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A methodology for intelligent support in the selection of manufacturing processes based on Generalized Matrix Learning Vector Quantization neural network

DOCTORAL DISSERTATION

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Abstract

The choice of the manufacturing process in an enterprise, as the result of the preceding managerial decision-making process, is a key prerequisite for achieving the enterprise's optimal industrial efficiency, its sustainable development, and the quality of the product offered to the market. The dissertation aims to develop and verify a methodology for intelligent support in selecting manufacturing processes based on the *Generalized Matrix Learning Vector Quantization* neural network, to alleviate subjective decision factors and leverage domain knowledge in addition to sustainability goals and the product-specific design requirements. Despite the existing body of work, there remains a lack of integrated decision support approaches that holistically consider domain expertise, sustainability goals, technological advancements, and evolving process capabilities in a dynamic manufacturing context. This dissertation seeks to fill this research gap using a two-faced approach of understanding the impact of cognitive and subjective decision factors on manufacturing process selection and developing a methodology for intelligent support in selecting manufacturing processes based on advanced neural networks. The research aims to understand and quantify how subjective decision factors, namely cognitive biases, personal preference, and groupthink, interact with domain knowledge to limit efficient manufacturing process selection using empirical evidence and to develop an intelligent methodology that leverages advanced neural network techniques to support optimal decision-making in manufacturing process selection. The research goal is achieved by investigating the negative influences of cognitive and social factors on decision quality in the selection of manufacturing processes and developing a methodology for intelligent support in the selection of manufacturing processes based on *Generalized Matrix Learning Vector Quantization* neural network. As such, the subject of the research is twofold; first, it concerns the interplay between subjective decision factors and the use of domain knowledge in manufacturing process selection, particularly in the era of Industry 5.0, where manufacturing is re-imagined with a stronger focus on human-centric decision-making. Secondly, it concerns a methodology for the intelligent selection of optimal manufacturing processes based on *Generalized Matrix Learning Vector Quantization* neural networks. In the current state of management theory and practice, decision-making is subordinated to subjective decision factors such as cognitive biases, self-interested motives, and groupthink, which suppress the use of

professional domain knowledge and expertise. The existence of such a state of affairs was confirmed in this dissertation through empirical research (chapter two of the dissertation), which justified the first of the two main research hypotheses concerning the limitations of the decision-making process in the selection of the manufacturing process. The research results show that the aforementioned subjective factors significantly deprive the managerial decision-making process of the proper use of professional domain knowledge, leading to poorer process selection and the degradation of the decision. For the purpose of justifying the second, conceptual main hypothesis of this dissertation, studies were conducted (presented in the subsequent three chapters) on the application of an enhanced *Generalized Matrix Learning Vector Quantization* neural network, which adapts to multidimensional, noisy, and heterogeneous production data, while simultaneously integrating expert knowledge to assess and select the most appropriate manufacturing processes objectively. In the first of the aforementioned conceptual research chapters, the issue of the intelligent selection of production processes using artificial neural networks, fuzzy logic, and genetic algorithms was presented. Next, the systematic examination of the *Generalized Matrix Learning Vector Quantization algorithm* with improvements and its applications for future production process selection was conducted. In the following chapters of this dissertation, the applications of *Generalized Matrix Learning Vector Quantization* for process selection with an experimental configuration were synthesized, along with an explanation of the dataset used and comparisons with conventional approaches such as *Support Vector Machine.* A detailed summary of the conclusions, findings, and areas for future research is devoted to the final part of the dissertation. The general conclusion was formulated as an observation that the generalized matrix learning vector quantization improves decision-making in the manufacturing process selection by eliminating human biases and enabling a more effective use of domain knowledge. The generalized matrix learning vector quantization model achieved one hundred percent accuracy in the selection of the manufacturing process, thus demonstrating its effectiveness in realistic scenarios. The research presented in this dissertation also proved the harmful consequences of subjective factors in decision-making on the quality of production decisions and showed that *Generalized Matrix Learning Vector Quantization* can be used as one of the possible alternatives to such biases, making decision-making more effective in the conditions of a production enterprise. In the cognitive scope of management sciences, a new data and information-based decision support method was introduced that balances subjective decision factors with objective information to make manufacturing process selection more accurate, efficient, and sustainable. With regard to future research directions on the topic of this dissertation, it was suggested to test the generalized matrix learning vector quantization model with more significant and diversified datasets and to examine its scalability and transferability value to other industrial applications.

Streszczenie

Wybór procesu produkcyjnego przedsiębiorstwa, jako rezultat poprzedzającego go procesu decyzyjnego zarządzania, jest kluczową przesłanką osiągania optymalnej efektywności przedsiębiorstwa, jego zrównoważonego rozwoju oraz jakości produktu oferowanego rynkowi.

Celem rozprawy jest opracowanie i weryfikacja metodologii inteligentnego wsparcia w wyborze procesów produkcyjnych w oparciu o sieć neuronowej *Generalized Matrix Learning Vector Quantization*, aby złagodzić subiektywne czynniki ludzkie i wykorzystać wiedzę domenową oprócz celów zrównoważonego rozwoju i wymagań projektowych specyficznych dla produktu. Pomimo istniejącego dorobku nadal brakuje zintegrowanych podejść do wsparcia decyzji, które holistycznie uwzględniają wiedzę specjalistyczną w dziedzinie, cele zrównoważonego rozwoju, postęp technologiczny i ewoluujące możliwości procesu w dynamicznym kontekście produkcji. Niniejsza rozprawa ma na celu wypełnienie tej luki badawczej przy użyciu dwustronnego podejścia polegającego na zrozumieniu wpływu poznawczych i subiektywnych czynników ludzkich na wybór procesu produkcyjnego oraz opracowaniu metodologii inteligentnego wsparcia w wyborze procesów produkcyjnych w oparciu o zaawansowane sieci neuronowe. Badania mają na celu zrozumienie i określenie ilościowe, w jaki sposób ludzkie uprzedzenia oddziałują na wiedzę domenową w celu ograniczenia efektywnego wyboru procesu produkcyjnego przy użyciu dowodów empirycznych i opracowanie inteligentnej metodologii wykorzystującej zaawansowane techniki sieci neuronowych w celu wsparcia optymalnego podejmowania decyzji w wyborze procesu produkcyjnego. Cel badawczy jest realizowany poprzez zbadanie negatywnych wpływów czynników poznawczych i społecznych na jakość decyzji w doborze procesów produkcyjnych oraz opracowanie metodologii inteligentnego wsparcia w doborze procesów produkcyjnych w oparciu o sieć neuronowej *Generalized Matrix Learning Vector Quantization*. Jako taki, przedmiot badań jest dwojaki; po pierwsze, dotyczy on wzajemnego oddziaływania subiektywnych czynników ludzkich i wykorzystania wiedzy domenowej w doborze procesów produkcyjnych, szczególnie w erze Przemysłu 5.0, gdzie produkcja jest wyobrażana na nowo z większym naciskiem na podejmowanie decyzji zorientowanych na człowieka. Po drugie, dotyczy on metodologii inteligentnego doboru optymalnych procesów produkcyjnych w oparciu o sieci neuronowej *Generalized Matrix Learning Vector Quantization*. Decyzja ta, w obecnym stanie teorii i praktyki zarządzania, jest podporządkowana subiektywnym czynnikom ludzkim takim jak: uprzedzenia poznawcze,

interesy egoistyczne i myślenie grupowe, które tłumią wykorzystanie profesjonalnej wiedzy domenowej. Fakt istnienia takiego stanu rzeczy potwierdzono w tej dysertacji badaniami empirycznymi (rozdział drugi dysertacji), uzasadniającymi pierwszą z dwóch głównych hipotez naukowych dotyczących ograniczeń decyzyjnego wyboru procesu produkcyjnego przedsiębiorstwa. Wyniki badań pokazują, że wymienione wyżej subiektywne czynniki znacząco pozbawiają proces decyzyjny zarządzania właściwego wykorzystania profesjonalnej wiedzy domenowej, co prowadzi do gorszego wyboru procesów i degradacji decyzji. Dla potrzeb uzasadnienia drugiej, konceptualnej hipotezy głównej tej dysertacji podjęto (przedstawione w jej kolejnych trzech rozdziałach) badania nad wykorzystaniem ulepszonej sieci neuronowej *Generalized Matrix Learning Vector Quantization*, która dostosowuje się do wielowymiarowych, zaszumionych i heterogenicznych danych produkcyjnych, jednocześnie integrując wiedzę ekspercką w celu obiektywnej oceny i wyboru najbardziej odpowiednich procesów produkcyjnych. W pierwszym z wymienionych wyżej konceptualnych rozdziałów badawczych zaprezentowano zagadnienie inteligentnego wyboru procesów produkcyjnych przy użyciu sztucznych sieci neuronowych, logiki rozmytej i algorytmów genetycznych. Następnie poddano systematycznym badaniom algorytm *Generalized Matrix Learning Vector Quantization* z ulepszeniami i zastosowaniami do przyszłego wyboru procesu produkcyjnego. W kolejnych dwóch rozdziałach tej dysertacji zsyntetyzowano zastosowania *Generalized Matrix Learning Vector Quantization* do wyboru procesu z eksperymentalną konfiguracją oraz wyjaśnienie użytego zestawu danych i porównania z konwencjonalnymi podejściami, takimi jak *Support Vector Machine*. Szczegółowemu podsumowaniu wniosków, ustaleń i obszarów przyszłych badań poświęcono końcową część tej dysertacji. Generalną konkluzję sformułowano w postaci konstatacji, że uogólniona kwantyzacja wektorów uczenia się macierzy usprawnia podejmowanie decyzji w procesie wyboru procesu produkcyjnego poprzez eliminację ludzkich uprzedzeń i efektywniejsze wykorzystanie wiedzy domenowej. Model uogólnionej kwantyzacji wektorów uczenia się macierzy osiągnął sto procent dokładności w wyborze procesu produkcyjnego, a tym samym wykazał swoją skuteczność w realistycznych scenariuszach. Badania zaprezentowane w treści tej dysertacji dowiodły także szkodliwych konsekwencji czynników subiektywnych w podejmowaniu decyzji na jakość decyzji produkcyjnych i pokazały, że uogólniona kwantyzacja wektorów uczenia się macierzy może być stosowana jako jedna z możliwych alternatyw dla takich uprzedzeń, a podejmowanie decyzji może być skuteczniejsze w warunkach przedsiębiorstwa produkcyjnego W zakresie poznawczym nauk o zarządzaniu wprowadzono nową metodę wspomagania decyzji opartego na danych i informacjach, które równoważy subiektywne czynniki ludzkie z obiektywnymi informacjami tak, aby podejmowanie decyzji produkcyjnych było dokładniejsze, wydajniejsze i bardziej zrównoważone. W odniesieniu do przyszłych kierunków badań nad tematem tej dysertacji zasugerowano przetestowanie modelu uogólnionej kwantyzacji wektorów uczenia się macierzy z bardziej znaczącymi i zróżnicowanymi zestawami danych oraz zbadanie jego skalowalności i wartości transferu do innych zastosowań przemysłowych.

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Acronyms

CBR	Case-based Reasoning
Adam	Adaptive-Moment Estimation
AHP	Analytical Hierarchy Process
AM	Additive Manufacturing
ANFIS	Adaptive-Network-based Fuzzy Inference System
ANN	Artificial Neural Network
ANP	Analytic Network Process Framework
APC	Alternative Process Consideration
ART	Adaptive Resonance Theory
ASTM	American Society for Testing and Materials
BFGS	Broyden-Fletcher-Goldfarb-Shan
CAD	Computer-aided design
CNN	Convolutional Neural Network
DEA	Data Envelopment Analysis
DED	Directed Energy Deposit
DSS	Decision Support System
EEG	Electroencephalogram
FAHP	Fuzzy Analytical Hierarchy Process
FANP	Fuzzy Analytic Network Process Framework
FDG-PET	Fluorodeoxyglucose Positron Emission Tomography
FL	Fuzzy Logic
GA	Genetic algorithms
GLVQ	Generalized Learning Vector Quantization
GMLVQ	Generalized Matrix Learning Vector Quantization
GRLVQ	Generalized Relevance Learning Vector Quantization
IDSS	Intelligent Decision Support System
IoT	Internet of Things
ISO	International Organization for Standardization
KNN	k-Nearest Neighbors
LVQ	Learning Vector Quantization
MCDA	Multi-criteria decision analysis
NN	Neural Network
PCA	Principal Component Analysis
PLS-SEM	Partial Least Squares Structural Equation Modeling
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluation
RBF	Radial Basis Function
RLVQ	Relevance Learning Vector Quantization
RSLVQ	Robust Soft Learning Vector Quantization
SNN	Siamese Neural Network
SOFM	Self-organizing feature map
SPSS	Statistical Package for Social Sciences
SSM	Scaled Sub-profile Model

STDEV	Standard Deviation
SVM	Support Vector Machines
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution

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1. Introduction

This chapter introduces the dissertation by describing the justification for the research topic. It acknowledges the significance of manufacturing in economic development and its impact on socio-economic and environmental aspects, requiring the adoption of sustainable and efficient approaches. This is further compounded by the Industry 5.0 paradigm shift, which emphasizes a human-centric approach to sustainable development in addition to efficiency and productivity. The chapter describes the main research hypotheses and the tasks to test them. The chapter also describes the dissertation's goal, the research aims, the research subject, the methodology, the scope, and the overall dissertation structure.

1.1. Justification for taking up the dissertation topic

The manufacturing sector has undergone several transformations to ensure sustainable development while meeting customer demands. As an essential component and driver of economic growth, especially in developing countries (Guo & Sun, 2023; Haraguchi et al., 2017; Hauge, 2023; Lakew, 2023; Zalva et al., 2023), manufacturing remains a top research area. Research reveals that manufacturing entities must lead innovations to withstand unprecedented global competition in the wake of intelligent manufacturing (Hauge, 2023). Critical managerial functions such as planning, implementing, and controlling manufacturing processes involve much decision-making, featuring a wide range of parameters and data. Decision-making processes aim to identify the optimal course of action from a pool of possibilities that guarantee high performance and sustainability. Manufacturers must embrace digital technologies to create high-quality and intelligent manufacturing systems that optimize performance (Hauge, 2023). The authors further pointed out that sustainable manufacturing concepts must be adopted to ensure cost-efficiency and management of complex product assembly (Jardim-Goncalves et al., 2017). Similar research argues that manufacturing processes and product design innovation remain crucial to industrial evolution (Abdulhameed et al., 2019). Given the growing uncertainty and complexity, efficient decision-making remains central to the rapid development of sustainable manufacturing paradigms.

Players across industries have adopted best practices to improve manufacturing operations, including total quality management, just-in-time flow, concurrent engineering, and supplier relationship management. Despite these efforts, the sector faces unprecedented pressures to ensure sustainability and improved product quality. Fierce competition, changing markets, increased uncertainty, growing customer demand for high-quality products at reduced costs, and increased calls for sustainable resource use continue to pressure the manufacturing sector. As noted in a recent study, modern organizations are increasingly complex, dynamic, and more uncertain (Tworek et al., 2019). Decisions on relevant and proper manufacturing processes are crucial but complex. Because of the increasing complexity and uncertainty within the manufacturing ecosystem, process designers and engineers are under constant pressure to ensure the selection of optimal manufacturing processes right from the beginning. Selecting the correct process to manufacture a product can solve common issues such as rework, which often lengthens lead time and increases the overall manufacturing cost. There are numerous mechanisms and strategies for handling uncertainties in manufacturing, such as rework strategies (Dai et al., 2014), in-line production traceability (Colledani & Angius, 2020), and integrated maintenance and quality (Gouiaa-Mtibaa et al., 2018). However, despite the progress, getting the manufacturing process right while designing the product remains crucial to the overall performance of the adopted manufacturing system operations.

