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Strategic decision-making in process optimization of healthcare technology manufacturing

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Abstract – The dynamic nature of the healthcare technology industry necessitates constant improvement and optimization of supply chain processes to maintain competitiveness. Manufacturing unit processes, as critical components of the supply chain, directly influence production efficiency, lead times, and overall supply chain performance. Therefore, a strategic focus on optimizing these processes can significantly enhance the responsiveness and cost-effectiveness of the entire supply chain. However, for large enterprises, determining the unit where optimization will be implemented is intricate, considering the multifaceted nature of the decision-making process. The complexity arises from the presence of diverse criteria, each assigned varying importance levels, along with multiple alternative stages to consider. This paper introduces a decision-making framework tailored for such complexities, employing a synergistic blend of two multi-criteria decision-making methods: Best Worst Method (BWM) and ELECTRE III. The application of the proposed framework is demonstrated through a practical case study involving a prominent healthcare technology company, Philips. First, six experts are carefully selected and interviewed to provide a set of criteria with their respective importance weights. Then, using this information, eight alternative processes within the manufacturing unit are ranked using ELECTRE III. The analysis results reveal that process complexity is the top priority for decision-makers when deciding which manufacturing units require optimization first. The findings delve into the intricacies of optimizing production processes in large health technology companies and offer practical solutions and further recommendations.

Keywords: Healthcare technology; supply chain performance; multi-criteria decision making; Best Worst Method; ELECTRE III

1. Introduction

In the contemporary business landscape, global companies engaged in operational management and various facets of the supply chain are fervently striving to enhance the overall efficiency of their processes. This imperative is driven by a variety of motivations, including cost minimization, meeting sustainability goals, expansion, and better adapting to a rapidly changing environment (Lichocik & Sadowski, 2013). Sustaining competitiveness requires continuous improvement and rapid adaptation ability across all spheres. The complexity of this endeavor is further exacerbated by the involvement of multiple decision-makers and stakeholders, each with distinct preferences and priorities, rendering consensus challenging. Additionally, a multitude of factors, both direct and indirect, quantitative and qualitative, influence the resolution of the underlying challenges (Wu et al., 2019). Consequently, there emerges a need for guidance to streamline and enhance the decision-making processes of these companies.

Among the industries struggling with these challenges, healthcare technology stands out due to its unique combination of strict cost constraints and the demand for continuous innovation. The need for constant

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technological evolution exemplifies the necessity for adaptability. Over time, technological advancements have significantly impacted health, care, and disease management (Vandemeulebroucke et al., 2022). Healthcare settings continually witness advancements aimed at preventing, managing, or resolving health-related issues, thereby improving the overall quality of life (World Health Organization, 2022). This trend is particularly pronounced in recent years and is anticipated to persist (Flear et al., 2013). As a result, companies involved in healthcare technology grapple with intricate challenges within healthcare supply chains, pressured to reduce costs while sustaining the innovation output. Given these challenges facing companies operating in the healthcare sector, supply chain management emerges as a critical component in balancing cost reduction with sustainable innovation (Elabed et al., 2021). Effective supply chain management involves improving procurement efficiency, manufacturing, and distribution activities to minimize costs while ensuring the delivery of advanced technologies (Christopher, 2016). In this context, process optimization has a crucial role in improving supply chain performance. By optimizing operational efficiency in the manufacturing units, companies could shorten lead times, improve resource utilization, and reduce production costs, all of which can significantly contribute to a resilient supply chain.

The optimization of manufacturing units refers to improving the productivity, performance, and efficiency of a process within a facility (Pierreval & Tautou, 1997). This requires reducing the cost, minimizing waste, and improving overall quality by constantly analyzing and enhancing elements of the production system. Extensive research addresses specific issues within manufacturing units like resource allocation (Wang et al., 2021), bottleneck identification (Mizgier et al., 2013), production scheduling optimization (Maccarthy & Liu, 1993), and technology selection (Farooq & O'Brien, 2012). However, in optimizing manufacturing units, the initial phase of the process is often overlooked. There stands an important question: Which operations require attention and action first? There is a lack of approaches to guide choosing a focus area for optimization. While many different processes may require optimization, clarity on which problem to address first is essential to maintain innovative capacity and adaptability to change. This is a critical and challenging task for companies that manage multiple products, processes, and departments where resources are limited, and prioritization is key. From this point of view, our study addresses a significant gap in manufacturing unit optimization: the lack of a systematic approach to prioritize processes requiring improvement. By treating this as a multi-criteria decision-making (MCDM) problem, we provide a framework to guide decision-making, supporting optimal resource allocation and sustained innovation.

A multi-criteria decision-making (MCDM) problem arises when decision-makers must choose a solution based on a specified criteria set (Majumder, 2015). Many challenges in supply chain management qualify as MCDM problems due to diverse objectives to consider when selecting a solution from available alternatives (Raut et al., 2017). This already complex problem becomes even more complicated due to the need to gather input from multiple stakeholders while making the decision. Most of the time, the evaluation requires consulting multiple experts. The involvement of decision-makers with varying perspectives across different company departments compounds the complexity into a group decision-making problem as it happens in our problem. By integrating two multi-criteria decision-making (MCDM) methods—the Best-Worst Method (BWM) and ELECTRE III—this study advances the development of manufacturing unit optimization frameworks for healthcare technology companies and demonstrates its applicability through a real-world case. A group of decision-makers, selected for their expertise across relevant domains, is first formed to identify the problem's criteria set. Then the BWM is employed to determine the relative importance of criteria, while ELECTRE III, a robust outranking method, is utilized to rank alternative processes based on these criteria.

Contributing to existing research in supply chain management and MCDM, this paper addresses the research gap in focusing on process optimization within manufacturing units. The combination of BWM and ELECTRE III introduces a systematic framework tailored to address the complexities of optimizing manufacturing unit processes in large healthcare technology companies. This framework is further validated through a real-world case study involving a prominent company. On a practical level, the paper offers a clear framework for diverse product portfolios, supply chain processes, and decentralized employees. Our application facilitates the resolution of complex multi-criteria decision-making problems, accommodating the varied preferences of decision-makers. The study also opens avenues for future research to test and refine the proposed framework across different supply chain problems and even in industries outside of healthcare technology.

The structure of the paper is organized as follows: Section 2 presents a comprehensive literature review, highlighting the research gap and contextualizing the study. Section 3 outlines the methodology, detailing the two MCDM methods (BWM and ELECTRE III) forming the research framework alongside other relevant methods.

Section 4 demonstrates the practical application of the proposed framework through a case study conducted in Philips's manufacturing unit. Section 5 presents insights into the obtained results. Finally, Sections 6 and 7 delve into the discussion of results and the main conclusions derived from this research, respectively.

2. Literature review

This section reviews the literature across four key dimensions: the supply chain management in healthcare technology and its connection to MCDM, the application of MCDM methods to manufacturing unit problems, the identification of relevant criteria for the problem in question, and key insights drawn from the existing body of work.

2.1. Supply chain management in the healthcare technology industry and MCDM

As highlighted by Mathew and John (2013), there is a significant increase in product and service prices within the healthcare sector. This upward trend was primarily attributed to the supply chain, recognized as a significant cost driver and a focal point for industry stakeholders. Similarly, Pinna et al. (2015) echo concerns about escalating costs, identifying supply chain innovation as a crucial research topic due to quantitative and qualitative factors (e.g., political and economic) causing a global impact on healthcare systems. They emphasize innovation, particularly in pharmaceutical supply chains, for maintaining quality and reliability while reducing costs. In another study, Dixit et al. (2019) review the literature on healthcare supply chain management and highlight the role of efficient management in improved outcomes. The main challenges are listed as high inventory costs, inefficient procurement systems, and fragmented operations. Like Mathew and John (2013) and Pinna et al. (2015), this study also reports a critical need for integrated systems to enhance coordination among suppliers, hospitals, and logistics providers. Technologies like Enterprise Resource Planning (ERP) and Radio Frequency Identification (RFID) were discussed as crucial support tools for supply chain enhancement, which increase information flow by lowering errors and enabling real-time inventory tracking. AbuKhousa and others (2014) discuss critical supply chain problems such as inventory mismanagement, fragmentation, rising costs, and technological gaps. Furthermore, they propose a simulation and modeling approach (SM), highlighting the need for tools that facilitate decision-making and address complexities by taking advantage of technological developments. Arya et al. (2015) focus on the challenges in the supply chain of high-technology products like heart stents and dental implants. Similar to other researchers, they discuss the high costs involved in phases such as procurement, manufacturing, and delivery. The overall supply chain performance was attributed to enhanced information transparency and improved cost management.

