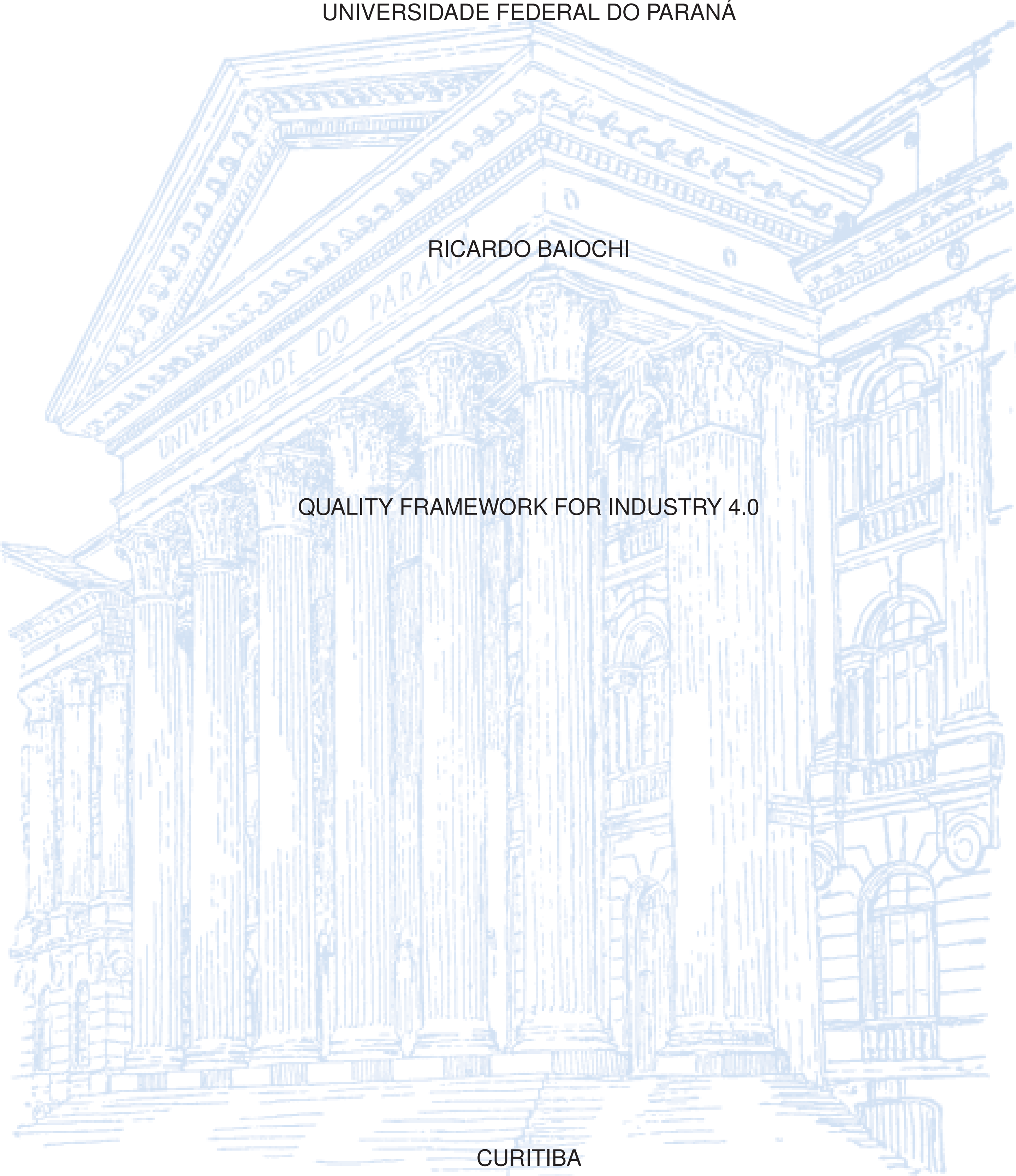

UNIVERSIDADE FEDERAL DO PARANÁ

RICARDO BAIOCHI

QUALITY FRAMEWORK FOR INDUSTRY 4.0

CURITIBA

2024

RICARDO BAIOCHI

QUALITY FRAMEWORK FOR INDUSTRY 4.0

Trabalho apresentado como requisito parcial para a obtenção do título de Mestre em Administração pelo Programa de Pós Graduação Gestão de Organizações, liderança e Decisão do Setor de Ciências Sociais Aplicadas da Universidade Federal do Paraná.

Orientador: Prof. Dr. Eduardo Alves Portela Santos

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ORGANIZAÇÕES, LIDERANÇA E DECISÃO - 40001016172P9

TERMO DE APROVAÇÃO

Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação GESTÃO DE ORGANIZAÇÕES, LIDERANÇA E DECISÃO da Universidade Federal do Paraná foram convocados para realizar a arguição da Dissertação de Mestrado de **RICARDO BAIOCHI** intitulada: **Quality Framework for Industry 4.0** , sob orientação do Prof. Dr. EDUARDO ALVES PORTELA SANTOS, que após terem inquirido o aluno e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.
A outorga do título de mestre está sujeita à homologação pelo colegiado, ao atendimento de todas as indicações e correções solicitadas pela banca e ao pleno atendimento das demandas regimentais do Programa de Pós-Graduação.

CURITIBA, 01 de Novembro de 2024.

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ATA Nº31

ATA DE SESSÃO PÚBLICA DE DEFESA DE MESTRADO PARA A OBTENÇÃO DO GRAU DE MESTRE EM GESTÃO DE ORGANIZAÇÕES, LIDERANÇA E DECISÃO

No dia um de novembro de dois mil e vinte e quatro às 14:00 horas, na sala Virtual, Plataforma Microsoft Teams, foram instaladas as atividades pertinentes ao rito de defesa de dissertação do mestrando **RICARDO BAIOCHI**, intitulada**: Quality Framework for Industry 4.0** , sob orientação do Prof. Dr. EDUARDO ALVES PORTELA SANTOS. A Banca Examinadora, designada pelo Colegiado do Programa de Pós-Graduação GESTÃO DE ORGANIZAÇÕES, LIDERANÇA E DECISÃO da Universidade Federal do Paraná, foi constituída pelos seguintes Membros: EDUARDO ALVES PORTELA SANTOS (UNIVERSIDADE FEDERAL DO PARANÁ), MAURO LIZOT (UNIVERSIDADE FEDERAL DO PARANÁ), EDUARDO DE FREITAS ROCHA LOURES (PONTIFICA UNIVERSIDADE CATÓLICA DO PARANA). A presidência iniciou os ritos definidos pelo Colegiado do Programa e, após exarados os pareceres dos membros do comitê examinador e da respectiva contra argumentação, ocorreu a leitura do parecer final da banca examinadora, que decidiu pela APROVAÇÃO. Este resultado deverá ser homologado pelo Colegiado do programa, mediante o atendimento de todas as indicações e correções solicitadas pela banca dentro dos prazos regimentais definidos pelo programa. A outorga de título de mestre está condicionada ao atendimento de todos os requisitos e prazos determinados no regimento do Programa de Pós-Graduação. Nada mais havendo a tratar a presidência deu por encerrada a sessão, da qual eu, EDUARDO ALVES PORTELA SANTOS, lavrei a presente ata, que vai assinada por mim e pelos demais membros da Comissão Examinadora.

CURITIBA, 01 de Novembro de 2024.

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“In God we trust,
All others must bring data.“
(W. Edwards Deming)

RESUMO

No dinâmico cenário das organizações modernas, a busca pela melhoria contínua é fundamental para manter a competitividade diante das demandas evolutivas do mercado. O Six Sigma tornou-se uma ferramenta indispensável para alcançar a excelência organizacional, focando na redução de defeitos e no controle da variação dos processos. No entanto, surgem desafios em ambientes da Indústria 4.0, especialmente ao enfrentar questões que requerem suporte de outras ferramentas para habilitar e aprimorar as aplicações dos princípios do Six Sigma, como dados não estruturados ou grandes conjuntos de dados, necessitando de metodologias adicionais baseadas em dados. Este estudo visa atender às necessidades evolutivas da Qualidade 4.0 investigando metodologias complementares baseadas em dados para o Six Sigma e explorando oportunidades inexploradas por meio de sua integração. Usando o Methodi Ordinatio como método de revisão sistemática da literatura, organizamos e sintetizamos a literatura existente sobre a integração do Six Sigma no contexto da Qualidade 4.0. Nossos achados revelam uma lacuna crítica de integração, enfatizando a necessidade de um framework. Identificamos uma coleção de metodologias que aprimoram cada estágio do processo Six Sigma, incluindo estrutura de execução (Agile), definição (Value Stream Mapping), medição (Process Mining), análise (Simulação), melhoria (MCDM) e controle (Big Data). Este estudo contribui para a área ao propor um framework para a melhoria da qualidade no contexto da Qualidade 4.0. Ao sintetizar várias metodologias baseadas em dados, oferece às organizações um roteiro para aprimorar a eficiência, eficácia e a excelência geral. A coleção identificada de metodologias fornece uma abordagem diferenciada para enfrentar desafios em cada estágio do processo Six Sigma, preenchendo uma lacuna vital na literatura atual. O estudo de caso resulta em uma robusta melhoria de processo, reduzindo o tempo de ciclo da equipe de operação em 45% e implementando um sistema de monitoramento digital para a operação.

Palavras-chaves: Framework; Qualidade 4.0; Seis sigma; Agile; Mapa de Fluxo de Valor; Mineração de Processos; Simulação; Critérios de multidecisão; Big Data.

ABSTRACT

In the dynamic landscape of modern organizations, the pursuit of continuous improvement is paramount to maintaining competitiveness in the face of evolving market demands. Six Sigma has become indispensable tools for achieving organizational excellence by focusing on defect reduction and process variation control. However, challenges arise in Industry 4.0 environments, especially when confronting issues that require support from other tools to enable and enhance Six Sigma principles applications, challenges such as unstructured data or large datasets, necessitating additional data-driven methodologies. This study aims to address the evolving needs of Quality 4.0 by investigating complementary data-driven methodologies to Six Sigma and exploring untapped opportunities through their integration. Using Methodi Ordinatio as a systematic literature review method, we organize and synthesize existing literature on the integration of Six Sigma in the context of Quality 4.0. Our findings reveal a critical integration gap, emphasizing the need for a framework. We identify a collection of methodologies that enhance each stage of the Six Sigma process, including execution framework (Agile), definition (Value Stream Mapping), measure (Process Mining), analysis (Simulation), improvement (MCDM) and control (Big Data). This study contributes to the field by proposing a framework for quality improvement in the context of Quality 4.0. By synthesizing various data-driven methodologies, it offers organizations a roadmap to enhancing efficiency, effectiveness, and overall excellence. The identified collection of methodologies provides a nuanced approach to address challenges in each stage of the Six Sigma process, filling a vital gap in the current literature. The case study results in a robust process improvement, reducing the cycle time of the operation team in 45% and implementing a digital monitoring system for the operation.

Key-words: Framework; Quality 4.0; Six sigma; Agile; Value Stream Mapping; Process Mining; Simulation; Multi-criteria decision making; Big Data.

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SUMÁRIO

1 INTRODUCTION

In the contemporary landscape of organizational management, the imperative of continual improvement resonates profoundly as enterprises strive to maintain competitiveness amidst dynamic market forces. Quality programs, a cornerstone of this pursuit (Escobar et al., 2022), have proven indispensable, with various methodologies playing pivotal roles in steering organizations towards excellence. Notable among these methodologies is Six Sigma, an analytically driven approach that accentuates defect reduction and process variation control.

From the various definitions found in the reviewed publications, it was possible to identify at least two streams of thought about Six Sigma. The first stream defines Six Sigma as a set of statistical tools adopted within the quality management to construct a framework for process improvement. The second stream defines Six Sigma as an operational philosophy of management which can be shared beneficially by customers, shareholders, employees and suppliers (Tjahjono et al., 2010). The aim to enhance the Six Sigma level of performance measures referred to as the Critical to Quality (CTQ) which reflects the customer requirements through a group of tools for the analysis of the data. Statistical tools identify the main quality indicator, which is the parts per million (PPM) of non-conforming products. Achieving a Six Sigma level means having a process that generates outputs with less than 3.4 defective parts per million (Tjahjono et al., 2010).

However, the efficacy of Six Sigma encounters limitations when confronted with issues that requires complementary methodologies to support an effective application, especially Green Belts and Black belts present as biggest limitation when facing with big data, unstructured data and the voluminous datasets that are characteristic of the Quality 4.0 environment (Antony et al., 2020). In such scenarios, a logical imperative emerges for the incorporation of one or more data-driven problem-solving methodologies (Antony et al., 2017).

Quality 4.0 refers to the application of Industry 4.0 technologies to enhance quality management processes (Sami Sader; Daroczi, 2022). It integrates digital tools, data analytics, and advanced technologies such as artificial intelligence (AI), the Internet of Things (IoT), and big data to improve quality control and assurance in manufacturing and other industries. The goal of Quality 4.0 is to create more efficient, effective, and responsive quality management systems that can better meet the demands of modern, complex production environments (Carvalho et al., 2021).

Six Sigma is enhanced by a collection of methodologies across its stages, such as the list below. These methodologies collectively contribute to a holistic approach to quality improvement.

- Execution Framework - Agile (Tripathi et al., 2021)
- Define - Value Stream Mapping (Fathurohman et al., 2021)
- Measure - Process Mining (Ramires; Sampaio, 2022)
- Analysis - Simulation (Uriarte et al., 2020b)
- Improvement - Multiple Criteria Decision Making (MCDM) (Yadav et al., 2019)
- Control - Big Data (Belhadi et al., 2020)

1.1 PROBLEM DEFINITION

The literature review conducted in the investigation identified a notable gap in the available literature on this topic, presenting an opportunity to contribute substantively to academic scholarship and support quality improvement efforts.

The study aims to address the evolving needs of Quality 4.0 by investigating complementary data-driven methodologies to Six Sigma and exploring untapped opportunities through their integration (Antony et al., 2020). The research aims to contribute by proposing a framework for quality improvement for Industry 4.0, synthesizing various data-driven methodologies to enhance Six Sigma.

1.2 RESEARCH QUESTIONS

The existing literature reveals a notable gap in the availability of frameworks that effectively integrate these methodologies to fulfill Six Sigma. This gap signifies a critical avenue for further research to develop a comprehensive framework that bridges the integration gap and facilitates quality enhancement in the modern industry.

To address this research gap, this thesis aims to investigate the key methodologies that enhance Six Sigma in the context of Quality 4.0 challenges. By conducting a quantitative analysis using Scopus and Web of Science databases, recent articles were analyzed to identify the main methodologies that boost Six Sigma performance.

The examination of the assembled portfolio of articles reveals a notable lacuna, indicating the need for further research to contribute substantively to academic scholarship and support corporate endeavors in the realm of quality enhancement. This research aims to fill this gap by providing insights into the key methodologies that enhance Six Sigma in the context of Quality 4.0 and by proposing a comprehensive framework that integrates these methodologies.

- *Q1. Which data-driven methodologies that enhance Six Sigma performance, considering the Quality 4.0 environment?*
- *Q2. Would it be possible to organize these methodologies within a framework??*

Research Question 1: This question arises from the need to understand the key methodologies that enhance Six Sigma in the context of Quality 4.0. By conducting a quantitative analysis and identifying the main methodologies through keyword searches, this question aims to generate foundational knowledge for the literature review and explore the potential synergies between these methodologies and Six Sigma.

Research Question 2: This question stems from the absence of existing frameworks that integrate the identified group of methodologies to fulfill Six Sigma. Despite conducting searches on various databases, no framework proposals were identified. This research question aims to explore the existing literature and determine if there are any comprehensive frameworks that bridge the integration gap between these methodologies and Six Sigma. The justification lies in the need to address this gap and develop a framework for integrating these methodologies with Six Sigma

These questions serve as the foundation for our exploration of the integration of Six Sigma and Quality 4.0, propelling us toward uncovering synergies and addressing existing gaps. Although the existing literature suggests potential synergies (Antony et al., 2020; Chiarini, 2020), the lack of a comprehensive framework requires further scholarly investigation. In response, this research aims to contribute to the development of such a framework, acknowledging the nuanced and multifaceted nature of quality improvement.

1.3 OBJECTIVES

The thesis aims to propose a framework to fulfill the gap identified on the literature review, facilitating quality improvement, and provide organizations with a comprehensive framework to adapt to the challenges of the modern industry.

- Identify on the literature, main data-driven methodologies that enhance Six Sigma performance
- Propose a framework for quality improvement for Industry 4.0 based on the data-driven methodologies previously identified

1.4 JUSTIFICATION

The existing literature reveals a significant gap in the availability of frameworks that integrate Six Sigma with Quality 4.0 methodologies. Despite conducting extensive searches on various databases, no framework proposals were identified. This gap represents an opportunity to contribute substantively to academic scholarship and support corporate endeavors in the field of quality enhancement.