Manufacturing processes and materials are rapidly evolving. Increasingly high demand for customized products and components, as well as other constraints such as performance, lead times, and complexity, drive the evolution of manufacturing processes and materials (Khaleeq uz Zaman et al., 2017). As a result, the selection of manufacturing processes is increasingly becoming a complex task involving a thorough analysis of multiple criteria and trade-offs. For instance, additive manufacturing adoption in the aerospace industry has been justified by technical advantages spanning from reduced mass, enhanced heat transfer, use of novel high-performance alloys, and complex geometry (Gradl et al., 2022), which makes them particularly useful in improving efficiency by reducing cost and lead time in the wake of increasingly complex design requirements (Madhavadas et al., 2022). However, selecting a suitable additive manufacturing process for a specific component involves trading technical advantages and constraints between design requirements, material properties, and the process parameters (Gradl et al., 2022). Additionally, specific part performance requirements, post-processing approaches, certification, and metallurgical considerations complicate the additive manufacturing process trade-off for aerospace components (Froes et al., 2019). Thus, selecting a manufacturing process is not considered a trivial exercise.

Traditionally, selecting appropriate processes for manufacturing a particular component relied on matching process capabilities and required properties. However, selection drivers have grown over the years to include sustainability goals and process-specific advantages such as flexibility, process time, efficiency, and cost (Jena et al., 2020; Mele & Campana, 2020; Muvunzi et al., 2022; Papacharalampopoulos et al., 2023; Sun et al., 2022). Selecting a successful manufacturing technique often includes analyzing the delicate interplay between design, material, and process characteristics. Several authors have studied the problem of manufacturing process selection in recent years, indicating its significance (Aichouni et al., 2021; Baghad & Mabrouk, 2023; Cortés et al., 2022; Krulčić et al., 2022; Martínez-Rivero et al., 2019; Papacharalampopoulos et al., 2023). Although managers have often relied on experience, the need for unbiased and systematic tools for comprehensively assessing process alternatives, desired requirements, and product designs has led to the use of Decision Support Systems (DSS) to aid decision-making. Using expert knowledge and experience alone can lead to incorrect decisions (Martínez-Rivero et al., 2019) due to various issues, including cognitive problems and the lack of analytical, systematic, and structured methods to verify their decisions. These experts' databases are not continuously updated with the latest information. Recent studies show that modern manufacturing enterprises embrace a paradigm shift towards socio-ecological and resource-efficient engineering processes to remain competitive (Ben Ruben et al., 2019). The research gap *is that despite the existing body of work on manufacturing process selection using various approaches, including expert systems and multi-criteria decision methods, there remains a lack of studies on integrated intelligent decision support approaches that holistically consider domain expertise, sustainability goals, technological advancements, and evolving process capabilities in a dynamic manufacturing context.* This dissertation seeks to fill this research gap using a two-pronged approach of understanding the impact of cognitive and subjective decision factors on manufacturing process selection and developing a methodology for intelligent support in selecting manufacturing processes based on advanced neural networks.

In conventional manufacturing, processes have been refined over decades; however, recent technological advances and the drive for sustainability have introduced new challenges, such as reducing environmental footprints and optimizing raw material use. Conversely, additive manufacturing, encompassing methods like vat photo-polymerization, material extrusion, material jetting, binder jetting, directed energy deposition, powder bed fusion, and sheet lamination, is evolving rapidly. Its layer-by-layer production approach inherently leads to poor inter-layer adhesion, surface finish defects, and material inconsistencies. Moreover, the relative novelty of these processes means that detailed, established knowledge about their parameters is often lacking in current studies (M. M. Mabkhot et al., 2019; White et al., 2022; Yurdakul et al., 2014). This scenario creates significant uncertainty when selecting a product's most appropriate manufacturing process. Conventional and additive manufacturing methods offer unique advantages and face distinct challenges, necessitating a decision-making approach that can accommodate diverse criteria and handle high-dimensional, heterogeneous data. Traditional methods, including neural networks, genetic algorithms, and fuzzy logic, have been employed to tackle these challenges; however, they sometimes struggle with the complexity and noise inherent in manufacturing datasets.

Generalized Matrix Learning Vector Quantization (GMLVQ) offers a promising solution. As an extension of the LVQ framework, GMLVQ introduces an adaptive relevance matrix that transforms the conventional Euclidean distance into a more flexible, generalized metric. This matrix-based approach allows the algorithm to weigh feature pairs, implicitly capturing correlations and rotations within the data. Such capability is particularly beneficial when dealing with the noisy, high-dimensional, and non-linearly separable datasets typical in modern manufacturing environments (Biehl et al., 2015). Moreover, extensive research has shown that GMLVQ can significantly outperform other classifiers, like support vector machines and decision trees, when enhanced by hybrid algorithms and novel training techniques (Biehl et al., 2015; LeKander et al., 2017). GMLVQ provides a robust framework capable of integrating data from multiple sources without explicit transfer learning by learning both prototype representations and an adaptive distance metric during training.

Consequently, this dissertation is motivated by the need to develop an intelligent support system for manufacturing process selection that leverages GMLVQ's advanced capabilities. By integrating GMLVQ’s feature relevance learning and adaptive metric framework, the proposed methodology aims to enhance decision-making accuracy and reliability in selecting the optimal manufacturing process, whether conventional or additive, thus addressing a critical challenge in modern manufacturing environments.

1.2. Research hypotheses

Given the evolving and highly dynamic manufacturing landscape, the challenge of manufacturing process selection remains compounded by the interplay of subjective decision factors and well-established domain knowledge. While significant advances have been made to support the selection of conventional and additive manufacturing processes, the decision-making process remains vulnerable to the inherent biases of the decision-makers. Factors such as cognitive biases, personal preferences, and groupthink can distort judgment, potentially leading to the selection of processes that do not fully leverage available expertise. The emerging Industry 5.0 paradigm shift takes a human-centric approach, emphasizing the pivotal role of humans in sustainable manufacturing besides efficiency and productivity (Golovianko et al., 2022). Industry 5.0 is envisioned to ensure sustainable development with industrial technicians at the center of manufacturing processes (Battini et al., 2022; S. Huang et al., 2022). As a result, several opportunities have been identified, including human-cyber-physical systems, human-robot collaboration, and human-digital twins (Coronado et al., 2022; S. Huang et al., 2022). Unlike its predecessor, Industry 4.0, which championed automation and machine intelligence, Industry 5.0 heralds a new synthesis of human talent with robotic precision. Against this backdrop, this research is driven by the need to unravel how these subjective elements interact with domain knowledge and to develop an intelligent decision-support methodology based on an improved GMLVQ neural network that leverages human expertise in the selection of manufacturing processes. With this approach, *the dissertation goal is to develop and verify a methodology for intelligent support in selecting manufacturing processes based on the GMLVQ neural network, to alleviate subjective decision factors and leverage domain knowledge in addition to sustainability goals and the product-specific design requirements*.

Therefore, this study is supported by two main hypotheses, as follows:

H1: Subjective decision factors, namely cognitive biases, personal preferences, and groupthink, contribute to the selection of inefficient manufacturing processes by limiting the effective use of domain knowledge in decision-making, which runs counter to the principles of Industry 4.0 and Industry 5.0.

H2: An intelligent decision support methodology utilizing an enhanced Generalized Matrix Learning Vector Quantization neural network significantly improves the efficiency of manufacturing process selection by mitigating the collective impact of subjective decision factors such as cognitive biases, personal preferences, groupthink, and cognitive load.

Hypothesis H1 consists of the following Sub-Hypotheses:

- **H1a**: Cognitive biases significantly contribute to selecting inefficient manufacturing processes.
- **H1b**: Personal preferences significantly contribute to selecting inefficient manufacturing processes.
- **H1c**: Groupthink within decision-making teams contributes to the selection of inefficient manufacturing processes.
- **H1d**: High cognitive load contributes to the selection of inefficient manufacturing processes.
- **H1e**: Limited utilization of knowledge of alternatives contributes to the selection of inefficient manufacturing processes.
- **H1f**: Limited utilization of knowledge on process variants contributes to the selection of inefficient manufacturing processes.
- **H1g**: Limited knowledge of process complexity contributes to the selection of inefficient manufacturing processes.
- **H1h**: Selecting inefficient manufacturing processes leads to rework and reprocessing.
- **H1i**: The selection of inefficient manufacturing processes increases waste materials.
- **H1j**: The selection of inefficient manufacturing processes leads to low-quality outcomes.
- **H1k**: Selecting inefficient manufacturing processes leads to extended lead time.
- **H1l**: Selecting inefficient manufacturing processes leads to increased safety concerns.

The first hypothesis postulates that human factors limit the effective utilization of domain knowledge by steering decision-makers away from data-driven insights and objective criteria, thereby contributing to less-than-optimal selection of manufacturing processes. The evolution toward Industry 5.0 marks a departure from purely automated systems to a new era where human expertise and advanced technologies are interwoven. To achieve the goals of Industry 5.0, integrating the rich domain knowledge possessed by human experts is essential. Based on empirical evidence from manufacturing companies in Poland, this research provides a comprehensive understanding of how subjective decision factors constrain the selection of efficient manufacturing processes, despite the availability of extensive technical expertise. This limitation undermines optimal decision-making in manufacturing, which should align with new social development concepts and integrate human ingenuity with intelligent machines. The second hypothesis is anchored on leveraging GMLVQ's adaptive metric learning capabilities. This approach is designed to handle high-dimensional, noisy, and heterogeneous manufacturing data and expert knowledge by dynamically learning the relevance of various features. The improved GMLVQ model is expected to integrate historical data and expert domain knowledge to objectively assess and select manufacturing processes.

The research problem is twofold. First, it concerns the interplay between subjective decision factors and the use of domain knowledge in manufacturing process selection, particularly in the era of Industry 5.0, where manufacturing is re-imagined with a stronger focus on human-centric decision-making. Second, it concerns a methodology for the intelligent selection of optimal manufacturing processes based on GMLVQ neural networks.

1.3. Research objectives

Building on the stated hypotheses that subjective decision factors can lead to inefficient manufacturing process selection and that an intelligent decision support system based on an enhanced GMLVQ neural network can improve this selection process, the objectives of this research are designed to address these challenges systematically. The overall goal of the research is *to understand and quantify how subjective decision factors, namely cognitive biases, personal preference, and groupthink, interact with domain knowledge to limit efficient manufacturing process selection using empirical evidence and to develop an intelligent methodology that leverages advanced neural network techniques to support optimal decision-making in manufacturing process selection.* To achieve this, the research goal is guided by two primary tasks:

i. To investigate the negative influences of subjective decision factors on decision quality in the selection of manufacturing processes.

ii. To develop a methodology for intelligent support in the selection of manufacturing processes based on Generalized Matrix Learning Vector Quantization neural network.

The first primary task seeks to contextualize the manufacturing process selection problem within broader industry challenges. This goal emphasizes aligning process selection with efficiency, quality, and sustainability targets, and is designed to quantify the impact of subjective decision factors on decision quality through empirical analysis. By so doing, this task aims to demonstrate how these subjective influences constrain the efficient utilization of domain knowledge, which in turn leads to inefficient selection of manufacturing processes. Therefore, the first primary task is complemented by the following two sub-tasks:-

i. To review and bridge the knowledge gap in manufacturing process selection and its significance in driving manufacturing efficiency, improving product quality, and achieving sustainable goals by identifying and analyzing recent advances, challenges, and opportunities.

ii. To study cognitive bias, high cognitive load, personal preference, groupthink, and limited domain-specific expertise, and analyze how these elements converge to shape manufacturing process selection outcomes using empirical evidence from Polish manufacturing companies.

The second primary task is developed for five reasons. First, it establishes a foundational understanding of how current intelligent systems are utilized to streamline and enhance the manufacturing process planning and execution. As such, it is the baseline for comparing existing methods with the proposed GMLVQ-based approach. Second, it seeks to capture the state-of-the-art in neural network applications within manufacturing by reviewing the latest literature and highlighting key methodologies, trends, and gaps that current research can address. Third, it intends to integrate insights from different artificial intelligence methods by examining various artificial intelligence-based approaches and techniques. Identifying strengths and limitations can inform the design of a more compelling intelligent support methodology for manufacturing process selection. Fourth, it involves a comprehensive analysis of LVQ methodologies, critically evaluating their evolution and performance, leading to GMLVQ. Understanding these variants is essential to justifying the selection of the GMLVQ approach and its potential improvements over traditional methods. Finally, it is designed to culminate in designing, implementing, and benchmarking a GMLVQ-based decision support model. The research will validate the model's ability to address the complex challenges identified in process selection by comparing its performance with established methods. Consequently, five complementary tasks to the second primary task are as follows:-

i. To review the potential of intelligent system support in managing the preparation and implementation of manufacturing processes
ii. To identify, synthesize, and comprehensively summarize recent studies on artificial neural network-based decision support systems applied in manufacturing processes.
iii. To synthesize existing knowledge on the use of intelligent support systems in manufacturing process selection, with a focus on methodologies and frameworks based on three artificial intelligence technologies, Neural Networks (NN), Genetic Algorithms (GA), and Fuzzy Logic (FL), and their hybrid combinations, as applied to conventional and additive manufacturing.
iv. To analyze extensively researched and well-documented Learning Vector Quantization (LVQ) variants with firm theoretical foundations and empirical evidence supporting their efficacy by synthesizing their development, enhancements, and defining characteristics.
v. To develop a methodology for optimal selection of manufacturing processes based on the Generalized Matrix Learning Vector Quantization neural network and perform a comparative analysis with similar existing methods to test and verify the developed model.

The two primary tasks and their respective complementary sub-tasks comprehensively address the human and technical dimensions of manufacturing process selection and provide a structured roadmap, from literature synthesis and empirical investigation to developing and validating a novel GMLVQ-based system. Thus, the outlined primary and specific objectives ensure that the research advances theoretical understanding and offers practical, data-driven solutions for improving manufacturing outcomes.

1.4. Research methodology and dissertation structure

The current research explores such intricate issues regarding selecting manufacturing processes, focusing on subjective decision factors that impact decision-making and their integration with domain-specific knowledge that eventually shapes such processes' efficacy. The research takes a multifaceted approach to empirical, theoretical, and practical aspects through framing two main hypotheses and seven complementary goals. Firstly, the research argues that subjective factors in decision-making, like cognitive biases, personal attitudes, and groupthink, have a profound adverse effect on the effective application of domain knowledge and, hence, make such decision-making inefficient with regard to manufacturing processes. This is analyzed with the help of empirical information derived from the manufacturing industry in Poland, where human decision-making is often influenced by biases that hamper judgment despite technical capabilities. The research then turns to intelligent decision-support systems like GMLVQ that utilize artificial neural network capabilities to deal with different metrics to make manufacturing process selection more effective. The second hypothesis argues that GMLVQ, as a state-of-the-art neural network paradigm, can help make decision-making more effective through managing high-dimensional, noisy, and heterogeneous information related to manufacturing. This research aims to bridge cognitive factors with data-oriented decision approaches by developing and testing a more efficient decision aid system based on GMLVQ to make more accurate, unbiased, and optimal choices in manufacturing operations.

