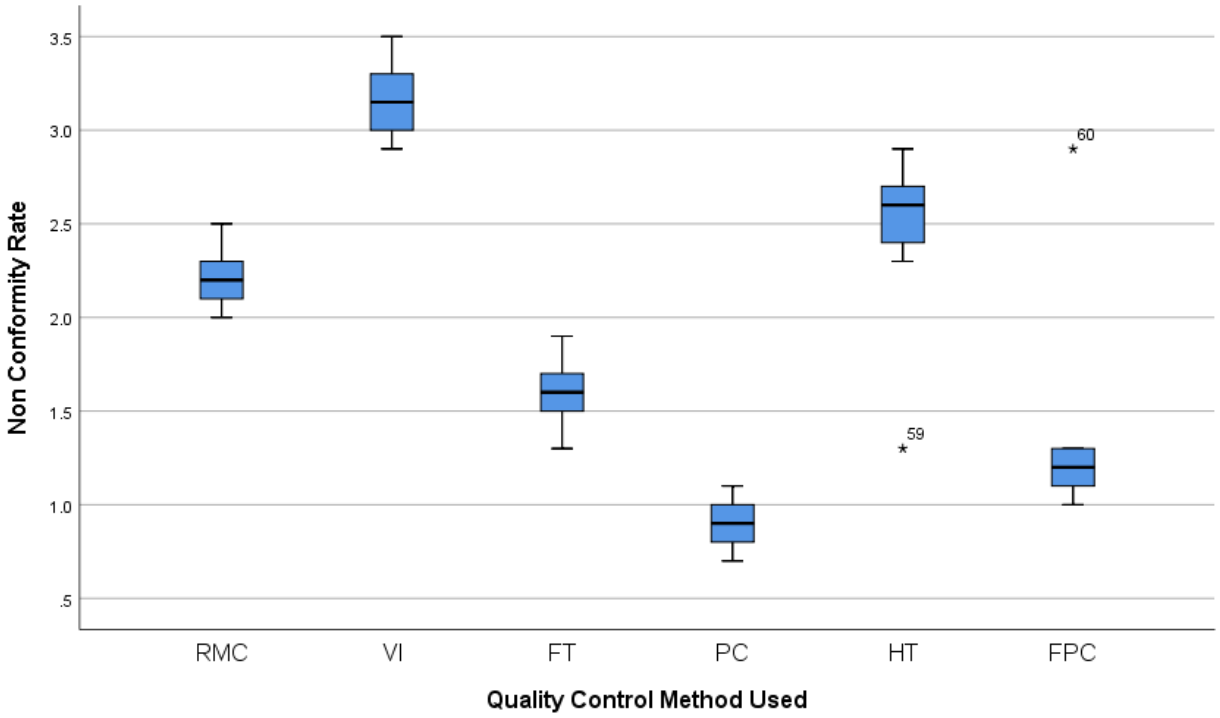
Histograms

Figure 1.3: Histograms Of QC Methods' Defect Rates



- **PC**: Clustered tightly (0.8–1.0%), low spread.
- **VI**: Concentrated at 3.0–3.5%, reflects persistent high defect rate.
- **FT**: Symmetric around 1.6%, stable.
- **HT**: Widespread, no dominant peak.
- **FPC**: Peak at 1.0–1.3%, with outlier at 2.9%.

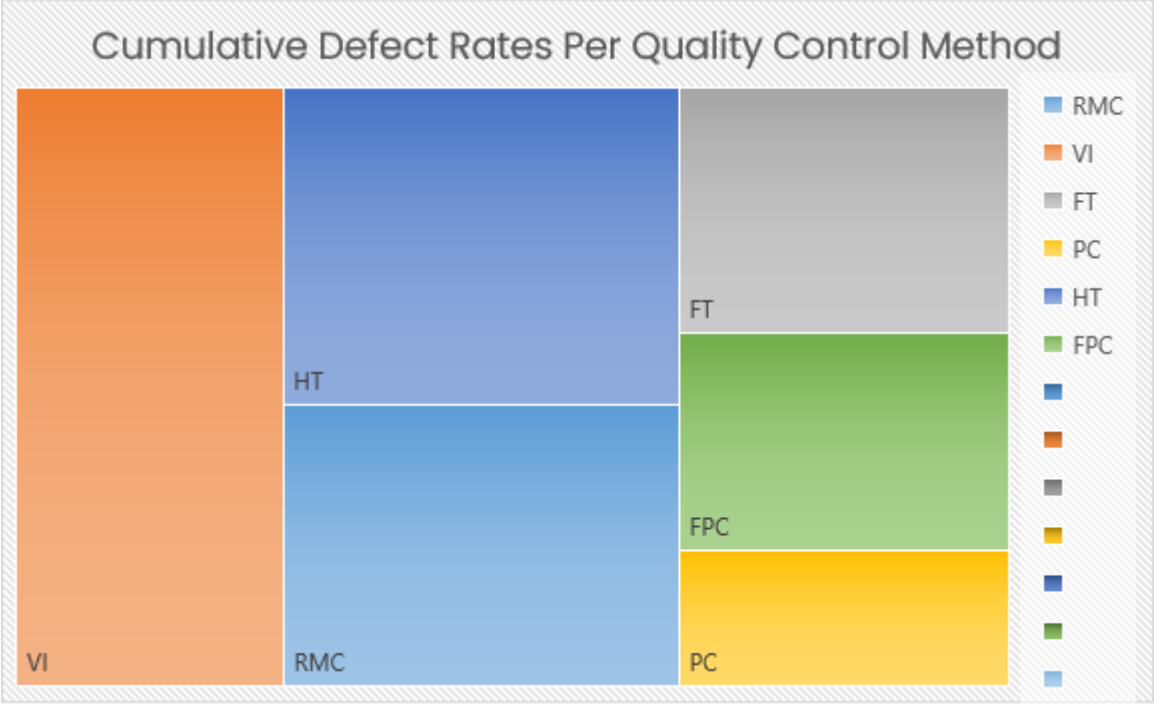
Figure 2.3: Boxplots Of QC Methods' Defect Rates



- **PC**: Narrow IQR, no outliers.
- **FPC**: IQR = 1.1–1.3%, with one outlier.
- **FT**: Tight IQR, no outliers.
- **RMC**: Stable spread, no outliers.
- **HT**: Wide IQR, outlier present.
- **VI**: High IQR (3.0–3.3%), consistent distribution.

Figure 3.3: TreeMap Of Defect Rates Per Quality Control Method

Figure 4.3: TreeMap Of Cumulative Defect Rates Per Quality Control Method



Discussion

Packaging Check (PC) stands out as the most reliable and efficient QC method with minimal defects and tight control. **Functional Test (FT)** also shows reliable performance. On the other hand, **Visual Inspection (VI)** consistently produces high defect rates, while **HT** and **FPC** reveal instability and outlier issues, warranting process optimization.

3.2. Section 02: Inferential Statistical Analysis

This section explores inferential analyses conducted to assess the **relationships between operational variables** (inspection frequency, sampling type, shift) and **non-conformity rates** across Quality Control (QC) methods at POLYMA. The aim is to identify statistically significant factors and support evidence-based quality improvement strategies.