Furthermore, the examined portfolio of articles indicates the need to bridge the gap between traditional quality management practices and the complexities of Industry 4.0. The integration of data-driven methodologies with Six Sigma is crucial to address this need and provide a dynamic and data-driven approach to quality improvement. This research aims to overcome the limitations of traditional quality management practices and offer practical solutions for organizations to adapt to the challenges of the modern industry.

The significance of this research lies in its potential to reply of industry 4.0 challenges proposing a framework, that integrates Agile principles, Value Stream Mapping, Process Mining, Simulation, Multi-criteria Decision Making, and Big Data within the Six Sigma, to enhance application and performance, ultimately leading to competitive advantage.

1.5 STUDY ORGANIZATION

This study is structured into five steps designed to provide a comprehensive exploration of the topic and contribute valuable information to the ongoing discourse on the integration of Six Sigma and Quality 4.0. (Figure 1)

In the initial step of this study, a systematic review of the literature was performed to identify valuable literature gaps and establish a foundation for research. This involved defining research questions and executing a comprehensive search strategy. Based on the literature review, research questions were formulated to address key methodologies to carry out Six Sigma and quantitative analysis. These questions aimed to understand the interconnections between various data-driven methodologies and their implications for quality improvement in the context of Quality 4.0.

The next phase sets the groundwork for the integration of methodologies and the proposition of a framework, and the next step of the study provides a case study in an automotive company.

The subsequent sections of this article discuss the development of the literature review on the chapter 2, data-driven methodologies background on the chapter 3, framework proposal on the chapter 4, application on a case study on the chapter

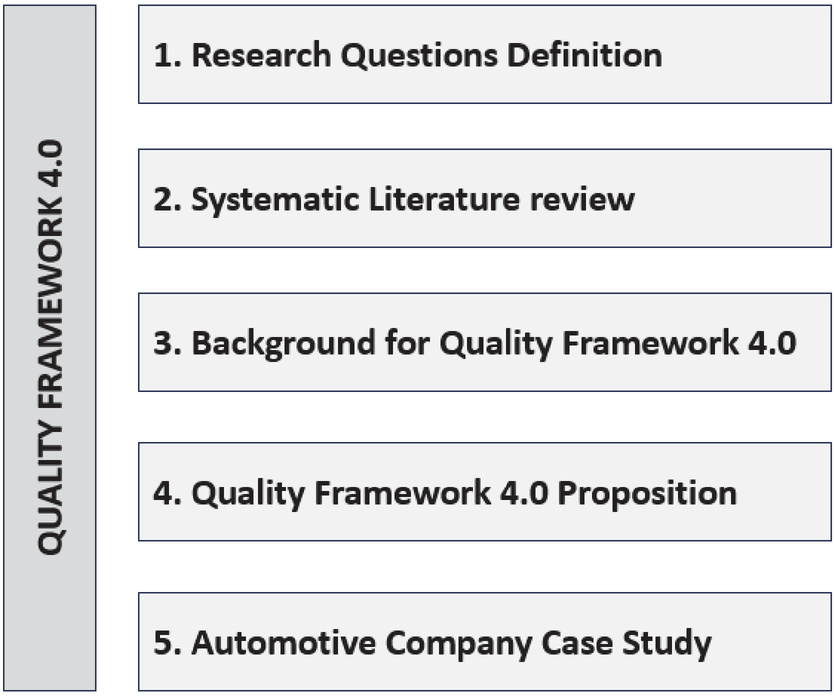

FIGURE 1 – Study structure

5, conclusions on the chapter 6, limitation of the research on the chapter 7 and additional opportunities on the chapter 8. Each section aims to provide a comprehensive exploration of the subject, contributing valuable insights to the ongoing discourse on the integration of Six Sigma and Quality 4.0.

2 SYSTEMATIC LITERATURE REVIEW

This review is organized into two stages (Figure 2). In the first stage, research definition, we focus on answering research questions 1 and 2, identifying valuable literature gaps. In the second stage, research execution, we apply all the knowledge to propose a reliable portfolio of articles to support the study.

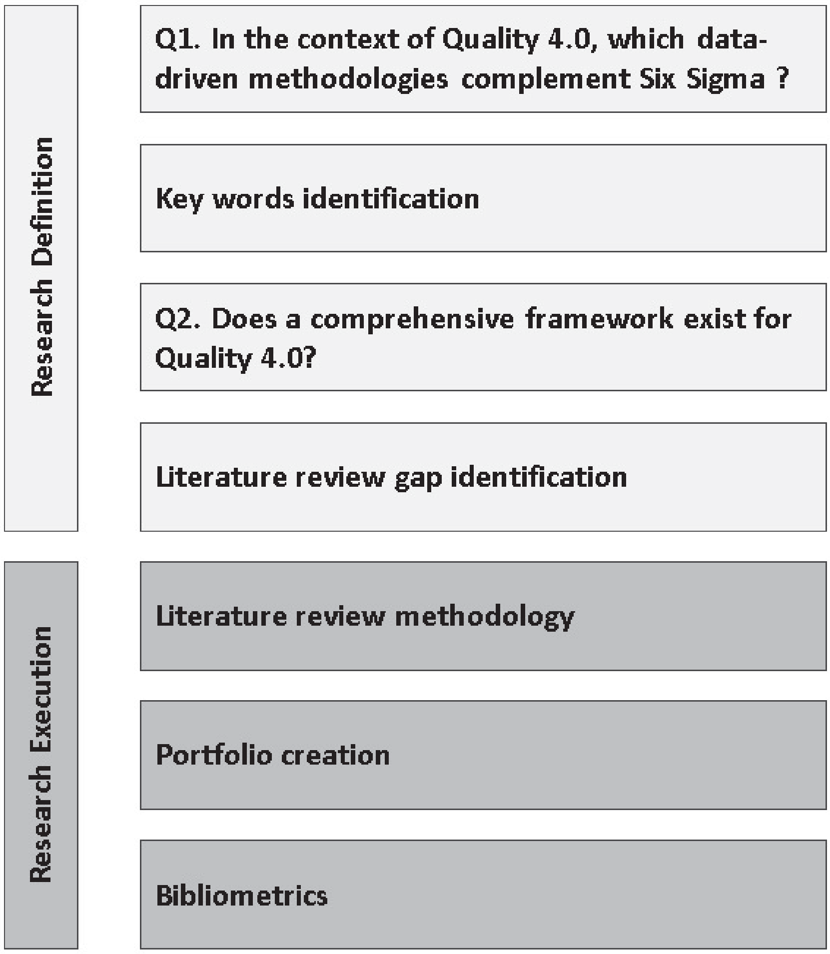

FIGURE 2 – Systematic literature review structure

2.1 RESEARCH QUESTION 1

This step of the review aims to understand the key methodologies to fulfill Six Sigma based on quantitative analysis, generating the foundational knowledge for the literature review.

To identify the key methodologies, a quantitative research based on Question 1 (Table 1) was applied to the Scopus and Web of Science databases, limited to the last 5 years (to find recent studies) and only articles (to ensure publication review).

Search	Main Key Words
SS + Q4.0	("six sigma"or "DMAIC"or "6 sigma") and ("quality4*"or "quality 4*" or "industry4*"or "industry 4*")

TABLE 1 – Question 1 Key words

The results (Table 2) were exported and counted for the number of similar keywords (Value Mapping or Stream mappning = Value Stream mapping | Fuzzy or AHP = MCDM | Digital Twin or Simulation = Simulation | Data science or Data Analytics = Big Data), which were then grouped into affinity clusters:

- Not a methodology (11,210 keywords) - includes keywords not related with the research, such as industry 4.0, KPI and Literature Review
- Quality (1,823 keywords) - includes keywords related to the quality environment, lean, Six Sigma, and tools.
- Methodologies (1,274 keywords) - includes keywords related to Six Sigma complementary methodologies.

Key word	Base	Articles	Key Words count
SS +	Scopus	2,902	14,307
Q4.0	WoS	2,121	

TABLE 2 – Question 1 quantitative result

From the 14.307 key words, presents on the Table 2, it was identified that 1.274 key words are related with methodologies, Table 3, bringing to lith that the methodologies that enhance six sigma performance are Agile, Value Stream Mapping (VSM), Process Mining, Simulation, Multi-Criteria Decision Making (MCDM), and Big Data.

2.2 RESEARCH QUESTION 2

Based on the findings of Research Question 1, a new search on the databases was proposed to identify existing frameworks that integrate this group of methodologies to fulfill Six Sigma (Table 3). Unfortunately, no results were identified; all searches with more than 3 keyword combinations resulted in 0 framework proposals on Scopus and Web of Science.

Methodology	Main Key Words	Sum
Big Data	"big data"	554
MCDM	"MCDM"or "multicri"	339
Value Stream Mapping	"VSM"	132
Simulation	"simulation"or "twin*"	97
Process Mining	"process mining"	66
Agile	"agile"	59
Sum		1,274

TABLE 3 – Cluster - Methodologies

2.3 LITERATURE REVIEW GAP

The examination of the assembled portfolio of articles reveals a notable lacuna that presents an opportunity to contribute substantively to academic scholarship and support corporate endeavors in the realm of quality enhancement. Specifically, there exists a discernible absence of a comprehensive framework adept at harmonizing diverse methodologies within the expansive domain of Quality 4.0.

As articulated by (Antony et al., 2020), the synergy between Six Sigma and Industry 4.0 remains under-explored, signifying a critical avenue for prospective research to delve into the formulation of an integration framework. Furthermore, insights underscore the pertinence of additional research in elucidating the framework and strategic considerations to guide industries and policymakers. Concomitantly, (Vinodh et al., 2020) identifies a dearth of studies concerning frameworks that seamlessly integrate Industry 4.0 tools with principles of continuous improvement.

Emphasizing the exigency of the matter, (Empl et al., 2023) asserts that the neglect of digital technology exploitation represents a pivotal gap warranting immediate attention. Recognizing the latent possibilities within Quality 4.0 technologies, (Escobar et al., 2022) advocates for the incorporation of a more diverse array of technologies into a unified framework, aligning with the sentiments expressed by (Chiarini, 2020). Regrettably, extant frameworks tend to be unifocal, adopting a solitary technique such as Data Mining (Ghosh; Maiti, 2014), Process Mining (Graafmans et al., 2021), or Big Data (Laux et al., 2017).

2.4 RESEARCH METHODOLOGY

Conducting a thorough literature review is a cornerstone in constructing a robust portfolio to support scholarly inquiries. In this regard, the Methodi Ordinatio methodology (Pagani et al., 2022) offers a structured and efficient approach, demonstrating pioneering efforts in handling input data for scientific publications. The procedural steps for ordination are illustrated in Figure 3, and visual maps depicting authors' co-citations, journal co-citations, and keyword co-occurrence networks were crafted using VOSviewer software, version 1.6.19 (Eck; Waltman, 2010).

Pagani's method, as showcased in Figure 3, presents a systematic means to curate an article portfolio based on impact factor, number of citations, and year of publication. This methodology has gained widespread adoption for supporting review studies, as evidenced by its inclusion in 180 articles according to Scopus data up until September 2023.

FIGURE 3 – Illustration of research method steps based on (Pagani et al., 2022)

Initiating with Steps 1 that involves articulating the research intention and devising key strategies for database searches. Following this preliminary exploration, Web of Science and Scopus were selected due to their extensive article coverage. Exclusively articles and publications from the past 5 years constituted the research filters. Step 2 setup key words identified on the research question 1 and filters based on the methodi ordinatio methodology. Step 3 means the execution of the searches on the selected databases, and Step 4 focused on cleaning the portfolio by removing any duplicate entries.

Step 5 involved collecting metrics such as Impact Factor (IF), Year of Publication, and Number of Citations (Ci). These metrics were retrieved from the publisher websites (Scopus and Web of Science). Defining parameters $\Delta = 7$, $\lambda = 5$, and $\Omega = 1$ aimed to accentuate new and pertinent publications. Step 6 applied the InOrdinatio calculation and remove low significant articles, coupled with the exclusion of studies with low importance (InOrdinatio < 50), as per Equation (2.1), and references detailed in Table 4.

$$\begin{aligned} InOrdinatio = [\Delta * (IF)] - [\lambda * (\frac{ResearchYear - PubYear}{CitedHalfLife})] \\ + [\Omega * (\frac{Ci}{(ResearchYear + 1) - PubYear})] \end{aligned} \tag{2.1}$$

Argument	Description
Δ	Value ranging from 0 to 10 Importance of research metrics
IF	Journal metric
λ	Value ranging from 0 to 10 Importance of portfolio currency research
Ω	Value ranging from 0 to 10 Importance of annual average citations
ResearchYear	Year when the research is conducted
PubYear	Year when the paper was published
CitedHalfLife	Median Cited Half-Life of Journals (JCR)
Ci	Number of Citations

TABLE 4 – InOrdinatio reference

Concluding with Steps 7, 8, and 9, filtering procedures for Title, Abstract, and Full article reading were executed, culminating in the formation of an article portfolio that harmoniously integrates both quantitative and qualitative evaluations.

2.5 PORTFOLIO CREATION

In light of the findings from Research Question 1, a set of keywords was established as outlined in Table 3. Subsequently, the Methodi Ordinatio was systematically applied to each combination of Six Sigma and various methodologies, as illustrated in Table 5, to identify the most pertinent and recent studies in the field. The synthesis of these investigations resulted in the formation of a comprehensive portfolio comprising 27 scholarly articles.

Key word	**Base**	**Search**	**Duplicates**	**Ordinatio**	**Filter Title**	**Filter Abstract**	**Filter Article**
SS +	Scopus	38	60	41	13	10	4
Agile	WoS	52					
SS +	Scopus	61	116	77	19	17	4
VSM	WoS	92					
SS +	Scopus	20	20	11	9	8	5
PM	WoS	5					
SS +	Scopus	116	209	141	25	14	5
Simulation	WoS	165					
SS +	Scopus	28	49	32	15	8	4
MCDM	WoS	39					
SS +	Scopus	31	68	49	20	16	5
Big data	WoS	55					
	Sum	702	522	351	101	72	27

TABLE 5 – Application of Methodi Ordinatio to Generate the Article Portfolio

TABLE 6 – Methodi ordinatio application to generate Article's portfolio - Agile

TYPE	Ranking	Authors	Title	Journal	FI	Year	Ci	InOrdinatio
Agile	7	Tripathi, V., Chattopadhyaya, S., Mukhopadhyay, A.K., Sharma, S., Singh, J., Pimenov, D.Y. and Giasin, K.	An innovative agile model of smart lean–green approach for sustainability enhancement in industry 4.0	Journal of Open Innovation: Technology, Market, and Complexity	5,1	2021	41	322
Agile	8	Thomas, A.	Developing an integrated quality network for lean operations systems	Business Process Management Journal	6,2	2018	31	260
Agile	14	Hariyani, D. and Mishra, S.	An analysis of drivers for the adoption of integrated sustainable-green-lean-six sigma-agile manufacturing system (ISGL-SAMS) in Indian manufacturing industries	BENCHMARKING-AN INTERNATIONAL JOURNAL	7,4	2023	12	135
Agile	40	Salleh, N.M. and Nohuddin, P.N.	Comparative study between lean six sigma and lean-agile for quality software requirement	International Journal of Advanced Computer Science and Applications	1,8	2019	6	54

TABLE 7 – Methodi ordinatio application to generate Article's portfolio - VSM

TYPE	Ranking	Authors	Title	Journal	FI	Year	Ci	InOrdinatio
VSM	13	Dinis-Carvalho, J., Guimaraes, L., Sousa, R.M. and Leao, C.P.	Waste identification diagram and value stream mapping A comparative analysis	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2019	18	176
VSM	18	Mishra, A.K., Sharma, A., Sachdeo, M. and Jayakrishna, K.	Development of sustainable value stream mapping (SVSM) for unit part manufacturing A simulation approach	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2019	14	148
VSM	46	Wang, F.-K., Rahardjo, B. and Rovira, P.R.	Lean Six Sigma with Value Stream Mapping in Industry 4.0 for Human-Centered Workstation Design	SUSTAINABILITY	5	2022	6	77
VSM	56	Fathurohman, D.M.H., Purba, H.H. and Trimarjoko, A.	Value stream mapping and six sigma methods to improve service quality at automotive services in Indonesia	Operational Research in Engineering Sciences: Theory and Applications	8,1	2021	1	63