The scope also encompasses a comprehensive review of intelligent support systems used in manufacturing, specifically focusing on integrating ANNs, Fuzzy Logic, and GA, emphasizing how these technologies have been applied to conventional and additive manufacturing processes. Based on a review of recent literature published between 2011 and 2021 and between 2013 and 2023 related to such methodologies, this study provides the framework for the subsequent application of the GMLVQ methodology, including theoretical derivation and empirical testing regarding choosing manufacturing operations. The investigation includes a critical evaluation of Learning Vector Quantization (LVQ) and its variants, establishing the theoretical justification for selecting GMLVQ as a superior method for process selection, particularly when human biases and cognitive overload limit the full utilization of domain knowledge. The research addresses real-world issues in production methodology selection concerning their interdependencies with subjective decision factors like cognitive load, personal bias, and groupthink, as well as domain-specific knowledge that affects decision outcomes. This study aims to create a decision-support system that will improve selection quality to maximize production efficiency, product quality, and technology related to sustainability. In summary, this study combines empirical information with enhanced machine learning algorithms to create a formalized framework that enables decision-making in production operations.

This research evaluates the GMLVQ model within multiple polymer processing techniques based on four different polymer processing technologies, focusing on their efficacy. Such evaluation is essential due to the distinctive complexity of material homogeneity, processing techniques, and production specifications in polymer processing. By narrowing it down to four such processing techniques of polymers, this study aims to demonstrate that the GMLVQ model can provide more accurate and information-based decision support in selecting the best production techniques that depend on the inherent nature of polymer materials and the context of manufacturing. By studying such issues, this research aims to develop a complete information-based decision-support system to enhance the decision-support mechanism that can improve manufacturing efficiency, product quality, and sustainability. Therefore, this research combines empirical research with high-level machine learning techniques to suggest a generic framework that focuses on decision-making in the context of the manufacturing industry, more specifically concerning the processing of polymers.

The dissertation involved three main research stages, including theoretical, empirical, and experimental. The theoretical stage covered a general literature review on current trends and future perspectives on manufacturing process selection approaches, intelligent decision support in manufacturing processes, and learning vector quantization neural networks. This was done in parallel with three systematic literature reviews. The first systematic review covered ANN-based decision support systems in manufacturing processes. The second systematic review covered intelligent support in manufacturing processes based on ANN, fuzzy logic, and genetic algorithms and aimed to discover current and future perspectives. While it overlapped with the general literature review, it followed the conclusion of the first systematic review. The third systematic literature review was built on the findings of the first two systematic reviews, and it served as the foundation for the GMLVQ-based methodology for manufacturing process selection. The empirical study included three stages: empirical study design, data collection, and hypothesis verification. These three stages were all preceded by the relevant literature review and contributed towards designing and refining the GMLVQ-based model, which was followed by data collection and pre-processing, training, optimization, tuning, evaluation, and hypothesis verification, as shown in **Figure 1.1**.

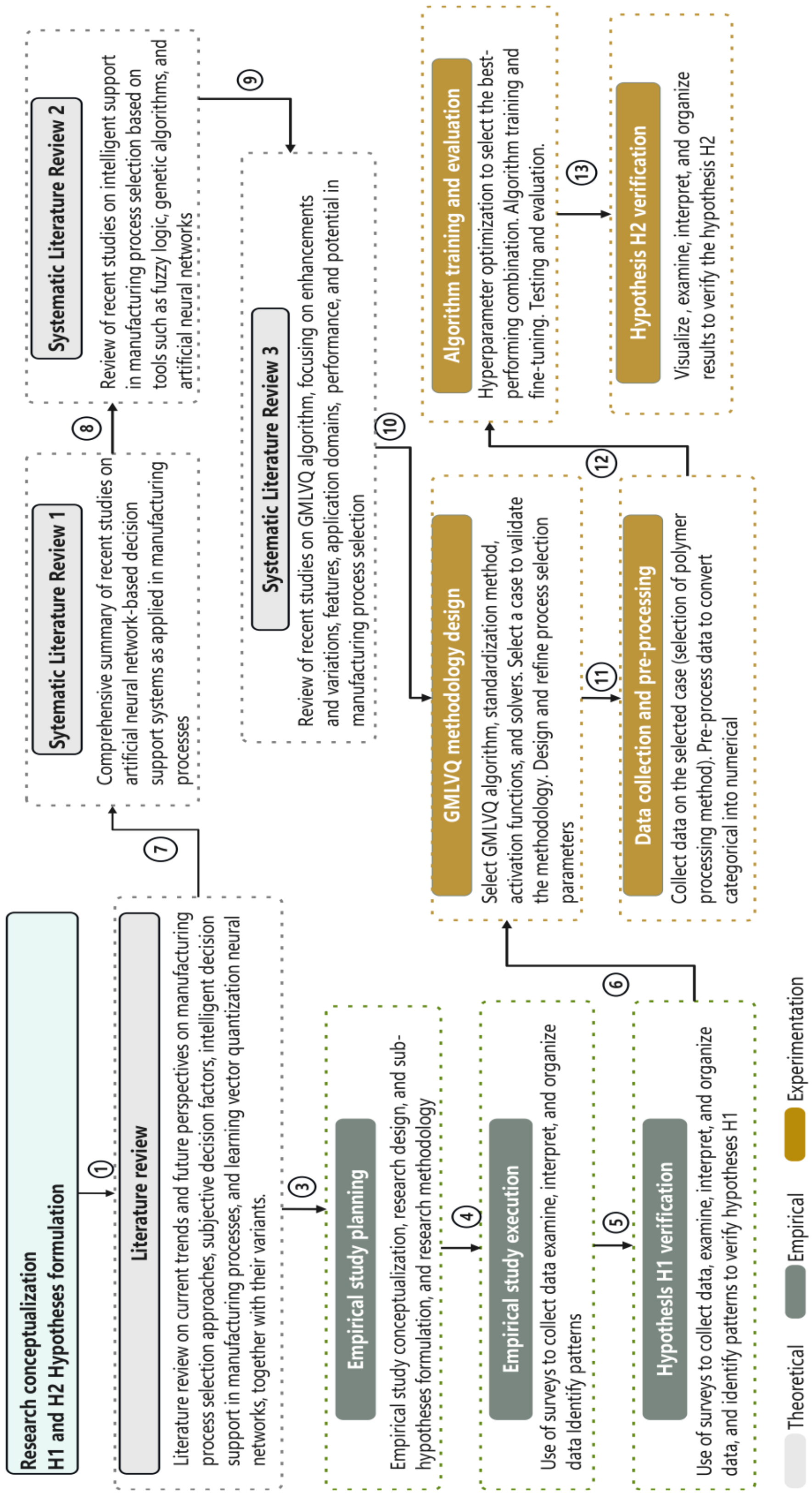

Figure 1.1. Research stages
Source: Own study

This dissertation comprises six lengthy chapters that all contribute meaningfully to studying intelligent support in manufacturing process selection. The chapters are formed, in part or in whole, of research results published or submitted for publication in international conferences and high-ranking journals. Chapter **1** lays out the building blocks of the research through explanations of motivations, hypotheses, and research aims. It describes why it is essential to study how cognitive biases, human factors, and domain knowledge influence process selection. The chapter also introduces the primary research aim of developing an intelligent decision-support system based on the GMLVQ model. Chapter **2** explores the subjective influences on process selection through empirical evidence from Poland's manufacturing sector. This section has its own hypotheses that are not part of the overall hypotheses of this dissertation. It examines how cognitive biases, personal preferences, and groupthink shape decision-making, impacting the optimal use of domain knowledge. It also provides insights into the limitations faced by decision-makers in practice. Chapter **3** systematically reviews advancements in intelligent decision-support methodologies, such as ANNs, fuzzy logic, and GA. This review, grounded in recent literature, identifies the strengths and weaknesses of current methods and introduces GMLVQ as a promising approach for overcoming the limitations of existing systems. Chapter **4** systematically reviews the GMLVQ algorithm, detailing its development, theoretical foundations, and recent applications in manufacturing process selection. The chapter explores the potential of GMLVQ to improve decision-making by dynamically adjusting the relevance of features and handling complex, high-dimensional data. Chapter **5** focuses on the practical application of the GMLVQ model for process selection. This chapter details the experimental setup, including the dataset, data preprocessing, tools used, and evaluation metrics. It also compares the performance of the GMLVQ model with SVM and analyzes the results, offering a thorough discussion of the implications and limitations of the proposed approach. This chapter is based on published and submitted papers, including one focused on the intelligent selection of polymer manufacturing processes using GMLVQ. Finally, Chapter **6** summarizes the research findings, offers conclusions based on the research hypotheses, and outlines directions for future research in intelligent manufacturing process selection. This structure allows for a comprehensive examination of theoretical and practical aspects, culminating in developing and testing a GMLVQ-based decision support system that bridges the gap between human decision factors and objective data-driven insights. The following are the research outcomes published or submitted for publication during the preparation of this dissertation:

2. Empirical Insights on Manufacturing Process Selection Limitations

This chapter examines how subjective decision factors and domain knowledge intersect in manufacturing process selection, particularly in the era of Industry 5.0, where manufacturing is being re-envisioned with a stronger emphasis on human-centric decision-making. The study acknowledges the evolving nature of human-machine collaboration, where machines support rather than replace human decision-makers. Therefore, understanding subjective decision factors is crucial for enhancing this collaboration and optimizing manufacturing processes. The study employs a combination of descriptive statistics, Spearman rank correlation, and Partial Least Squares Structural Equation Modeling to analyze survey data collected from manufacturing companies in Poland. This mixed-method approach is used to comprehensively assess the impact of subjective decision-making factors on applying domain knowledge in selecting optimal manufacturing processes. The findings underscore that optimizing manufacturing processes is inextricably linked to the human elements of cognition and expertise. The chapter highlights the detrimental impact of cognitive biases, groupthink, and personal preferences on the effective use of domain knowledge in decision-making. It underscores the importance of promoting sustainable and efficient manufacturing outcomes. The research extends beyond the immediate context of manufacturing process selection, highlighting the significant role of knowledge management, particularly in applying and creating knowledge within the realm of decision-making in manufacturing. The chapter includes implications for a pivotal industry shift towards recognizing and harnessing the unique contributions of human insight and domain knowledge in complex manufacturing environments. The chapter uncovers the need to balance technological advancements with human cognitive factors in manufacturing decision-making processes through the application of intelligent support methodologies that incorporate human expertise with the prevailing capabilities in selecting optimal manufacturing processes.

2.1. Introduction and literature review on manufacturing process selection

In pursuing sustainability, modern manufacturing enterprises have embraced engineering paradigms emphasizing ecological and resource-efficient processes to remain competitive (Ben Ruben et al., 2019). Knowledge management and decision-making have long been the bedrock of organizational success. Historically, the reliance on heuristic and probabilistic models allowed decision-makers to navigate complex business landscapes using informed estimates and patterns derived from available data (Korn & Bach, 2018). Over the years, this paradigm has experienced a profound transformation, especially with the information explosion and advanced computational capabilities. The advent of Industry 4.0 marked a significant shift towards automation, where artificial intelligence and machine learning began to play pivotal roles (Behl et al., 2023). These technologies have augmented human decision-making and reshaped the fabric of knowledge management, transitioning from human-led processes to systems that can learn, adapt, and make autonomous decisions based on real-time data. Despite the advances, human factors remain crucial in manufacturing decision-making.

Industry 4.0 represents a paradigm shift in how organizations harness technology and data. With its core built around the Internet of Things (IoT), cyber-physical systems, and big data analytics, Industry 4.0 has created an ecosystem where machines are not just tools but collaborators. Industry 4.0 is heavily associated with digitalization and industrial automation. Researchers have outlined the adoption of information systems, automation, and automatic data exchange in manufacturing as the three progress points of Industry 4.0 (Behl et al., 2023). Both the interconnectivity of devices and the analytics power of big data have enabled a level of automation and precision that was previously unattainable. The fourth industrial revolution is driven by rapid innovation and the emergence of novel manufacturing technologies, materials, and processes (Kamble et al., 2018). Vast troves of operational intelligence now inform decisions, leading to better resource optimization and a step-change in productivity.

In the emergent narrative of Industry 5.0, the pivotal role of human skills and decision-making is gaining unparalleled recognition. Industry 5.0 is introduced as a re-imagined human-centric industrial revolution that focuses beyond efficiency and productivity (Golovianko et al., 2022). Industry 5.0 is envisioned to ensure sustainable development with industrial technicians at the center of manufacturing processes (Battini et al., 2022; S. Huang et al., 2022). As a result, several opportunities have been identified, including human-cyber-physical systems, human-robot collaboration, and human-digital twins (Coronado et al., 2022; S. Huang et al., 2022). Unlike its predecessor, which championed automation and machine intelligence, Industry 5.0 heralds a new synthesis of human talent with robotic precision.

While Industry 4.0 focused on core technologies such as the Internet of Things, Cloud Computing, Big Data, and Artificial Intelligence (Xu et al., 2021), Industry 5.0 shifts the focus toward human-robot collaboration, renewable sources, bionics, and innovative materials (Coronado et al., 2022). This hybrid ecosystem values the creative and strategic input that only humans can provide while capitalizing on the accuracy and efficiency of machines. The essence of this approach lies not in relegating humans to a supervisory role but in promoting a symbiotic relationship where both entities learn from and complement each other. Human ingenuity is, thus, not overshadowed by digital prowess. Still, it is integrated to enhance innovation, problem-solving, and customization, laying the groundwork for a manufacturing landscape that is adaptable, resilient, and intrinsically human-centric. Therefore, the role of domain knowledge in decision-making remains crucial for a sustainable, human-centric, and resilient manufacturing industry envisioned under Industry 5.0 paradigms.

However, this integrated approach presents nuanced challenges, particularly in decision-making. The research delves into how subjective decision factors, such as cognitive biases, personal preferences, and groupthink, can inadvertently disrupt the potential harmony of human-machine interfaces. The propensity for these subjective factors to skew judgment is amplified in a complex environment where decision-making is shared between human insight and machine algorithms. Such distortions can lead to inefficient choices in process selection, resource allocation, and strategic planning, thereby diminishing the benefits of the collaborative model. Research indicates that organizations have grown in complexity, and a modern organization is described as increasingly highly dynamic and uncertain (Tworek et al., 2019). Addressing these challenges is a strategic necessity for fully realizing sustainable manufacturing.

No existing studies focus on the intricate connections between subjective decision factors and domain knowledge and their collective influence on the choice and performance of manufacturing processes. Instead, a vast majority of existing research on manufacturing process selection has focused on improving the approaches (Bikas et al., 2021; Lukic et al., 2017), with a vast majority focusing on the selection of additive manufacturing (Dohale et al., 2021; Wortmann et al., 2019). These studies have presented valuable insights into how these variables affect the results of decision-making processes. Therefore, there is a need for more integrated research that examines the combined influence of these factors and their interactions in a manufacturing process selection context. By forging pathways to counteract biases and fostering a culture where informed, data-driven technology is complemented by nuanced domain knowledge and human expertise, the manufacturing sector can achieve a balance that aligns with the quest for sustainability. Ensuring that decision-making processes are robust, inclusive, and reflective of empirical knowledge and human values is critical. This study delves into a comprehensive investigation of the combined influence of cognitive influences, interpersonal dynamics, and the use of domain knowledge in manufacturing process selection, using empirical evidence from Poland's manufacturing sector.

While manufacturing plays a vital role in the growth and development of the global economy (Lima et al., 2022), the industry is currently navigating a landscape of unprecedented change and complexity. This dynamic environment is primarily shaped by rapidly shifting market demands, continuous technological evolution, and a growing emphasis on sustainability (Haraguchi et al., 2017; Mumali, 2022). Recent studies highlight the vulnerability of manufacturing companies to large-scale disruptions from various issues, including geopolitics, trade wars, and pandemics (D. Chen et al., 2022; Kapoor et al., 2021). In addition, manufacturing systems have become more complex over the past decades in pursuit of less costly, timely, flexible, and high-quality components and parts manufacturing (Efthymiou et al., 2016). The rapid evolution of customer needs is described as the hallmark of the twenty-first century, driving market turbulence. Changing market demands require manufacturers to be highly responsive and flexible, adapting their processes promptly to meet changing consumer preferences and emerging trends. Concurrently, technological evolution, especially in digitalization and automation, radically alters how manufacturing operations are conceived and executed (Chong et al., 2018; S. Mittal et al., 2019; Zeba & Dabi, 2021). These technological advancements are not only incremental improvements but also represent significant leaps that redefine the boundaries of what is feasible in manufacturing.