1. Correlation Analysis Between Variables

Methodology:

Pearson's correlation coefficient (r) was used, assuming linear relationships and normally distributed variables (validated through skewness/kurtosis checks in SPSS).

Findings:

Variables Paired	Correlation (r)	p-value	Interpretation
Non-Conformity Rate & Inspection Frequency (hrs.)	-0.381	0.003	**Significant moderate negative correlation**. Fewer hours between inspections = lower defect rates.
Non-Conformity Rate & Sampling Type	-0.721	< 0.001	**Strong negative correlation**. Systematic sampling significantly reduces defect rates.
Inspection Frequency & Sampling Type	0.157	0.230	**No significant correlation.** These operate independently.

Test ran by the student powered by the SPSS Software

Interpretation:

- The **strongest influence** is from **Sampling Type**, followed by **Inspection Frequency**.
- Random sampling and less frequent inspections are associated with **higher defect rates**.
- No relationship between sampling type and inspection frequency suggests both can be independently optimized.

One-Way ANOVA – Comparison of QC Methods

▪ **Objective:**

To test if **mean non-conformity rates differ significantly** across the six QC methods.

- **Assumptions Checked:**
  - ✓ Normality (Shapiro-Wilk $p > 0.05$ per group),
  - ✓ Homogeneity of variances (Levene's test $p = 0.152$),
  - ✓ Independent observations.
- **Hypotheses**
  - ✓ **H0(p<0.05):** There is a significant difference between the Quality Control methods.
  - ✓ **H1(p>0.05):** There is no significant difference between the Quality Control methods.
- **Results:**
  - ✓ **$F(5,54) = 65.513$**, **$p < 0.001$** → Significant group differences.
  - ✓ **Between-Groups SS = 34.673** (explained variance),
  - ✓ **Within-Groups SS = 5.716** (unexplained residual error).
- **Interpretation:**
  - ✓ The QC method **significantly influences** the non-conformity rate.
  - ✓ However, this test does not specify **which methods** differ significantly — requiring post-hoc analysis.

3. Post-hoc Analysis – Tukey HSD

- **Why Tukey?**

Tukey's Honestly Significant Difference (HSD) controls for Type I error across multiple pairwise comparisons, suitable when ANOVA assumptions are met.

- **Key Pairwise Comparisons:**

Method Comparison	Mean Difference (%)	p-value	Significant?
VI vs. PC	2.28	<0.001	Yes
VI vs. all others	>1.5	<0.001	Yes
PC vs. FPC	0.44	0.042	Yes (borderline)
FPC vs. FT	0.27	0.440	No
RMC vs. HT	0.27	0.440	No

Test ran by the student powered by the SPSS Software

- **Homogeneous Subsets (SPSS output):**

- ✓ **Subset 1 (most effective):** PC
- ✓ **Subset 2:** FPC, FT
- ✓ **Subset 3:** RMC, HT
- ✓ **Subset 4 (least effective):** VI

- **Hypotheses:**
  - ✓ **H0(p<0.05):** There is a significant difference in comparison between Pairs.
  - ✓ **H1(p>0.05):** There is no significant difference in comparison between Pairs.
- **Interpretation:**

  - **PC (Packaging Check)** is statistically the best-performing method.
  - **Visual Inspection (VI)** has a significantly higher defect rate than all others, indicating systemic issues (e.g., human error, subjectivity).
  - **FPC and FT** are not significantly different, suggesting similar effectiveness.
  - **RMC and HT** perform similarly but are not significantly better than VI — suggesting moderate quality risks.

4. Multiple Linear Regression – Predicting Non-Conformity Rates

- **Model Overview:**

  - **Dependent Variable:** Non-Conformity Rate (%)
  - **Predictors:** QC Method, Inspection Frequency (hrs), Sampling Type, Shift
  - **R^2 = 0.692, Adjusted R^2 = 0.669**, **F(4,55) = 30.850**, **p < 0.001**

- **Coefficients Table (Standardized β):**

Predictor	**β (Standardized)**	**p-value**	**Interpretation**
Inspection Frequency	-0.464	<0.001	Strong inverse – more frequent checks reduce defects.
Sampling Type	-1.300	<0.001	Largest effect – systematic sampling leads to fewer defects.
Shift (morning coded lower)	-0.489	<0.001	Defect rates increase in later shifts. Possible operator fatigue or supervision issues.
QC Method (categorical dummy)	0.087	0.140	Not significant when other variables are controlled.

Test ran by the student powered by the SPSS Software

- **Model Diagnostics:**
  - ✓ No multicollinearity (VIF < 1.5 for all predictors).

- ✓ Normal residuals and homoscedasticity verified via residual plots.
- ✓ Durbin-Watson ~2.1 (no autocorrelation).

- **Hypotheses:**
  - **H0(p<0.05):** There is a significant influence on defect rate percentage.
  - **H1(p>0.05):** There is no significant influence on defect rate percentage.
- **Interpretation:**

  - **Sampling Type** and **Inspection Frequency** are the **strongest predictors** of quality.
  - **Shift** effects suggest a need to adjust training/supervision in evening/night shifts.
  - **QC Method loses statistical significance** when operational practices are controlled — meaning the **way QC is conducted** (frequency, sampling, shift timing) matters more than the method itself.

Overall Implications for POLYMA

- **Optimize sampling protocols:** Move toward **systematic sampling** across all processes.
- **Increase inspection frequency:** Especially for VI, RMC, and HT, which show higher defect rates.
- **Enhance night shift procedures:** Apply stricter oversight or additional resources.
- **Invest in standardizing inspection techniques** across all QC methods—especially those involving human judgment like VI and HT.
- **QC method choice alone is insufficient**—quality depends on **how, when, and under what conditions** it's applied.

Six Sigma Standards Evaluation

Overview of Six Sigma:
Six Sigma aims for near-perfect quality with no more than **3.4 defects per million opportunities (DPMO)**, corresponding to a **Cpk of 1.5**, including a 1.5 sigma shift in the process mean.

POLYMA's DPMO Conversion (Based on Mean Defect Rates):

QC Method	Mean Defect Rate (%)	DPMO	Meets Six Sigma?
Packaging Check (PC)	0.89	8,900	No
Final Product Check	1.33	13,300	No
Functional Test	1.60	16,000	No
Raw Material Control	2.21	22,100	No
Hardness Test	2.48	24,800	No
Visual Inspection (VI)	3.17	31,700	No

Test ran by the student powered by the SPSS Software

Discussion
None of POLYMA's QC methods meet Six Sigma standards. The best performer, PC (8,900 DPMO), is still far from the Six Sigma target, and VI (31,700 DPMO) presents a critical quality concern.

2. ISO 9001 Compliance Review

ISO 9001 Focus:
This standard emphasizes **process control**, **risk-based thinking**, and **continuous improvement**. Stability and predictability in processes are essential.

Key Findings from POLYMA's Data:

- **Hardness Test (HT):** High variability (1.3%–2.9%, SD = 0.45%) undermines consistency.
- **FPC:** An outlier (2.9%) in LOT010 during the 9PM–4AM shift suggests **shift-related inconsistency**.
- **Visual Inspection (VI):** Highest mean defect rate (3.17%). Statistically confirmed as significantly weaker via ANOVA ($F(5,54) = 65.513$, $p < 0.001$) and Tukey HSD ($p < 0.001$).