TABLE 8 – Methodi ordinatio application to generate Article's portfolio - PM

TYPE	Ranking	Authors	Title	Journal	FI	Year	Ci	InOrdinatio
PM	1	Butt J.	A conceptual framework to support digital transformation in manufacturing using an integrated business process management approach	Designs	3,4	2020	45	338
PM	2	Graafmans T.; Turetken O.; Poppelaars H.; Fahland D.	Process Mining for Six Sigma: A Guideline and Tool Support	Business and Information Systems Engineering	8,9	2021	17	181
PM	5	Kregel I.; Stemann D.; Koch J.; Coners A.	Process Mining for Six Sigma: Utilising Digital Traces	Computers and Industrial Engineering	9,7	2021	10	137
PM	7	Ramires F.; Sampaio P.	Process mining and lean six sigma: a novel approach to analyze the supply chain quality of a hospital	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2022	2	64
PM	8	Yu C.-M.; Huang T.-H.; Chen K.-S.; Huang T.-Y.	Construct Six Sigma DMAIC Improvement Model for Manufacturing Process Quality of Multi-Characteristic Products	Mathematics	2,9	2022	6	62

TABLE 9 – Methodi ordinatio application to generate Article's portfolio - Simulation

TYPE	Ranking	Authors	Title	Journal	FI	Year	Ci	InOrdinatio
Simulation	7	Uriarte, A.G., Ng, A.H.C. and Moris, M.U.	Bringing together Lean and simulation: a comprehensive review	INTERNATIONAL JOURNAL OF PRODUCTION RESEARCH	14,6	2020	39	375
Simulation	14	Arafeh, M., Barghash, M.A., Haddad, N., Musharbash, N., Nashawati, D., Al-Bashir, A. and Assaf, F.	Using six sigma DMAIC methodology and discrete event simulation to reduce patient discharge time in king hussein cancer center	Journal of Healthcare Engineering	2,9	2018	36	272
Simulation	20	Bhat, V.S., Bhat, S. and Gijo, E.V.	Simulation-based lean six sigma for Industry 4.0: an action research in the process industry	INTERNATIONAL JOURNAL OF QUALITY AND RELIABILITY MANAGEMENT	4,9	2021	29	237
Simulation	38	Ahmed, A., Page, J. and Olsen, J.	Enhancing Six Sigma methodology using simulation techniques: Literature review and implications for future research	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2020	13	141
Simulation	93	Ahmed, A., Page, J. and Olsen, J.	A comparison of three simulation methodologies for a Lean Six Sigma manufacturing project - a business case study	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2019	4	78

TABLE 10 – Methodi ordinatio application to generate Article's portfolio - MCDM

TYPE	Ranking	Authors	Title	Journal	FI	Year	Ci	InOrdinatio
MCDM	2	Yadav, G., Luthra, S., Huisingh, D., Mangla, S.K., Narkhede, B.E. and Liu, Y.	Development of a lean manufacturing framework to enhance its adoption within manufacturing companies in developing economies	JOURNAL OF CLEANER PRODUCTION	15,8	2020	119	943
MCDM	11	Rehman, S.T., Khan, S.A., Kusi-Sarpong, S. and Hassan, S.M.	Supply chain performance measurement and improvement system: A MCDA-DMAIC methodology	Journal of Modelling in Management	3,7	2018	31	242
MCDM	15	Pakdil, F., Toktas, P. and Can, G.F.	Six sigma project prioritization and selection: a multi-criteria decision making approach in healthcare industry	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2021	15	155
MCDM	17	Singh, M., Rathi, R., Antony, J. and Garza-Reyes, J.A.	A toolset for complex decision-making in analyze phase of Lean Six Sigma project: a case validation	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2023	11	127

TABLE 11 – Methodi ordinatio application to generate Article's portfolio - Big

BIG	3	Belhadi, A., Kamble, S.S., Zkik, K., Cherrafi, A. and Touriki, F.E.	The integrated effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the environmental performance of manufacturing companies: The case of North Africa	JOURNAL OF CLEANER PRODUCTION	15,8	2020	115	915
BIG	22	Koppel, S. and Chang, S.	MDAIC - a Six Sigma implementation strategy in big data environments	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2021	9	113
BIG	31	Escobar, C.A., Macias, D., McGovern, M., Hernandez-de-Menendez, M. and Morales-Menendez, R.	Quality 4.0-an evolution of Six Sigma DMAIC	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2022	4	78
BIG	38	Ahmed, A., Olsen, J. and Page, J.	Integration of Six Sigma and simulations in real production factory to improve performance - a case study analysis	INTERNATIONAL JOURNAL OF LEAN SIX SIGMA	7,2	2022	2	64
BIG	46	Kumar, P., Bhadu, J., Singh, D. and Bhamu, J.	Integration between Lean, Six Sigma and Industry 4.0 technologies	International Journal of Six Sigma and Competitive Advantage	1,8	2021	6	54

2.6 BIBLIOMETRICS

Bibliometrics provides a systematic method for evaluating academic publications and their impact. It involves the quantitative analysis of bibliographic data, such as citations, to gain insight into patterns of publication, authorship, and research influence. Bibliometric techniques are widely used in academia and research institutions to assess the impact of research papers, journals, and even individual researchers. By examining citation patterns and publication trends, bibliometrics allows scholars to gauge the significance and influence of specific works within a particular field, (Borgman; Furner, 2002).

Table 12 presents the list of Journals indicating an alignment with the article scope. Figure 4 shows that the most cited authors are Garza-Reyes J. and Antony J. and reinforces the discovery that there is no multifeature framework.

Journal	Articles
I. J. OF LEAN SIX SIGMA	10
J. OF CLEANER PRODUCTION	2
SUSTAINABILITY	1
MATHEMATICS	1
DESIGNS	1
JOURNAL OF HEALTHCARE ENGINEERING	1
OPERATIONAL RESEARCH IN E. S.	1
I. J. OF PRODUCTION RESEARCH	1
BUSINESS AND INFORMATION SYSTEM E.	1
COMPUTERS IN INDUSTRY	1
J. OF MODELLING IN MANAGEMENT	1
I. J. OF SIX SIGMA AND COMPETITIVE	1
JOURNAL OF OPEN INNOVATION	1
BUSINESS PROCESS MANAGEMENT J.	1
I. J. OF BENCHMARKING	1
I. J. OF ADVANCED COMPUTER S. and A.	1
I. J. OF QUALITY AND RELIABILITY	1
COMPUTERS AND INDUSTRIAL ENG	1
SUM	27

TABLE 12 – Portfolio list of journals

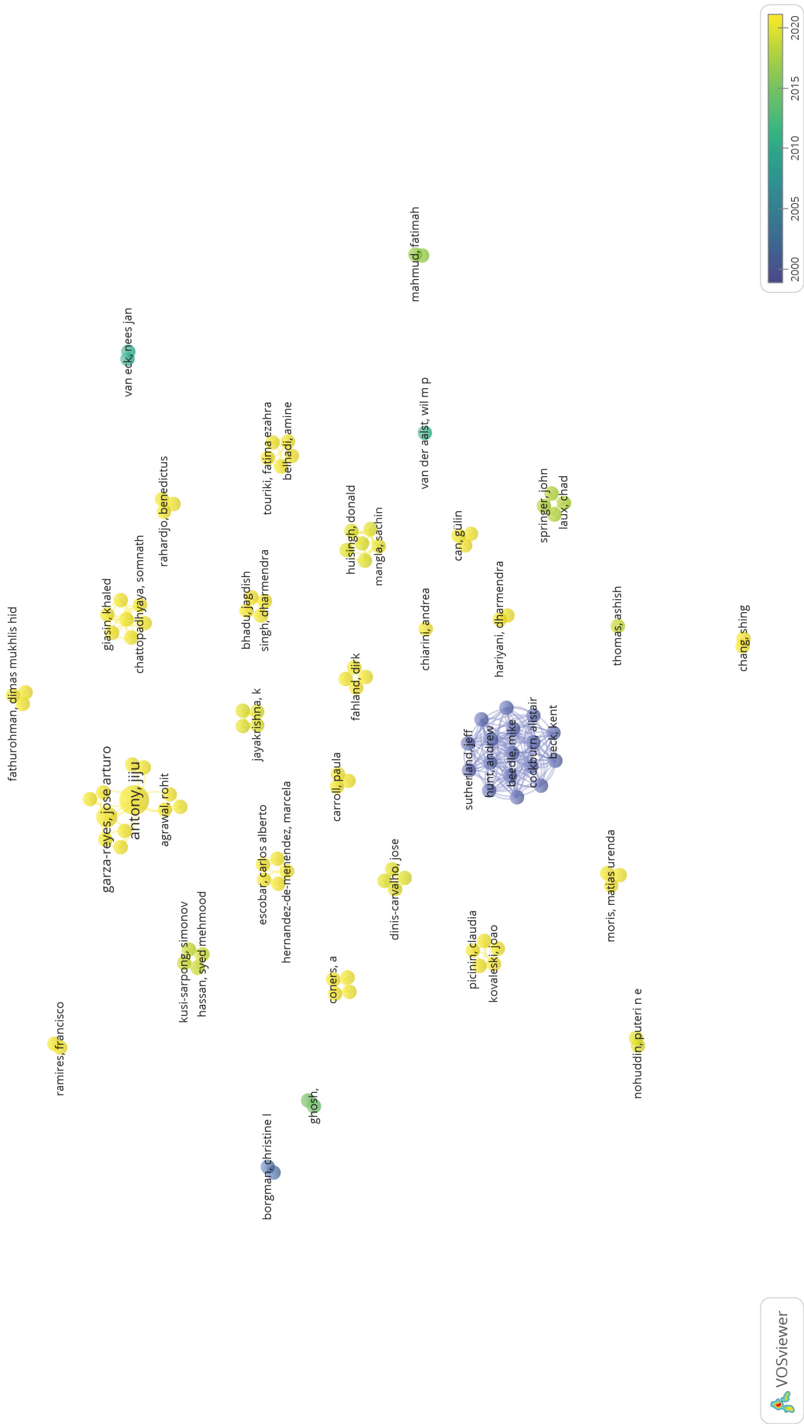

FIGURE 4 – Portfolio author network generated on VOSviewer

Each methodology presents an isolated cluster formation. The word cloud, Figure 5, shows that the portfolio of the article is consistent with the research proposal to integrate a group of methods within a Six Sigma environment.

The raw publication year distribution presents a growing trend and selected articles follow a similar trend. (Figure 6)

The bibliometric analysis conducted as part of the study provides valuable

FIGURE 5 – Portfolio key words cloud

Raw portfolio	
Year	**Articles**
2018	25
2019	76
2020	90
2021	98
2022	143
2023	120
Sum	**552**

Final portfolio	
Year	**Articles**
2018	3
2019	4
2020	5
2021	8
2022	5
2023	2
Sum	**27**

FIGURE 6 – Portfolio publication year distribution

insights into the research topic. The analysis reveals a trend of increasing articles published since 2018, indicating the growing importance and interest in the integration of Six Sigma and Quality 4.0. It also highlights the limited interaction among the authors presented in the network connection, suggesting a need for more collaboration and knowledge sharing in this field. Furthermore, the analysis confirms the alignment of the research portfolio with related journals and keywords, ensuring that the study is grounded in relevant literature and contributes to the ongoing discourse in the field.

3 BACKGROUND

This chapter aims to provide a vital contextual lens for understanding the methodologies. By delving into bibliometric, foundational principles and integrations with Six Sigma that have shaped the current landscape. As we unravel the tapestry of each methodology, the background introduction sets the path for a comprehensive framework that will be covered in the following section.

3.1 AGILE

Agile methods emerged in the 1990s, primarily focused on the software development environment, challenging established traditional management methods. However, Agile methods have found applications in various fields, including industry. In 2011, Google Trends data showed a shift from the term "agile software development"to "agile portfolio management,"indicating its relevance in other areas as well (Beck et al., 2001).

- Flexibility and Iterative Approach

Agile methods emphasize the development of flexible plans that allow for changes throughout the project, even after the finalization phase. These methods utilize short and iterative cycles with deliverables at the end of each cycle. The focus is on the efficiency of small teams, regardless of the project's actual size (Salleh; Nohuddin, 2019).

- Time-Boxing and Scrum

One of the key processes in Agile methods is the concept of time-boxing. It aims to deliver specific activities within a defined time frame, regardless of their completion status. The priority is to obtain feedback on the project's results, allowing for analysis and adjustments during each sprint. This approach provides better control for the product owner, enabling them to prioritize tasks before the next deadline. (Tripathi et al., 2021)

Scrum, one of the most widely used Agile methods, is known for its simplicity, few artifacts, and rules. It focuses on maintaining the visibility of the project's progress, ensuring that all team members are aware of the project's stage and necessary changes to achieve desired goals. A crucial facilitator in Scrum is the Scrum Master, who possesses extensive knowledge of Scrum rules and practices, and is responsible for the project's success (Schwaber, 2004).

- Agile Manifesto

In February 2001, sixteen individuals with extensive experience in Agile methods came together to identify commonalities among the various Agile methods they had practiced. This gathering resulted in the Agile Manifesto. Based on shared values such as trust and respect among team members, the Agile Manifesto promoted an organizational model focused on individuals, where people would work towards a common goal beyond delivering high-quality products to customers (Beck et al., 2001).

The manifesto emphasizes that the term "methodology"should not be taken as something rigid, but rather as a means to achieve balance, using only what is necessary and simple. The Agile Manifesto aims to help software developers, methods, and organizations become more agile through four objectives and twelve principles (Beck et al., 2001).

- Objectives:

1. Individuals and interactions over processes and tools.
2. Working software over comprehensive documentation.
3. Customer collaboration over contract negotiation.
4. Responding to change over following a plan.

- Principles:

1. Satisfy the customer through early and continuous delivery of valuable software.
2. Welcome changing requirements, even late in development. Agile processes harness change for the customer's competitive advantage.
3. Deliver working software frequently, from a couple of weeks to a couple of months, with a preference for shorter timescales.
4. Business people and developers must work together daily throughout the project.
5. Build projects around motivated individuals. Give them the environment and support they need, and trust them to get the job done.
6. The most efficient and effective method of conveying information within a development team is face-to-face conversation.
7. Working software is the primary measure of progress.

8. Agile processes promote sustainable development.
9. The sponsors, developers, and users should be able to maintain a constant pace indefinitely.
10. Continuous attention to technical excellence and good design enhances agility.
11. Simplicity - the art of maximizing the amount of work not done - is essential.
12. The best architectures, requirements, and designs emerge from self-organizing teams.
13. At regular intervals, the team reflects on how to become more effective, then tunes and adjusts its behavior accordingly.

- Integration Agile & Six Sigma:

Six Sigma integrates Agile practices for adaptability in complex environments. An iterative approach integrates various lean tools sequentially, ensuring cumulative impact across operational phases (Thomas, 2018). Implement Six Sigma's Define, Measure, Analyze, Improve, and Control (DMAIC) phases in iterative cycles, ensuring that each cycle contributes to incremental enhancements. Figure 7

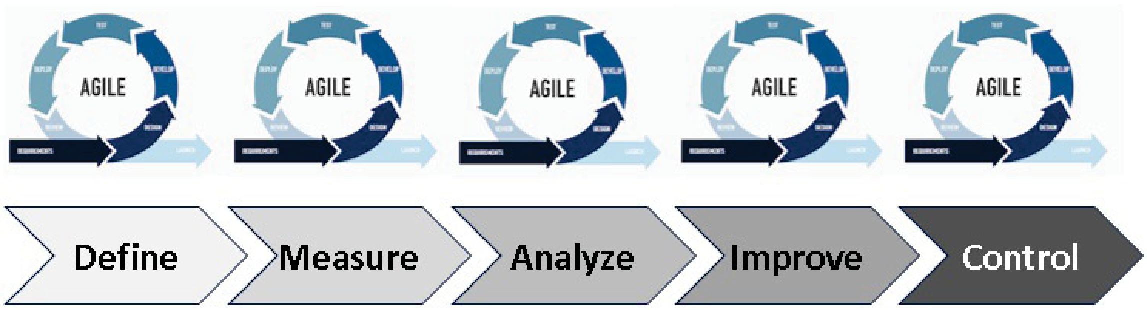

FIGURE 7 – Six Sigma-Agile cycle (Tripathi et al., 2021; Thomas, 2018)

Agile accelerates Six Sigma deployment, fine-tuning parameters, and optimizing quality improvement (Hariyani; Mishra, 2023).

3.2 VALUE STREAM MAPPING

Value Stream Mapping (VSM) is a lean process improvement technique developed by Rother and Shook in 1999. VSM aims to understand the value-added and non-value-added activities in both information and material flow within a value stream.

It has been proven to be effective in increasing the visibility and transparency of the process, as well as reducing lead time and inventory (Rother, 1999).

In 1995, VSM was introduced as a set of techniques for the identification of waste within individual value streams. These techniques included process activity mapping, supply chain response matrix, production variety funnel, quality filter mapping, demand amplification mapping, decision point analysis, and physical structure mapping. However, these techniques were limited in their ability to reveal and visualize the link between information and physical flows from the perspective of the value stream. To address this limitation, Rother and Shook proposed an improved version of VSM in 1999. This version aimed to clarify the value-adding and non-value-adding activities in both information and physical flows through a systematic lean strategy for waste elimination and continuous improvement from the users' perspective (Mishra et al., 2019) and (Dinis-Carvalho et al., 2019).