World Health Organization (WHO) defines health technology as the "application of organized knowledge and skills in the form of devices, medicines, vaccines, procedures, and systems developed to solve a health problem and improve quality of lives" (World Health Organization [WHO], 2010). These technologies often involve highly specialized components and precise engineering practices in a globalized environment. Therefore, the role of effective supply chain management becomes even more crucial for healthcare technology manufacturing processes (Herndon et al., 2007). The interaction between innovation, production, delivery, and post-market activities requires effective supply chain practices to ensure reliability across all components. For example, García-Villarreal, Bhamra, and Schoenheit (2019) investigated the critical success factors of health technology supply chains by particularly focusing on Germany. They reported significant pressure from healthcare funding limitations, referring to the importance of cost management as in the previously discussed studies. Furthermore, supply chain integration and collaborations among stakeholders, flexibility and agility for quick adaptation to market demands, quality assurance and safety standards, and adaptation of advanced technologies were also reported as critical success factors. The study provides insights into how health technology supply chains can achieve innovation, regulatory compliance, and operational and financial efficiency for a balanced success. In another study, Bhalaji et al. (2022) investigate key challenges in collaborative health technology supply chains and introduce an MCDM-based model to systematically evaluate and prioritize risk factors. While doing so, supplier reliability, logistical difficulties, production delays, and quality assurance were among the identified criteria for further assessment. Their analyses reveal four crucial areas that posit high risk and are in need of particular consideration: Supplier dependence, technological integration, environmental risks, and regulatory hurdles. If these factors are addressed effectively, collaborations of partners can be enhanced to improve the performance of the supply chain. From a slightly different point of view, Miller et al. (2021) examine the resilience of global health supply chains by using the pandemic case. They identify a few key weak points, such as over-reliance on particular suppliers, lack of redundancy, and inefficient inventory management. They claim that dependence on international suppliers for raw materials and manufacturing activities propagates risks in extreme cases like pandemics. As a solution to this problem, they propose diversification of sources and increasing stockpiles while further improving government policies for potential disruptions. These findings were in line with a similar study conducted by Gereffi (2020) on the influence of the pandemic on global value chains for healthcare supplies. The over-reliance on cost optimization and single-source suppliers were identified as two primary reasons for the problems encountered. Building resilience by diversification and redundancy and the active role of governments were pointed out as potential solutions. These suggested strategies are further supported by Singh and Parida (2022) in their comprehensive review of healthcare supply chain distortions. As in the previously discussed studies, dependency on limited suppliers and lack of redundancy were among the main problems. In addition, MADM frameworks were suggested as a valuable approach for stability and risk minimization within healthcare supply chains. The authors anticipate the growing importance of MCDM in both academic and practical contexts to maintain or increase competitiveness in the healthcare sector.

MCDM methods have been utilized in various problems concerning healthcare supply chain management (Chakraborty et al., 2023). Examples include measuring the performances of distribution networks (El Mokrini et al., 2018), selecting suppliers (Ganguly et al., 2019; Khumpang & Arunyanart, 2019), identifying critical success factors of a supply chain (Sumrit, 2021) and comparing potential improvement strategies (Moosivand et al., 2021). BWM is also preferred in many problems because of its simplicity and adaptability with other MCDM methods. It has been proven effective in addressing various supply chain issues, including forecasting customer churn (Duchemin & Matheus, 2021), supplier selection (Rahmawati & Salimi, 2022), and partner selection for environmental management (Govindan et al., 2019). More specifically, a review by Gulum Tas (2022) revealed that BWM is widely applied in healthcare supply chain management. The consistent findings across these studies underscore the utility of BWM in addressing a spectrum of issues in decision-making processes.

The revealed results of these applications collectively underscore the effectiveness of MCDM methods in addressing diverse challenges in healthcare supply chain management. In particular, their ability to systematically address complex and multi-dimensional problems, stakeholder alignment, and transparency make these methods powerful tools that can be used in strategic supply chain decisions. In this context, the next subsection discusses the use of MCDM methods in different manufacturing unit problems as an important component of supply chain management.

2.2. MCDM in manufacturing unit problems

There are numerous problems related to manufacturing operations, such as process optimization, inventory management, location selection, facility layout, product development, quality control, and risk management (National Research Council, 1995). MCDM methods can be utilized to solve many of these problems and help practitioners to make informed decisions.

A frequently encountered example of using MCDM methods in manufacturing unit problems is the location selection studies for launching a new unit (Ayyildiz & Erdogan, 2024). For instance, Canbolat and others (2007) addressed this challenge, proposing a solution that combines Multi-Attribute Utility Theory (MAUT) and a decision tree. The combination of these methods allowed researchers to consider uncertainty throughout the evaluation. In a similar vein, Kirkwood (1982) applied the MAUT to solve a location selection problem for a nuclear power plant, while Chang and Lin (2015) adopted the Analytic Hierarchy Process (AHP) for a similar problem. In another research by Kheybari and others (2019), the Best-Worst Method was utilized to identify the best location for bioethanol production in Iran. Some researchers extended the AHP by integrating it with other decision-making methods. For example, Mousavi and others (2013) presented a hybrid approach consisting of the Delphi method, AHP, and preference ranking organization method for enrichment evaluations (PROMETHEE). In their application, the decision criteria were determined by the Delphi method and the relative weights of these criteria were calculated with AHP. Finally, the alternatives were ranked using PROMETHEE, demonstrating the advantages of utilizing multiple methods in a systematic manner. In another study, Gorener and others (2012) combined AHP with the Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis to evaluate various factors for a manufacturing firm, demonstrating the versatility of AHP in strategic management.

MCDM methods are prevalent not only in location selection but also in facility layout problems. For example, Athawale and Chakraborty (2010) employed the PROMETHEE II method to address facility layout selection for an industrial workplace. The adopted method was proven to be effective while providing a transparent tool for users. Similarly, Shanshan and others (2020) integrated Analytical Network Processing (ANP), Delphi, Entropy, and PROMETHEE for a comprehensive evaluation framework in an aircraft assembly process. In a slightly different case for an aeronautic component assembly line, ANP and TOPSIS were integrated to evaluate the performance of the layout of the facilities (Shanshan et al., 2018). Farahani and Asgari (2007) studied the warehouse distribution centers in a military logistics system with TOPSIS and Multi-Objective Decision Making (MODM). MCDM applications in manufacturing operations are not limited to these studies. There are various combinations in process optimization (Ghaleb et al., 2020), inventory management (Vukasović et al., 2021), and quality control (Jusoh et al., 2018), highlighting the prevalence of various methods in this field.

2.3. The relevant criteria

In order to identify relevant criteria for the specific problem addressed in this paper, an extensive literature review was conducted, focusing on scientific works in healthcare technology supply chains, manufacturing unit challenges, and general supply chain problems. The criteria identified in the literature, along with their respective sources, are presented in Table 1 below.

Given the intricate nature of the problem and the multitude of influencing factors, a systematic approach was taken to group the criteria into clusters. These clusters are further divided into criteria that, in turn, branch out into sub-criteria. This grouping methodology aligns with the framework established by Alimardani et al. (2013). The resulting structure will serve as a foundational basis for defining a comprehensive list of criteria to be applied in a real-case scenario within Philips.

2.4. Key insights from the literature review

The literature review commenced with a broad exploration of current trends in healthcare technology and healthcare supply chains, emphasizing the role of Multiple Criteria Decision Making (MCDM) in addressing challenges arising from these trends. The initial findings underscore the significance of various MCDM methods as valuable tools in healthcare supply chain management. Subsequently, an in-depth review of existing MCDM methods was conducted, evaluating their strengths, weaknesses, and applicability to the specific case studied. This process led to the selection of a decision-making approach combining Linear Best Worst Method (BWM) and ELECTRE III.

The choice of this combination was informed by several factors. Firstly, the computational advantages of the BWM over other pairwise comparison methods and its performance across different manufacturing problems make it a promising method for our case study. Second, among the non-compensatory methods ELECTRE III is a robust method widely applied to successful supply chain management issues. Moreover, its combination with BWM, which has been proven to be an effective combination by Makarevic and Stavrou (2022), further strengthened the selection. A subsequent brief literature review confirmed the use of diverse MCDM methods in addressing manufacturing unit issues. The various versions of ELECTRE and BWM were elucidated, setting the foundation for the subsequent analysis. Additionally, a comprehensive review identified relevant criteria for the research topic, serving as a starting point for selecting the criteria applicable to the Philips case.