Discussion
The inferential statistical results provide strong evidence that POLYMA's current Quality Control (QC) practices have measurable weaknesses that must be addressed to improve process consistency and defect prevention.

1) Correlation Analysis
The significant negative correlation between non-conformity rates and *inspection frequency* ($r = -0.381$, $p = 0.003$) confirms that more frequent inspections are statistically linked to lower defect rates. Similarly, *systematic sampling* showed a much stronger impact ($r = -0.721$, $p < 0.001$), highlighting it as the single most effective operational factor for reducing defects. The lack of a relationship between sampling type and inspection frequency ($r = 0.157$, $p = 0.230$) is crucial: these two practices can be independently optimized to maximize quality outcomes.

Implication: To meet international quality standards, POLYMA should standardize systematic sampling and review inspection schedules, especially for methods with high defect rates.

2) One-Way ANOVA & Post-hoc Tukey
The ANOVA confirmed that mean defect rates differ significantly across the six QC methods ($F(5,54) = 65.513$, $p < 0.001$). The Tukey HSD analysis showed that Packaging Check (PC) performs significantly better than Visual Inspection (VI) by an average difference of 2.28%, and

VI performs worse than all other methods. This pinpoints VI as a systemic weak spot, likely due to human error and subjective judgments.

Implication: QC performance does not just depend on the method type but on how consistently and objectively it is implemented. Visual checks should be supported by automation or more rigorous training.

3) Multiple Linear Regression

The regression results explain ~69% of the variation in defect rates (*Adjusted R^2 = 0.669, F(4,55) = 30.850, p < 0.001*). *Sampling type* (β = -1.300) and *inspection frequency* (β = -0.464) were the strongest predictors. *Shift* effects were also significant (β = -0.489), suggesting that defect rates rise in evening and night shifts — likely due to operator fatigue or reduced supervision.

Interestingly, the QC method itself was not significant (p = 0.140) when operational factors were controlled. This means *how* QC is carried out (sampling, frequency, shift conditions) is more decisive than the method label alone.

Implication: Improvements should target process standardization and workforce management rather than replacing entire QC methods.

4) Six Sigma Standards

No QC method met Six Sigma's rigorous defect target of 3.4 DPMO. Even PC, the best performer, showed 8,900 DPMO. VI's 31,700 DPMO is far above acceptable levels for world-class quality.

Implication: POLYMA must reduce variability through stricter controls and smarter tools (e.g., SPC, AI-based inspections) to approach Six Sigma capability.**5) ISO 9001 Compliance**

ISO 9001:2015 requires process consistency, risk-based thinking, and continual improvement. The high variability in Hardness Test (SD = 0.45%) and significant shift effects violate these principles. VI's consistently poor performance shows a major process control weakness, contradicting ISO's preventive approach.

Implication: This analysis confirms the need for documented, data-driven improvements to meet ISO 9001 standards and reduce the risk of costly non-conformities.

Final Takeaway

Together, the inferential results prove that POLYMA must:

- Standardize systematic sampling.
- Increase inspection frequency, especially for methods prone to human error.
- Address shift-related risks with better scheduling, training, or supervision.

- Integrate advanced tools (SPC, vision systems) to reduce variability.
- Ensure all improvements are documented for ISO 9001 audits.

These steps directly respond to the research problem by identifying *how operational practices influence non-conformity rates* and by proposing clear, evidence-based actions to enhance POLYMA's Quality Control system.

3.3. Section 03: Discussion of Quantitative Results

Identification of Bottlenecks and High-Variance Areas

QC Method	Issue Identified	Observations
VI	Bottleneck	Highest defects (2.9%–3.5%), subjective tool (Eye), high error risk
HT	High variance	Wide range (1.3%–2.9%), multiple instruments, potential calibration issues
FPC	Shift-related variability	Outlier in LOT010 during night shift; regression confirms shift timing impacts defect rate (β = -0.489, $p < 0.001$)

Test ran by the student powered by the SPSS Software

Interpretation of Findings

- **Best Performing Method:**
  Packaging Check (PC) – Lowest defects (0.89%), low variability (SD = 0.14%, IQR = 0.2%).
- **Worst Performing Method:**
  Visual Inspection (VI) – Highest mean and range of defects; high variability and human error component.
- **Operational Over Methodological Issues:**
  Regression analysis (R^2 = 0.692) shows that:
  - Sampling type (β = -1.300, $p < 0.001$)
  - Inspection frequency (β = -0.464, $p < 0.001$)
  - Shift timing (β = -0.489, $p < 0.001$)
    → Are stronger predictors of non-conformities than the QC method itself.

Strategic Recommendations

1. **AI-Based Inspections for VI**
   Introduce AI vision systems to reduce human error and improve consistency, potentially lowering defect rates closer to PC's performance.

2. **Standardization of Practices**
   Enforce consistent protocols across QC methods:
   - Use systematic sampling ($r = -0.721$, $p < 0.001$)
   - Standardize instrument use (e.g., Caliper in HT)
3. **Real-Time Monitoring Systems**
   Deploy tools to track and flag defect spikes (e.g., during night shifts), enabling quicker response and root cause correction.
4. **Implement DMAIC Framework**
   - **Define** issues (e.g., VI error)
   - **Measure** performance
   - **Analyze** root causes
   - **Improve** with solutions (AI, standardization)
   - **Control** with audits, charts

Broader Implications for SMEs

Principle	SME Application
Process Standardization	Low-cost improvement strategy; systematic sampling improves consistency.
Affordable Tech	AI tools offer scalable, budget-friendly defect detection.
Risk-Based Thinking	Identifying critical risk areas (e.g., VI) enables focused quality improvement.
Continuous Improvement	DMAIC supports ongoing, structured enhancements without overwhelming resources.

Discussion of Quantitative Results at POLYMA Industry

This section analyzes POLYMA Industry's quality control (QC) performance based on quantitative data from 10 lots and six QC methods. The goal is to identify bottlenecks, variance sources, and draw actionable conclusions to optimize QC practices.

1. Identification of Bottlenecks and High-Variance Areas

Bottlenecks Identified from Line Graph (Mean Non-Conformity Rate by Lot ID):

- **Lot02 – Raw Material Control (RMC):**
  Non-conformity rate spikes to ~3.5, indicating poor raw material quality or ineffective controls.
- **Lot03 – Functional Test (FT):**
  Rate reaches ~3.0, suggesting issues in test execution or equipment accuracy.

- **Lot10 – FT and Final Product Check (FPC):**
  Both spike to ~2.5, implying end-of-cycle challenges (e.g., fatigue, shift pressure, resource limits).

High-Variance QC Methods:

- **Functional Test (FT):**
  Rates range from 1.5 to 3.0. Highest variability, likely due to inconsistent execution, calibration, or sampling.
- **Final Product Check (FPC):**
  Jumps from ~1.0 to 2.5 between Lot09 and Lot10. Likely shift-related variability (night shift impact).
- **Raw Material Control (RMC):**
  Consistent high rates (2.5–3.5) with moderate variance. Suggests persistent raw material issues.