- VSM Phases:

The application of VSM involves a four-phase procedure for value and waste analysis in a value stream 5:

1. Selecting a product family.
2. Drawing the current state map (CSM), which involves collecting process data to depict the value-adding and non-value-adding activities of the current state.
3. Drawing the future state map (FSM), which outlines improvement guidelines based on Rother and Shook's VSM theory.
4. Achieving the future state by developing a value stream plan and implementing management guidelines.

- Integration VSM & Six Sigma:

Value Stream Mapping has found widespread use in various companies, including both manufacturing and services. It proves useful for understanding the ongoing process conditions and is highly effective in identifying sub-process bottlenecks that impact current issues. These conditions encompass both the current stage and the future stage, as illustrated in Figure 8, and are closely related to the Define phase in Six Sigma (Fathurohman et al., 2021).

While VSM and DMAIC each have their advantages and disadvantages, they can be integrated to leverage their strengths and mitigate their weaknesses. VSM excels

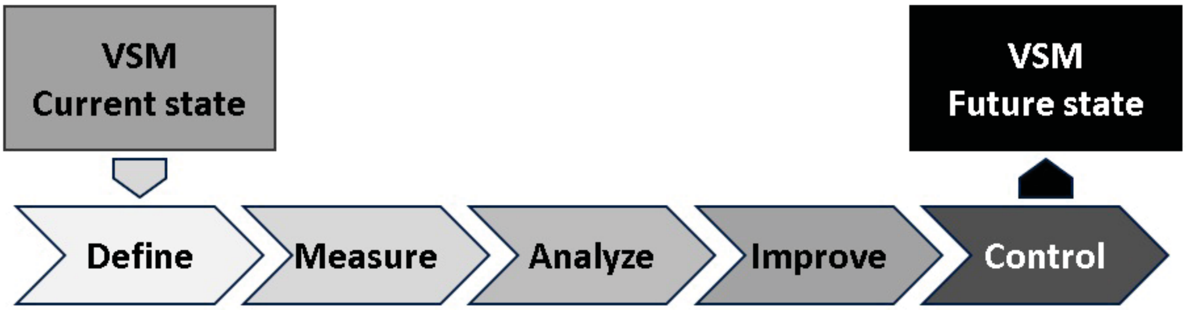

FIGURE 8 – Current and Future states

at accurately identifying production problems but may lack solutions, whereas DMAIC provides a structured problem-solving approach but may struggle to identify production issues. Therefore, integrating VSM and DMAIC becomes a feasible approach to harness their advantages and address their limitations (Wang et al., 2022).

3.3 PROCESS MINING

In this section, we will dive into the techniques and concepts related to process mining. The main objective of process mining is to abstract event logs and leverage them to gain insights into process performance, identify bottlenecks, and drive continuous improvement. We will begin by introducing event data as stored in event logs. Next, we will provide an in-depth overview of the different aspects of process mining, including process discovery, conformance checking, and enhancement techniques. (Zelst et al., 2021)

The rapid transition towards Industry 4.0 in business processes has found a powerful ally in Business Process Management (BPM). Emerging technologies present a significant challenge for organizations in controlling and managing information flow across numerous devices. Process Mining (PM) complements traditional business process modeling techniques to address this challenge. (Ramires; Sampaio, 2022)

- Event Logs

Event logs serve as the foundation for process mining analysis. They capture the sequence of activities performed within cases (instances of the process). Each row in the event log represents an event, which corresponds to the execution of a specific activity. The columns in the event log contain attributes associated with the events. In addition to the mandatory attributes like Case Identifier, Timestamp, and Activity, event logs may also include information about the resource executing the activity and transactional data indicating the activity's state. (Leoni; Dündar, 2020)

The composition of an event log includes various attributes associated with the events recorded within the log. These attributes help provide a comprehensive understanding of the executed activities and their context. The main attributes applied on the study are presented on the Figure 9.

Case	Activity	Start	End	Resource
1	Alert	11/05/2023 10:35:00	11/05/2023 17:22:00	ANA1

FIGURE 9 – Event Log reference

- Case Identifier: This attribute identifies the case or instance to which the event belongs. It helps group related events together.
- Timestamp: The timestamp attribute indicates the date and time at which the event occurred. It provides a chronological order of events within the log.
- Activity: The activity attribute represents the specific action or task that was executed. It captures the name or description of the activity.
- Resource: This attribute identifies the resource or person responsible for executing the activity. It helps track the involvement of different resources in the process.

- Process Models

Alongside event logs, process mining techniques utilize process models to provide a visual representation of how a process should be executed. Process models offer a formal description of the process flow, enabling organizations to analyze and improve their processes systematically. The Business Process Model and Notation (BPMN) formalism has become the industry standard for process modeling due to its mathematical grounding and human interpretability. (Aalst, 2011) and (Aalst, 2016)

- Process Discovery

Process discovery is a fundamental aspect of process mining. It involves automatically constructing a process model based on the event log data. Various algorithms and techniques have been developed for process discovery, including heuristic mining, alpha-algorithm, and fuzzy mining. These algorithms analyze the event log to identify common patterns, dependencies, and control flow within the process, ultimately generating a process model that represents the observed behavior. (Augusto et al., 2017)

- Conformance Checking

Conformance checking is another crucial component of process mining. It aims to compare the actual execution of a process, as recorded in the event log, with the expected behavior defined by the process model. By conducting conformance checking, organizations can identify deviations, inefficiencies, or non-compliance within their processes. Conformance checking techniques include token-based replay, alignments, and fitness measures, which provide quantitative assessments of how well the observed data align with the modeled process. (Carmona et al., 2018)

- Enhancement Techniques

Process mining also offers enhancement techniques to improve process performance and address identified issues. These techniques leverage the insights gained from event logs and process models to optimize process flows, eliminate bottlenecks, and reduce inefficiencies. Enhancement techniques include process redesign, resource allocation optimization, and predictive analytics based on historical process data(Prado et al., 2023).

- Integration PM & Six Sigma:

The utility and applicability of PM in each DMAIC (Define, Measure, Analyze, Improve, Control) phase were categorized and summarized in Table 13. Here, (H) indicates high integration and impact, (M) signifies medium, and (L) denotes low, (Kregel et al., 2021), resulting on high impact on the Measure, Analysis and Control phases (Parulian et al., 2024).

PM Aspect	D	M	A	I	C
Discovery	M	H	H	L	H
Conformance	L	M	H	L	H
Enhancement	L	L	L	M	L
Benefits	L	H	H	L	M

TABLE 13 – PM Usability in SS from (Kregel et al., 2021)

Through the integration of PM and Six Sigma (SS) as illustrated in Figure 10, practitioners enhance their toolkit with an automated means to reorganize large volumes of process data. This rendering provides a clear structure for analysis, enabling the easier tracking of defective processes compared to other process analysis techniques.

Using a substantial amount of process-related data with agility and reliability, this integration proves valuable (Graafmans et al., 2021) and (Butt, 2020).

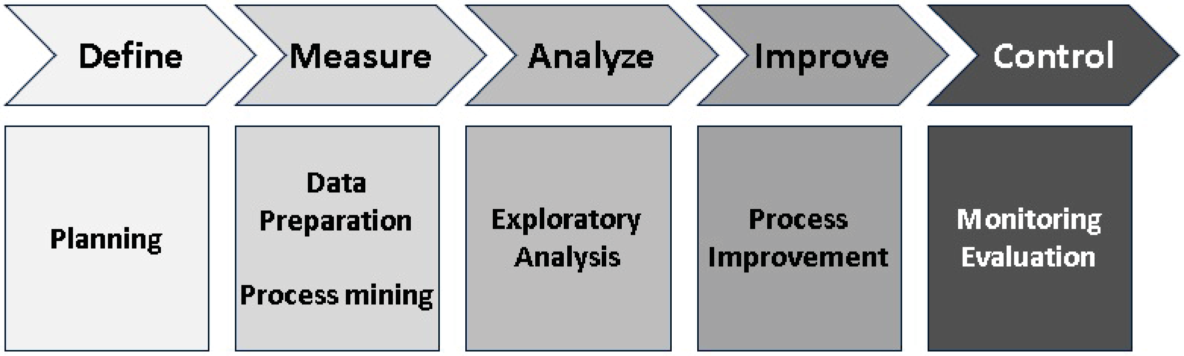

FIGURE 10 – integration PM and SS

The process mining methodology provides organizations with a powerful framework for analyzing, understanding, and improving their processes. Using event logs and process models, organizations can gain valuable insights into process performance, identify areas for improvement, and drive continuous optimization. The combination of process discovery, conformance checking, and enhancement techniques enables organizations to achieve higher efficiency, reduce costs, and enhance customer satisfaction. (Carmona et al., 2018)

3.4 SIMULATION

Six Sigma studies focusing on the improvement of production and service systems can benefit significantly from system simulation. Simulation provides a flexible platform for testing and verifying process improvement actions and plans. Literature indicates a growing interest in employing simulation in Six Sigma applications to enhance the quality and performance of various sectors such as manufacturing firms, healthcare systems, supply chain and logistics systems, banking, and government operations,(Ahmed et al., 2020).

Simulation is a powerful tool used before the construction of a new system or the alteration of an existing one. Its primary objective is to reduce the risk of not meeting specifications, optimize system performance, prevent under- or overuse, and eliminate unforeseen bottlenecks. Simulation models are composed of several critical components, including performance measures, input variables, system entities, and functional relationships.

System simulation paradigm that constructs a mathematical model of a complex, nonlinear system using stocks and flows. Inspired by control theory from electronics engineering. Simulation explains dynamic system behaviors through feedback loops. This approach is particularly beneficial for understanding and managing complex systems in a holistic manner.

Several simulation tools are available to support Six Sigma projects, each offering unique advantages:

- Discrete Event Simulation (DES): Useful for modeling systems where events occur at discrete points in time, DES helps in analyzing workflow, resource utilization, and process efficiency.
- Monte Carlo Simulation: This method uses random sampling to model the probability of different outcomes, providing a robust framework for risk analysis and decision-making.
- Agent-Based Modeling (ABM): ABM simulates the actions and interactions of autonomous agents, offering insights into complex systems and emergent behaviors.
- System Dynamics (SD): As mentioned, SD is ideal for modeling feedback loops and understanding the dynamic behavior of complex systems over time.

- Integration Simulation & Six Sigma:

Although the literature on the use of simulations in the define and measure phases of Six Sigma is limited, simulations can significantly augment Six Sigma methodologies. Simulation tools can complement existing tools during the define phase, providing a comprehensive set of instruments to complete the loop of knowledge. Specifically, Simulation offers valuable support during the define phase, helping Six Sigma professionals visualize and analyze complex interactions and dependencies. (Uriarte et al., 2020a)

Simulation allows for the exploration of infinite hypothetical scenarios, both positive and negative, that may impact the process. This capability is particularly valuable in the Analyze, Improve, and Control phases of the DMAIC (Define, Measure, Analyze, Improve, Control) cycle. By simulating various scenarios, professionals can identify potential issues, test solutions, and optimize processes before implementing changes in the real world. (Ahmed et al., 2020).

The integrated methodology illustrated in Figure 11 proposes that the "define"stage of DMAIC specifies the set of Key Performance Indicators (KPIs) that characterize the performance of the system. In the "analysis"phase, data is prepared for simulation, including current KPI measures. A simulation model estimates the performance of the underlying system during the "analysis"stage. Multiple simulation runs generate average KPI values estimated under stochastic and dynamic conditions, presenting challenges for subsequent DMAIC stages of analysis and improvement, (Bhat et al., 2021) and (Arafeh et al., 2018).

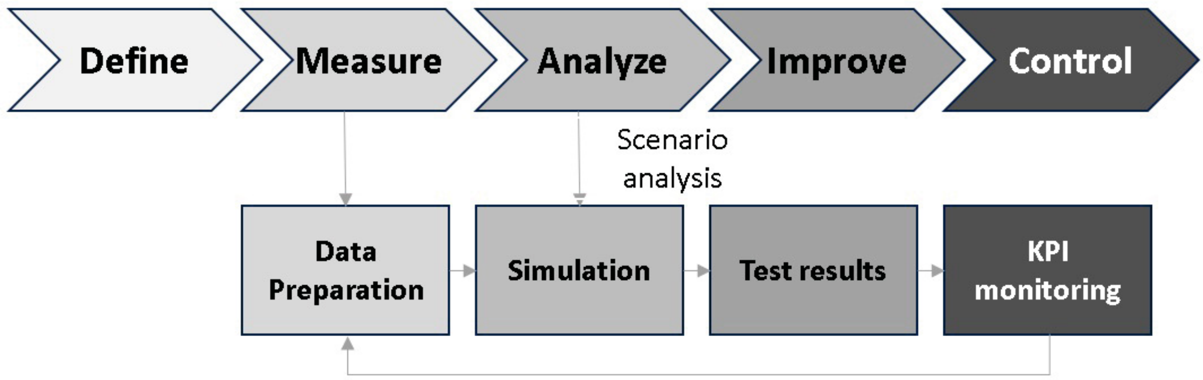

FIGURE 11 – Integration of Simulation and SS

3.5 MULTI-CRITERIA DECISION MAKING (MCDM)

Multi-criteria Decision Making (MCDM) is a field of decision science that has evolved over the past 40 years and has captivated researchers due to its diverse applications and methodologies. During this period, almost 70 MCDM techniques have been developed and explored. (Sriram et al., 2022).

The diversity of MCDM techniques is both a strength and a challenge. This diversity offers flexibility in choosing the most suitable technique for a given problem from a wide array of options. However, the extensive variety also makes the selection of the appropriate technique more complex, as each method has its own strengths and weaknesses. (Aruldoss et al., 2013).

One of the most renowned MCDM techniques is the Analytic Hierarchy Process (AHP), developed by Thomas L. Saaty in the 1980s. Although several variants of AHP have been introduced over time, the fundamental procedure remains highly effective for complex decision-making problems. The AHP methodology can be broken down into three main steps: Decomposition of the problem, Comparative Judgment, and Generation of Priorities. (Saaty et al., 2022).

- Decomposition: This step involves breaking down the decision problem into a hierarchy of criteria and sub-criteria. The assessment is conducted through a series of pairwise comparisons, where decision-makers answer questions such as, "How much more important is criterion A than criterion B?"

- Comparative judgment: In this phase, pairwise comparisons are used to evaluate the alternatives with respect to each criterion. Decision-makers assess the relative preference of alternatives by answering questions like, "With respect to criterion A, how much more do you prefer alternative X to alternative Y?"
- Generation of priorities: The final step in AHP involves synthesizing the results of pairwise comparisons to generate a set of priorities. This is done by combining the weights of the criteria with the scores of the alternatives to calculate a total score for each option, which can then be used to rank the alternatives. (Rehman et al., 2018).

The AHP methodology is particularly powerful due to its ability to handle both qualitative and quantitative data, making it applicable to a wide range of decision-making scenarios. Despite its complexity, AHP provides a structured and systematic approach to tackling decision problems, ensuring that all relevant factors are considered and appropriately weighted. (Singh et al., 2023).

- Integration MCDM & Six Sigma:

Between the "analyze"and "improve"phases, as depicted in Figure 12, after determining the root causes of problems (defects) and understanding why defects have occurred, the comparison and prioritization of solution opportunities take place, (Pakdil et al., 2020) and (Yadav et al., 2020).

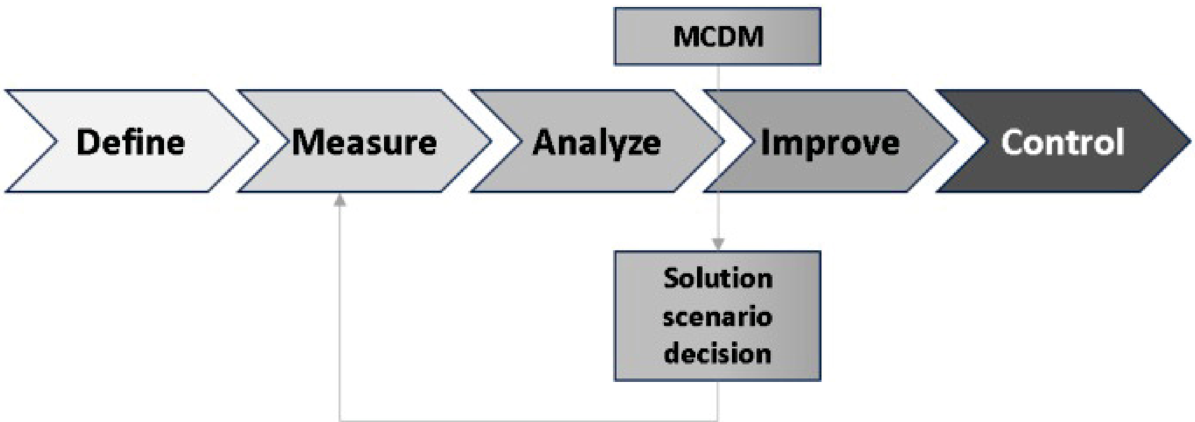

FIGURE 12 – Integration of MCDM and SS

3.6 BIG DATA

The dawn of the digital age has brought about an unprecedented explosion of data. Firms in 2010 generated approximately seven exabytes of data, a figure dwarfed by the six exabytes generated by consumers in the same period. This data deluge presents both a challenge and an opportunity for organizations committed to quality improvement. Big Data analytics (BDA) emerges as a powerful tool to harness these data, offering insights that can revolutionize the way businesses approach quality. (Manyika et al., 2011).