Conclusively, the literature revealed a research gap in utilizing MCDM methods to identify focus areas for process optimization within manufacturing units of healthcare technology companies. While existing research predominantly focuses on solving specific problems post-focus area determination, a clear pathway for the preliminary decision-making step is lacking. The application of BWM in this context presents an opportunity for scientific contribution, considering its underutilization in research. Moreover, the combination of BWM and ELECTRE III represents a novel approach, supported by evidence of its efficacy in manufacturing unit location selection. This combined methodology is poised to fill the existing gap and provide a comprehensive framework for companies embarking on process optimization within manufacturing units in the supply chain, from initial focus area determination to implementation.

Table 1. Relevant criteria from the literature

Cluster	Criteria	Sub-criteria	Sources
Performance	Time	Transportation time	(Wu et al., 2009), (Ghaleb et al., 2020), (Arya et al., 2015), (Bhalaji et al., 2022)
		Distribution time	(Wu et al., 2009), (Ghaleb et al., 2020), (Arya et al., 2015), (Bhalaji et al., 2022)
		On-time response to request	(Sari et al., 2008), (Büyüközkan & Cifci, 2011), (Bhalaji et al., 2022)
		Delivery time	(Sari et al., 2008), (Büyüközkan & Cifci, 2011), (Ghaleb et al., 2020)
	Progress	Customer satisfaction	(Alimardani et al., 2013), (Bhalaji et al., 2022)
		Customer-driven innovations	(Sharifi & Zhang, 1999), (Pinna et al., 2015)
	Quality	Information quality	(Büyüközkan & Cifci, 2011), (Pinna et al., 2015), (Jusoh et al., 2018)
		Product quality	(Luo et al., 2009), (Wu et al., 2009), (Ghaleb et al., 2020), (Pierreval & Tautou, 1997).
		Service level	(Luo et al., 2009), (Wu et al., 2009), (García-Villarreal et al., 2019), (Miller et al., 2021)
Cost	Caution cost	-	(Sari et al., 2008)
	Operating expenditure	Support system cost	(Tam & Tummala, 2001), (Ghaleb et al., 2020), (Arya et al., 2015)
		Maintenance cost	(Tam & Tummala, 2001), (Ghaleb et al., 2020)
		Production cost	(Tam & Tummala, 2001), (Ghaleb et al., 2020), (Arya et al., 2015)
	Capital expenditure	-	(Tam & Tummala, 2001), (Arya et al., 2015)
Flexibility	Manufacture flexibility	-	(Tsourveloudis & Valavanis, 2002), (Lin et al., 2006), (Ghaleb et al., 2020)
	Establishment flexibility	-	Wu et al. (2009), Ghaleb et al. (2020)
	Multi-skilled and flexible people	Employee skills utilization	Ghaleb et al. (2020)
		Continuous training and development	(Tsourveloudis & Valavanis, 2002), (Ghaleb et al., 2020)
	Product volume flexibility	-	(Tsourveloudis & Valavanis, 2002), (Ghaleb et al., 2020)
	Product flexibility	-	(Sharifi & Zhang, 1999), (Ghaleb et al., 2020)
	Complexity	-	(Ghaleb et al., 2020)
Technology	Future technology development	-	(Sharifi & Zhang, 1999), (Tam & Tummala, 2001), (AbuKhousa et al., 2014)
	Interoperability with other systems	-	(Tam & Tummala, 2001), (Tsourveloudis & Valavanis, 2002), (Dixit et al., 2019), (Pinna et al., 2015), (Herndon et al., 2007)
	Compliance with international standards	-	(Tam & Tummala, 2001), (Lin et al., 2006), (García-Villarreal et al., 2019)
	System redundancy	-	(Tam & Tummala, 2001), (Miller et al., 2021), (Singh &Parida, 2022)
	System reliability/availability	-	(Tam & Tummala, 2001), (Lin et al., 2006), (Tam & Tummala, 2001), (Lin et al., 2006), (García-Villarreal et al., 2019), (Herndon et al., 2007).
	Technical features/characteristics	-	(Sharifi & Zhang, 1999), (Büyüközkan & Cifci, 2011)

3. Methodology

This section presents the methodology applied in this paper, as illustrated in Figure 1, and introduces the detailed explanations of BWM and ELECTRE III methods. Moreover, MCDM and group decision-making are briefly discussed within the context of the application.

3.1. MCDM Methods

MCDM methods include compensatory and non-compensatory (outranking) methods (Majumder, 2015). Compensatory methods evaluate alternatives systematically, allowing trade-offs between criteria, while outranking methods eliminate dominated alternatives by comparing based on individual criteria (Mulliner et al., 2016). Some common compensatory methods are Multi-Attribute Utility Theory (MAUT), Analytic Hierarchy Process (AHP), and TOPSIS, and non-compensatory methods include ELECTRE and PROMETHEE (Mulliner et al., 2016). Literature reviews by Wątróbski et al. (2019), Ceballos et al. (2016), and Velasquez and Hester (2013) identified forty-nine MCDM methods. Commonly used methods include MAUT, AHP, Analytic Network Process (ANP), and the Case-Based Reasoning (CBR) (Velasquez & Hester, 2013). MAUT extends Multi-Attribute Value Theory, addressing uncertainty (Velasquez & Hester, 2013). AHP, introduced by Saaty (1977, 1980), yields different weights for alternatives in a multivariate environment (Bernasconi et al., 2010), while ANP is a non-linear extension of AHP (Saaty, 2006). PROMETHEE has various versions, including PROMETHEE I and PROMETHEE II by Brans (1982) and later versions for different scenarios (Velasquez & Hester, 2013). It is widely used but lacks a systematic weight assignment process and clear guidance for determining values (Behzadian et al., 2010; Velasques & Hester, 2013).

One method that was not included in the assessed literature reviews due to its novelty is the Best Worst Method (BWM). This method was introduced by Rezaei (2015). Within BWM, the relevant decision-makers are asked to define the “best” and “worst” criteria from the set, after which all the other criteria are compared with respect to the “best” and “worst” ones. This is followed by obtaining the weights of the criteria by making use of pairwise comparison (Rezaei, 2015). The main advantage of this method is better reliability due to a better consistency ratio that stems from the smaller number of pairwise comparisons needed to be done (Rezaei, 2015).

ELECTRE is an outranking method that is often applied to all kinds of supply chain decision-making problems (Uysal, 2014). It makes use of concordance analysis, and its main advantage over other methods is that it takes into account uncertainty (Velasquez & Hester, 2013). ELECTRE II was introduced by Roy and Bertier (1973), and ELECTRE III was introduced by Roy (1978). There are other versions of ELECTRE that are also frequently used in MCDM literature (Sevkli, 2010).

3.2. Best Worst Method

The Best Worst Method (BWM) was first introduced by Rezaei (2015) as a novel MCDM method featuring a nonlinear minimax model that occasionally yielded multiple optimal solutions. To address the preference for obtaining a single optimal solution, Rezaei (2016) later introduced a linear BWM model. Other variants of BWM include the Best-Worst Tradeoff Method (BWT), designed to consider the ranges of attributes used in pairwise comparisons (Liang et al., 2022a). The Nonadditive BWM is employed when interactions between criteria are present, incorporating the Choquet integral into the computational steps (Liang et al., 2022b). Lastly, the Bayesian BWM is applied in group decision-making problems involving multiple decision-makers with varying preferences, providing a method to aggregate weights and determine final criteria weights (Mohammadi & Rezaei, 2020).

BWM offers several advantages compared to other MCDM methods. The data collection process for analysis is characterized by its simplicity, facilitating communication with decision-makers who may not possess extensive knowledge of MCDM. This feature enhances the accessibility of the method.