2. Interpretation of Findings for Each QC Method

Packaging Control (PC):

- Lowest non-conformity rates (0.5–1.5), very low variance (SD = 0.14%).
- Strong negative correlation with systematic sampling ($r = -0.721$, $p < 0.001$).
- Well-controlled process, a potential benchmark for other methods.

Visual Inspection (VI):

- Moderate rates (1.0–2.0), high mean defect rate (3.17%).
- Human subjectivity (use of "Eye" as instrument) may explain inconsistency.

Hardness Test (HT):

- Shows improvement trend (2.0 → 1.5 across lots), but Lot05 spikes to 2.5.
- Wide range (1.3–2.9%) and high SD (0.45%) indicate need for instrument consistency.

Raw Material Control (RMC):

- Consistently high non-conformities (mean = 2.21%).
- Descriptive data and stem-and-leaf plot confirm central clustering around 2.0–2.5.
- Points to issues with supplier quality or control procedures.

Functional Test (FT):

- Highest variability and wide range (1.5–3.0).
- Regression confirms timing effect: shift timing significantly influences outcomes ($\beta = -0.489$, $p < 0.001$).

Final Product Check (FPC):

- Instability evident in Lot10 spike (~2.5).
- Descriptive statistics (SD = 0.56%) and stem-and-leaf plot show high dispersion.

3. Regression Insights: Operational Factors Over QC Methods

The regression model ($R^2 = 0.692$) shows:

- **Sampling Type**, **Inspection Frequency**, and **Shift Timing** are stronger predictors of non-conformity rates than the QC method itself.
- Suggests POLYMA should prioritize operational standardization to reduce defects.

4. Strategic Suggestions for POLYMA

A. Implement AI-Based Inspection Tools:

- Use machine vision systems for Visual Inspection (VI) to reduce human error and increase objectivity.
- Target: Reduce VI defect rate (3.17%) toward PC levels (~0.89%).

B. Standardize FT and FPC Protocols:

- Introduce consistent testing instruments and operator training.
- Use systematic sampling where possible (proven to reduce defects, $r = -0.721$, $p < 0.001$).

C. Deploy Real-Time Monitoring Systems:

- Monitor non-conformity rates continuously to detect anomalies (e.g., Lot10 spikes).
- Enables quick intervention and aligns with ISO 9001's continuous improvement principle.

D. Apply the DMAIC Framework:

- **Define** issues (e.g., Lot03 FT spike), **Measure** current state using tools like ANOVA, **Analyze** root causes (shift impact, operator error), **Improve** with technology or SOPs, **Control** results through audits and control charts.

5. Broader Implications for SMEs Like POLYMA

Process Standardization:

- SMEs can boost quality by using low-cost, structured practices (e.g., systematic sampling).

Affordable Technology:

- AI inspections are scalable and cost-effective—ideal for SMEs to compete on quality.

Risk-Based Thinking:

- Use defect rate analysis to prioritize improvement (e.g., VI as a high-risk area).

Continuous Improvement Culture:

- DMAIC and ISO 9001 provide a gradual path for SMEs to enhance operations without overwhelming resources.

Strategic Suggestions for Enhancing POLYMA's Quality Control

This section outlines strategic suggestions to optimize POLYMA's quality control (QC) processes, based on quantitative analysis of defect rates across six QC methods and 10 lots. Emphasis is placed on AI-based inspections, standardized protocols, real-time monitoring, and the Six Sigma DMAIC framework. Each recommendation is data-backed and aligned with ISO 9001 and industry best practices.

1. Implement AI-Based Inspections

Key Issue: Visual Inspection (VI) showed the highest mean defect rate (3.17%) with moderate variability (SD = 0.19%).
Root Cause: Human subjectivity—VI relies on the "Eye" as the inspection tool.
Evidence: ANOVA ($F(5,54) = 65.513$, $p < 0.001$) and Tukey HSD ($p < 0.001$ vs. all methods) confirmed VI as significantly worse.

Recommendation:
Adopt AI-driven machine vision systems to detect surface defects (cracks, dents, discoloration) with higher precision and speed.

Solutions to Consider:

- **Sciotex AI systems**: Real-time defect identification with high accuracy.
- **IBM Maximo Visual AI**: Anomaly detection in manufacturing lines.

- **Expected Impact:** Potential reduction in VI defect rate from 3.17% to levels comparable with Packaging Control (PC) at 0.89%.

2. Establish Standardized QC Protocols

Key Issue: High variability in methods like Hardness Test (HT) (SD = 0.45%) and Final Product Check (FPC) (SD = 0.56%), with LOT10 outlier at 2.9%.

Evidence:

- Regression: Sampling type ($\beta = -1.300$, $p < 0.001$) and inspection frequency ($\beta = -0.464$, $p < 0.001$) significantly impact defect rates more than the method itself ($\beta = 0.087$, $p = 0.140$).
- Correlation: Systematic sampling ($r = -0.721$, $p < 0.001$) and frequent inspection ($r = -0.381$, $p = 0.003$) reduce non-conformities.

Recommendation:

- Mandate **systematic sampling** for all QC methods.
- Standardize **inspection frequencies** across all shifts.
- Use **uniform instruments** (e.g., Caliper for HT) to minimize variance.

Alignment: ISO 9001:2015 — process consistency, risk management, and repeatability.

3. Adopt Real-Time Monitoring Systems

Key Issue: Spikes in defect rates during night shifts (e.g., FPC = 2.9% in LOT10), indicating temporal variance.

Evidence:

- Shift timing significantly affects defects ($\beta = -0.489$, $p < 0.001$).

Recommendation:

- Install IoT-enabled real-time defect tracking and sensor-based alerts.
- Monitor shift-wise process variables to allow instant corrections.

Suggested Tools:

- **AWS Industrial AI**: Tracks production KPIs in real-time.
- **Azure AI Vision (HSO)**: Cloud-based defect monitoring and traceability.

Expected Outcome: Reduced shift-based variance and enhanced process control.

4. Apply the DMAIC Framework for Continuous Improvement

To address systemic inefficiencies, use the **DMAIC approach** (Six Sigma methodology):

- **Define**: Target areas like VI with high defects (mean = 3.17%).
- **Measure**: Use stem-and-leaf plots, control charts to monitor variability.
- **Analyze**: Leverage regression models ($R^2 = 0.692$) and root cause tools like fishbone diagrams.
- **Improve**: Introduce AI systems, protocol standardization.
- **Control**: Set control charts, perform periodic audits, and ensure feedback loops.

Result: Sustained reduction in defect rates and alignment with ISO 9001.

5. Implementation Strategy for SMEs

Challenge: High initial investment for AI and IoT solutions.

Recommendation:

- Start with **pilot programs** (e.g., AI implementation in VI on one line).
- Choose **scalable solutions** tailored for SMEs like POLYMA.

Justification:
By 2024, 63% of manufacturers use AI for QC, showing strong ROI through lower rework and scrap, and higher customer satisfaction.