BDA methodologies can be broadly categorized into three fundamental types: descriptive, predictive, and prescriptive. Each approach offers a unique lens through which to analyze data and extract actionable insights. (Sivarajah et al., 2016).

Descriptive analytics focuses on understanding the current state of affairs. It answers questions like "What is happening?"and "Why is it happening?"by analyzing historical data and identifying trends, patterns, and anomalies. This approach is particularly valuable for the following purposes: (Delen; Demirkan, 2013)

- Tracking Key Performance Indicators (KPIs): Monitoring metrics such as sales figures, inventory levels, and customer acquisition costs to gain a clear picture of operational efficiency.
- Identifying Areas for Improvement: Uncovering bottlenecks, inefficiencies, and deviations from expected performance, highlighting opportunities for optimization.
- Understanding Customer Behavior: Analyzing customer data to gain insights into purchasing patterns, preferences, and pain points, facilitating targeted improvements.

Predictive analytics takes historical data analysis a step further by using statistical models and machine learning algorithms to forecast future outcomes. This forward-looking approach enables organizations to: (Gandomi; Haider, 2015)

- Anticipate Demand Fluctuations: Predicting future product demand, enabling proactive inventory management and optimized production planning.
- Identify Potential Risks: Detecting patterns that suggest potential quality issues, allowing for preventative measures to be implemented before problems arise.
- Personalize Customer Experiences: Predicting customer needs and preferences, enabling businesses to offer customized solutions and targeted recommendations.

Prescriptive analytics represents the most advanced stage of BDA. It goes beyond simply predicting future results by recommending specific actions to achieve desired results. This proactive approach empowers businesses to: (Gupta et al., 2018)

- Optimize Processes in Real-Time: Continuously analyzing data and providing real-time recommendations to adjust processes, allocate resources, and maximize efficiency.
- Automate Decision-Making: Using predefined rules and algorithms to automate routine decisions, freeing up human resources for more complex tasks.
- Drive Innovation and Competitive Advantage: Identifying new opportunities for product development, market expansion, and strategic decision-making based on data-driven insights.

- Integration Big Data & Six Sigma:

The marriage of BDA and LSS methodologies presents a particularly potent synergy for Quality 4.0 initiatives. LSS, with its focus on waste reduction and process optimization, finds a powerful ally in BDA's ability to provide deep, data-driven insights. (Kumar et al., 2021).

- Continuous Process Improvement: BDA empowers organizations to monitor LSS project implementations in real-time, identifying deviations from expected outcomes and facilitating timely adjustments.
- Data-Driven Decision Making: BDA provides objective data to support decision-making throughout the DMAIC cycle (Define, Measure, Analyze, Improve, Control), ensuring that improvements are based on evidence rather than assumptions.

By aligning Six Sigma with smart, digital, and intelligent technologies, firms can enhance efficiency and customer value. Figure 13 illustrates the interdependence between Six Sigma methodology and Big Data characteristics, (Koppel; Chang, 2021), (Belhadi et al., 2020) and (Kumar et al., 2021).

One of the uses is for prescriptive analytics in the "control"phase, which relates to decisions optimizing performance by interpreting predictive analytics' results and early significant deviations to alert the quality system, (Ahmed et al., 2022) and (Escobar et al., 2022).

Chapter 3 of the thesis provided a comprehensive background for understanding the methodologies and contextualizing the research. The review conducted in this chapter aimed to identify valuable literature connection and establish the foundation for the framework.

The background provided crucial insights into the methodologies, their foundational principles, and integration's with Six Sigma, setting the stage for the development of

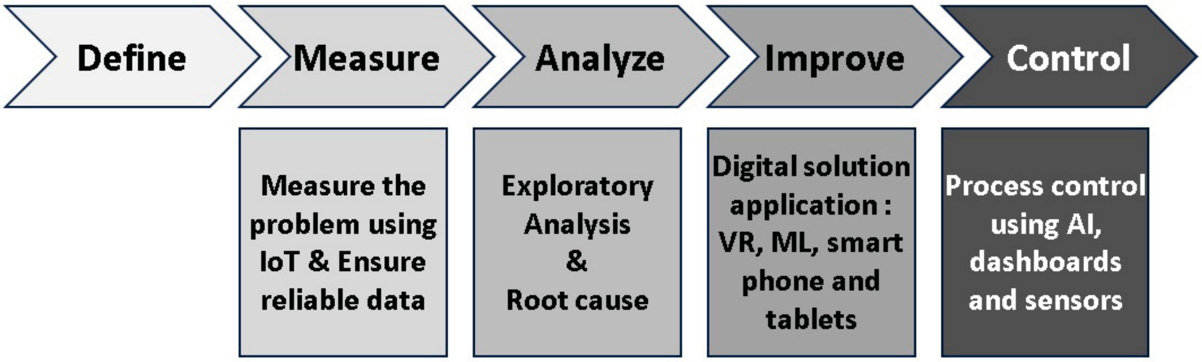

FIGURE 13 – Integration of Big Data and SS

a comprehensive framework. The insights gathered in this section form the bedrock for the proposed quality framework, elucidating the interconnections between diverse data-driven methodologies. This enables organizations to navigate the path toward Quality 4.0 concepts, fostering heightened efficiency, effectiveness, and overall excellence.

This chapter served as a contextual lens for understanding the methodologies and laid the groundwork for the subsequent sections that delve into the development of the framework proposition, case study, and further opportunities.

4 QUALITY FRAMEWORK FOR INDUSTRY 4.0

As we navigate the transformative landscape of Industry 4.0, the integration of advanced methodologies and technologies becomes imperative to achieve superior quality management. This chapter introduces a comprehensive Quality Framework for Industry 4.0, designed to seamlessly connect Agile principles with the visualization capabilities of Value Stream Mapping, the analytical power of Process Mining, the predictive insights from Simulation, the informed decision-making facilitated by Multi-criteria Decision Making, and the data-driven intelligence derived from Big Data analytics. Each element is strategically intertwined within the DMAIC (Define, Measure, Analyze, Improve, Control) framework, creating a cohesive and dynamic approach to quality improvement.

4.1 DEFINE

In the traditional DMAIC approach, the Define phase involves clearly outlining project objectives and scope (Tjahjono et al., 2010). Integrating Agile principles into this phase enhances this process by fostering a collaborative environment where project definitions and scope are continuously refined through team interactions (Hariyani; Mishra, 2023). Concurrently, Value Stream Mapping offers a visual representation of current processes, which helps create a shared understanding among cross-functional teams and aligns them towards common goals (Fathurohman et al., 2021). This combination ensures that project definitions are both well-informed and dynamically adjusted to evolving needs.

Define outcomes:

- Input: Project artifacts
- Output: Current Status / Non-value Process / Goals

4.2 MEASURE

During the Measure phase, Process Mining proves instrumental by leveraging data logs to deliver immediate and precise insights into process metrics. This capability is complemented by Agile iterations, which allow for ongoing adjustments to measurement strategies based on real-time data and shifting priorities (Zelst et al., 2021). While the standard DMAIC framework might follow a static measurement plan, the integration of Agile and Process Mining introduces flexibility and responsiveness, enhancing the accuracy and relevance of the measurement process (Graafmans et al., 2021).

Measure outcomes:

- Input:Event log / Define output
- Activities performances, conformity and compliance measurement

4.3 ANALYZE

In the Analyze phase, the traditional DMAIC methodology relies on systematic data analysis to identify root causes. By incorporating Agile experimentation, this phase gains the advantage of rapid scenario testing, allowing for iterative refinement of hypotheses (Ahmed et al., 2020). Additionally, Simulation provides a virtual environment to evaluate the impact of potential changes, improving the precision of root cause analysis. This dynamic interaction between Agile and Simulation enhances the traditional approach, ensuring that solutions are more accurately aligned with process complexities (Arafeh et al., 2018).

Analyze outcomes:

- Input:Measure output
- Constrains & Limitations identification / Future status simulation

4.4 IMPROVE

The Improve phase in standard DMAIC focuses on implementing solutions based on root cause analysis. The proposed data-driven framework integrates Agile's iterative improvement cycles with Multi-Criteria Decision Making (MCDM), (Saaty et al., 2022), which systematically evaluates and prioritizes multiple improvement opportunities. This combination ensures that the improvements are not only iterative and adaptable but also based on a comprehensive assessment of various criteria, thereby optimizing the effectiveness of the enhancement efforts (Pakdil et al., 2020).

Improve outcomes:

- Input:Analysis output
- Best performance scenario / Solution implementation

4.5 CONTROL

The Control phase aims to maintain process stability and ensure that improvements are sustained. In a traditional DMAIC framework, this involves monitoring process performance to ensure consistency. The integration of Big Data analytics significantly enhances this phase by enabling real-time processing of extensive data volumes (Manyika et al., 2011). This capability allows Agile teams to proactively identify and address deviations from the desired process performance, thereby ensuring continuous control and ongoing optimization in a way that traditional methods alone might not achieve (Escobar et al., 2022).

Control outcomes:

- Input:Improvement output
- Sustainable process feedback system / Final delivery

The proposed framework, Figure 14, leverages the strengths of each methodology, ensuring that the DMAIC process is enhanced with agility, precision, and data-driven insights. Agile principles foster a collaborative and adaptive environment, while Value Stream Mapping provides a clear visual representation of processes, promoting a shared understanding among cross-functional teams. Process Mining offers precise and real-time insight into process metrics, and simulation enables the testing of potential changes in a virtual environment. Multicriteria Decision Making systematically evaluates and prioritizes improvement opportunities, and Big Data analytics empower real-time monitoring and control of process performance.

In concluding this section have established the foundational principles of our proposed quality improvement framework. In the next section, a case study will present practical application in a real-world setting, highlighting the significant benefits achieved in efficiency, patient outcomes, and stakeholder interaction. It will also address the limitations encountered during implementation, offering a balanced perspective on the challenges of applying theoretical models in practice.

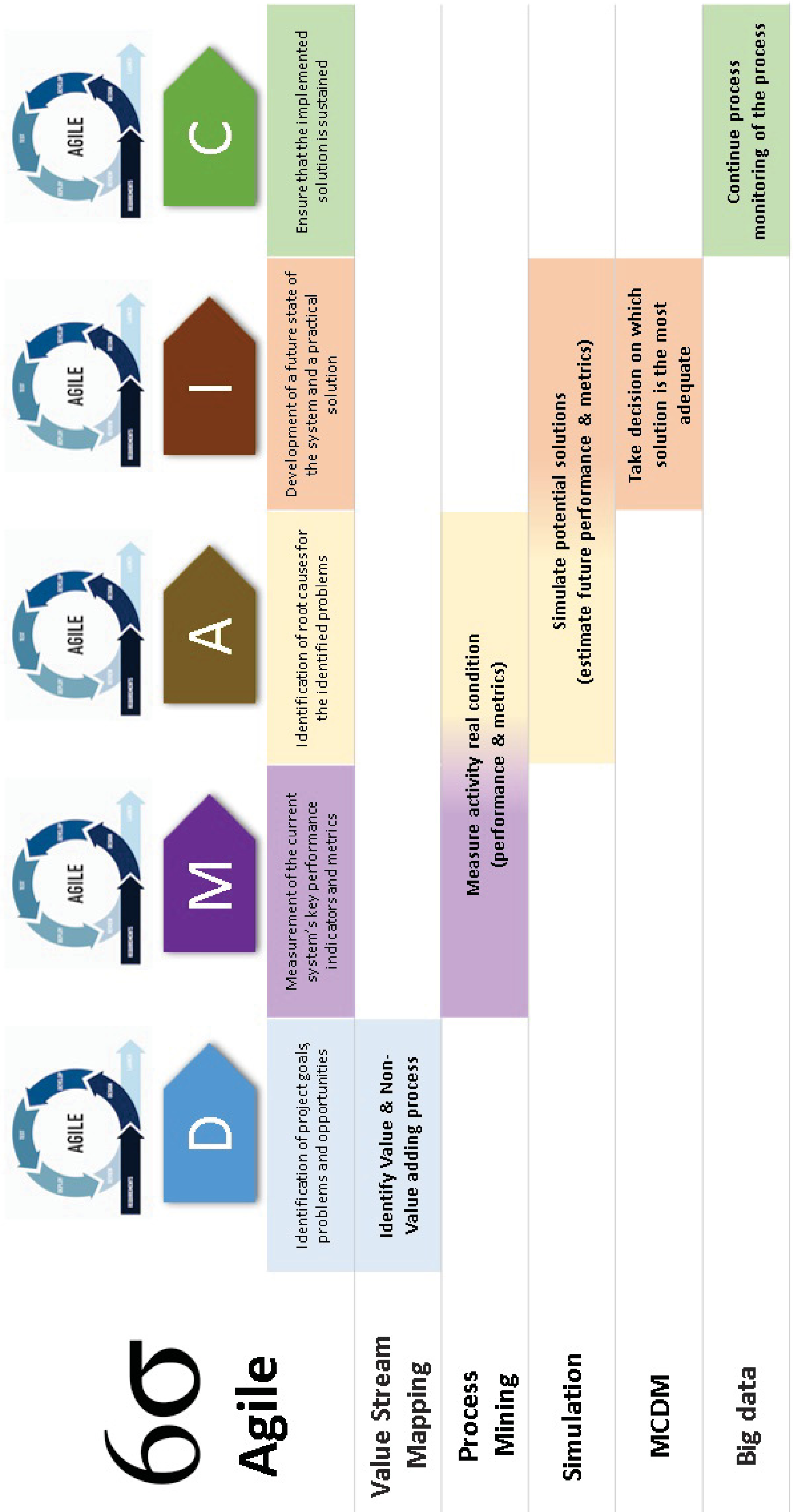

FIGURE 14 – Comprehensive framework

5 CASE STUDY

This chapter delves into a comprehensive case study of an automotive company, a leading global automotive manufacturer renowned for its innovative approaches and strategic initiatives. It´s Customer Quality Team plays a key role in converting customer feedback into actionable process improvements, translating to business indicator, each day delayed to improve a problem represents several dollars of warrant cost. This case study explores the impact of implementing the Quality Improvement Framework 4.0, showcasing how a structured and data-driven approach can drive significant advancements in quality management.

5.1 OBJECTIVES AND GOALS

The primary objective of implementing Framework 4.0 was to refine company's quality management processes by leveraging data and technology. The key goals include:

- Enhancing the accuracy and timeliness of customer feedback analysis.
- Streamlining the process of identifying and addressing quality issues.
- Promoting a culture of continuous improvement across all levels of the organization.

5.2 DEFINE - VSM

Value Stream Mapping (VSM) is a lean management tool used to visualize and analyze the flow of materials and information required to bring a product or service from conception to delivery. By mapping out each step in the process, organizations can identify areas of inefficiency, highlight non-value-added (NVA) activities, and streamline operations. In this section, we explore how VSM was employed to define project objectives and identify high NVA steps in company's Customer Quality Improvement process.

1. Mapping the Current State

To identify NVA steps, the first step was to map the current state of the Customer Quality Improvement process. This involved creating a detailed visual representation of the entire process, from the initial receipt of customer feedback through to the implementation of corrective actions. Figure 13 illustrates this simplified process, highlighting key stages such as data collection, analysis, decision-making, and solution deployment. Figure 15.