There is a growing recognition of the need for sustainable manufacturing practices. Manufacturing is among the leading sources of emissions and resource consumption (C. Liu et al., 2022; J. Liu et al., 2022; H. Sun et al., 2020; L. Sun et al., 2020; L. Zhang et al., 2022). The growing imperative for sustainability is driven not only by regulatory pressures and environmental concerns but also by growing consumer demand for eco-friendly products and processes (Jum'a et al., 2022; Nogueira et al., 2023; Rantala et al., 2023). Sustainability in manufacturing transcends the traditional focus on cost and efficiency, demanding a broader view that encompasses the environmental impact, resource efficiency, and long-term viability of manufacturing processes (Jum'a et al., 2022). Sustainability is a firm benchmark standard that significantly impacts external image and decision-making at various organizational levels (Kazakova & Lee, 2022). Sustainability is a highly sought-after strategy across the manufacturing landscape, alongside high productivity and agility, because of the recent shift toward customer-driven and highly dynamic manufacturing markets (Peres et al., 2020). Sustainable manufacturing anchored on resource-efficiency, high productivity, and low to zero environmental impact is a prerequisite for attaining and maintaining competitive advantage.

In this multifaceted and challenging landscape, decision-making in the manufacturing process selection remains critical. Choosing an optimal manufacturing process in Additive Manufacturing (AM) and traditional manufacturing is intricate and demands a comprehensive grasp of design parameters, materials, methods, and their interconnections (Bikas et al., 2019). Selecting manufacturing processes is one of several complex decision-making dilemmas across the entire manufacturing cycle (W. Yu & Meng, 2020). The authors further argue that choosing among several criteria is complicated, and an optimal choice is typically a group of non-dominant alternatives (C. Yu et al., 2020). Manufacturing process selection has long been identified as a multi-attribute decision-making problem based on complex, uncertain, and imprecise parameters during the initial design stage. Today, manufacturing process selection goes beyond simple cost calculations and capacity considerations as it involves a delicate balancing act where manufacturers must weigh a complex mix of factors, including production efficiency, product quality, cost-effectiveness, adaptability, and sustainability (Goala & Sarkar, 2023; Hodonou et al., 2019; Kek & Vinodh, 2016; P. C. Priarone & Ingarao, 2017; Sihag et al., 2019). As such, manufacturing process selection remains a crucial research area.

Manufacturing process selection challenges are not limited to conventional and AM (Bikas et al., 2019). While interest in AM has increased because of the shorter development cycles, choosing the most suitable manufacturing processes remains a significant challenge (Mançanares et al., 2015). AM is a new class of technologies involving the direct construction of physical products and components from computer-aided design (CAD) models by adding materials layer by layer (Colosimo et al., 2018). The official standard ISO-ASTM 52900 defines AM as the "process of joining materials" to fabricate parts and components from 3D model data in a layer-upon-layer format, in contrast to constructive and subtractive manufacturing approaches (Bourell & Wohlers, 2020). AM has revolutionized the low production runs of components with complex geometric properties and shapes (Bourell & Wohlers, 2020), and its rapid development is conspicuous. AM technologies are increasingly used to develop products and components in the aerospace, automotive, biomedical, and consumer goods industries (Haruna & Jiang, 2020; Y. Huang et al.., 2015). Current commercially viable AM processes are categorized into seven groups, each featuring one or more processes, as shown in **Table 2.1** below.

Table 2.1: Additive manufacturing processes

Technology	Processes	
Vat polymerization	Stereolithography (SL) Direct Light Processing (DLP) Continuous Direct Light Processing (CDLP)	
Material jetting	PolyJet technology NanoParticle Jetting (NPJ) Drop-On Demand (DOD)	
Powder bed fusion	Laser Fused	Selective Laser Sintering (SLS) Direct Metal Laser Sintering
	Electron Beam fused	Electron Beam Melting (EBM)
	Fused with agent and energy	Multi Jet Fusion (MJF)
	Thermally fused	Selective heat sintering (SHS)
Directed energy deposition	Laser-based DED Electron beam-based DED Plasma or Electric arc-based DED Powder-based DED Wire-based DED	
Material extrusion		
Binder jetting	Furan Binder Silicate Binder Phenolic Binder Aqueous-Based Binder	
Sheet lamination	Laminated Object Manufacturing (LOM) Selective Lamination Composite Object Manufacturing (SLCOM) Plastic Sheet Lamination (PSL) Computer-Aided Manufacturing of Laminated Engineering Materials (CAM-LEM) Selective Deposition Lamination (SDL) Composite-Based Additive Manufacturing (CBAM) Ultrasonic Additive Manufacturing (UAM)	

Source: own study based on ISO-ASTM 52900 as described by Bourell and Wohlers(Bourell & Wohlers, 2020)

Conventional manufacturing processes can be classified as primary, secondary, and tertiary based on the desired product or component outcomes. Primary processes generate the main shapes and forms of final products or components. These include metal-forming processes, forging, rolling, casting, molding, and extrusion. Secondary processes generate the main shape and form and refine the manufactured part's features. They include material removal processes, such as turning, drilling, milling, and grinding; bulk heat treatment processes, such as hardening, annealing, and tempering; and surface treatment processes, such as plating. Finally, tertiary processes are used after the primary and secondary processes. As such, they impact the geometry and main shape of the manufactured part. This category comprises finishing processes, such as heat and surface treatments. Each primary process, such as casting, involves numerous processes for producing a particular product or component. **Table 2.2** illustrates some different casting types, forging, and extrusion processes.

Table 2.2: Examples of casting, extrusion, and forging processes

Casting Processes	Extrusion	Forging
Investment casting	Direct extrusion	Roll forging
Plastic-mold casting	Indirect extrusion	Automatic hot forging
Sand casting	Hot extrusion	Press forging
Plaster-mold casting	Cold extrusion	Sagging
Die casting	Continuous extrusion	Impression-die drop forging
Shell-mold casting	Discreet extrusion	Upset forging
Permanent-mold casting		Open-die hammer

Source: own study

Irrespective of the adopted approach, AM or conventional, the choice of manufacturing processes should be free from cognitive bias, and the complexity of each process's parameters and their interconnectivity with product requirements and business strategy should be considered. Researchers have addressed critical decision-making problems in selecting and optimizing conventional and additive manufacturing processes based on multiple criteria decision-making methods (Altuger-Genc & Tzitzimititla, 2015; Gayathri & Nagaraju, 2016; Ghaleb et al., 2020; C. Shi et al., 2017; Zheng et al., 2017). Decision-support tools have been developed over the years, incorporating techniques such as the Analytical Hierarchy Process (AHP), analytic network process framework (ANP), a method for order preference by similarity to ideal solution (TOPSIS), and Case-Based Reasoning (CBR), to help streamline manufacturing process selection decision-making(Antony & Joseph, 2017; Kek & Vinodh, 2016; Kumru & Kumru, 2015; M. M. M. M. Mabkhot et al., 2019; Nallusamy et al., 2015; Nouri et al., 2015; Peko et al., 2018; Ransikarbum & Khamhong, 2021). These have been further improved through hybrids such as the fuzzy analytic network process (FANP) and fuzzy analytic hierarchy process (FAHP) (Khamhong et al., 2019; Ransikarbum & Khamhong, 2021; Sadeghian & Sadeghian, 2016; Vinodh et al., 2010; Zare Banadkouki et al., 2021). However, some of these techniques, such as the widely used AHP, have inherent shortcomings, such as the inability to handle subjective, inaccurate, and vague information. In addition, the manufacturing environment continues to evolve at an unprecedented pace, leading to increased complexity and uncertainty in process parameters. The evolution has also led to increased data generation, paving the way for adopting artificial intelligence-based computation techniques capable of handling large volumes of unstructured data.

2.2. Theoretical framework and empirical insights' research hypotheses

Heuristic and expertise theories are adopted to guide the investigation into the intersection between human factors and choosing optimal manufacturing processes. Tversky and Daniel Kahneman primarily developed the theory of heuristics through extensive research on cognitive bias and decision-making (Morvan & Jenkins, 2017). The study demonstrated that cognitive bias leads to the developing of heuristics as mental shortcuts used in decision-making processes (Morvan & Jenkins, 2017). Heuristic decision-making limits the efforts to reflect and weigh the objectives and alternatives consciously (Methling et al., 2022). In this study, heuristic theory helps to explore whether employing mental shortcuts or heuristics to simplify decision-making when choosing the appropriate manufacturing processes leads to inefficient choices.

While there are several theories on expertise, this study adopts the expert performance approach proposed by K. Anders Ericsson. Ericsson's approach alludes to the fact that domain knowledge involves repeatedly reproducing superior performance (Ericsson, 2018). This theory emphasizes the development of domain knowledge through experience and knowledge acquisition and the use of it to make better decisions. Although the theory is extensive and includes the development of expertise, this study focuses only on using domain knowledge and expertise in decision-making. In manufacturing process selection, expert performance theory can help evaluate whether critically analyzing the complexity of process parameters and considering potential alternatives and variants of manufacturing processes leads to better outcomes.

Combining heuristic and expertise theories can provide valuable insights into the intersection between cognitive and human factors and domain knowledge and their combined influence on the choice of manufacturing processes, as illustrated in **Figure 2.1** below. The theories provide a framework to interpret and analyze empirical evidence, helping to identify patterns, relationships, and insights regarding the impact of using heuristics and mental shortcuts to simplify decision-making when using domain knowledge and knowledge when choosing manufacturing processes, and the collective impact on process effectiveness.

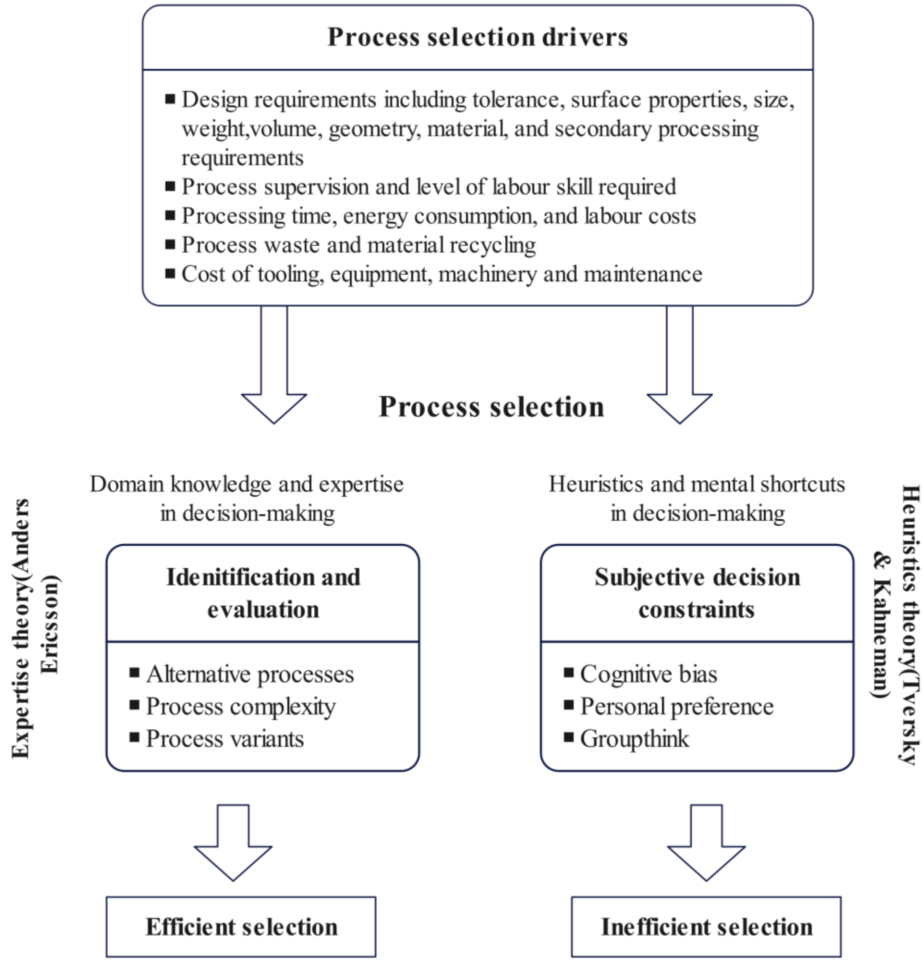

Figure 2.1: The underlying theoretical framework
Source: Own study

The relationship between cognitive bias and decision-making outcomes has been studied across disciplines, including medicine, law, psychology, management, and engineering (Korteling et al., 2023; Paulus et al., 2022). Existing research shows contrasting impacts of cognitive biases, with some reporting an influence on productivity while others reveal adverse impacts on decision-making (Mahesh Babu et al., 2023). In the manufacturing process selection context, product engineers and designers may overestimate the precision of their judgment, incorrectly believing current outcomes were all along predictable, and seek specific pieces of information that validate the existing beliefs (Berthet, 2022). Such biases can hinder the effective utilization of domain knowledge during the selection of manufacturing processes. Thus, the first sub-hypothesis of **H1 is** defined as:

H1a: Cognitive biases significantly contribute to the selection of inefficient manufacturing processes.

Like cognitive bias, personal preferences significantly affect decision-making and have been studied across disciplines (Ariail et al., 2015; Herzog et al., 2021). Personal preference is a highly likely phenomenon in the initial design and selection of manufacturing processes. However, this can adversely affect the capacity to thoroughly exploit the vast data to guide optimal solutions. Therefore, the second sub-hypothesis of **H1**, aimed at establishing whether personal preference impacts the quality of decisions made concerning knowledge utilization, is developed as follows:

H1b: Personal preferences significantly contribute to the selection of inefficient manufacturing processes.

Decisions around product design and manufacturing processes are often made in cross-functional teams, drawing upon knowledge from different aspects of the organization. Consequently, groupthink, a psychological phenomenon that occurs when the desire for harmony and consensus within the team results, is not uncommon. Similarly, several recent research studies attempt to decipher the role of groupthink in effective decision-making (Cha et al., 2020; Harel et al., 2021; Yim & Park, 2021). Groupthink often leads to an irrational or dysfunctional decision-making outcome due to the tendency to prioritize consensus and conformity over critical evaluation of alternatives and independent thinking (Tarmo & Issa, 2022). To understand the impact of groupthink on manufacturing process selection, the third sub-hypothesis of **H1** is, therefore, formulated as follows:

H1c: Groupthink within decision-making teams contributes to the selection of inefficient manufacturing processes.

Cognitive load describes the mental burden of cognitive requirements that are subject to an individual, given that human cognitive resources are limited (Wickens, 2002), as are attention span and working memory capacity. Several scholars have studied the concept of cognitive load concerning decision-making (Ball et al., 2023; Collins & Collins, 2021; McCarty et al., 2021). While high cognitive load could indicate intensive knowledge utilization in decision-making, levels more significant than the cognitive capacity may lead to poor decisions and ineffective knowledge by hindering learning (Ball et al., 2023). While cognitive load is not a subjective decision factor, it is closely related to and influences subjective decision-making. High cognitive load increases reliance on heuristics or biases. Studies have found that cognitive load significantly impacts problem-solving (Collins & Collins, 2021). A recent study postulates that the lack of clarity generates cognitive load due to sense-making (Collins & Collins, 2021). In addition, decision fatigue, which results from the repetitive use of cognitive resources in complex environments, affects cognitive load in decision-making (Collins & Collins, 2021). To understand the role of cognitive load in the selection of manufacturing processes, the fourth sub-hypothesis of **H1** is formulated as follows:

H1d: High cognitive load contributes to the selection of inefficient manufacturing processes.