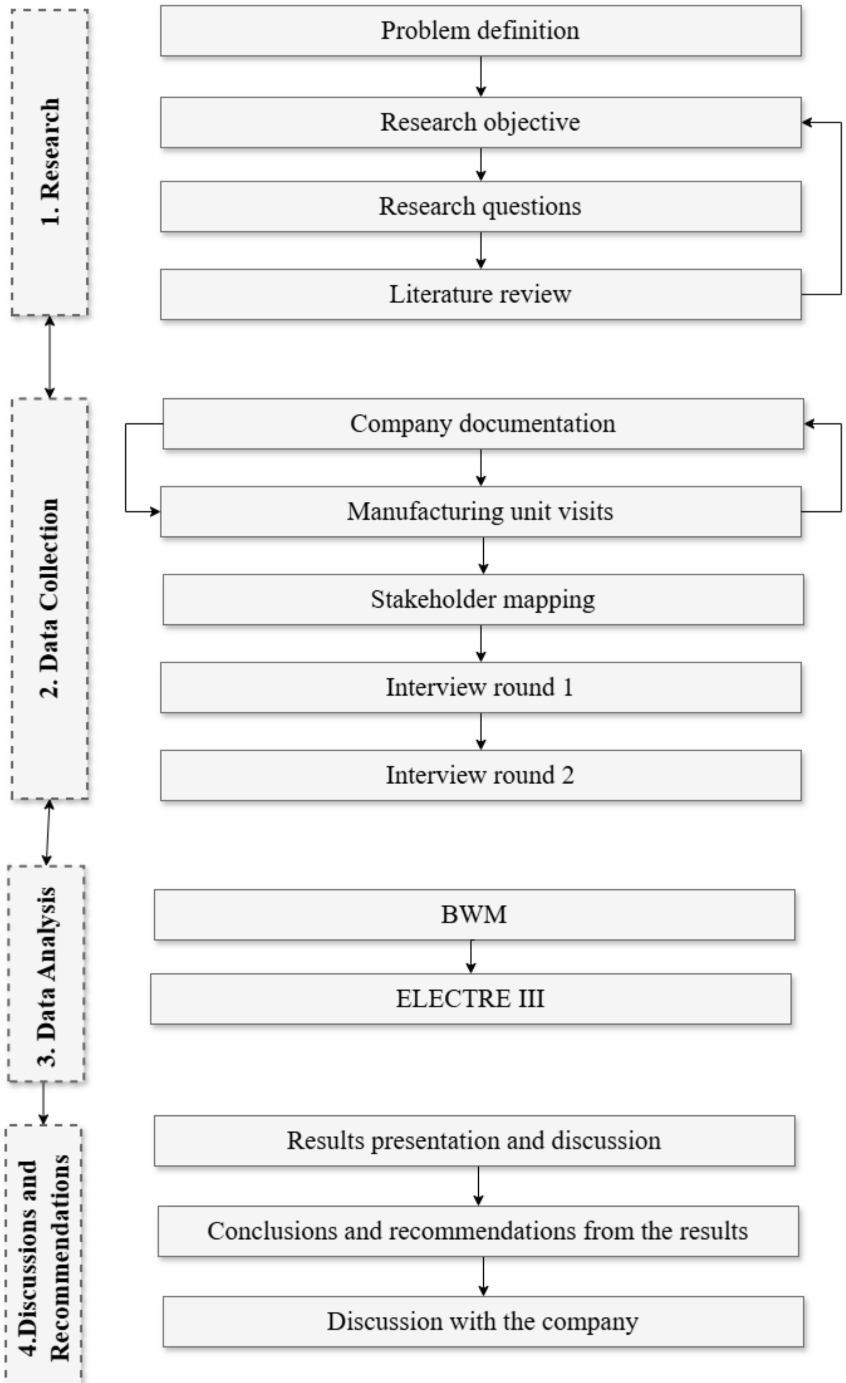

Figure 1. Scheme of the framework design

Additionally, BWM is expected to reduce the likelihood of biases such as anchoring bias (Rezaei et al., 2022a) and equalizing bias (Rezaei et al., 2022b), thereby ensuring more accurate and unbiased decision-making processes. Here, we describe the steps of Linear BWM formulated by Rezaei (2015, 2016). The steps are as follows:

Step 1: The set of relevant criteria $(c_1, c_2, \dots, c_n)$ is presented to the decision-makers.

Step 2: The decision-makers are asked to select the best and the worst criteria from the set $(c_1, c_2, \dots, c_n)$, according to their preferences.

Step *3:* The decision-makers are asked to assign values ranging from 1 to 9 to express their preference of the best criterion over the other criteria from the set. This information is then used to form the Best-to-Others vector A_B:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn})$$

where a_{Bj} is the preference of the best criterion (B) over criterion j. Here, the value of 1 indicates that the chosen criterion is equally important as the best criterion, and the value of 9 indicates that the best criterion is extremely more important than the criterion in question.

Step 4: The decision-makers are asked to assign values ranging from 1 to 9 to express their preference of the criteria from the set over the worst criterion. This information is then used to form the Others-to-Worst vector A_W:

$$A_W = (a_{1W}, a_{2W}, \dots, a_{nW})^T$$

where a_{jW} is the preference of the criterion j over the worst criterion (W).

Step 5*:* The optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ are calculated. This is done by computing a solution where the maximum differences of $|w_B - a_{Bj}w_j|$ and $|w_j - a_{jW}w_W|$ are minimized. This step corresponds to the mathematical model that follows:

$$\begin{gathered} \min max_j\{\, |w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W| \,\} \\ \textit{such that} \\ \sum_j w_j = 1, \\ w_j \geq 0, for\ all\ j. \end{gathered} \tag{1}$$

which is equivalent to:

$$\begin{gathered} \min \xi, \\ \textit{such that} \\ |w_B - a_{Bj}w_j| \\ \leq \xi, for\ all\ j, \\ |w_j - a_{jW}w_W| \leq \xi, for\ all\ j, \\ \sum_j w_j = 1, \\ w_j \geq 0, for\ all\ j. \end{gathered} \tag{2}$$

The solution of this model is the optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ and ξ^*.

Step 6: The consistency ratio CR is calculated according to Liang et al. (2020) as follows:

$$CR = \max_j CR_j$$

where

$$CR_j = \begin{cases} \dfrac{\left|a_{Bj} \times a_{jW} - a_{BW}\right|}{a_{BW} \times a_{BW} - a_{BW}}, & a_{BW} > 1, \\ 0, & a_{BW} = 1. \end{cases} \tag{3}$$

Then, the consistency ratio is compared to the threshold values for input-based BWM presented below in Table 2 (Liang et al., 2020).

Table 1. Thresholds for input-based BWM (Liang et al., 2020)

Scales	**Criteria**						
	3	**4**	**5**	**6**	**7**	**8**	**9**
3	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667
4	0.1121	0.1529	0.1989	0.2206	0.2527	0.2577	0.2683
5	0.1354	0.1994	0.2306	0.2546	0.2716	0.2844	0.2960
6	0.1330	0.1990	0.2643	0.3044	0.3144	0.3221	0.3262
7	0.1294	0.2457	0.2819	0.3029	0.3144	0.3251	0.3403
8	0.1309	0.2521	0.2958	0.3154	0.3408	0.3620	0.3657
9	0.1359	0.2681	0.3062	0.3337	0.3517	0.3620	0.3662

3.3. ELECTRE III

The ELECTRE method, introduced by Bernard Roy in 1968, has evolved into various versions, including ELECTRE I, II, III, IV, and TRI (Yu et al., 2018). For ranking problems, ELECTRE III, developed by Roy in 1978, stands out. ELECTRE III introduces concordance and discordance indices, enabling detailed analysis of outranking relationships, even with inaccurate data. It incorporates criteria weights and thresholds for concordance and discordance, making it precise for expressing preferences and handling uncertain data (Roy, 1991). The computational steps of ELECTRE III, formulated by Roy (1978, 1991), are described below.

In ELECTRE III, the preferences are modeled by making use of outranking relations (S), which means ‘‘at least as good as’’. Furthermore, a preference relation incomparability (R) is introduced. If there are two alternatives a and b, then there are four possible cases (Figueira et al., 2016):

1. aSb and not bSa, that is a is preferred to b ($a \succ b$)
2. bSa and not aSb, that is b is preferred to a ($b \succ a$)
3. aSb and bSa, that is a is indifferent to b (aIb)
4. Not aSb and not bSa, that is a is incomparable to b (aRb)

The basis for an outranking relation is in two key concepts (Figueira et al., 2016), namely:

1. Concordance: “For an outranking aSb to be validated, a sufficient majority of criteria should be in favor of this assertion.”
2. Non-discordance: “When the concordance condition holds, none of the criteria in the minority should oppose too strongly to the assertion aSb.”

All ELECTRE methods consist of two main procedures, namely aggregation and exploitation. Aggregation involves the process of making outranking relations so that the alternatives can be compared, whereas aggregation refers to the results, i.e. the ranking/choice/sorting of the alternatives (Figuiera et al., 2016). In further text, Steps 1-4 refer to aggregation, and step 5 corresponds to the exploitation procedure.

Step 1: The decision-makers are asked to assign values to their preference (p_j), indifference (q_j) and veto (v_j) thresholds.

Step 2: For every pair of the alternatives a and b, the concordance indices $C(a,b)$ are calculated as follows:

$$C(a,b) = \frac{1}{W}\sum_{j=1}^{n} w_j c_j(a,b) \tag{4}$$

where

$$W = \sum_{j=1}^{n} w_j \tag{5}$$

$C(a,b)$ always has a value in between 0 and 1. If $C(a,b)$ = 0, the alternative a is worse than the alternative b, with respect to all the criteria in the set. $c_j(a,b)$ is the comparison index for every criterion j, and it is computed based on the performance of the alternatives.