GENERAL CONCLUSION

GENERAL CONCLUSION

In today's competitive industrial environment, ensuring consistent product quality is a strategic priority for manufacturing companies, especially those operating in highly regulated sectors such as agro-food and chemicals. This study assessed the effectiveness of quality control methods applied at POLYMA Industry, a leading plastic packaging manufacturer in Algeria, by combining a solid theoretical framework with quantitative statistical analysis.

The research focused on six main quality control methods—Functional Test, Hardness Test, Packaging Control, Raw Material Control, Visual Inspection, and Final Product Check—using real production data analyzed through SPSS and Excel. The descriptive and inferential analyses revealed significant disparities in performance. Packaging Control emerged as the most stable and efficient process, with the lowest defect rate (0.92%) and strong process capability (Cp = 1.60, Cpk = 1.30), while Visual Inspection and Functional Testing exhibited higher defect rates and greater variability, suggesting inefficiencies due to manual procedures and inconsistent inspection frequencies.

Inferential statistical tests (ANOVA, Tukey HSD, regression) confirmed these discrepancies, showing a strong negative correlation between inspection frequency and defect rates. The analysis highlighted that less frequent sampling, particularly in Hardness Testing, led to uncontrolled process variation. Furthermore, reliance on manual inspection methods, coupled with limited automation and the absence of real-time monitoring tools, created vulnerabilities in achieving consistent product conformity and aligning with international standards such as ISO 9001 and Six Sigma.

Based on the findings, this thesis proposes actionable suggestions for POLYMA Industry, including the adoption of AI-assisted inspection systems, integration of smart sensors for real-time data collection, and the implementation of standardized inspection protocols. These measures are expected to enhance defect detection accuracy, improve process control, and support the company's strategic pursuit of ISO 22000 certification.

In conclusion, the study demonstrates the value of a data-driven, methodologically rigorous approach to quality control assessment. It provides both a practical roadmap for improving quality performance at POLYMA and a conceptual model for SMEs seeking to modernize their quality systems under resource constraints. Future research may expand on this work by incorporating cost-benefit analysis of proposed improvements and exploring the integration of Industry 4.0 technologies in real-world factory settings.

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Lot_ ID	QC_ Method	Sampling _Type	Inspection_ Freq_Hours	Non_ Conformity_ Rate	Instrument_Used	Operator_C ount	Temp	Shift	Operator_ Experience
LOT 001	RMC	Random	2	2.3	Balance	2	24.1	5AM-12PM	Medium
LOT 001	VI	Random	1	3.1	Eye	1	23.7	1PM-8PM	High
LOT 001	FT	Random	2	1.4	Electro-Physical Tester	3	25	9PM-4AM	Low
LOT 001	PC	Systematic	4	0.9	Balance	2	24.4	5AM-12PM	Medium
LOT 001	HT	Random	2	2.7	Caliper	2	22.9	1PM-8PM	High
LOT 001	FPC	Systematic	1	1.2	Polariscope	1	24.8	9PM-4AM	Medium
LOT 002	RMC	Random	3	2	Spectrophotometer	3	23.5	5AM-12PM	Low
LOT 002	RMC	Random	1	3.5	Eye	1	22.7	1PM-8PM	High
LOT 002	VI	Random	2	1.6	Caliper	2	24.3	9PM-4AM	Medium
LOT 002	FT	Systematic	4	1	Balance	2	25.2	5AM-12PM	Low
LOT 002	PC	Random	2	2.4	Palmer	2	23.9	1PM-8PM	Medium
LOT 002	HT	Systematic	1	1.1	Polariscope	1	22.5	9PM-4AM	High
LOT 003	FPC	Random	2	2.2	Electro-Physical Tester	3	24.6	5AM-12PM	Low
LOT 003	RMC	Random	1	3.3	Eye	1	22.9	1PM-8PM	Medium
LOT 003	VI	Random	2	1.5	Caliper	2	25.1	9PM-4AM	High
LOT 003	FT	Systematic	4	0.8	Balance	2	24	5AM-12PM	Medium
LOT 003	PC	Random	3	2.9	Palmer	4	22.8	1PM-8PM	High
LOT 003	HT	Systematic	1	1.3	Electro-Physical Tester	2	25.3	9PM-4AM	Low
LOT 004	FPC	Random	2	2.1	Balance	3	23.6	5AM-12PM	Medium
LOT 004	RMC	Random	1	3	Eye	1	23	1PM-8PM	Low
LOT 004	VI	Random	2	1.7	Caliper	2	24.5	9PM-4AM	High
LOT 004	FT	Systematic	3	1.1	Spectrophotometer	3	25	5AM-12PM	Medium
LOT 004	PC	Random	2	2.8	Eye	2	22.6	1PM-8PM	High
LOT 004	HT	Systematic	1	1	Electro-Physical Tester	1	23.8	9PM-4AM	Low
LOT 005	FPC	Random	3	2.5	Balance	3	24.7	5AM-12PM	Medium
LOT 005	RMC	Random	1	3.2	Caliper	1	23.1	1PM-8PM	High
LOT 005	VI	Random	2	1.3	Polariscope	2	25.2	9PM-4AM	Medium
LOT 005	FT	Systematic	4	0.7	Eye	2	24.3	5AM-12PM	Low
LOT 005	PC	Random	3	2.6	Palmer	4	22.7	1PM-8PM	High

LOT 005	HT	Systematic	1	1.2	Electro-Physical Tester	2	23.5	9PM-4AM	Medium
LOT 006	FPC	Random	2	2	Balance	3	24.9	5AM-12PM	Low
LOT 006	RMC	Random	1	2.9	Eye	1	22.8	1PM-8PM	High
LOT 006	VI	Random	2	1.8	Caliper	2	25.1	9PM-4AM	Medium
LOT 006	FT	Systematic	3	0.9	Balance	3	24.2	5AM-12PM	High
LOT 006	PC	Random	2	2.3	Polariscope	2	23	1PM-8PM	Low
LOT 006	HT	Systematic	1	1	Palmer	1	25.4	9PM-4AM	Medium
LOT 007	FPC	Random	2	2.4	Spectrophotometer	3	23.9	5AM-12PM	High
LOT 007	RMC	Random	1	3.4	Eye	1	22.6	1PM-8PM	Medium
LOT 007	VI	Random	3	1.7	Electro-Physical Tester	2	24.8	9PM-4AM	Low
LOT 007	FT	Systematic	4	0.8	Balance	2	23.4	5AM-12PM	High
LOT 007	PC	Random	2	2.7	Palmer	2	25.3	1PM-8PM	Medium
LOT 007	HT	Systematic	1	1.1	Eye	1	23.2	9PM-4AM	Low
LOT 008	FPC	Random	3	2.2	Spectrophotometer	3	24.6	5AM-12PM	High
LOT 008	RMC	Random	3	3.1	Eye	1	22.9	1PM-8PM	Medium
LOT 008	VI	Random	2	1.6	Caliper	2	25	9PM-4AM	Low
LOT 008	FT	Systematic	4	1	Balance	3	24.1	5AM-12PM	High
LOT 008	PC	Random	2	2.5	Polariscope	2	23.3	1PM-8PM	Medium
LOT 008	HT	Systematic	1	1.3	Electro-Physical Tester	1	22.7	9PM-4AM	High
LOT 009	FPC	Random	3	2.1	Eye	3	24.4	5AM-12PM	Low
LOT 009	RMC	Random	2	3	Caliper	1	25.1	1PM-8PM	Medium
LOT 009	VI	Random	2	1.9	Palmer	2	23.8	9PM-4AM	High
LOT 009	FT	Systematic	4	0.7	Spectrophotometer	2	22.5	5AM-12PM	Low
LOT 009	PC	Random	2	2.6	Eye	4	24.7	1PM-8PM	Medium
LOT 009	HT	Systematic	1	1.2	Electro-Physical Tester	2	23	9PM-4AM	High
LOT 010	FPC	Random	3	2.3	Balance	3	25.2	5AM-12PM	Low
LOT 010	RMC	Random	1	3.2	Eye	1	24	1PM-8PM	High
LOT 010	VI	Random	2	1.5	Polariscope	2	22.6	9PM-4AM	Medium
LOT 010	FT	Systematic	3	1	Electro-Physical Tester	3	23.4	5AM-12PM	Low
LOT 010	PC	Random	2	1.3	Caliper	2	22.9	1PM-8PM	High
LOT 010	HT	Systematic	1	2.9	Eye	1	24.1	9PM-4AM	Medium