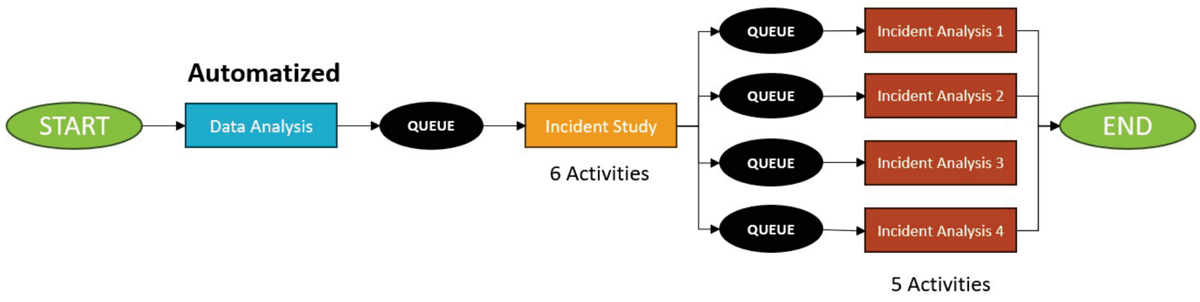

FIGURE 15 – BPM simplified process

- Analyzing the Value Stream

The value stream analysis involved evaluating each step to determine whether it added value from the customer's perspective. Activities such as data entry, manual review, and interdepartmental communications were reviewed to identify areas where delays and inefficiencies occurred. The VSM analysis revealed specific stages where lead times were extended due to non-value-adding activities, such as redundant approval processes, delays in data processing, and lack of real-time information sharing. Figure 16.

FIGURE 16 – Customer Quality simplified process

- High NVA identification

Incident Study & Analysis are the process steps that spend the most time with opportunity to improve.

5.3 MEASURE - PM

Process Mining is a powerful analytical technique that is used to examine and visualize the actual flow of processes based on system logs and data. It helps organizations understand how processes are executed in practice compared to how they are intended to operate according to Business Process Models (BPM). This section discusses the application of process mining to analyze discrepancies between the real process flow and standard BPM, identify bottlenecks, and implement improvements.

- Data Extraction

The system logs were extracted from the company data lake, which serves as a centralized repository for all process-related data. These logs include detailed records of system interactions, process activities, and time stamps, providing a comprehensive view of the actual process execution.

- Data Treatment

The raw data extracted from the data lake were treated to ensure accuracy and consistency. This process involved:

Data Cleaning: Removal of inconsistencies and errors from the logs using Python.

Data Aggregation: Combining data from various sources to a unified view.

Data anonymization : Remove personal information from data.

Data Transformation: Converting the data into a format suitable for PM analysis.

Resulting into a reliable and anonymized dataset for process mining analysis, as presented on Figure 17.

Trace	Activity	Start	End	Resource
		......		
102	Alert	20/03/2023 09:32:21	20/03/2023 16:24:13	Stu_1
102	Coverage check	20/03/2023 16:24:13	21/03/2023 13:43:35	Stu_1
102	Report	21/03/2023 13:43:35	23/03/2023 15:17:38	Stu_1
102	E0	23/03/2023 15:17:38	25/03/2023 09:41:02	Ana_4
102	E1	25/03/2023 09:41:02	27/03/2023 17:05:31	Ana_4
102	Creation	27/03/2023 17:05:31	27/03/2023 17:05:31	Ana_4
		......		

FIGURE 17 – Real event log anonymized

- Process Mining Analysis

Using Process Mining techniques, the real process flow was visualized, Figure 18, and the activities were measured by frequency and time, using PM4PY - Python library.

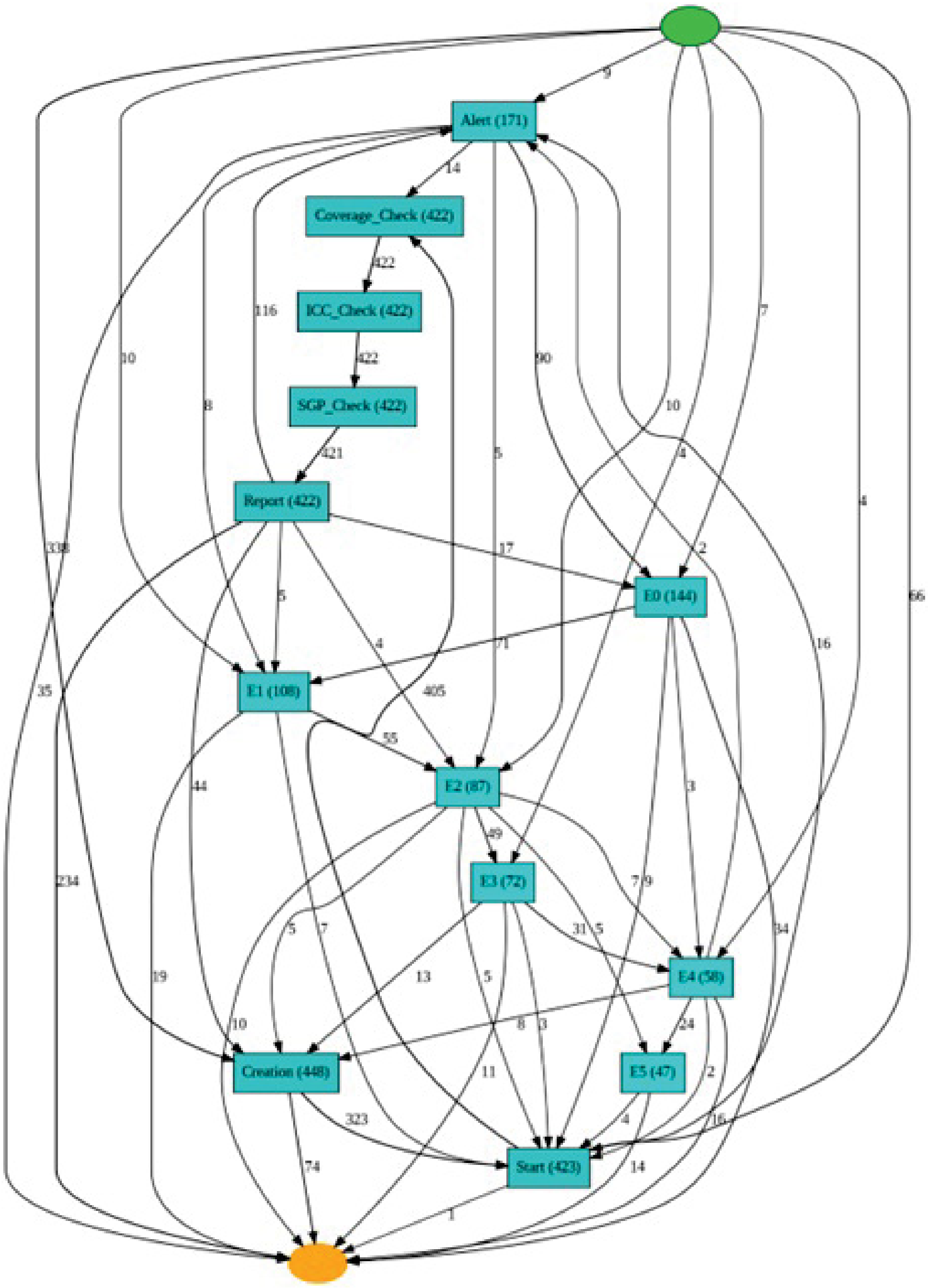

FIGURE 18 – Real process flow

- Identification of Compliance

Process compliance: Based on the discovery, non-compliance and loops are highlighted problems for the process.

Issue: Several paths variations to the same way generating delay and rework.

Solution for Process compliance: Clearly definition of input and output for each activity was setup and shared across the organization. Non compliance's will be monitored by the system and must require quality approval.

Figure 18 was simplified and measured the proportional average cycle time for each activity 1 cycle time = 100%), Figure 19, resulting on the identification of 2 bottlenecks. For Study team was identified that activity "report"uses 5% of total cycle time and for Analysis team the activity "Alert"uses 21% of total cycle time. Activity "backlog Creation"was not selected because it´s just a waiting time to pick next topic.

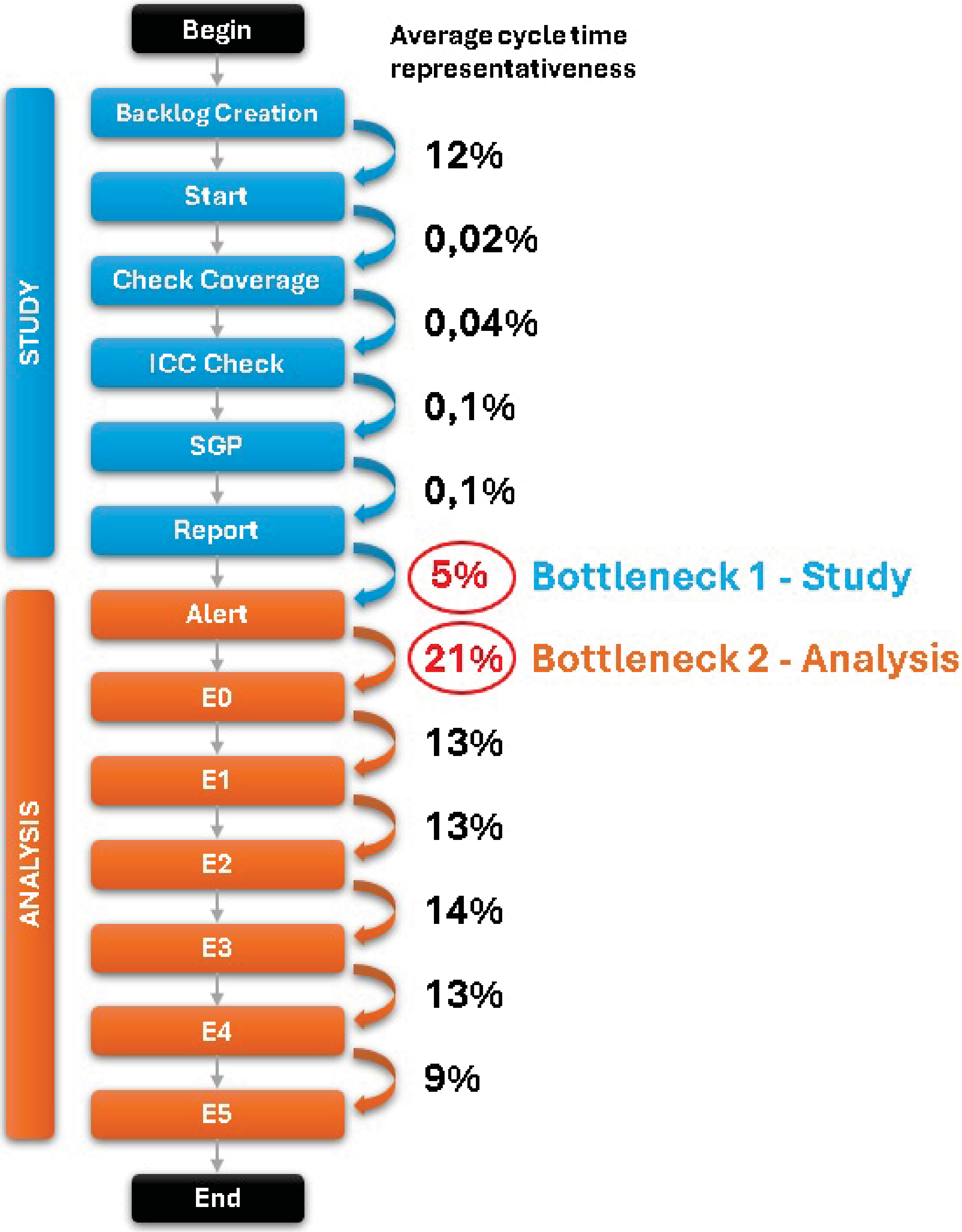

FIGURE 19 – Process simplification and bottlenecks identification

- Identification of Bottlenecks

The Process Mining analysis revealed significant high executing time for two primary bottlenecks in the Customer Quality Improvement process:

Bottleneck 1: Activity 6 - Incident Study Team -> Business Case (Report)

Issue: This stage involved the development of a business case report, which was identified as a bottleneck due to delays in processing and approval.

Impact: The delays at this stage affected the overall lead time and responsiveness to quality issues.

Bottleneck 2: Activity 1 - Incident Analysis Team -> Report Understanding and Problem Definition

Issue: This initial activity, which focused on understanding the report and defining the problem, was a significant bottleneck due to inefficient handling and communication.

Impact: Delays in understanding and defining problems led to slower resolution times and longer lead times.

- Implementation of Improvements

Based on the identification of these bottlenecks, targeted improvements were implemented:

Improvement for Bottleneck 1

Action taken: Streamlined the process for developing and approving business case reports by introducing a standardized template and reducing the number of approval layers.

Outcome: The time required to generate and approve reports was significantly reduced, leading to faster resolution of quality issues.

Improvement for Bottleneck 2

Action taken: Improved the efficiency of the report understanding and problem definition stage by providing additional training and resources to the Incident Analysis Team.

Outcome: Enhanced problem definition accuracy and faster response times.

- Post-Improvement Measurement and Analysis

Following the implementation of improvements, the process was remeasured and analyzed to assess the impact of the changes:

Findings: The analysis revealed that while the primary bottlenecks were addressed, the overall distribution of resources among the teams was not balanced. This imbalance led to significant variations in team performance and efficiency.

Outcome: The overall performance of the Customer Quality Improvement process showed improvement in addressing bottlenecks, but the imbalance in resource distribution highlighted the need for further optimization. Performance metrics, such as lead time and resolution rates, showed improvements, however, there were noticeable differences in team performance due to the uneven distribution of resources.

5.4 ANALYSIS/IMPROVEMENT - SIMULATION/MCDM

To optimize the resource allocation between the Study team and the Analysis team (ANA), the Analytic Hierarchy Process (AHP) was utilized as part of a Multi-Criteria Decision-Making (MCDM) approach. This methodology facilitated the convergence of various stakeholders' viewpoints into a single decision criterion, allowing for a more informed and balanced decision-making process.

- Definition of Decision Criteria

AHP was chosen to integrate stakeholder opinions on the importance of different decision criteria. Stakeholders rated the criteria on a Likert scale from 1 to 9, where 1 indicates low importance and 9 indicates high importance. This rating helped in prioritizing the criteria based on their perceived significance.

- Construction of the Decision Matrix

Understanding the profiles of stakeholders, Figure 14, is pivotal for optimizing resource allocation and enhancing the effectiveness of quality improvement initiatives. Stakeholders in this context typically vary across several dimensions, including age, years of experience, organizational level, and related areas of expertise. This diversity is crucial for a comprehensive decision-making process that incorporates a wide range of perspectives and expertise.

The decision matrix was populated with stakeholders' ratings. Table 15 presents the AHP decision matrix, showcasing how different activities were compared in terms of their importance and priority.

- Relocation of Resources

Stakeholder	Age	Years of experience	Level	Related area
1	40 - 50	20 - 30	Manager	Customer Quality
2	50 - 60	30 - 40	Director	Industrial Quality
3	50 - 60	30 - 40	Director	Manufacturing

TABLE 14 – Stakeholder profile

ANA	1	2	3	4	Priority
1	1	0,11	0,11	1	5%
2	9	1	1	9	45%
3	9	1	1	9	45%
4	1	0,11	0,11	1	5%

TABLE 15 – AHP - Decision Matrix

The main objective was to determine the optimal reallocation of 2 resources from the Study team to the Analysis team. Based on stakeholder input and AHP analysis, five potential scenarios for resource reallocation were defined.

- Definition of Scenarios

Table 16 outlines the five scenarios considered for resource reallocation. Each scenario represents a different distribution of resources between the Study team and the Analysis teams (ANA_1, ANA_2, ANA_3, ANA_4). Stakeholders play a crucial role to set premises for the scenarios creation, resulting into only viable opportunities.

#	Study	ANA_1	ANA_2	ANA_3	ANA_4
S1	-2		+1	+1	
S2	-2	+1			+1
S3	-2	+1		+1	
S4	-2			+1	+1
S5	-2		+1		+1

TABLE 16 – Simulation scenarios

- Simulation Results

Each scenario was simulated to assess the impact on cycle time for the analysis teams. Table 17 presents the results of these simulations, showing the cycle time (in days) for each Analysis team under the different scenarios.

#	ANA1	ANA2	ANA3	ANA4	Rank
S1	47	59	56	48	1
S2	32	137	134	33	5
S3	32	135	56	49	3
S4	47	136	56	33	4
S5	47	59	131	34	2

TABLE 17 – Simulation results

- Optimal Scenario Identification

The simulation revealed that Scenario S1 resulted in the lowest average cycle time across all Analysis teams, thus being ranked as the optimal scenario. Table 18 summarizes the process improvement gains achieved through the optimal scenario. The table compares the average cycle time for both the Study team and the Analysis teams before and after the implementation of the optimal scenario.

The optimal scenario (S1) resulted in a 13% reduction in cycle time for the Study team and a notable 45% reduction for the Analysis teams. These gains highlight the effectiveness of the resource reallocation in improving overall process efficiency.