Decision-making is significant in manufacturing as it allows us to compare alternatives and select optimal choices to increase productivity and quality. Much existing literature highlights the critical importance of considering alternatives in decision-making (Jing et al., 2020; J. Lim et al., 2022). Multi-criteria decision methods have been developed primarily to allow decision-makers to compare alternatives more easily across disciplines (Asadi et al., 2022; Jamwal et al., 2021; Ponhan & Sureeyatanapas, 2022). The field of manufacturing process selection has not been left behind, with numerous studies documenting multi-criteria decision methods for aiding decision-making (Raja et al., 2022). To understand the effect of utilizing knowledge of alternatives during the selection of manufacturing processes, the fifth sub-hypothesis of **H1** is formulated as follows:

H1e: Limited utilization of knowledge of alternatives contributes to the selection of inefficient manufacturing processes.

The manufacturing sector is experiencing significant technological advancements that are fostering innovation. This innovation leads to the creation of new processes and involves the continuous development of process variations. Recent studies document performance among process variants in attempts to isolate economically viable solutions (T. A. Rodrigues et al., 2019). Knowledge of process variants is, therefore, crucial in manufacturing process selection. To understand the utilization of process variant knowledge in manufacturing process selection, the sixth sub-hypothesis of **H1** is developed as follows:

H1f: Limited utilization of knowledge on process variants contributes to the selection of inefficient manufacturing processes.

Recent studies have reported on the growing complexity of manufacturing processes (Stavropoulos et al., 2021; Touzé et al., 2022). The increased complexity of manufacturing processes has been attributed to the dynamic market demand, high-quality requirements, low cost, expanded customization, and the pressing need for short lead times (Efthymiou et al., 2016). There are significant gaps in the details of the complexities of manufacturing processes, leading to increased misconceptions and poor decision-making frameworks. Based on this revelation, the following seventh sub-hypothesis of **H1** is proposed:

H1g: Limited knowledge of process complexity contributes to selecting inefficient manufacturing processes.

Making optimal decisions requires keen consideration of process description, suitable materials, process variations, economic concerns, typical use cases, design aspects, and quality issues. Using a inefficient process to manufacture a component results in deviations from the required attributes, including quality. Such components are considered defects and may need rework, which can happen immediately after a normal manufacturing cycle or delay. In this case, it commences with the depletion of perfect components in the inventory (Nobil et al., 2020). In addition, reproduction and rework costs for defective and deficient components are higher than standard work-in-progress costs (Nobil et al., 2020). This is because additional resources are often required, including energy, raw materials, and labor.

Rework and reprocessing lead to extra waste, increasing the net carbon footprint for the component and possibly causing extended lead times. Failure to understand the complexity of selected manufacturing processes may lead to safety risks when proper steps are not followed during manufacturing. Using inappropriate processes may also lead to increased generation of waste materials. For instance, additive manufacturing processes produce complex products accurately with less material waste than conventional processes (M. Javaid et al., 2021). Besides, additive manufacturing processes improve resource efficiency in the introduction and use stages and extend the product life cycle (Ford & Despeisse, 2016). To understand how subjective decision factors and domain knowledge influence these outcomes, the following five additional sub-hypotheses of **H1** are formulated:

H1h: The selection of inefficient manufacturing processes leads to rework and reprocessing.

H1i: The selection of inefficient manufacturing processes leads to increased waste materials.

H1j: The selection of inefficient manufacturing processes leads to low-quality outcomes.

H1k: Selection of inefficient manufacturing processes leads to extended lead time.

H15: The selection of inefficient manufacturing processes increases safety concerns during manufacturing.

2.2.1. Research methodology of the empirical study on subjective decision factors' impact on manufacturing process selection

2.2.2. Research design and approach, survey description, and study population

This study used quantitative surveys to provide a rich, nuanced analysis of cognitive bias, cognitive load, personal preference, and groupthink and how they intersect with the use of domain knowledge to influence the quality of decision-making. An anonymous survey questionnaire with 12 questions, as highlighted in **Table 2.3** and **Table 2.4** below is used to comprehensively investigate the combined influence of cognitive factors, human factors, and domain-specific expertise in manufacturing process selection. The survey questions are self-created, based on the developed hypotheses, which are based on the discussed literature and the underlying theoretical framework illustrated in **Figure 2.1**, which shows that typical selection drivers are numerous and complex. These drivers are used in developing selection criteria for evaluating potential processes to pick the most optimal. Process alternatives, complexity, and variants are analyzed based on criteria developed from the selection drivers presented in **Figure 2.1**. Twenty-seven companies, from small- and medium-sized companies to international corporations, were reached for participation in the survey. In addition, the survey questionnaire link was distributed to 30 professionals on LinkedIn whose profiles matched the relevant roles, including production workers, production planners, manufacturing engineers, production managers, and quality engineers. They were requested to participate in the survey and share it with their colleagues in similar environments.

The first part of the survey comprises four questions designed to identify and measure the presence of cognitive bias, personal preference, groupthink, and cognitive load in the selection of manufacturing processes. For each question, occurrence is evaluated using a five-point Likert scale. The second part comprises three questions designed to uncover whether the complexity of process parameters, alternatives, and variants is considered during the selection of manufacturing processes. Similarly, the responses are based on a five-point Likert scale. The third part comprises five questions aimed at identifying potential adverse impacts of selected manufacturing processes, including rework and reprocessing, increased scrap or waste production rate, inconsistencies in quality, extended lead times, and safety issues attributed to poorly chosen manufacturing processes. The survey includes three additional questions related to demographic data, although these questions are not considered in the scope of this research.

2.2.3. Variables, measures, and data analysis techniques

The study involved seven independent variables drawn from the formulated hypotheses. The variables were measured using the 5-Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neither Agree nor Disagree, 4 = Agree, and 5 = Strongly Agree. **Table 2.3** below shows the operationalization of the independent variables.

Table 2.3: Independent variables

Question	Variable Name	Abbreviation	Operationalization
Q1	Cognitive Bias	CB	Level of agreement with the statement "Cognitive biases influence decision-making."
Q2	Personal Preference	PP	Level of agreement with the statement "Personal preferences impact decision-making."
Q3	Cognitive Load	CL	Level of agreement with the statement "Cognitive load affects decision-making."
Q4	Groupthink	GT	Level of agreement with the statement "Groupthink influences decision-making."
Q5	Process Complexity Consideration	PCC	Level of agreement with the statement "Consideration of process complexity affects decision-making."
Q6	Alternative Process Consideration	APC	Level of agreement with the statement "Consideration of alternative processes impacts decision-making."
Q7	Process Variant Consideration	PVC	Level of agreement with the statement "Consideration of process variants influences decision-making."

Source: Own study

Seven dependent variables were similarly drawn from the corresponding formulated hypotheses. The variables were measured based on the 5-Likert scale where 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Often, and 5 = Always. **Table 2.4** below shows the operationalization of the dependent variables.

Table 2.4: Dependent variables

Question	Variable	Abbreviation	Operationalization
Q8	Rework	RW	Frequency of rework occurrence in decision-making.
Q9	High Waste Material Rate	HMWR	Frequency of high waste material rate occurrence in decision-making.

Q10	Quality Inconsistency	QI	Frequency of quality inconsistency occurrence in decision-making.
Q11	Extended Lead Times	ELT	Frequency of extended lead times occurrence in decision-making.
Q12	Safety Concerns	SC	Frequency of safety concerns occurrence in decision-making.

Source: Own study

The collected data was analyzed using three statistical tools: IBM SPSS version 26, RStudio 2023.06.0 Build 421, and SmartPLS4. Given the ordinal nature of the collected data through the 5-point Likert scale survey, IBM SPSS performs Spearman rank-order correlations. Spearman's rank correlation is a nonparametric test, which makes it especially suitable for analyzing ordinal data. The role of RStudio was limited to generating visualizations to aid the descriptive analysis of data. Partial least squares structural equation modeling (PLS-SEM) was adopted because of the intricate nature of the research design and the underlying conceptual framework (Ringle et al., 2022). Before actual analysis, a conceptual PLS-SEM model was developed with three latent variables: subjective human decision factors, domain knowledge utilization, and process ineffectiveness, as shown in **Figure 2.2** below.

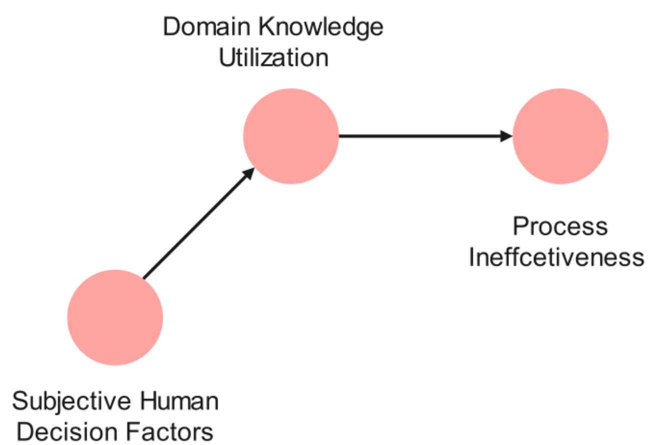

Figure 2.2. Conceptual Partial Least Squares-Structural Equation Modeling
Source: Own study

2.3. Empirical research findings

2.3.1. Findings overview

A total of 355 responses were received between March and July 2023, with the respondents comprising a mix of roles ranging from entry-level workers to directors directly involved with manufacturing processes. **Figure 2.3** shows the results obtained for the independent variables.

The proportion of responses that neither agree nor disagree is stable for most independent variables, ranging between 36% and 38%, except for groupthink, which stands at 46%. A significant presence of cognitive bias and personal preference is reported in 47% of each, while 34% of responses report the presence of groupthink in picking the most suitable manufacturing processes. Surprisingly, there was little cognitive load as only 16% of responses confirmed its presence, 39% neither confirmed nor disputed, and 45% disagreed. Similarly, considering alternative processes, process complexity and process variants were less prevalent, as only 12%, 13%, and 16% of respondents agreed, compared to 52%, 50%, and 52% who disagreed.

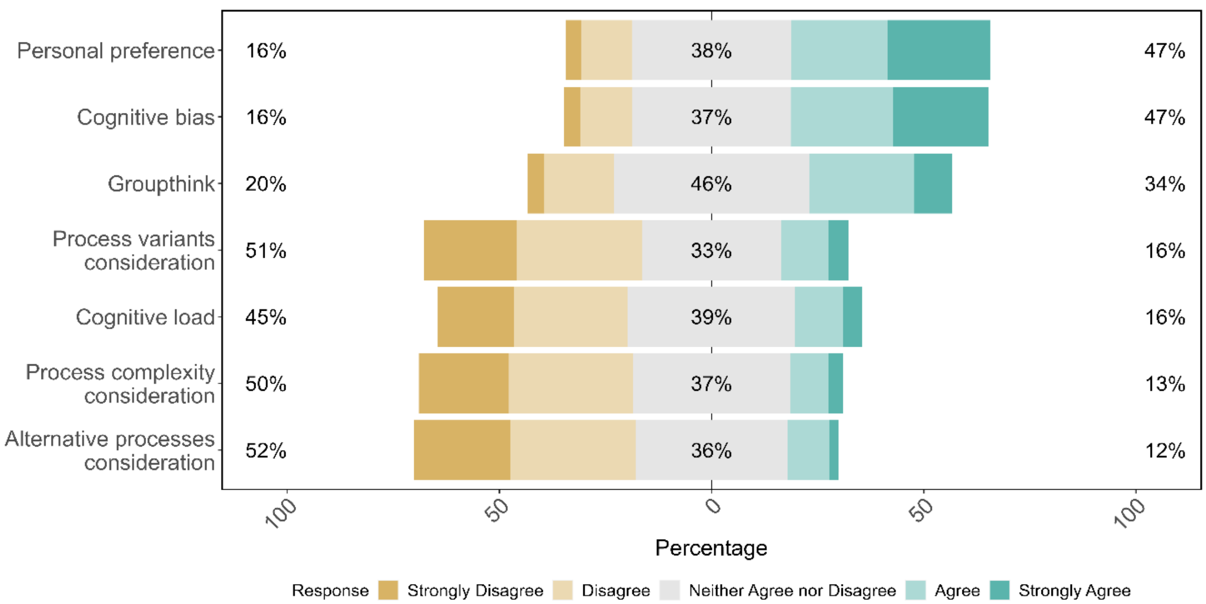

Figure 2.3. Likert plot for independent variables
Source: Own study

Similarly, the results for median dependent responses were stable, ranging from 16% to 19%. Rework, increased waste material rate, quantity inconsistency, extended lead time, and safety concerns due to selecting inefficient manufacturing processes are strongly confirmed by 48%, 43%, 42%, 40%, and 32% of responses, respectively. The plot shown in **Figure 2.4** below summarizes the findings for dependent variables.

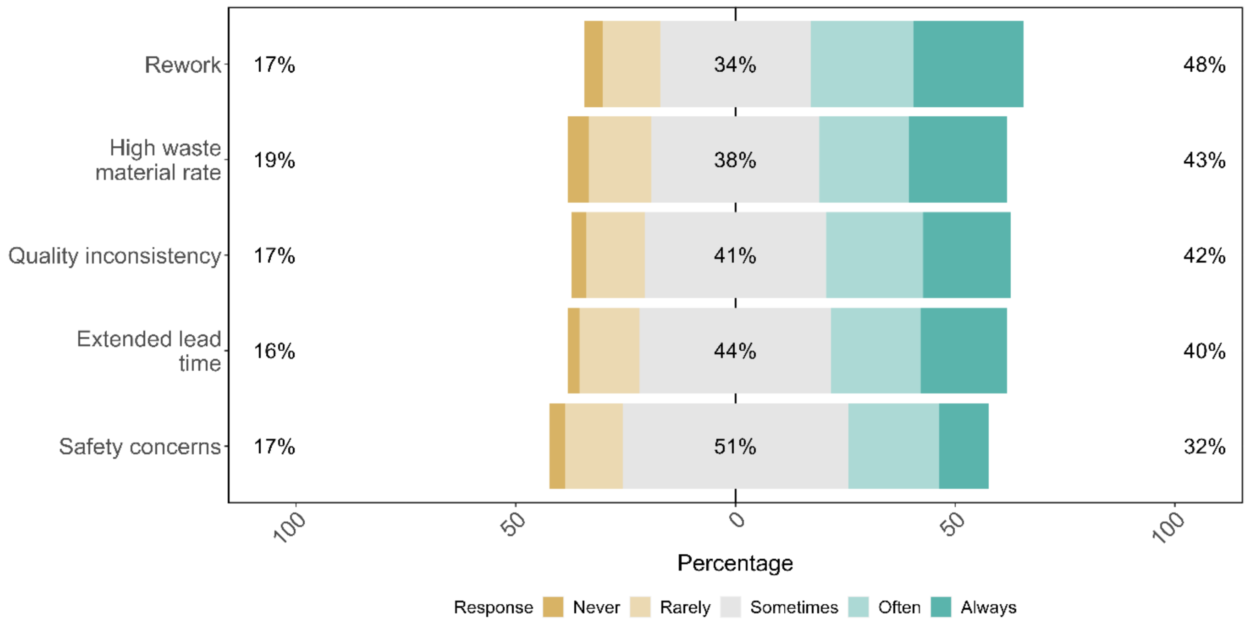

Figure 2.4. Dependent variables
Source: Own study

The responses for dependent variables were counted and analyzed for comparison. A stacked bar plot was created as shown in **Figure 2.5**. Only a small minority of responses indicated the absence of rework, high water material generation rate, quality issues, extended lead time, and safety concerns. This was followed by a slightly bigger but still low number of responses pointing to rarity. Most responses indicated that these phenomena are sometimes, often, or always witnessed.