Case 1 If the alternative a is either equivalent to or better than the alternative b minus the indifference threshold for criteria j:

$$c_j(a,b) = 1 \; if \; \mathrm{g_j}(a) + q_j(g_j(a)) \geq \mathrm{g_j}(b) \tag{6}$$

Case 2 If the performance of alternative a plus the performance threshold is less than the performance of the alternative b, then alternative a is not better than b with respect to this selected criterion:

$$c_j(a,b) = 0 \; if \; g_j(a) + p_j(g_j(a)) \leq g_j(b) \tag{7}$$

Case 3 In all other cases:

$$c_j(a,b) = \frac{g_j(a) - g_j(b) + p_j(g_j(a))}{p_j\left(g_j(a)\right) - q_j(g_j(a))} \tag{8}$$

Step 3: The discordance index ($D(a,b)$) is computed. Its purpose is to utilize the veto threshold (v_j) and consider the cases in which one alternative is better than the other in general, but there is one or more (veto) criteria where it performs worse than the other alternative. The calculations are as follows:

Case 1 If the alternative b is not better than the alternative a by a more than v_j:

$$D_j(a,b) = 0 \; if \; g_j(b) \leq g_j(a) + p_j(g_j(a)) \tag{9}$$

Case 2 If the alternative b is better than the alternative a by a more than v_j:

$$D_j(a,b) = 1 \; if \; g_j(b) \geq g_j(a) + v_j \tag{10}$$

Case 3 In all other cases:

$$D_j(a,b) = \frac{g_j(b) - g_j(a) - p_j(g_j(a))}{v_j - p_j(g_j(a))} \tag{11}$$

<u>Step 4:</u> The credibility ($S(a,b)$) is computed by combining the results obtained from the concordance and discordance calculations in the following manner:

Case 1 If there is no discordance or veto threshold:

$$S(a,b) = C(a,b) \; if \; D_j(a,b) \leq C(a,b), \forall_j \tag{12}$$

Case 2 In all other cases:

$$\mathrm{S}(a,b) = \mathrm{C}(a,b) \prod_{\mathrm{j}=1}^{\mathrm{n}} \frac{1 - D_j(a,b)}{1 - C(a,b)} \tag{13}$$

<u>Step 5:</u> The ultimate ranking is determined by evaluating the performance of each option in the preceding steps. Specifically, whenever alternative a surpasses alternative b, it receives a score of +1, whereas the other one receives a score of -1. Once all scores are summed up, a final score is calculated, which decides the ranking.

3.4. Group decision-making in MCDM

Group decision-making in multi-criteria decision-making (MCDM) involves multiple individuals making decisions based on various criteria or factors that influence the outcome. It is a collaborative process where individuals with diverse perspectives, knowledge, and expertise converge to reach a consensus or make a joint decision, considering different criteria (Hirokawa & Poole, 1996).

The objective of group decision-making is to integrate the preferences and judgments of individual group members, leading to a final decision that incorporates the collective wisdom and expertise of the group. This approach offers several advantages, including the utilization of diverse knowledge and perspectives, improved decision quality, and enhanced understanding and acceptance of the decision among stakeholders. However, it also introduces challenges such as information overload, conflicts of interest, and difficulties in achieving consensus.

Various approaches and methods have been proposed to facilitate group decision-making in MCDM, including analytic hierarchy process (AHP) (Saaty, 1980), TOPSIS (Wang & Elhag, 2006), fuzzy sets theory (Zadeh, 1965), and multi-objective optimization techniques (Boix-Cots et al., 2023), among others. These approaches provide frameworks and algorithms to aggregate individual preferences, resolve conflicts, and ultimately support the group in reaching a collective decision.

Research in the field of group decision-making in MCDM has explored various aspects such as group dynamics, preference elicitation techniques, consensus measurement, and decision support systems. The aim is to enhance the effectiveness and efficiency of group decision-making processes, understand group dynamics better, and develop methodologies that can effectively handle complex decision problems (Bose et al., 1997; Morente-Molinera et al., 2015; Tanino, 1988). For example, Belton and Pictet (1997) propose three ways to address different views of decision-makers: sharing, aggregating, and comparing. Sharing involves seeking a common element through consensus, achieved through deliberative discussions and negotiation. Aggregating seeks a common element through compromise, often via voting or calculating a representative value, focusing on minimizing differences without explicit discussions. Comparing aims to obtain individual elements and potentially reach a consensus by negotiating independent results, acknowledging differences without actively diminishing them. The choice among these methods depends on the context of the MCDM issue. In this research, the method chosen is sharing, as it ensures a shared understanding by dealing with potential different interpretations from decision-makers from the beginning. This approach addresses differences explicitly, reducing the likelihood of overlooking them, unlike aggregating and comparing, which may only recognize differences in later stages (Belton & Pictet, 1997).

4. Case study

This section presents the results of a case study conducted at Phillips. It begins with a brief introduction to the company, followed by a detailed discussion of the interviews and data collection processes. Subsequently, the alternatives and criteria are outlined.

4.1. The company

Philips is highly customer-oriented, and the entire company is structured around application domains, reflecting its commitment to addressing patient needs. The three Business Clusters within Philips are Personal Health, Diagnosis & Treatment, and Connected Care. The research is conducted within the Image-Guided Therapy (IGT) Business, which is part of the Diagnosis & Treatment Cluster.

In recent decades, image-guided therapies have quietly revolutionized the healthcare industry, moving from invasive surgeries requiring lengthy hospital stays to minimally invasive procedures that allow for shorter recovery times and, in some cases, same-day discharge. These procedures, guided by advanced medical imaging technologies such as X-ray, MR, CT, and ultrasound, involve small incisions and offer benefits like reduced patient trauma, shorter recovery and hospitalization times, faster patient throughput, and lower healthcare costs. Philips IGT Systems is a global leader in innovation within the field of image-guided intervention (Philips, 2020).

The IGT Business focuses on image-guided minimally invasive treatments, which are further categorized into IGT Devices and IGT Systems. The IGT Systems Business provides fully integrated health systems consisting of interventional X-ray systems and software solutions. These systems enable doctors to perform personalized, minimally invasive procedures. IGT Devices enhance the functionality of IGT Systems by integrating navigational tools like catheters and guide wires with advanced software, facilitating optimal treatment guidance and confirmation at the point of care.

Within IGT Systems, Fixed and Mobile Surgery solutions are available to meet diverse customer needs. The Fixed systems are part of the Azurion series, while the Mobile systems are within the Zenition series. The focus of the research is on the assembly process of a specific part of the Fixed (Azurion) Systems – the stand of the floor-mounted Azurion systems with a rotation point on the floor. This type of stand can be found in multiple Azurion Systems, and the assembly steps carried out in the manufacturing unit are consistent across all systems of this kind.

The assembly of IGT Systems occurs in Philips's Manufacturing Units, where factory operators assemble the systems following detailed, pre-defined, and documented procedures known as 'Work instructions.' These instructions are created by Manufacturing employees based on the system design provided by R&D employees. The Work instructions outline the exact steps for assembly. Studying these instructions and observing operators on the factory floor provides a comprehensive understanding of each step in the assembly process. Deconstructing the process into steps facilitates a thorough analysis to identify the most promising focus area for improvement. In this context, the alternative focus areas used in the Multi-Criteria Decision-Making (MCDM) analysis are the process steps of the Azurion Floor Stand assembly.

Based on stakeholder mapping, six representative decision-makers with various professional roles were selected for interviews.

R&D Designer: Generates the ideas and forms the designs of the systems.
Development Engineer: Implements the changes in the design.
Manufacturing Engineer: Creates work instructions based on R&D input and tackles engineering processes in the manufacturing unit.
Product Industrialization Engineer: Between R&D and manufacturing engineers, represents the manufacturing unit during the design process and reviews R&D designs.
Production Improvement Manager: Manages the manufacturing unit operators, responsible for improvements in production processes.
QA Engineer: Performs quality assurance practices in the factory.

4.2. Interviews

In choosing the relevant decision-makers who were interviewed, several factors needed to be considered in order to ensure the reliability of the results. First, it was important that the decision-makers hold different positions within the company so that they could represent the preferences of different company sectors. On top of this, it was important that they have spent enough time in the company to be familiar with the relevant products and processes, so that they could effectively assess the importance of the criteria. The relevant company sectors and the employees within them were identified by stakeholder mapping, which was done based on company documentation, as well as daily experience in the company. After this, a power/interest grid was constructed to make sure that the chosen decision-makers had the power to influence the problem at hand, as well as interest in tackling it.