Trace	Study			Analysis		
	Before	After	Gain	Before	After	Gain
Ana1	2,1	1,8	0,3	66	47	19
Ana2	2,3	4,2	1,9	132	59	73
Ana3	3,4	1	2,4	133	56	77
Ana4	1,8	1,3	0,5	55	48	7
Average	2,4	2,1	0,3	96	52	44
Gain			13%			45%

TABLE 18 – Process improvement gains (days)

5.4.1 IMPROVEMENT VALIDATION : TEST OF DIFFERENCES IN MEANS

The t-test summarized in Table 19 presents the results of the testing before and after samples. The t-test is used to compare the means of two groups to determine if there is a significant difference between them, presented on Figures 20, 21, 22, 23, 24, 25, 26, 27 .

Team	T	df	p-value	X	Y
Stu_1	0,45187	23,908	0.6554	2,071429	1.833333
Stu_2	-1.6496	57.986	0.1044	2,305085	4.238095
Stu_3	Low sample to evaluate				
Stu_4	1.1085	31.452	0.2761	1,772727	1,25
Ana_1	1,123	19,587	0,275	66,42857	45,08333
Ana_2	5,1368	77,667	0,000002023	132,18644	55,57143
Ana_3	Low sample to evaluate				
Ana_4	0,57325	21,85	0,523	55,5	47,25

TABLE 19 – T-test results

Argument	Description
T	T statistics
df	Degrees of freedoms
p-value	probability to identify a difference P<0,05 for 95% of confidence
X	Mean of sample Before
Y	Mean of sample After

TABLE 20 – T-test reference

Stu_1 (Figure 20): The t-value is 0.45187 with 23.908 degrees of freedom and a p-value of 0.6554. This result indicates that the t-distribution is relatively close to the normal distribution and there is no statistically significant difference between the means of the two groups, as the p-value is well above the conventional alpha level of 0.05. The effect size, calculated from the means (X = 2.071429 and Y = 1.833333). Resulting that removing 1 resource does not impact the performance on the team.

Stu_2 (Figure 21): The t-value is -1.6496 with 57.986 degrees of freedom and a p-value of 0.1044. This result indicates that the t-distribution is close to the normal distribution and although the p-value is low, it is still above the 0.05 threshold, indicating a marginal statistically significant. This suggests that there may be a trend towards a difference, but it is not strong enough to be considered significant on a confidence level 95%. Resulting that removing 1 resource does not impact the performance on the team.

Stu_3 (Figure 22): The data was insufficient for evaluation, as noted by the "Low sample to evaluate"remark. This indicates that the sample size was too small to provide reliable results, and any conclusions drawn from this test would be unreliable.

Stu_4 (Figure 23): The t-value is 1.1085 with 31.452 degrees of freedom and a p-value of 0.2761. This result indicates that the distribution t is close to the normal distribution and also does not show significant differences between the two means (X = 1.772727 and Y = 1.25), since the p-value exceeds the level of alpha 0.05. Resulting that removing 1 resource does not impact the performance on the team.

Ana_1 (Figure 24): The t-value is 1.123 with 19.587 degrees of freedom and a p-value of 0.275. This result indicates that the t-distribution is relatively close to the normal distribution and the p-value is greater than 0.05, suggesting that there is no statistically significant difference between the means (X = 66.42857 and Y = 45.08333). Resulting no changing following no resource addiction.

Ana_2 (Figure 25): The t-value is 5.1368 with 77.667 degrees of freedom and a remarkably low p-value of 0.000002023. This indicates a highly significant difference between the means (X = 132.18644 and Y = 55.57143). The very low p-value suggests that the observed difference is not due to random chance and is statistically significant. Resulting on an improvement based on the resource increase.

Ana_3 (Figure 26): Similar to Stu_3, the data for Ana_3 was insufficient for evaluation due to a low sample size. This prevents any meaningful interpretation of the results.

Ana_4 (Figure 27): The t-value is 0.57325 with 21.85 degrees of freedom and a p-value of 0.523. This result indicates that the t-distribution is close to the normal distribution and p-value, which is significantly higher than 0.05, indicates that there is no significant difference between the means (X = 55.5 and Y = 47.25). Resulting no changes following no resource addiction.

In summary, the Study teams maintain consistent performance despite reductions in resources, as indicated by the p-values evaluation. In contrast, the Analysis teams demonstrate substantial reductions in means as results of the resource reallocation. To enhance the reliability of these findings, it is required to extend the sampling amount, table 21. This would help mitigate variability, increase statistical power, reduce sensitivity to deviations, and eliminate low samples.

Team	Samples before	Samples after
Stu_1	14	12
Stu_2	59	21
Stu_3	9	1
Stu_4	22	12
Ana_1	14	12
Ana_2	59	21
Ana_3	9	1
Ana_4	22	12