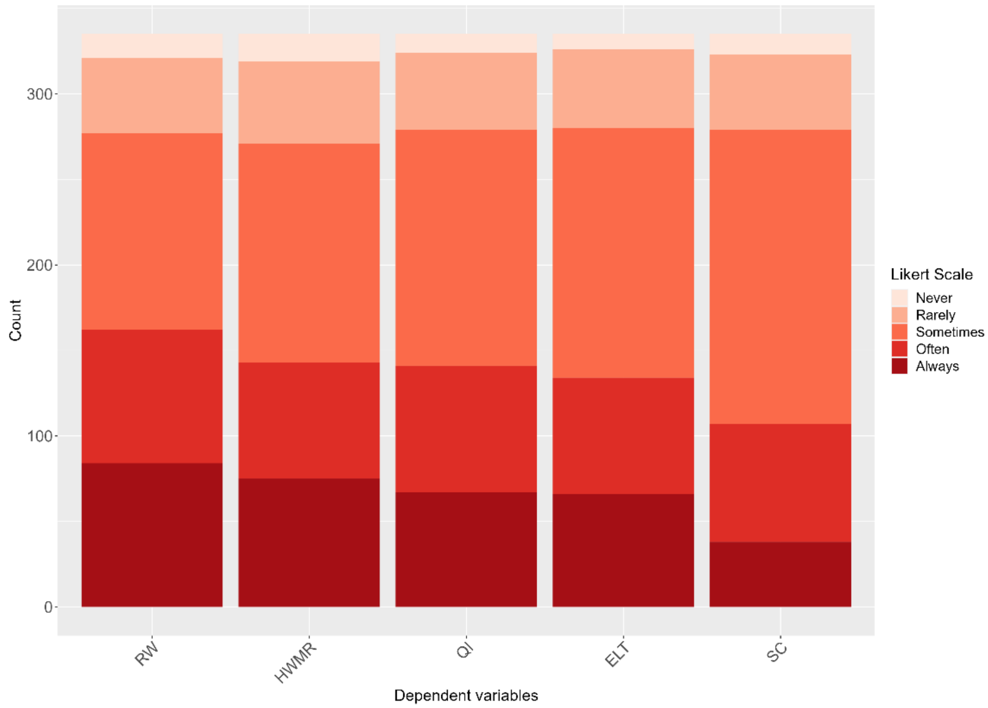

Figure 2.5. Stacked bar plot for dependent variables
Source: Own study

Similarly, independent variables were analyzed and presented as a stacked bar chart to distinguish the presence or absence of cognitive bias, personal preference, groupthink, cognitive load, process complexity consideration, alternative process consideration, and process variant consideration. The results, as shown by **Figure 2.6** below, indicates that only a fraction of the responses denied the presence of cognitive bias, personal preference, and groupthink. However, the overall number of responses that agreed or strongly agreed with the tested independent variables was significantly higher than those who disagreed or strongly disagreed.

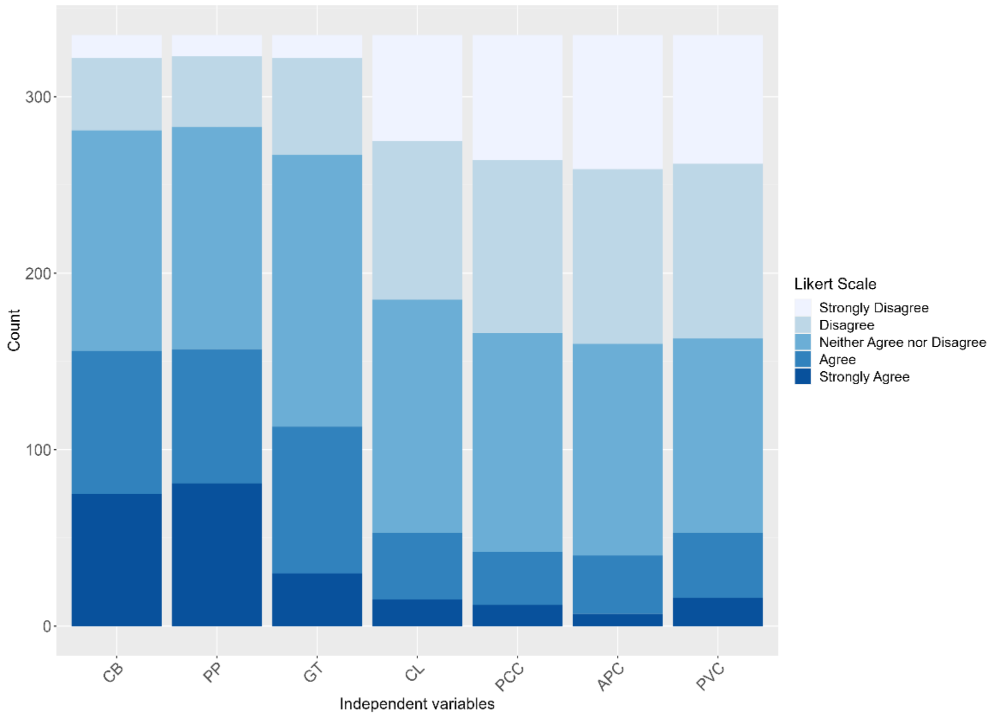

Figure 2.6. Stacked bar plot for independent variables
Source: Own study

2.3.2. Spearman's Rank correlation

Spearman's rank correlation, a nonparametric measure of the strength and direction of association between two ranked variables, was used to test how well the relationship between selected variables is described by a monotonic function. The result of Spearman's rank correlation obtained from IBM SPSS is as shown in **Table 2.5** below.

Table 2.5: Spearman rank order correlations

		CB	PP	GT	CL	PCC	APC	PVC	RW	HWMR	QI	ELT	SC
CB	Correl. Coeff	1.000	.261**	.166**	-.225**	-.308**	-.304**	-.291**	.408**	.281**	.257**	.250**	.179**
	Sig.		0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
PP	Correl. Coeff	.261**	1.000	.131*	-.263**	-.286**	-.277**	-.285**	.286**	.316**	.257**	.280**	0.102
	Sig.	0.000		0.016	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.062
GT	Correl. Coeff	.166**	.131*	1.000	-.133*	-.200**	-.206**	-.117*	.154**	.220**	0.084	.250**	0.085
	Sig.	0.002	0.016		0.015	0.000	0.000	0.032	0.005	0.000	0.127	0.000	0.119
CL	Correl. Coeff	-.225**	-.263**	-.133*	1.000	.188**	.262**	.200**	-.124*	-.189**	-.237**	-.187**	-0.073
	Sig.	0.000	0.000	0.015		0.001	0.000	0.000	0.023	0.001	0.000	0.001	0.182
PCC	Correl. Coeff	-.308**	-.286**	-.200**	.188**	1.000	.263**	.196**	-.272**	-.197**	-.201**	-.237**	-.121*
	Sig.	0.000	0.000	0.000	0.001		0.000	0.000	0.000	0.000	0.000	0.000	0.027
APC	Correl. Coeff	-.304**	-.277**	-.206**	.262**	.263**	1.000	.241**	-.293**	-.313**	-.228**	-.201**	-0.086

	Sig.	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.115
PVC	Correl. Coeff	-.291**	-.285**	-.117*	.200**	.196**	.241**	1.000	-.292**	-.240**	-.304**	-.168**	-.135*
	Sig.	0.000	0.000	0.032	0.000	0.000	0.000		0.000	0.000	0.000	0.002	0.013
RW	Correl. Coeff	.408**	.286**	.154**	-.124*	-.272**	-.293**	-.292**	1.000	.200**	.271**	.233**	0.083
	Sig.	0.000	0.000	0.005	0.023	0.000	0.000	0.000		0.000	0.000	0.000	0.129
HWMR	Correl. Coeff	.281**	.316**	.220**	-.189**	-.197**	-.313**	-.240**	.200**	1.000	.215**	.337**	0.094
	Sig.	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000		0.000	0.000	0.086
QI	Correl. Coeff	.257**	.257**	0.084	-.237**	-.201**	-.228**	-.304**	.271**	.215**	1.000	.144**	.121*
	Sig.	0.000	0.000	0.127	0.000	0.000	0.000	0.000	0.000	0.000		0.008	0.027
ELT	Correl. Coeff	.250**	.280**	.250**	-.187**	-.237**	-.201**	-.168**	.233**	.337**	.144**	1.000	.152**
	Sig.	0.000	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.000	0.008		0.005
SC	Correl. Coeff	.179**	0.102	0.085	-0.073	-.121*	-0.086	-.135*	0.083	0.094	.121*	.152**	1.000
	Sig.	0.001	0.062	0.119	0.182	0.027	0.115	0.013	0.129	0.086	0.027	0.005	

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

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Own study

As shown in **Table 2.5** above, independent variables show a mix of positive and negative correlations. Cognitive bias, groupthink, and personal preference significantly correlate with each other and with rework, high waste rate, quality inconsistency, extended lead time, and safety concerns. However, the actual correlation coefficient varies. These three independent variables negatively correlate with the cognitive load, the process complexity consideration, the alternative process consideration, and the process variant consideration. In contrast, process complexity consideration, alternative processes consideration, and process variant consideration show significant positive correlations with each other and cognitive load while negatively correlating with cognitive bias, personal preference, groupthink, rework, high waste rate, quality inconsistency, extended lead time, and safety concerns. All significant correlations appear either small or weak. Many of them are significant at 0.01 and 0.5. The results give a general impression of the impact of subjective human decision factors on applying domain knowledge and the subsequent impact on process effectiveness. Based on these findings, the low cognitive load indicates less mental effort during the selection of manufacturing caused by preference, bias, and groupthink.

2.3.3. Partial Least Squares-Structural Equation Modeling (PLS-SEM)

A PLS-SEM model was created with observable and latent variables by modifying the conceptual model illustrated in **Figure 2.1**. Subjective human decision factors constituted the first latent variable derived from cognitive bias, personal preference, and groupthink. It was a reflective model as it caused observable variables. Domain knowledge utilization was the second latent variable derived from alternative process consideration, process complexity consideration, and process variant consideration. The cognitive load was added to domain knowledge utilization, as the observed low cognitive load implied the lack of thorough analysis during decision-making. Domain knowledge was a formative model as it caused observable variables. The last latent variable was process effectiveness, as shown below in **Figure 2.7**.

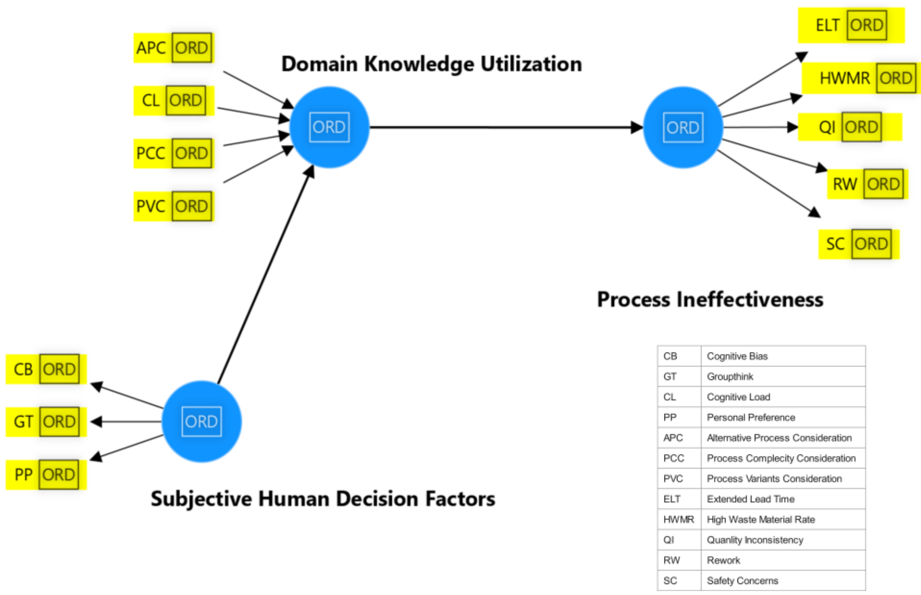

Figure 2.7. PLS-SEM model
Source: Own study

The results after executing the PLS-SEM algorithm are as shown in **Figure 2.8** below. In this study, theory supports the argument that subjective decision factors often contribute to poor decisions. However, the model is not intended to confirm the theory but rather to explore the relationship between the variables implied in the theory. Therefore, in this study, the outer loading path coefficients of at least 0.4 are acceptable, even though they imply moderate relationships. The outer loadings for the subjective human decision factors were high, especially for cognitive bias and personal preference, which are 0.744 and 0.725, respectively. Groupthink had an outer load of 0.454, below 0.7 but higher than 0.4, hence acceptable. These findings confirm sub-hypotheses **H1a**, **H1b**, and **H1c**. The loadings for domain knowledge were relatively strong, as all 3 observable variables have outer loadings above 0.4, and only cognitive load has an outer loading of 0.243; hence, hypotheses **H1e**, **H1f**, and **H1g** are supported. Process effectiveness had solid outer loadings. Four dependent variables have loading values ranging between 0.584 and 0.649, while only the safety concern had a much lower value of 0.299, indicating a less substantial impact. Thus, hypotheses **H1h**, **H1i**, **H1j**, and **H1k** were strongly supported.

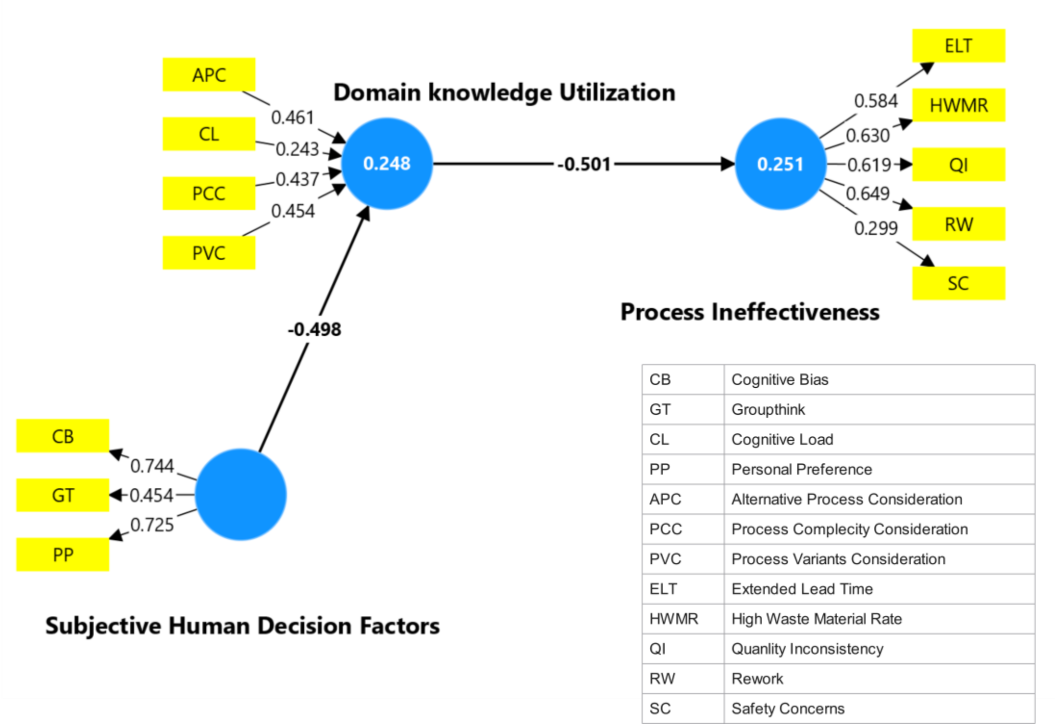

Figure 2.8. PLS-SEM model calculation
Source: Own study.