The interviews were conducted in two rounds. Both interviews were carried out with all the chosen decision-makers at the same time and were composed of semi-structured interviews (Kallio et al., 2016). This was done in order to ensure that each decision-maker could freely express their preferences and so that, ultimately, the agreed-upon preferences were indeed representative of the whole company. Furthermore, a rigid interview structure is not beneficial when stakeholders with different roles in the company are brought together with the end goal being them reaching an agreement. This method of conducting interviews is also in line with enabling group decision-making through sharing (Belton & Pictet, 1997).

The two interviews were organized as face-to-face sessions lasting one hour each. The first fifteen minutes of the sessions were allocated for explaining the methodology, the goals and the outputs that needed to be collected. The aim of the first interview was to formulate a set of relevant criteria for the MCDM problem. First, the criteria from the literature were presented to the decision-makers. They were then asked to assess together whether those criteria were relevant to the specific issue, as well as if there were certain criteria that should be added to the set, some of which were suggested by the interviewer based on her findings from the company. The output of this interview was the final set of 7 criteria described before.

After the criteria were chosen, the data for BWM and ELECTRE III needed to be collected. The second interview once again involved the six relevant decision-makers. This time, the two methods and the kind of information they needed to provide for the analysis were explained. More specifically, the meaning behind the numbers ranging between 1 and 9 for BWM vectors was clarified, as well as the preference, indifference, and veto thresholds for ELECTRE III. The decision-makers then together discussed their preferences, eventually agreeing on the values assigned to the criteria for BWM, as well as the thresholds for ELECTRE III.

4.3. Alternatives

The set of alternatives chosen by Philips represents the possible focus areas where process optimization will be introduced first. The focus areas are all the steps that are being done in the manufacturing unit and in the assembly process of the Azurion Floor Systems Stand. The steps are divided and named according to the main action that is being performed throughout the step. A detailed description of each step is not given due to confidentiality, as well as due to the nature of the research. Namely, as the focus is not on the engineering design and details of the process, it is not necessary for that kind of information to be included in this research.

There are 8 steps, and in order of assembly, they are: Preparation, Mounting 1, Cabling 1, Mounting 2, Adjustment, Cabling 2, Testing, and Mounting 3. Mounting refers to the attachment of smaller parts of the system, such as the motor and covers, onto the larger parts, such as the stand and the floor arm. Cabling involves all routing and connecting of the cables for the system. Adjustment involves processes such as calibrating the X-ray, while Testing refers to the tests that are being carried out on the system in order to confirm that the assembly was performed correctly and that the product meets the quality standards. It is important to note that there is no significant relationship between the 8 steps, although they are set up in sequence and together make up an integrated system. Namely, the implementation of process optimization in one of the steps is not expected to influence the performance of other steps.

4.4. Criteria

The set of criteria that was used in the MCDM analysis of the issue within Philips was derived by combining the findings from literature and discussions with different decision-makers within Philips in the first interview. In order to arrive at the final set of criteria, the criteria found in the literature were first presented to the decision-makers. The main factor that needed to be taken into account was that the existing literature mainly addresses specific problems with the alternatives in the form of different locations, supplier companies, and so on. In contrast, the alternatives in the case of Philips are process steps, which makes the criteria selection increasingly difficult, as it is not possible to assess certain criteria ‘per process step’, and some criteria are simply irrelevant from a stepwise perspective. These are criteria such as customer satisfaction, cost, compliance, reliability and so on. For the sake of more clarity, the decision-makers thought that it would be useful to select the main criteria, which would then be described by other criteria. So, Flexibility, Requirements, and Technology were deemed the main criteria, described by a total of 7 criteria. These criteria are either taken directly from the literature or they were adjusted to fit the application. A schematic overview is presented in Figure 2 below. All the criteria and the reasons for their selection are described in detail in the following.

Flexibility: An important factor to consider when deciding on where process optimization should be applied is Flexibility, as it addresses whether there exists an opportunity for implementing any changes within the process. Higher flexibility indicates that it is easier to introduce design improvements. To sufficiently assess this, the Flexibility criterion is assessed through 3 sub-criteria, namely R&D Flexibility, Manufacturing Flexibility, and Complexity. R&D Flexibility indicates the willingness and ability of R&D to influence the step in question. The value of the criterion is assigned on a scale from 1 to 5, where 1 represents no willingness and ability from the R&D side and 5 stands for a high level of both willingness and ability for influencing the alternative from R&D. The values of this criteria are determined by knowledgeable decision-makers from IGT Systems R&D in Philips. In the same way, the values are assigned for Manufacturing Flexibility, but in this case, they are assigned by knowledgeable decision-makers from Manufacturing. The final criterion in the Flexibility cluster is Complexity. The higher the Complexity of the step, the lower the Flexibility, and vice-versa. Additionally, Complexity also addresses quality in the sense that a more complex step normally results in more mistakes i.e., more issues arise in the quality assessment process. This criterion also ranges from 1 to 5, but the values are assigned by decision-makers from both R&D and Manufacturing based on how much complexity is there in the design of this step, as well as how much knowledge and practice are necessary to carry out the step on the factory floor. The value of 1 indicates a very low level of complexity, whereas 5 represents the opposite, namely a very complex step to carry out and design. This means that the Complexity is inversely proportionate to the performance of the alternatives, namely it is desirable to have a low level of Complexity for process optimization. This property is considered and included in the computational steps of ELECTRE III.

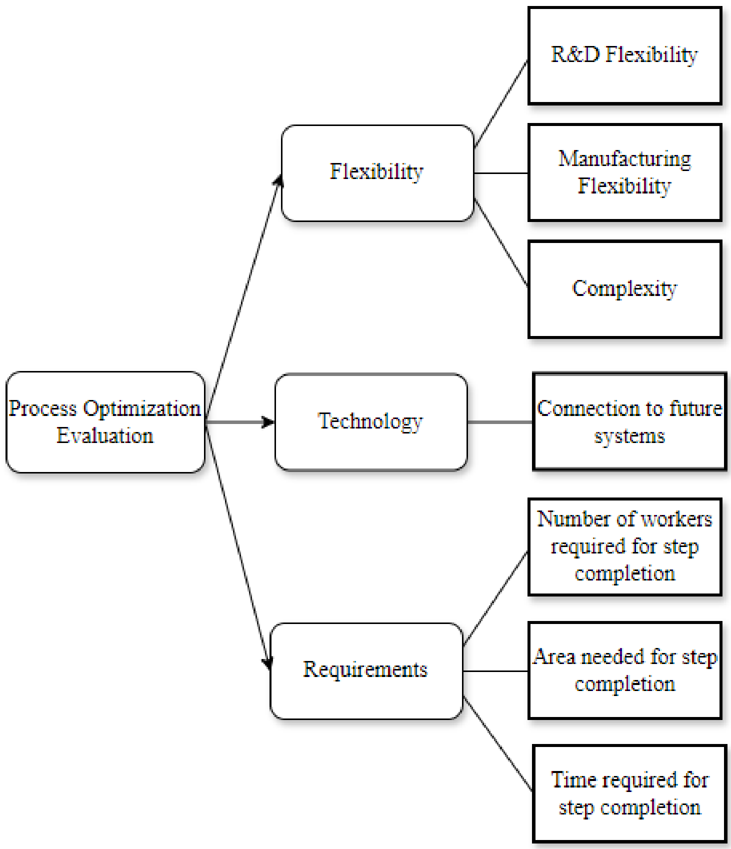

Figure 2. Criteria used in the MCDM analysis

Technology: In the healthcare technology industry, it is necessary for technology to be incorporated into any kind of assessment. In the case of Philips, aside from implementing process optimization in the already existing process steps, it adds great value if some of the learnings from this particular issue can later be applied to similar systems within the portfolio, as well as to new, future systems. For this reason, the Technology criterion is expressed by Connection to future systems and backwards compatibility. The value for the alternatives when it comes to this sub-criterion are assigned by knowledgeable decision-makers within the company and ranges from 1 to 5. A score of 1 indicates that the step in question has no connection to other existing systems nor the innovations planned for the future, whereas 5 indicates that it is certain that this step will be involved in the assembly of new planned systems and is already frequently seen in the currently-made systems. The alternatives with the corresponding values of the criteria are presented in Table 3 below.

Requirements: When dealing with complex manufacturing processes, certain requirements play a big part in carrying out process optimization. In this case, the Requirements criterion is defined by the sub-criteria Number of workers required for step completion, Area needed for step completion and Time required for step completion. These sub-criteria are crucial, as it is quite difficult to determine the cost per step in euros/another currency, and when tackling process optimization, cost minimization is normally one of the main goals of the whole process. So, the Requirements criterion also makes it possible to express the cost per step of the process in terms of human labor necessary, the area in m2 and the time utilized for the particular step.