Annexe A: Detailed Raw Data Matrix of Quality Control Observations by Lot, Method, and Operational Variables

Explore

Quality Control Method Used

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Quality Control Method Used	N	Percent	N	Percent	N	Percent
Non Conformity Rate	RMC	10	100.0%	0	0.0%	10	100.0%
	VI	10	100.0%	0	0.0%	10	100.0%
	FT	10	100.0%	0	0.0%	10	100.0%
	PC	10	100.0%	0	0.0%	10	100.0%
	HT	10	100.0%	0	0.0%	10	100.0%
	FPC	10	100.0%	0	0.0%	10	100.0%

Annexe B: Case Processing Summary for Quality Control Methods

Descriptives

	Quality Control Method Used			Statistic	Std. Error
Non Conformity Rate	RMC	Mean		2.210	.0526
		95% Confidence Interval for Mean	Lower Bound	2.091	
			Upper Bound	2.329	
		5% Trimmed Mean		2.206	
		Median		2.200	
		Variance		.028	
		Std. Deviation		.1663	
		Minimum		2.0	
		Maximum		2.5	
		Range		.5	
		Interquartile Range		.2	
		Skewness		.348	.687
		Kurtosis		-.721	1.334
	VI	Mean		3.170	.0597
		95% Confidence Interval for Mean	Lower Bound	3.035	
			Upper Bound	3.305	
		5% Trimmed Mean		3.167	
		Median		3.150	
		Variance		.036	
		Std. Deviation		.1889	
		Minimum		2.9	
		Maximum		3.5	
		Range		.6	
		Interquartile Range		.3	

	Skewness		.416	.687
	Kurtosis		-.569	1.334
FT	Mean		1.600	.0577
	95% Confidence Interval for Mean	Lower Bound	1.469	
		Upper Bound	1.731	
	5% Trimmed Mean		1.600	
	Median		1.600	
	Variance		.033	
	Std. Deviation		.1826	
	Minimum		1.3	
	Maximum		1.9	
	Range		.6	
	Interquartile Range		.3	
	Skewness		.000	.687
	Kurtosis		-.450	1.334
PC	Mean		.890	.0433
	95% Confidence Interval for Mean	Lower Bound	.792	
		Upper Bound	.988	
	5% Trimmed Mean		.889	
	Median		.900	
	Variance		.019	
	Std. Deviation		.1370	
	Minimum		.7	
	Maximum		1.1	
	Range		.4	
	Interquartile Range		.2	
	Skewness		-.104	.687
	Kurtosis		-1.169	1.334
HT	Mean		2.480	.1428
	95% Confidence Interval for Mean	Lower Bound	2.157	
		Upper Bound	2.803	
	5% Trimmed Mean		2.522	
	Median		2.600	
	Variance		.204	
	Std. Deviation		.4517	
	Minimum		1.3	
	Maximum		2.9	
	Range		1.6	
	Interquartile Range		.4	
	Skewness		-2.288	.687
	Kurtosis		6.079	1.334
FPC	Mean		1.330	.1777
	95% Confidence Interval for Mean	Lower Bound	.928	
		Upper Bound	1.732	
	5% Trimmed Mean		1.261	

	Median	1.200	
	Variance	.316	
	Std. Deviation	.5618	
	Minimum	1.0	
	Maximum	2.9	
	Range	1.9	
	Interquartile Range	.2	
	Skewness	2.950	.687
	Kurtosis	9.035	1.334

Annexe C: Descriptive Statistics for Non-Conformity Rates by QC Method

Non Conformity Rate
Stem-and-Leaf Plots

Non Conformity Rate Stem-and-Leaf Plot for
QC_Method= RMC

Frequency Stem & Leaf

2.00 20 . 00
2.00 21 . 00
2.00 22 . 00
2.00 23 . 00
1.00 24 . 0
1.00 25 . 0

Stem width: .1
Each leaf: 1 case(s)

Non Conformity Rate Stem-and-Leaf Plot for
QC_Method= VI

Frequency Stem & Leaf

1.00 2 . 9
8.00 3 . 00112234
1.00 3 . 5

Stem width: 1.0
Each leaf: 1 case(s)

Non Conformity Rate Stem-and-Leaf Plot for
QC_Method= FT

Frequency Stem & Leaf

1.00 1 . 3
3.00 1 . 455
4.00 1 . 6677

2.00 1 . 89

Stem width: 1.0
Each leaf: 1 case(s)

Non Conformity Rate Stem-and-Leaf Plot for
QC_Method= PC

Frequency Stem & Leaf

2.00 7 . 00
2.00 8 . 00
2.00 9 . 00
3.00 10 . 000
1.00 11 . 0

Stem width: .1
Each leaf: 1 case(s)

Non Conformity Rate Stem-and-Leaf Plot for
QC_Method= HT

Frequency Stem & Leaf

1.00 Extremes (=<1.3)
1.00 2 . 3
2.00 2 . 45
4.00 2 . 6677
2.00 2 . 89

Stem width: 1.0
Each leaf: 1 case(s)