Cognitive load and safety concerns were dropped from the model because of their less substantial contribution to the latent variables. Therefore, hypotheses **H1d** and **H1l** were weakly confirmed. A new PLS-SEM calculation yielded new results, as shown in **Figure 2.9** below. The refined model had better results with all outer loading values higher than 0.4. The path coefficient describing the relationship between subjective human decision factors and domain knowledge utilization was -0.480, indicating a moderate negative relationship. Similarly, the path coefficient for the link between domain knowledge utilization and process effectiveness revealed a moderate negative relationship of -0.487. The R^2 for domain knowledge utilization is 0.231, indicating that 23.1% of its variance is attributed to subjective human decision factors. The R^2

for process ineffectiveness was 0.237, meaning that negative human decision factors and domain knowledge utilization can explain 23.7% of its variance.

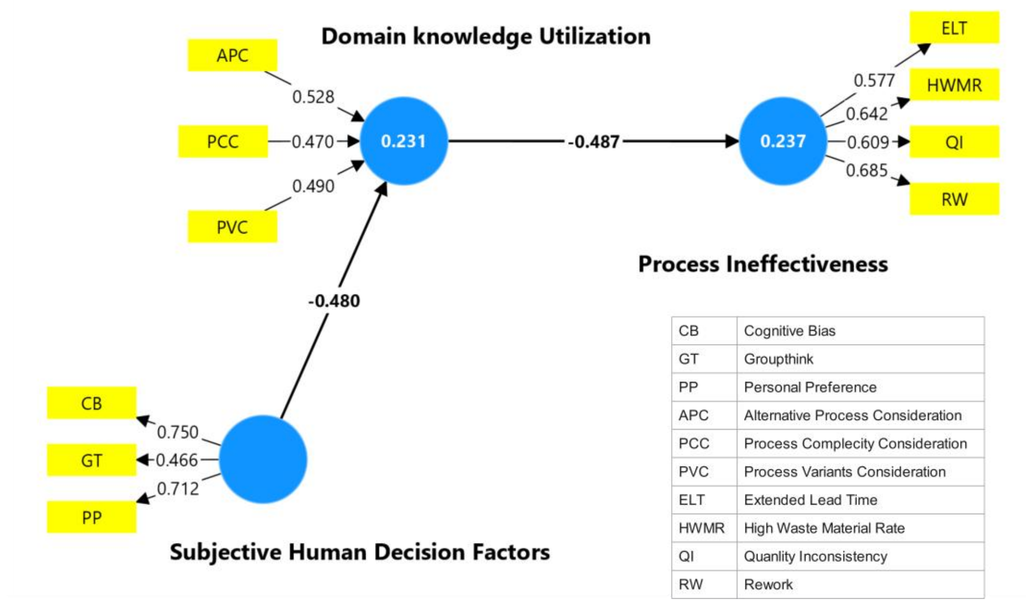

Figure 2.9. Refined PLS-SEM model results
Source: Own study

Bootstrapping was done to evaluate the statistical importance of the PLS-SEM model calculation. Bootstrapping estimated several measures, including path coefficients, by creating their distribution. This study calculated bootstrapping using 5000 subsamples and a percentile bootstrap as the confidence interval method. The test type was set to two-tailed with a significance level of 0.05. **Table 2.6** below shows the descriptives of bootstrapping results for the PLS-SEM model. **Figure 2.10** below shows the results of the bootstrapped PLS-SEM model.

Table 2.6: Bootstrapping descriptives

	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness	Observations	Cramér-von Mises test statistic	Cramér-von Mises p value
APC	2.391	2	1	5	1.007	-0.527	0.23	335	2.577	0.000
CB	3.49	3	1	5	1.084	-0.605	-0.192	335	2.405	0.000
ELT	3.406	3	1	5	1.035	-0.597	0.05	335	3.115	0.000
GT	3.185	3	1	5	0.944	-0.1	-0.014	335	3.355	0.000
HWMR	3.412	3	1	5	1.124	-0.708	-0.115	335	2.406	0.000
PCC	2.445	2	1	5	1.032	-0.323	0.304	335	2.545	0.000
PP	3.519	3	1	5	1.089	-0.663	-0.182	335	2.495	0.000

PVC	2.475	2	1	5	1.092	-0.45	0.369	335	2.208	0.000
QI	3.421	3	1	5	1.053	-0.589	-0.044	335	2.763	0.000
RW	3.519	3	1	5	1.125	-0.725	-0.238	335	2.229	0.000

Source: Own study

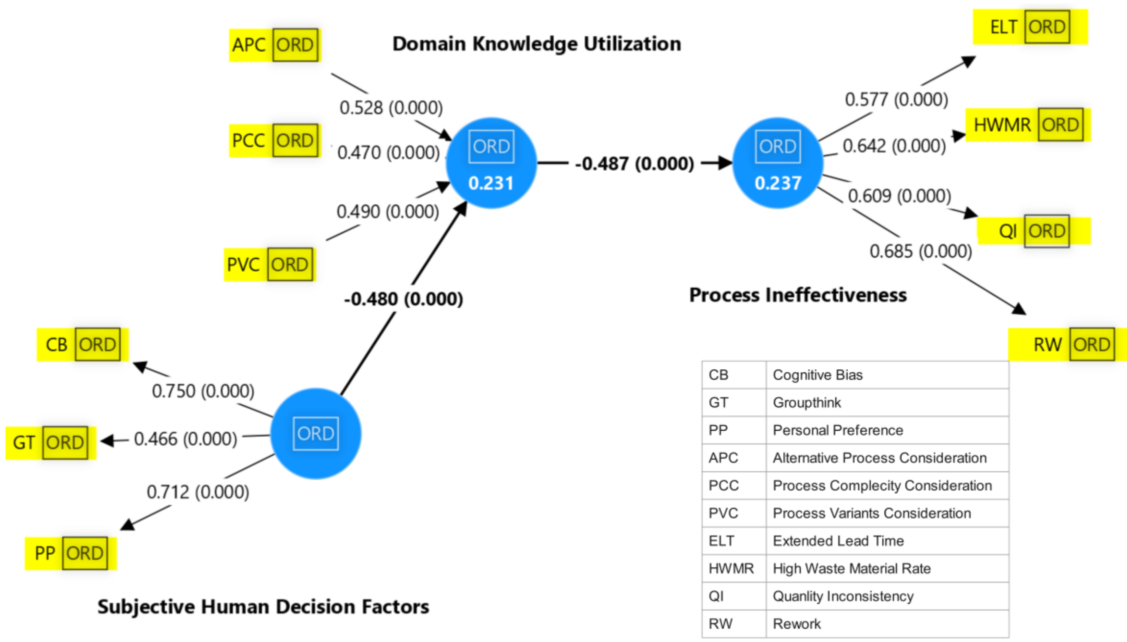

Figure 2.10. PLS-SEM bootstrapping
Source: Own study

Key findings from bootstrapping included path coefficients, outer loadings, outer weights, and total effects. Path coefficients depict the hypothesized intersection between the latent variables in the PLS-SEM model by measuring their direct influence on each other. They also show the intensity and direction of the links between latent variables. **Table 2.7** and **Table 2.8** The results for the outer loadings and outer weights are below.

Table 2.7: Outer loadings

	Original sample (O)	Sample mean (M)	Standard deviation	T statistics (|O/STDEV|)	P values
APC -> Domain knowledge utilization	0.716	0.711	0.074	9.658	0.000
CB <- Subjective human decision factors	0.75	0.746	0.055	13.563	0.000
ELT <- Process Ineffectiveness	0.577	0.572	0.073	7.935	0.000
GT <- Subjective human decision factors	0.466	0.461	0.1	4.682	0.000
HWMR <- Process Ineffectiveness	0.642	0.636	0.064	10.012	0.000
PCC -> Domain knowledge utilization	0.646	0.64	0.084	7.672	0.000
PP <- Subjective human decision factors	0.712	0.707	0.065	10.995	0.000

PVC -> Domain knowledge utilization	0.651	0.644	0.072	9.008	0.000
QI <- Process Ineffectiveness	0.609	0.605	0.076	8.042	0.000
RW <- Process Ineffectiveness	0.685	0.682	0.063	10.792	0.000

Source: Own study

Table 2.8: Outer weights

	Original sample (O)	Sample mean (M)	Standard deviation	T statistics (|O/STDEV|)	P values
APC -> Domain knowledge utilization	0.528	0.525	0.087	6.051	0.000
CB <- Subjective human decision factors	0.591	0.588	0.063	9.427	0.000
ELT <- Process Ineffectiveness	0.317	0.314	0.062	5.067	0.000
GT <- Subjective human decision factors	0.337	0.334	0.082	4.091	0.000
HWMR <- Process Ineffectiveness	0.401	0.396	0.057	7.082	0.000
PCC -> Domain knowledge utilization	0.47	0.465	0.093	5.056	0.000
PP <- Subjective human decision factors	0.561	0.556	0.071	7.929	0.000
PVC -> Domain knowledge utilization	0.49	0.484	0.079	6.181	0.000
QI <- Process Ineffectiveness	0.385	0.382	0.064	6.015	0.000
RW <- Process Ineffectiveness	0.475	0.473	0.065	7.353	0.000

Source: Own study

As shown by **Table 2.7** and **Table 2.8** all observed variables significantly influenced latent variables, as indicated by the p-value of 0.00. The T-statistics confirmed the statistical significance, with most variables having more than 7.6 values, except groupthink and subjective human decision factors. However, the most important results are shown in **Table 2.9** below, depicting the bootstrapped path coefficients.

Table 2.9: Bootstrapped path coefficients

	The original sample (O)	Sample mean (M)	Standard deviation	T-statistics (|O/STDEV|)	P values
Subjective human decision factors -> Domain knowledge utilization	-0.480	-0.490	0.048	10.095	0.000
Domain knowledge utilization -> Process Ineffectiveness	-0.487	-0.498	0.042	11.622	0.000

Source: Own study

The results showed an original sample path coefficient of -0.480 for the relationship between subjective human decision factors and domain knowledge utilization. The negative sign indicated that as subjective human decision factors increased, domain knowledge utilization decreased and vice versa. The bootstrapped path coefficient mean (M) is -0.490, indicating that the average relationship across all bootstrap samples is slightly more robust than in the original sample. The standard deviation (STDEV) is 0.048, indicating a slight variability in the path coefficients across bootstrap samples. The T-statistic value was 10.095, more significant than the typical critical value of 1.96 at a 95% confidence level, indicating that the path coefficient was statistically significant. The P value was 0.000, also indicating statistical significance. The original sample path coefficient for the relationship between domain knowledge utilization and process effectiveness was -0.487, showing a negative relationship between these constructs. The results are as expected since domain knowledge is limited in this case because of the influence of subjective human decision factors. Therefore, the more limited the use of domain knowledge in decision-making, the more process effectiveness decreases and vice versa. The T-statistic value was 11.622, and the p-value is 0.000, indicating that this relationship was statistically significant.

2.4. Empirical insights discussion

2.4.1. Hypothesis verification and subjective decision factors

As defined by hypothesis **H1**, subjective decision factors such as cognitive biases, personal preferences, and groupthink significantly contribute to the selection of inefficient manufacturing processes by limiting the use of domain knowledge in decision-making. This was confirmed by the empirical evidence presented, which strongly supported 10 sub-hypotheses of **H1**, with only two being weakly confirmed, as shown in **Table 2.10** below.

Table 2.10: Sub-hypotheses testing

Hypothesis	Statement	Conclusion
H1a	Cognitive biases significantly contribute to the selection of inefficient manufacturing processes.	Confirmed
H1b	Personal preferences significantly contribute to the selection of inefficient manufacturing processes.	Confirmed
H1c	Groupthink within decision-making teams contributes to the selection of inefficient manufacturing processes.	Confirmed
H1d	High cognitive load contributes to the selection of inefficient manufacturing processes.	Weakly confirmed
H1e	Limited utilization of knowledge of alternatives contributes to the selection of inefficient manufacturing processes.	Confirmed
H1f	Limited utilization of knowledge on process variants contributes to the selection of inefficient manufacturing processes.	Confirmed
H1g	Limited knowledge of process complexity contributes to the selection of inefficient manufacturing processes.	Confirmed
H1h	The selection of inefficient manufacturing processes leads to rework and reprocessing.	Confirmed
H1i	The selection of inefficient manufacturing processes leads to increased waste materials.	Confirmed
H1j	The selection of inefficient manufacturing processes leads to low-quality outcomes.	Confirmed
H1k	The selection of inefficient manufacturing processes leads to extended lead time.	Confirmed

H1l	The selection of inefficient manufacturing processes leads to increased safety concerns during	Weakly confirmed

Source: Own study

The research findings indicate that subjective decision factors, namely cognitive bias, groupthink, and personal preference, significantly affect the choice of manufacturing processes. The findings are unsurprising as long-standing research has shown that human decision-making frequently involves cognitive biases caused by dependence on judgmental heuristics. Importantly, this phenomenon is practiced to some extent by laypeople, experienced specialists, and experts. As shown in Spearman rank correlations in **Table 2.5**, *c*ognitive bias significantly correlates with rework, quality inconsistency, increased waste material rate, and extended lead times. At the same time, cognitive bias has a strong negative correlation with alternative process consideration, process complexity consideration, and process variant consideration.

Similarly, groupthink has been found to limit the exploration of alternative processes and process variants, as indicated by a significant negative correlation, as shown in **Table 2.5** thereby confirming that Manufacturing process selection is often a collaborative effort involving several groups, including product designers, production planners, and quality control specialists. These groups work together to make informed decisions based on various factors such as product requirements, production capabilities, and quality standards. Together, these groups leverage their collective knowledge and expertise to evaluate and decide on the best manufacturing method that meets the product requirements while ensuring efficiency, quality, and cost-effectiveness. However, they are not immune to groupthink, as shown. While there are many other forms of cognitive bias, this study treated groupthink as a particular case. It elevated it to a variable because of the collaborative nature of the manufacturing process selection, where decisions are often made in cross-functional teams.

Personal preferences derived from an individual’s prior experiences, inherent biases, and comfort levels can significantly influence decision-making in manufacturing process selection. These findings align with existing research, which shows that personal preference makes decision-makers rely mainly on the information they deliberately search for when making critical decisions. Existing research alludes to human decision-making in complex, dynamic, and fast-paced environments such as manufacturing, which is often biased, leading to inefficient performance (Kessler & Arlinghaus, 2022). The negative correlation between personal preference and the consideration for alternatives, variants, and complexities observed reveals the inherent problem of overreliance on personal preferences, which is the prevention of objective evaluation of all available options. In effect, it can limit potential solutions to the decision-maker who has had a good experience and is already comfortable. This limitation can have significant implications for manufacturing efficiency and effectiveness, as shown by the positive correlation between preference and variables reflecting process ineffectiveness, such as rework, extended lead time, and quality inconsistency.