Table 3. The alternatives and their performance according to the criteria

Process step	R&D Flexibility (1-5)	Manufacturing Flexibility (1-5)	Complexity (1-5)	Number of workers required for step completion	Area needed for step completion (m2)	Time required for step completion (min)	Connection to future systems and backward compatibility (1-5)
Preparation	1	2	1	1	6	55	4
Mounting 1	2	3	2	2	6	190	3
Cabling 1	3	2	1	1	6	90	5
Mounting 2	3	3	3	1	6	185	4
Adjustment	1	4	5	1	6	40	5
Cabling 2	4	4	2	2	9	200	5
Testing	2	2	2	1	6	20	4
Mounting 3	1	3	3	1	6	40	3

5. Results

This section first outlines the results obtained by the linear BWM and then introduces the ranking obtained by using ELECTRE III. The values for the BWM vectors were achieved through consensus of the 6 decision-makers. The explanations of the criteria were supplied to them beforehand and were then briefly addressed once again at the beginning of the interview session. The first question posed to them was to decide on the Best and the Worst criterion. When choosing the Best, from the beginning, there was a discussion on whether this should be Complexity or Connection to future systems and backward compatibility. The interviewer then explained the meaning of these two criteria in more detail so that the decision-makers would gain more clarity and possibly come to an agreement with more ease. The latter criterion was deemed very important as Philips is focused on constantly innovating and introducing new products. Furthermore, backward compatibility plays a great role, as the company has been making significant efforts with respect to modularization and standardization of their systems. On the other hand, Complexity encompasses R&D, Manufacturing, as well as Quality. In the healthcare technology industry, quality plays a crucial role, as there are a number of rules to comply with, and it is extremely important that the number of mistakes is minimized, as the end users are human patients. For this reason, the decision-makers agreed on selecting Complexity as the Best criterion. The choice for the Worst one again was between two criteria, this time R&D Flexibility and Manufacturing Flexibility. The main reason for this was that it was deemed that if there is little flexibility in either sector, this is something that could be overcome and disregarded if the opportunity for improvement proved to be good enough with respect to other factors. Ultimately, the chosen one was R&D Flexibility, as one of the decision-makers pointed out that although the lack of both of these could be overcome if all the other criteria are satisfied, there could be some obstacles in Manufacturing that would not be possible to surpass.

After the choices for the Best and the Worst criterion were made, the decision-makers were asked to assign values ranging from 1 to 9 to all the criteria, with respect to the Best one (Complexity), which was assigned the value of 1. In the same manner, R&D Flexibility was then assigned the value of 9. Taking into account the previous discussion, the decision-makers decided that Connection to future systems and backward compatibility should be given the value of 2 and Manufacturing Flexibility the value of 8, as these were both considered close in importance to the Best and the Worst, respectively. The three criteria used to describe the main criteria Requirements, namely Number of workers required for step completion, Area needed for step completion and Time required for step completion were said to be quite close in importance for the decision-makers, as they all describe what is necessary for the completion of the process steps. It was also pointed out that they are all considered much closer to the Best criterion than to the Worst. However, among the three, the Time required for step completion was agreed upon as the most important, which is why it was awarded the value of 3. The area needed for step completion was discussed next among the interviewees and was awarded a 4, closely followed by the Number of workers required for step completion, which was awarded a 5. The input from the decision-makers more involved with the operations carried out in the manufacturing unit was that the number of workers didn't matter as much, as it is quite flexible, namely the factory operators frequently help each other in carrying out the steps. The input from the interviews was then organized to form The Best-to-Others and Others-to-Worst vectors for the computational steps of BWM, as presented in Tables 4 and 5, respectively.

Table 4. Best-to-Others vector

Best to Others	R&D Flexibility	Manufacturing Flexibility	Complexity	Number of workers required for step completion	Area needed for step completion	Time required for step completion	Connection to future systems and backward compatibility
Complexity	9	8	1	5	4	3	2

The Others-to-Worst vector was formulated as follows:

Table 5. Others-to-Worst

Others to the Worst	R&D Flexibility
R&D Flexibility	1
Manufacturing Flexibility	2
Complexity	9
Number of workers required for step completion	5
Area needed for step completion	6
Time required for step completion	7
Connection to future systems and backward compatibility	8

Based on the values of the Best-to-Others and Others-to-Worst vectors, the obtained weights of the criteria were calculated as in Table 6.

Table 6. Weights of the criteria

Weights	R&D Flexibility	Manufacturing Flexibility	Complexity	Number of workers required for step completion	Area needed for step completion	Time required for step completion	Connection to future systems and backward compatibility
	0.0310	0.0543	0.3570	0.0869	0.1086	0.1449	0.2173

The input-based consistency ratio (CR) calculated for this case was 0.2222. The threshold that this value is compared to is 0.3517 from Table 2 (Liang et al., 2020). As CR is lower than the threshold, the consistency level is deemed acceptable. After calculating the importance weights of the criteria, we moved to ELECTRE III. The relevant decision-makers together supplied one set of preference (p), indifference (q) and veto (v) thresholds. The first step in collecting this data was a detailed explanation of the meaning of the different thresholds to the decision-makers. This step of the interviews required more involvement from the interviewer, as the decision-makers normally do not come across similar tasks in their day-to-day work. So, the interviewer provided examples of what certain values of the thresholds would imply in terms of decision-makers' preferences. There were no significant discrepancies and disagreements between the decision-makers with respect to assigning the values to the thresholds, and once the method was well-explained, agreement was reached with no problems. The assigned values of the thresholds are presented in Table 7 below.

Table 7. Preference, indifference, and veto thresholds of the decision-makers in Philips

	R&D Flexibility	Manufacturing Flexibility	Complexity	Number of workers required for step completion	Area needed for step completion	Time required for step completion	Connection to future systems and backward compatibility
p	2.2	2.9	2.4	1.3	1.1	103	4.2
q	1	2	1	1	1	10	3
v	/	/	3	/	8	180	3

Not all criteria were assigned a value for the veto threshold (v). This is because the decision-makers determined that not all criteria have veto power, but only those that are deemed important enough that above a certain level, all other relations can be neglected. The cutting level (λ) for the Credibility index was set to 0.7 in order to obtain more accurate results (Figueira et al., 2016). The credibility matrix that resulted from the ELECTRE III computational steps is presented in Table 8 below. After the Credibility matrix, the final ranking was obtained, as presented in the last column of Table 8. The focus areas were ranked from 1 to 8, where 1 represents the alternative with the highest score.

Table 8. The credibility matrix

	Preparation	Mounting 1	Cabling 1	Mounting 2	X-ray alignment	Cabling 2	Testing	Mounting 3	Final Ranking
Preparation	1	0.86	0.94	0.57	0.64	0.72	1	0.75	5
Mounting 1	1	1	1	1	0.64	0.87	1	1	4
Cabling 1	1	0.86	1	0.61	0.64	0.75	1	0.75	7
Mounting 2	1	1	1	1	0.75	0.88	1	1	2
Adjustment	0	0	0	0.83	1	0	1	1	3
Cabling 2	1	1	1	1	0.64	1	1	1	1
Testing	0.96	0.77	0.91	0.86	0.63	0	1	0.98	8
Mounting 3	0.99	0.86	0.91	0.83	0.75	0.65	1	1	6

6. Discussion

When it comes to the weights of the criteria computed by BWM, Complexity was deemed the best criterion by the decision-makers with a weight of 0.3570. This result is due to the fact that this criterion encompasses both the complexity from R&D's point of view, as well as Manufacturing. Furthermore, it also addresses quality, which is a very important factor when it comes to healthcare, as there are numerous standards that need to be met. The criterion that has the second-highest weight at 0.2173 was Connection to future systems and backward compatibility. This result could stem from the fact that Philips is an innovation-driven company in a highly competitive industry. Namely, in order to gain/maintain competitive advantage, the company needs to constantly look ahead into the future and make improvements that will remain valuable in the long term. In the case of process optimization, it makes sense to focus on a process that will be present in future systems, as these new systems will eventually substitute the ones currently in place. Even if this is not the case, being able to reuse the same practices in multiple systems that are already being produced increases the modularity of the systems and so makes the company more adaptable to the fast-changing environment. The next criterion by weight is the Time required for step completion with a weight factor of 0.1449, which is closely followed by the Area needed for step completion with a weight of 0.1086. These two criteria both address the resources required for each step of the process, so it makes sense that they would be ranked high, as one of the main goals of process optimization is always cost minimization, and cost in terms of area and time is expressed through these two criteria. The fifth criterion, according to the weight, is the Number of workers required for step completion, with a weight of 0.0869. Although this criterion is also a measure of cost, in terms of human labor necessary, it is not considered as important as the two aforementioned ones. The reason for this is that although there is an exact number of workers necessary for the step, some steps are often performed with more workers than necessary anyway in order to save time. So, it makes sense that the Time required for step completion precedes this criterion in terms of importance (weight). The two criteria with the lowest weights are Manufacturing Flexibility and R&D Flexibility, with weights of 0.0543 and 0.0310, respectively. This means that R&D Flexibility was deemed the worst criterion by the decision-makers. The main reason for this could be that decision-makers consider these criteria as something that can be overcome. For instance, the R&D department possesses the necessary competencies to tackle challenging projects that have to do with steps that are regarded as highly inflexible, and their willingness to do so is subject to change if something proves to be a good opportunity for improvement. The same goes for the manufacturing sector.