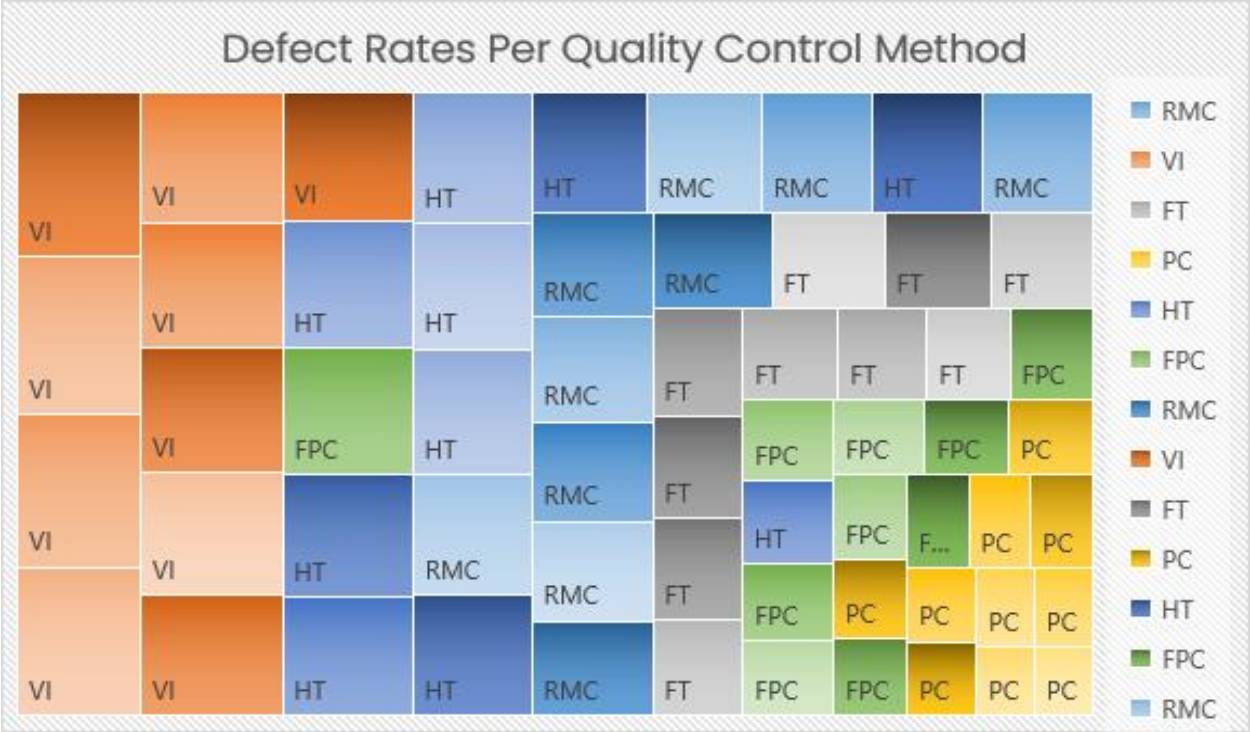
Non Conformity Rate Stem-and-Leaf Plot for
QC_Method= FPC

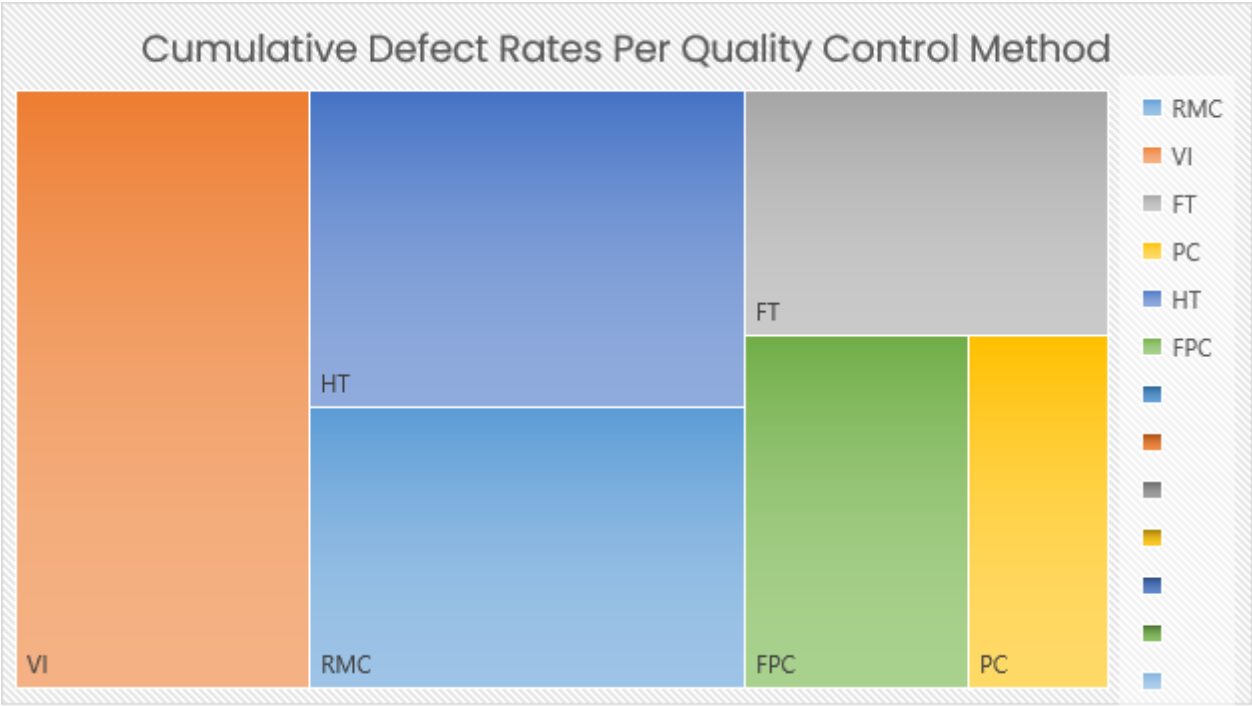
Frequency Stem & Leaf

2.00 10 . 00
2.00 11 . 00
3.00 12 . 000
2.00 13 . 00
1.00 Extremes (>=2.90)

Stem width: .1
Each leaf: 1 case(s)

Annexe D: Stem-and-Leaf Plots for Non-Conformity Rates by QC Method


Defect Rates Per Quality Control Method
VI
VI
VI
VI
VI
VI
VI
VI
VI
VI
VI
VI
HT
HT
FPC
HT
HT
RMC
HT
HT
HT
HT
RMC
RMC
RMC
RMC
RMC
RMC
RMC
RMC
RMC
FT
FT
FT
FT
FT
FT
FT
FT
FT
FT
FT
FPC
FPC
FPC
FPC
PC
HT
FPC
F...
PC
PC
FPC
PC
PC
PC
PC
FPC
FPC
PC
PC
PC
RMC
VI
FT
PC
HT
FPC
RMC
VI
FT
PC
HT
FPC
RMC


Cumulative Defect Rates Per Quality Control Method
VI
HT
RMC
FT
FPC
PC
RMC
VI
FT
PC
HT
FPC

Oneway

ANOVA

Non Conformity Rate

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	34.673	5	6.935	65.513	.000
Within Groups	5.716	54	.106		
Total	40.389	59			