TABLE 21 – T-test Samples

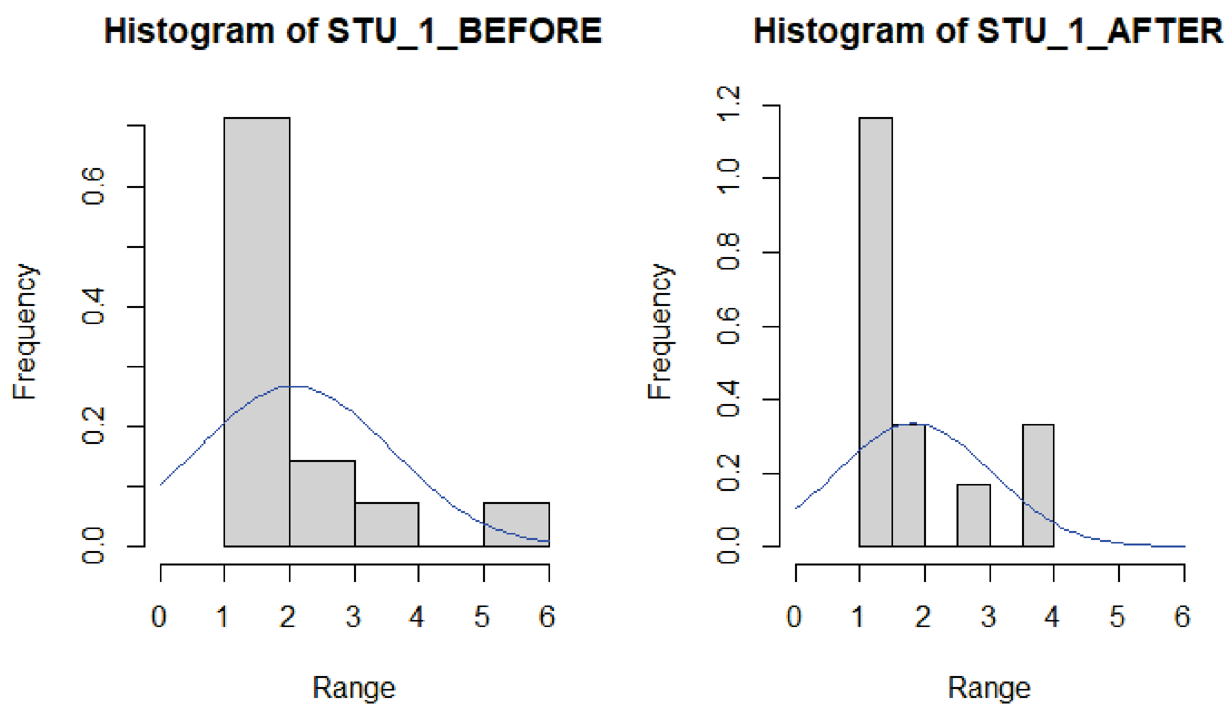

FIGURE 20 – Process improvement Study 1

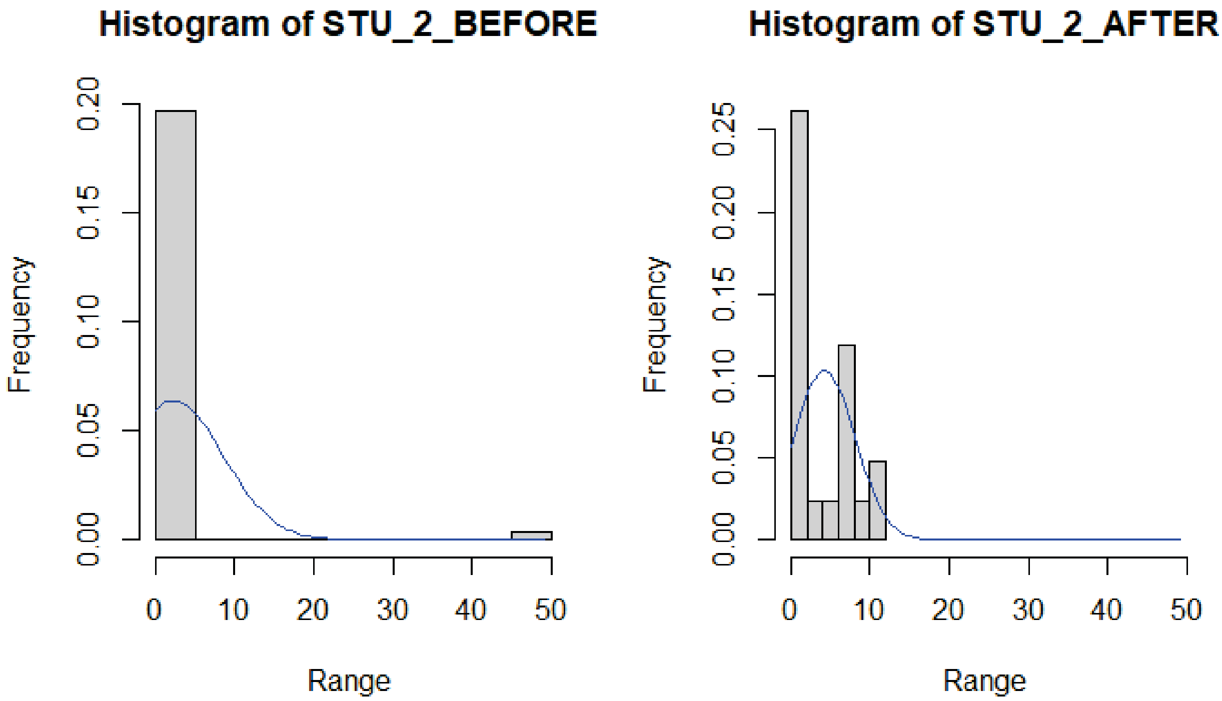

FIGURE 21 – Process improvement Study 2

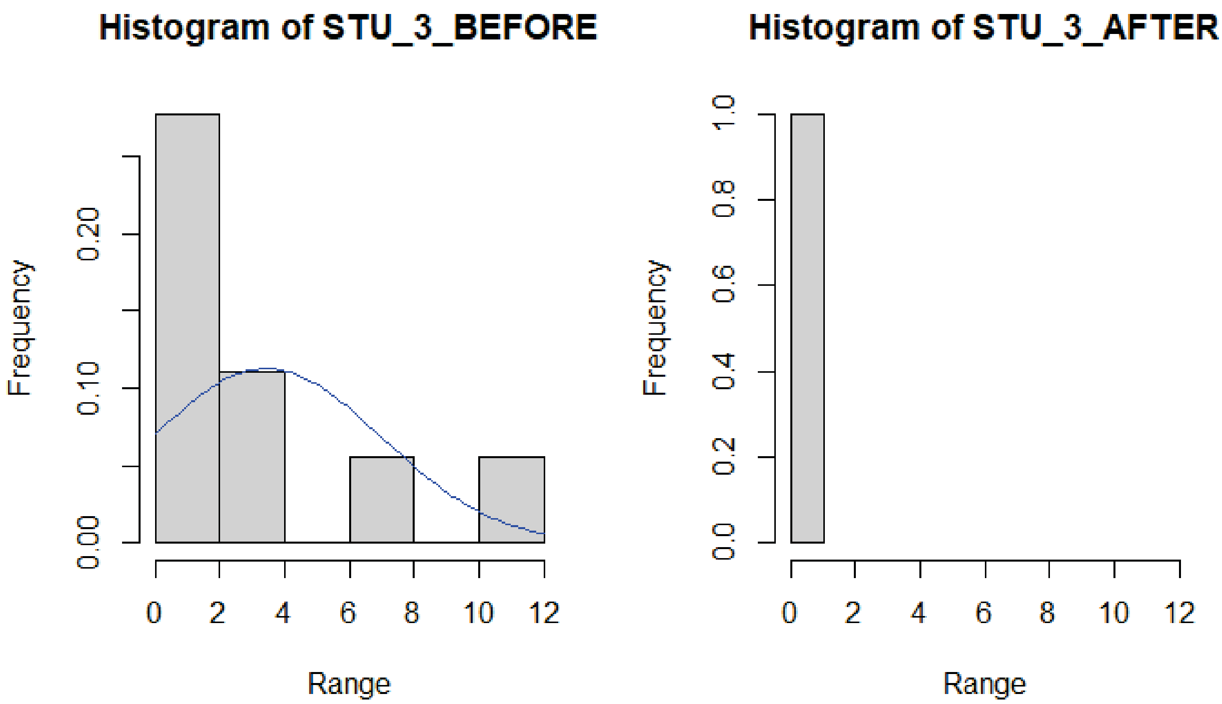

FIGURE 22 – Process improvement Study 3

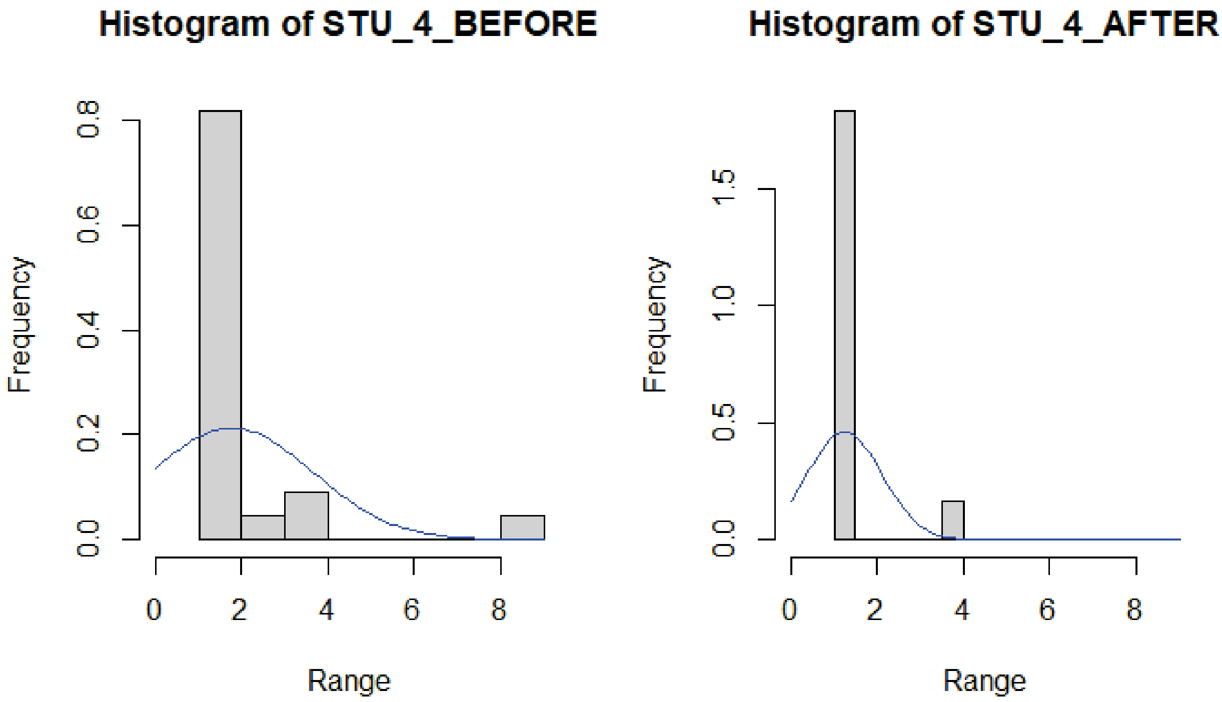

FIGURE 23 – Process improvement Study 4

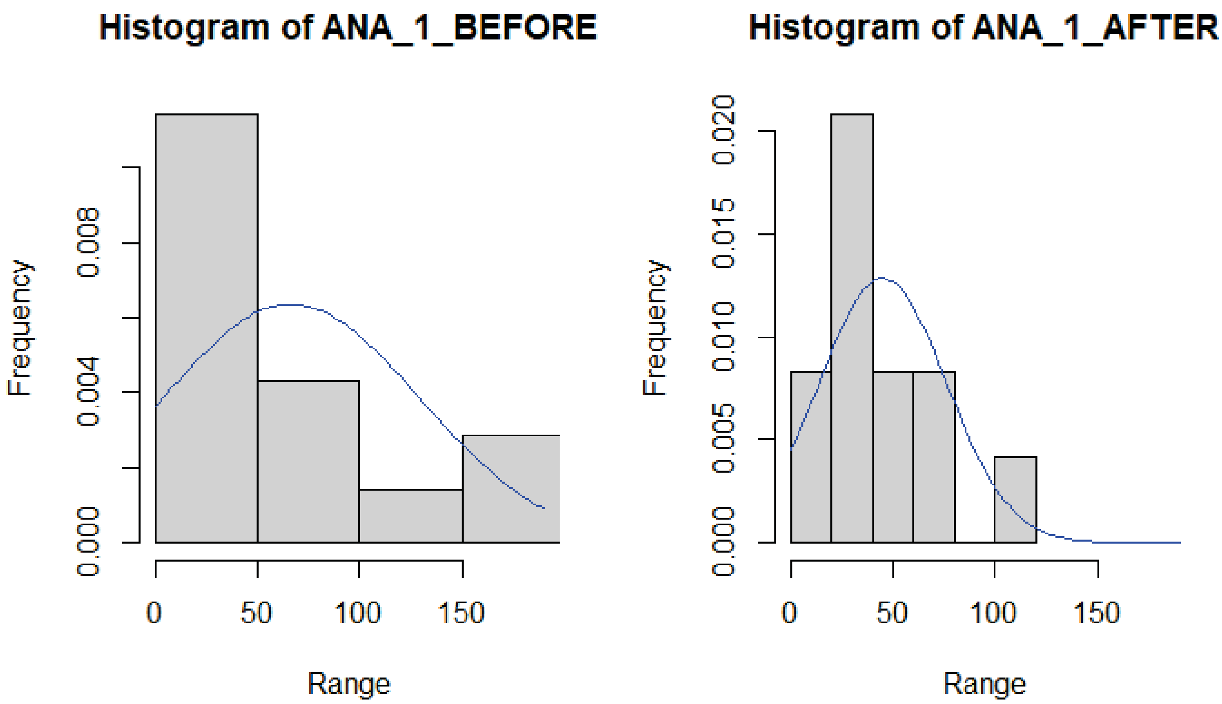

FIGURE 24 – Process improvement Analysis 1

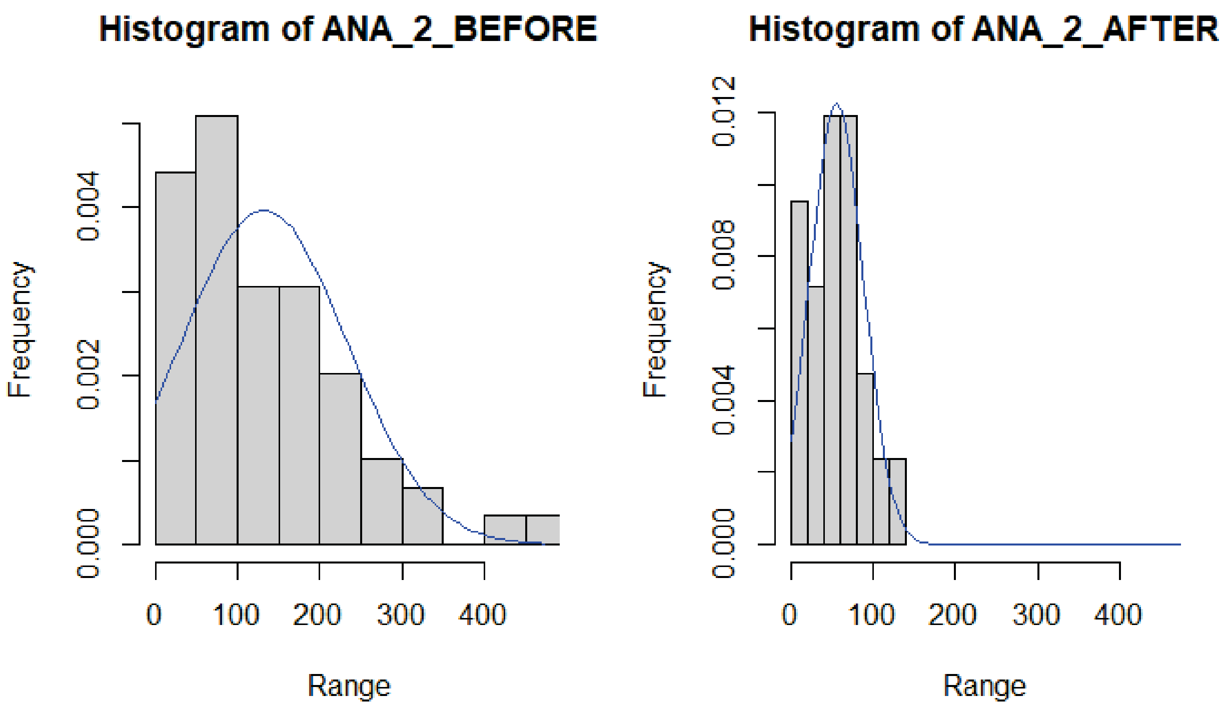

FIGURE 25 – Process improvement Analysis 2

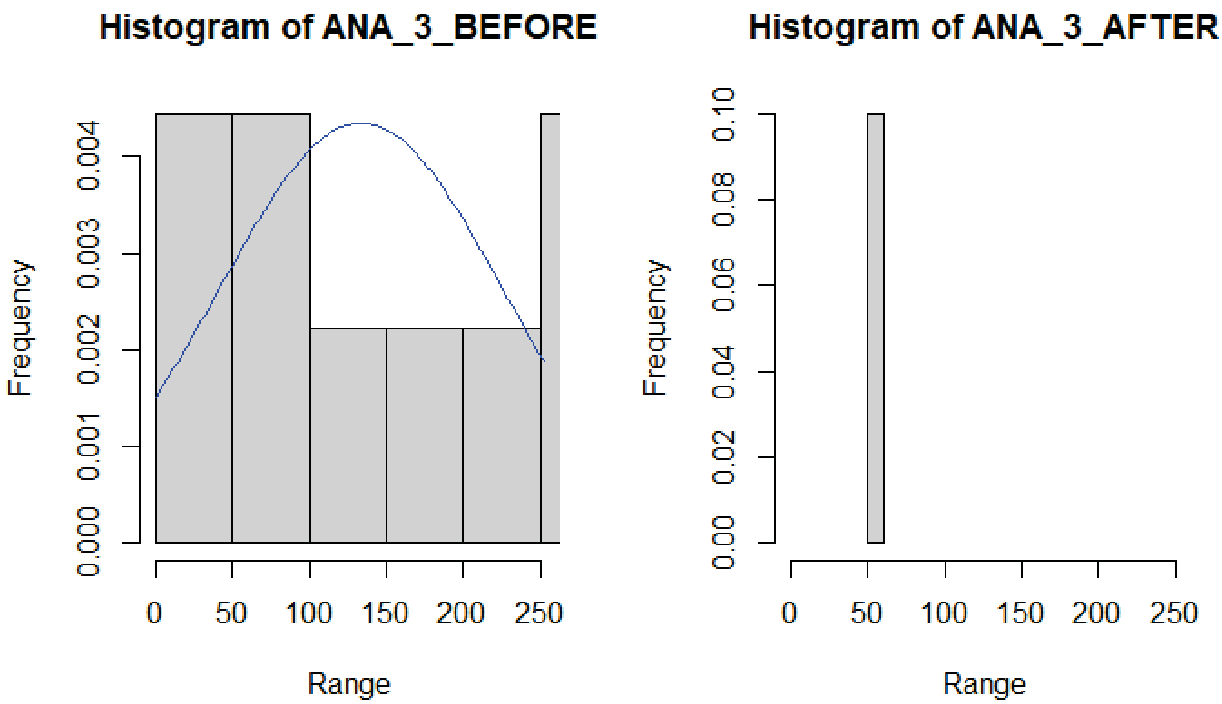

FIGURE 26 – Process improvement Analysis 3

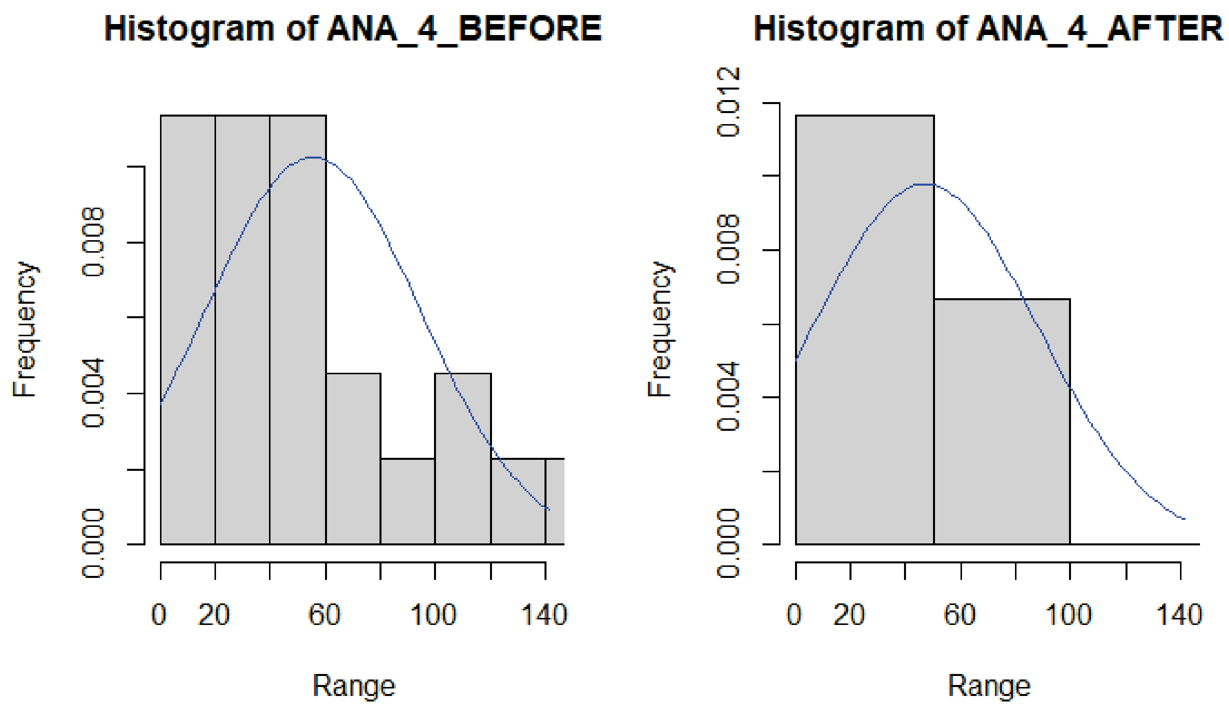

FIGURE 27 – Process improvement Analysis 4

5.5 CONTROL - BIG DATA

Incorporating Big Data tools into Six Sigma initiatives can significantly enhance the effectiveness of performance measurement and control mechanisms. Using the vast amounts of available data, organizations can gain deeper insights into their processes, identify patterns and trends, and make more informed decisions. This integration supports continuous monitoring and improvement, ensuring that Six Sigma projects are not only effective in the short term but also sustainable over the long term.

The practical application of these concepts have employed specific Big Data tools to enhance visual management and performance measurement:

Kanban: A visual management system used to manage and track work as it moves through a process. Kanban boards help visualize workflow, identify bottlenecks, and improve process efficiency. The digital Kanban board used in this study is shown in Figure 28.

Dashboard: A tool for live process monitoring that provides real-time insights into performance metrics and identifies blocking points. Dashboards offer a comprehensive view of key performance indicators (KPIs) and other critical data, facilitating quick and informed decision-making. The dashboard used for monitoring and performance measurement is shown in Figure 29.

This case study illustrates the transformative impact of implementing the Quality Improvement Framework 4.0 within a leading global automotive manufacturer. By adopting a structured, data-driven approach to quality management, the company effectively achieve the 3 objectives:

1)Improving accuracy and timeliness of customer feedback analysis

- Reducing process variations and performance gain of 45% on the analysis teams.

2) Streamlining identification and resolution of quality issues

- Team was trained with problem solving tools VSM, PM, Simulation, MCDM and Big data.

3) Fostering a culture of continuous improvement throughout the organization

- Process improvement and bottleneck solution were proposed by operational teams.

- Stakeholder actively participate into all validations gates and share relocation constrains.

Definition phase was enhanced with the objectivity of Value Stream Mapping,

FIGURE 28 – Digital Kanban

guiding problem understanding by Non Value Aggregated, that is directly associated with cost reduction. In this study case each day reduced represents one production day of warranty cost reduction for a determinate failure.

Measure & Analysis phase has been speedup by applying Process Mining, were all metrics about the process could be immediately analysed. Allowing to quickly identify compliance and bottlenecks.

FIGURE 29 – Dashboard

Analysis & Improve phase applied Simulation and Multi Criteria Decision Making to delivered a customized solution that attend stakeholder constrains and optimize process based on the resource relocation, resulting on Study team without impact even with 2 resources reduction and a improvement of 45% on the Analysis team.

The control phase digitalizes the process by incorporating Big Data tools into Six Sigma initiatives and adds a layer of ongoing performance measurement and control, ensuring that improvements are sustainable and adaptive to future challenges. Kanban and Dashboard, allowing KPIs real-time measurement, immediate performance feedback for teams and insights generations.

In conclusion, this case study not only showcases the successful implementation of the Quality Improvement Framework 4.0 but also serves as a blueprint for other organizations aiming to improve their quality management processes. By fostering a culture of continuous improvement and leveraging data-driven insights, organizations can achieve significant operational benefits and better meet customer expectations. The findings emphasize the importance of systematic approaches to quality management in the automotive industry and highlight the potential for ongoing innovation in response to evolving market demands.

6 CONCLUSION

The overall objective was to explore and integrate untapped opportunities for quality improvement by developing a comprehensive framework that integrates Six Sigma with data-driven methodologies in the context of Quality 4.0. This objective was addressed by conducting a systematic literature review and proposing a Quality Framework 4.0 that incorporates Agile principles, Value Stream Mapping, Process Mining, Simulation, Multi-criteria Decision Making, and Big Data analytics within the DMAIC framework. This thesis has significant implications for both academic and industry practices, offering practical solutions and guidance for organizations seeking to optimize their quality improvement initiatives and achieve a competitive advantage in the digital era.

In conclusion, the Quality Framework for Industry 4.0 is a groundbreaking approach to quality management that leverages the power of emerging technologies and data-driven insights. This case study has shown its effectiveness by increase Study team performance, that even with less 2 resources maintain the level of delivery and Analysis team reduced up to 45% of the cycle time.

The integration of Agile principles, Six Sigma, Value Stream Mapping, Process Mining, Simulation, Multi-criteria Decision Making, and Big Data analytics within the DMAIC framework ensures a holistic and comprehensive approach to quality improvement. Each methodology brings unique strengths to the table, such as flexibility, process visualization, real-time insights, predictive analysis, informed decision making, and real-time monitoring and control.

By merging these methodologies, the Quality Framework for Industry 4.0 overcomes the limitations of traditional quality management practices. It provides a dynamic and data-driven approach that is well-suited to the complexities and rapid changes of Industry 4.0. This integrated framework not only enhances the accuracy and efficiency of quality improvement initiatives but also ensures sustained process optimization and competitive advantage.

In summary, the Quality Framework for Industry 4.0 represents a significant advancement in the field of quality management. Its synergistic approach, combining various methodologies and technologies, offers a robust and adaptable solution to meet the evolving challenges of the modern industry. As organizations embrace digital transformation, this comprehensive framework will play a crucial role in driving innovation, efficiency, and excellence in quality improvement.

7 LIMITATIONS

The current literature predominantly highlights pairwise integration's of DMAIC and one data-driven methodology, which limits the scope of research coverage. Additionally, sample availability may influence the validation tests that require a longer time to ensure reliability.

Although the proposed framework offers a comprehensive approach to quality management, several limitations warrant consideration. First, its effectiveness may vary across diverse organizational contexts, industries, and scopes of projects. In addition, successful implementation relies heavily on the promotion of effective collaboration among cross-functional teams, which can be hampered by communication barriers or cultural challenges. Another limitation pertains to the reliance on availability and data quality; inadequate or sub-par data can compromise the accuracy of insights and decision-making processes. Finally, the framework presupposes a certain level of technological infrastructure and digital maturity within organizations. Those lacking such capabilities may encounter obstacles in adopting and leveraging certain methodologies, thus impeding the framework's full potential impact.

8 FUTURE WORK

Future research could focus on conducting case studies to validate the efficacy of the proposed framework in improving organizational effectiveness and efficiency, thus addressing quality challenges and enhancing business performance on other segments. Furthermore, advances in data collection, management, and analysis techniques hold promise in mitigating challenges associated with methodologies like Process Mining, Simulation, and Big Data. This requires a focused effort to improve the quality, accessibility and usability of data to foster more precise information and informed decision-making. In addition, further investigations could explore customized adaptations of the integrated framework tailored to specific industries or project contexts. Customization may involve integrating industry-specific methodologies or refining the proposed framework to better accommodate unique challenges and requirements within these contexts.

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