As the chosen criteria in great part stemmed from existing literature, the weights computed based on the preferences of the decision-makers in Philips were also compared to the weights in the literature, and several observations can be made. Ghaleb et al. (2020) conducted an MCDM analysis for manufacturing process selection and made use of seven criteria, including Complexity and Flexibility. In their analysis, these two criteria were found to have very similar weight factors, namely 0.104459 and 0.102623, respectively. Furthermore, these criteria were located in the middle with respect to the weights of the other criteria in the study. This is quite a significant difference, as Complexity was deemed as the most important criterion by Philips, and Manufacturing Flexibility and R&D Flexibility were regarded among the least important ones. Tam and Tummala (2001) use the criteria of Future technology development and Interoperability with other systems, which can be considered equivalent to the criterion of Connection to future systems and backward compatibility in the case of Philips. In the analysis of Tam and Tummala (2001), Future technology development and Interoperability with other systems are ranked 13 and 18, respectively, based on their weights and out of 26 chosen criteria. This result also represents quite a discrepancy from the ones obtained in this analysis, as the criterion Connection to future systems and backward compatibility was considered the second most important one, closely following Complexity in terms of weight. These differences could stem from the company culture and structure, as well as the fact that every MCDM issue is unique and very complex. Furthermore, it is also important to note that the set of relevant criteria for Philips represents a combination of criteria from existing literature and criteria deemed relevant by the decision-makers, and so although it is interesting to observe the differences between literature and real-case application, it is difficult to draw conclusions when the sets of criteria are in fact different.

The ranking that resulted from ELECTRE III placed Cabling 2 as the number one focus area for process optimization. This alternative had the second-best score possible (2) with respect to the best criterion, Complexity. Furthermore, in comparison to the other alternatives, it also performed the best in the three highest-weighing criteria following the best one, namely Connection to future systems and backward compatibility, Time required for step completion, and Area needed for step completion. Therefore, it is clear why it was ranked first. The process step that was ranked last is Testing. This step performed poorly with respect to almost all the most important criteria.

6.1 Strategies and recommendations for the company

Based on the ranking results, the overall recommendation for Philips would be to implement process optimization within the Cabling 2 step of the assembly process. The first step in this process would be to explore ways in which this could be done. For instance, a brainstorm with R&D and Manufacturing Engineers could be organized in order to foster idea generation for possible solutions. From these ideas, it would then be possible to select a set of the most promising solutions, which could then be considered as a new set of alternatives for another MCDM analysis. The outcome of the analysis would then be the ranking of specific solutions for process optimization within the Cabling 2 process step. Of course, it is important to note that the set of relevant criteria in this case would significantly differ from the one used in determining the focus area for process optimization.

In any case, one of the most important steps before implementing a specific solution for process optimization is assessing the feasibility of the solution. Namely, it is necessary to carry out a thorough financial analysis in order to sufficiently determine both the costs and the benefits that stem from the chosen solution. The financial feasibility could also already be taken into account when choosing the relevant criteria for Cabling 2 process optimization through one or more measurable criteria, as this was not possible in the MCDM analysis related to choosing the focus area due to the nature of the alternatives, so the cost was expressed through the Requirements criterion.

Finally, in case the company decides to look for an additional focus area for process optimization later in the future, an analysis such as the one carried out in this research should be done again from the beginning. This means that the choice of criteria, their weights, as well as the performance of the alternative focus areas should be reassessed, as the healthcare technology industry is a dynamic one and the various qualitative and quantitative parameters can vary over time. On top of this, the choice of relevant decision-makers should be reassessed as well by means of performing stakeholder mapping and constructing a new power/interest grid depending on the scope of the new project.

6.2 Limitations of the study and possibilities for further research

The choice of any MCDM method for the analysis could be argued both for and against. Naturally, the use of MCDM methods other than the ones chosen was considered. For instance, the use of AHP for both obtaining the weights and the ranking was considered, as this method is widely used for MCDM problems (Aziz et al., 2016). However, BWM utilizes a smaller number of pairwise comparisons and yields more consistent comparisons (Amiri et al., 2021). PROMETHEE was also considered for use instead of ELECTRE III. However, ELECTRE III was said to outperform PROMETHEE (Majdi, 2013).

When it comes to the selected criteria, it is important to mention that Flexibility and Technology may not be fully objective because the values for the performance of the alternatives with respect to these criteria were assigned by people working within Philips, as opposed to the Requirements criterion, for which the values were measured by a device and can therefore be considered as more objective.

The possibility of the presence of different kinds of cognitive and motivational biases must be addressed in the context of MCDM, as this can be a cause of distortion of the analysis of decision-making problems. Cognitive biases are defined by Montibeller and von Winterfeldt (2015) as “faulty mental processes that lead judgments and decisions to violate commonly accepted normative principles.” A cognitive bias worth mentioning for this particular case is the anchoring bias. This bias could occur when there is a given initial value, i.e., the anchor, that then serves as a basis for estimating the final answer (Tversky & Kahneman, 1974). Within the methods used in this research, the anchoring bias could be present in the elicitation of the weights. However, BWM does involve a debiasing strategy for anchoring, in that the weights are computed first based on the Best-to-Others vector and afterward on the Others-to-Worst vector. The weights cancel out the biasing effects, leading to a less biased final answer. Motivational biases are “conscious or subconscious distortions of judgments and decisions because of self-interest, social pressures, or organizational context” (Montibeller & von Winterfeldt, 2015). Confirmation bias is a type of motivational bias that stems from the desire to confirm a belief of someone else, which results in unconscious selectivity with respect to gathering and using evidence (Nickerson, 1998). In the case of Philips, this bias is mitigated by involving multiple decision-makers with different roles and points of view in the decision-making process. Biases overall can also be classified in terms of whom they affect, namely, there are individual and group biases. The aforementioned anchoring bias and confirmation bias are both individual biases. Although they are applicable to the decision-makers involved on an individual level, group biases must be mentioned as well, as the problem at hand is regarded as a group decision-making issue. One such bias that could have occurred in the analysis process is Groupthink. This bias tends to be present in cohesive groups whose main focus is achieving a consensus, no matter at what cost, which could lead to a lack of realistic exploration of different solutions (Janis, 1972). The suggested debiasing strategy involves the use of multiple decision-makers with different viewpoints (Montibeller & von Winterfeldt, 2018), which was done in the case of Philips.

Finally, when it comes to possibilities for further research, the effectiveness of other MCDM methods could be explored, as there is no literature addressing the issue of choosing a focus area. In addition to this, the combination of BWM and ELECTRE III could be applied to different cases, so that this approach is further validated. Furthermore, the elicitation of suitable criteria for supply chain management issues represents a good research opportunity. This part of relevant MCDM studies still remains without a clear framework due to the fact that every MCDM issue is unique in terms of relevant qualitative and quantitative factors that are involved.

7. Conclusion

The main aim of this paper was to present a framework for healthcare technology industry companies looking to choose a focus area for process optimization within a manufacturing unit. This was done by supplementing a new decision-making approach for group decision-making, which utilizes a combination of two MCDM methods, namely Linear BWM for the elicitation of the weights of the relevant criteria and ELECTRE III for the ranking of the possible focus areas regarded as alternatives. Aside from the two MCDM methods, tools such as stakeholder mapping and power/interest grid were used to determine the relevant decision-makers who were involved in the analysis. In order to illustrate its effectiveness, the approach was applied to a real case, namely the assembly process of an Azurion Floor Stand, which is a stepwise process occurring within a manufacturing unit of Philips IGT Systems in The Netherlands. The outcome of the analysis was the final ranking of the focus areas, where the Cabling 2 process step was ranked first, so the recommendation for Philips was to implement process optimization in this particular step. Overall, it can be said that the framework fulfills its purpose while also contributing to the existing research in the field of MCDM and supply chain management.

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