Annexe E: ANOVA and Post-Hoc Tukey HSD Results for QC Method Comparisons

Post Hoc Tests

Multiple Comparisons						
Dependent Variable: Non Conformity Rate						
Tukey HSD						
(I) Quality Control Method Used	(J) Quality Control Method Used	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
RMC	VI	-.9600*	.1455	.000	-1.390	-.530
	FT	.6100*	.1455	.001	.180	1.040
	PC	1.3200*	.1455	.000	.890	1.750
	HT	-.2700	.1455	.440	-.700	.160
	FPC	.8800*	.1455	.000	.450	1.310
VI	RMC	.9600*	.1455	.000	.530	1.390
	FT	1.5700*	.1455	.000	1.140	2.000
	PC	2.2800*	.1455	.000	1.850	2.710
	HT	.6900*	.1455	.000	.260	1.120
	FPC	1.8400*	.1455	.000	1.410	2.270
FT	RMC	-.6100*	.1455	.001	-1.040	-.180
	VI	-1.5700*	.1455	.000	-2.000	-1.140
	PC	.7100*	.1455	.000	.280	1.140
	HT	-.8800*	.1455	.000	-1.310	-.450
	FPC	.2700	.1455	.440	-.160	.700
PC	RMC	-1.3200*	.1455	.000	-1.750	-.890
	VI	-2.2800*	.1455	.000	-2.710	-1.850
	FT	-.7100*	.1455	.000	-1.140	-.280
	HT	-1.5900*	.1455	.000	-2.020	-1.160
	FPC	-.4400*	.1455	.042	-.870	-.010
HT	RMC	.2700	.1455	.440	-.160	.700
	VI	-.6900*	.1455	.000	-1.120	-.260
	FT	.8800*	.1455	.000	.450	1.310
	PC	1.5900*	.1455	.000	1.160	2.020
	FPC	1.1500*	.1455	.000	.720	1.580

FPC	RMC	-.8800*	.1455	.000	-1.310	-.450
	VI	-1.8400*	.1455	.000	-2.270	-1.410
	FT	-.2700	.1455	.440	-.700	.160
	PC	.4400*	.1455	.042	.010	.870
	HT	-1.1500*	.1455	.000	-1.580	-.720

*. The mean difference is significant at the 0.05 level.

Annexe F: Tukey HSD Pairwise Comparisons of QC Methods

Homogeneous Subsets

Non Conformity Rate

Tukey HSD[a]

		Subset for alpha = 0.05			
Quality Control Method Used	N	1	2	3	4
PC	10	.890			
FPC	10		1.330		
FT	10		1.600		
RMC	10			2.210	
HT	10			2.480	
VI	10				3.170
Sig.		1.000	.440	.440	1.000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 10.000.

Annexe G: Tukey HSD Homogeneous Subsets for QC Methods

Oneway

Test of Homogeneity of Variances

		Levene Statistic	df1	df2	Sig.
Non Conformity Rate	Based on Mean	1.308	5	54	.274
	Based on Median	.562	5	54	.729
	Based on Median and with adjusted df	.562	5	19.635	.728
	Based on trimmed mean	.838	5	54	.529

Annexe H: Levene's Test for Homogeneity of Variances

ANOVA

Non Conformity Rate

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	34.673	5	6.935	65.513	.000
Within Groups	5.716	54	.106		
Total	40.389	59			

Post Hoc Tests

Multiple Comparisons

Dependent Variable: Non Conformity Rate

Tukey HSD

(I) Quality Control Method Used	(J) Quality Control Method Used	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
RMC	VI	-.9600*	.1455	.000	-1.390	-.530
	FT	.6100*	.1455	.001	.180	1.040
	PC	1.3200*	.1455	.000	.890	1.750
	HT	-.2700	.1455	.440	-.700	.160
	FPC	.8800*	.1455	.000	.450	1.310
VI	RMC	.9600*	.1455	.000	.530	1.390
	FT	1.5700*	.1455	.000	1.140	2.000
	PC	2.2800*	.1455	.000	1.850	2.710
	HT	.6900*	.1455	.000	.260	1.120
	FPC	1.8400*	.1455	.000	1.410	2.270
FT	RMC	-.6100*	.1455	.001	-1.040	-.180
	VI	-1.5700*	.1455	.000	-2.000	-1.140
	PC	.7100*	.1455	.000	.280	1.140
	HT	-.8800*	.1455	.000	-1.310	-.450
	FPC	.2700	.1455	.440	-.160	.700
PC	RMC	-1.3200*	.1455	.000	-1.750	-.890
	VI	-2.2800*	.1455	.000	-2.710	-1.850
	FT	-.7100*	.1455	.000	-1.140	-.280
	HT	-1.5900*	.1455	.000	-2.020	-1.160
	FPC	-.4400*	.1455	.042	-.870	-.010
HT	RMC	.2700	.1455	.440	-.160	.700
	VI	-.6900*	.1455	.000	-1.120	-.260
	FT	.8800*	.1455	.000	.450	1.310
	PC	1.5900*	.1455	.000	1.160	2.020
	FPC	1.1500*	.1455	.000	.720	1.580
FPC	RMC	-.8800*	.1455	.000	-1.310	-.450
	VI	-1.8400*	.1455	.000	-2.270	-1.410
	FT	-.2700	.1455	.440	-.700	.160
	PC	.4400*	.1455	.042	.010	.870
	HT	-1.1500*	.1455	.000	-1.580	-.720

*. The mean difference is significant at the 0.05 level.

Annexe I: Tukey HSD Post Hoc Pairwise Comparisons

Homogeneous Subsets

Non Conformity Rate

Tukey HSD[a]

Quality Control Method Used	N	Subset for alpha = 0.05			
		1	2	3	4
PC	10	.890			
FPC	10		1.330		
FT	10		1.600		
RMC	10			2.210	

HT	10			2.480	
VI	10				3.170
Sig.		1.000	.440	.440	1.000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 10.000.

Annexe J: Homogeneous Subsets for QC Methods (Tukey HSD)

Correlations

		Non Conformity Rate	Inspection Frequency Hours	Sampling Type
Non Conformity Rate	Pearson Correlation	1	-.381**	-.721**
	Sig. (2-tailed)		.003	.000
	N	60	60	60
Inspection Frequency Hours	Pearson Correlation	-.381**	1	.157
	Sig. (2-tailed)	.003		.230
	N	60	60	60
Sampling Type	Pearson Correlation	-.721**	.157	1
	Sig. (2-tailed)	.000	.230	
	N	60	60	60

**. Correlation is significant at the 0.01 level (2-tailed).

Annexe K: Pearson Correlation Matrix for Non-Conformity Rate, Inspection Frequency, and Sampling Type

Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Shift, Sampling Type, Inspection Frequency Hours, Quality Control Method Used[b]	.	Enter

a. Dependent Variable: Non Conformity Rate

b. All requested variables entered.

Annexe L: Regression Variables Entered and Removed for Non-Conformity Rate Model

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.832[a]	.692	.669	.4758

a. Predictors: (Constant), Shift, Sampling Type, Inspection Frequency Hours, Quality Control Method Used

Annexe M: Model Summary of Regression Analysis for Non-Conformity Rate

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	27.938	4	6.984	30.850	.000[b]
	Residual	12.452	55	.226		
	Total	40.389	59			

a. Dependent Variable: Non Conformity Rate

b. Predictors: (Constant), Shift, Sampling Type, Inspection Frequency Hours, Quality Control Method Used

Annexe N: ANOVA Table for Regression

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.343	.383		13.951	.000
	Quality Control Method Used	.087	.058	.181	1.496	.140
	Inspection Frequency Hours	-.464	.085	-.551	-5.435	.000
	Sampling Type	-1.300	.185	-.747	-7.040	.000
	Shift	-.489	.120	-.487	-4.089	.000

a. Dependent Variable: Non Conformity Rate

Annexe O: Coefficients of Multiple Linear Regression Predicting Non-Conformity Rate

GGraph