2.4.2. Domain knowledge in decision-making

Domain knowledge, particularly regarding different categories of manufacturing processes, their capabilities, and inherent complexities, is pivotal in effective decision-making when selecting optimal manufacturing processes. The knowledge acquired equips individuals or groups with the necessary capabilities to analyze selection drivers and develop criteria critically, consider process alternatives, their complexities, and variants, and evaluate the potential for rework or extended lead times and to meet quality and sustainability standards. However, this research illuminates an alarming phenomenon whereby the use of domain knowledge is hampered significantly by subjective decision factors, including cognitive bias, groupthink, and personal preference, ultimately compromising the effectiveness of manufacturing processes. Spearman rank correlation coefficients and the PLS-SEM model indicate a negative relationship between variables related to domain knowledge utilization and the effectiveness of the selected manufacturing processes. The results reinforce the need to integrate domain knowledge when designing and selecting manufacturing processes. Existing studies have proposed methods for incorporating knowledge synthesis in product and component design, and the selection of appropriate processes for manufacturing (Kessler & Arlinghaus, 2022). The study suggests incorporating the ideals of process selection and manufacturing constraint integration in the early stages of product design (Kessler & Arlinghaus, 2022). Failure to utilize domain knowledge when choosing manufacturing processes leads to inefficient processes, disregarding essential constraints.

2.4.3. Intersection between subjective decision factors and domain knowledge

This study has unveiled the complex interplay between subjective decision factors and domain knowledge in the selection of manufacturing processes. The findings show that these factors, while seemingly benign, can undermine the use of specialized knowledge in the selection of manufacturing processes. These subjective human decision factors influence decision-makers to deviate from informed critical analysis based on domain knowledge and instead favor decisions influenced by cognitive biases, groupthink, and personal preferences. The negative correlation between these two latent variables underscores that an increase in subjective decision factors significantly hampers the effective deployment of domain knowledge in the process selection. This study elucidates the critical interplay between subjective decision factors and the use of domain knowledge in selecting manufacturing processes.

Subjective decision factors such as cognitive biases, groupthink, and personal preferences may appear inconsequential. However, these factors are far from benign, as they substantially negatively impact the effective use of domain knowledge. Cognitive biases, for instance, tend to skew judgment and distort the perception of reality, causing deviations from logical, rational decision-making. Consequently, this needs to be improved to maintain the value of domain knowledge and expertise, leading to potentially poor decisions when choosing manufacturing processes. Groupthink, which is common in the group decision-making process involving a group of people or elements (Orłowski et al., 2019), can stifle individual creativity and independent thinking. It promotes conformity and unanimity at the expense of critical evaluation and thorough exploration of options, effectively sidelining valuable domain knowledge. Personal preferences tend to favor familiarity and convenience over novelty and optimization. As a result, decision-makers need to pay more attention to relevant domain knowledge that could guide them toward superior solutions, which might require more effort or entail more risk.

Collectively, these factors signify a potent detriment to the effective deployment of domain knowledge in the selection of manufacturing processes. The observed negative correlation between the two latent variables under study confirms that the rise in subjective decision factors corresponds to a significant decrease in the use of domain knowledge, thereby impeding optimal process selection. The intricate interplay among these variables presents a formidable challenge that manufacturers must address to optimize their decision-making processes and improve sustainability across the product life cycle.

Within the manufacturing realm, various studies have attempted to address the roles of domain knowledge and subjective decision factors separately. Juxtaposing our findings with these recent studies reveals significant points of convergence and divergence. Our findings show the negative influence of subjective decision factors such as cognitive bias, groupthink, and personal preference on the quality of decision-making. Similar conclusions are drawn in several recent studies (Grube & Killick, 2023; V. Li, 2023; Mahesh Babu et al., 2023). A recent empirical investigation into the relationship among lean tools, biases, and waste in manufacturing concludes that cognitive bias significantly leads to inefficient decisions, which increase waste generation by limiting lean tools (Purushothaman et al., 2022). In a separate study, the authors demonstrate that cognitive biases hinder the effective implementation of lean methodologies in manufacturing by degrading the quality of decision-making (Mahesh Babu et al., 2023). While most studies link cognitive bias to inefficient decision-making, one study shows the positive impact of cognitive bias on employee product creativity in manufacturing technology firms, which enhances product performance (Cristofaro et al., 2022). Subjective decision factors affect the effective use of knowledge in decision-making. Recent studies emphasize the importance of knowledge in decision-making (Canonico et al., 2022; Fattah et al., 2022; Kałkowska & Kozlov, 2016; Razavian et al., 2023). Our study demonstrates the critical need for manufacturing organizations to eliminate subjective decision factors and foster knowledge utilization in decision-making for optimal choices.

2.4.4. Study limitations and conclusions

While this study provides valuable empirical insights into the interplay between subjective decision factors and domain knowledge utilizationd when deciding on the appropriate manufacturing processes, several limitations should be acknowledged. First, the study used a questionnaire for data collection, introducing sampling bias. Despite efforts to ensure a representative sample, the responses overrepresent certain companies more inclined to participate. Thus, the results may not be fully generalized to all settings within the manufacturing industry in Poland. Second, the responses were subjective and self-reported, potentially containing biases. Third, this cross-sectional study provides a snapshot of the interplay between subjective decision factors and domain knowledge usage at a particular point in time. A longitudinal study might yield more robust insights into the dynamics of these factors over time and how they eventually affect process selection, efficiency, and sustainability. Lastly, some of the latent variables developed in PLS-SEM might not have been perfectly captured due to the limitations in the questionnaire design or the use of Likert scale responses, which assume equal intervals between response options.

Based on Polish findings, this study deeply analyzes subject decision variables and the utilization of domain knowledge in selecting appropriate manufacturing processes. This study affirms that cognitive bias, personal preference, groupthink, and underutilization of expertise in decision-making play essential roles in selecting inefficient manufacturing processes. The study provides insight into the perverse effects of groupthink, cognitive bias, and personal preference on the practical application of domain knowledge, leading to inefficient decision-making that compromises efficiency and manufacturing operations' sustainability. The negativity of such variables provides a complicated decision-making situation in manufacturing that is tightly intertwined with human subjectivity and domain knowledge. The research stresses that. Decision makers and managers must be cognizant of the increased role played by such subject variables, particularly in knowledge management and the application of decision making. Applying high-level decision aid systems can be a helpful tool that directs decision makers to make decisions that maximize efficiency, quality, lead time, and safety in manufacturing.

3. Intelligent Support in Selection of Manufacturing Processes

This chapter delves into how technological advances, dynamic customer needs, growing uncertainty, and the imperative for sustainable development continue to pressure manufacturing enterprises to enhance productivity and competitiveness. In this challenging landscape, decision-making in manufacturing process selection is critical. The chapter revolves around the premise that adopting intelligent support is essential for balancing performance and costs through optimal process selection. This chapter involves a comprehensive review of 93 studies published between 2013 and 2023 on intelligent methodologies that support the selection of manufacturing processes. Through the review, this chapter aims to provide a profound understanding of intelligent support in manufacturing process selection. The findings, which indicate significant interest in intelligent methodologies for manufacturing process selection, are of great importance. Fuzzy logic is prevalent in additive manufacturing due to its ability to handle complex and imprecise data. At the same time, artificial neural networks are favored in conventional manufacturing for leveraging extensive historical data. Genetic algorithms are primarily used for optimization challenges. This chapter seeks to identify gaps in current research on the selection of manufacturing processes. As manufacturing evolves with new technologies and complex materials, this chapter advocates adopting a generalized matrix learning vector quantization neural network for efficient and intelligent process selection in additive and conventional approaches due to its capacity to leverage historical data and handle complex and high-dimensional data that includes expert knowledge.

3.1. Introduction and related works on intelligent computational methods

While manufacturing plays a vital role in the growth and development of the global economy (Lima et al., 2022), the industry is currently navigating a landscape of unprecedented change and complexity. This dynamic environment is primarily shaped by rapidly shifting market demands, continuous technological evolution, and a growing emphasis on sustainability (Haraguchi et al., 2017; Mumali, 2022). Recent studies highlight the vulnerability of manufacturing companies to large-scale disruptions from various issues, including geopolitics, trade wars, and pandemics (D. Chen et al., 2022; Kapoor et al., 2021). In addition, manufacturing systems have become more complex over the past decades in pursuit of less costly, timely, flexible, and high-quality components and parts manufacturing (Efthymiou et al., 2016). The rapid evolution of customer needs is described as the hallmark of the twenty-first century, driving market turbulence. Changing market demands require manufacturers to be highly responsive and flexible, adapting their processes promptly to meet changing consumer preferences and emerging trends. Concurrently, technological evolution, especially in digitalization and automation, radically alters how manufacturing operations are conceived and executed (Chong et al., 2018; S. Mittal et al., 2019; Zeba & Dabi, 2021). These technological advancements are not only incremental improvements but also represent significant leaps that redefine the boundaries of what is feasible in manufacturing.

Artificial intelligence techniques are a pivotal development toward creating systems capable of performing tasks that typically require human intelligence. Artificial intelligence encompasses various computational methods and techniques that enable the mimicking of human intelligence, such as machine learning (ML), deep learning, natural language processing, computer vision, expert systems, fuzzy logic, neural networks, and evolutionary algorithms (L. Chen et al., 2020; M. Johnson et al., 2022; Walavalkar, 2023). Although computational methodologies were constrained by manual inputs and limited by the scope of human analytic capabilities in the past, they have undergone unprecedented growth in potential because of the artificial intelligence infusion, enabling algorithms to self-refine, learn from vast datasets, and accurately predict outcomes. Artificial intelligence has brought significant transformations across sectors, including education, healthcare, economics, manufacturing, and security (Capuano et al., 2022; L. Chen et al., 2020; Enholm et al., 2022; K. W. Johnson et al., 2018; Patel & Shah, 2022; Sanusi et al., 2022). There has been a revolutionary paradigm shift across industries due to artificial intelligence-based support adoption (Mumali, 2022; Mumali & Kałkowska, 2020; Waqar, 2024). Artificial intelligence-based support systems have notably garnered interest recently, with a plethora of research on intelligent manufacturing for efficiency and sustainability (Mumali, 2022; Mypati et al., 2023; N. O. Sadiku et al., 2019; A. K. Sharma et al., 2023; Tran, 2021; Zeba et al., 2021). Given the complexities and significant impact of manufacturing process selection, adopting intelligent support is crucial for balancing performance and manufacturing cost through the intelligent selection of optimal processes.

Consequently, integrating intelligent support techniques into manufacturing process selection is an incremental improvement and a transformative shift that addresses the multi-dimensional challenges of the modern manufacturing landscape. These techniques are based on artificial intelligence, representing a convergence of technological innovation with strategic decision-making, paving the way for a new era of efficient, sustainable, competitive manufacturing (Papacharalampopoulos et al., 2023). Early computational techniques in manufacturing process selection relied on prototypes involving multi-attribute decision models and relational databases that differentiated preferences and actual decision constraints. The field has experienced a significant leap in methodologies, ranging from simple multi-attribute criteria models to intelligent decision support systems based on complex mathematical models (Yousefi et al., 2023). This advancement has expanded the limits of what was previously considered possible, taking computational research into areas that were once thought to be purely theoretical.

Artificial intelligence is a cross-disciplinary research area with immense potential for addressing critical manufacturing process selection decision challenges. The selection of manufacturing processes is an example of a crucial multi-dimensional decision problem in manufacturing, as choosing a suitable manufacturing process for a particular product or component depends on various criteria, including material, time, cost, and sustainability implications (Hernández-Castellano et al., 2019; Lukic et al., 2017; Martínez-Rivero et al., 2019). The selection of optimal manufacturing processes is crucial for efficiency from the onset of the production cycle and goes a long way to address common issues such as rework, which often causes extended lead times and inflated manufacturing costs (Colledani & Angius, 2020; Gouiaa-Mtibaa et al., 2018). Analyzing and optimizing processing parameters is essential to ensuring the effective implementation of the selected manufacturing process. In recent years, significant progress has been made in decision-making methods for process selection in additive and conventional manufacturing, owing to the strong interest in multiple-attribute decision-making methods (Gokuldoss et al., 2017; Hodonou et al., 2019; P. C. C. Priarone & Ingarao, 2017). Selecting a suitable manufacturing process for a particular component or finished product involves many constraints and conditions (Djassemi, 2017; Saidi et al., 2018). For instance, the decision-maker must consider the required product's processing time, volume, cost, environmental impact, and mechanical, physical, and chemical properties.

The unprecedented effort to push manufacturing processes to their limits to ensure the sustainable and cheap production of high-quality products and components is accelerating the adoption of more integrated and automated intelligent decision support systems in process selection and design. Existing studies have introduced and described decision-support models and intelligent methods for selecting manufacturing processes (Abbas & Mostafa, 2016; Gojković et al., 2021; Hamzeh & Xu, 2019; Raigar et al., 2020; Ransikarbum & Khamhong, 2021; Sadeghian & Sadeghian, 2016; K. N. N. Shi et al., 2019; Yan & Melkote, 2023). However, to our knowledge, a comprehensive review of literature on intelligent support methodologies focused on application in manufacturing process selection, including a discussion of adopted artificial intelligence technologies and their limitations, and examining future perspectives, is yet to be undertaken. This study addresses this gap by examining and synthesizing current knowledge on intelligent support methodologies based on artificial neural networks, genetic algorithms, fuzzy logic, and hybrid combinations. The primary goal of this review is to methodically collate and comprehensively synthesize the existing body of research on artificial intelligence-based techniques in the sphere of manufacturing process selection.

Our contribution is in the pursuit of a deep understanding of the transformative impact of artificial intelligence on manufacturing process selection. This contribution is achieved by unearthing insights into how intelligent support technologies have redefined traditional practices and examining how artificial intelligence has enhanced process selection efficiency, accuracy, and adaptability. The review intends to illuminate the path for future innovations and improvements in this field. This review's scope is broad and meticulously defined, encompassing a diverse range of studies published between 2013 and 2023. This time frame is selected to capture the most recent and relevant developments in the field, ensuring that the review reflects the current state of the art.

Recent technological advances in computation methods have resulted in the development of intelligent systems capable of replicating human intelligence processes (Abioye et al., 2021). Intelligent systems use logical arguments, soft computing techniques, and other machines to produce human-like capabilities of observing, learning, inference, and decision-making (Ertel, 2017; Neapolitan & Jiang, 2018; Salehi & Burgueño, 2018; Shehab et al., 2020). In recent years, intelligent systems have shown significant progress in supporting decision-making, planning, and design activities in manufacturing, including prediction, design, and control of manufacturing processes, leveraging manufacturing digitalization (Mozaffar et al., 2022). Key areas that influence manufacturing, such as energy, have benefited from intelligent methodologies, including in processes such as load forecasting (Grzeszczyk & Grzeszczyk, 2022). The principal classical methodologies for Intelligent Systems are biologically inspired and include artificial neural networks (ANNs), fuzzy logic, evolutionary algorithms such as genetic algorithms and genetic programming, particle swarm optimization, and colony optimization. **Figure 3.1** below shows neural networks, fuzzy logic, genetic algorithms, and their hybrid combinations that dominate the intelligent support domain.

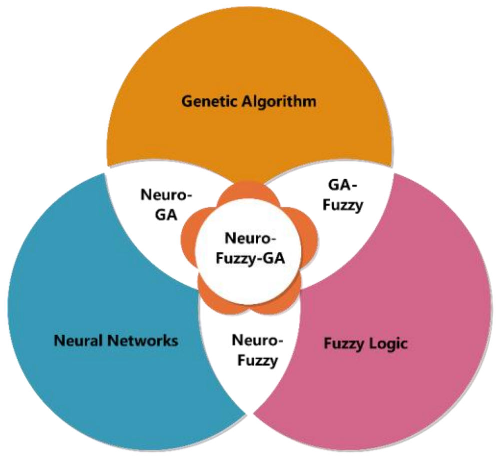

Figure 3.1.NN, FL, GA, and their Hybrid combinations
Source: Own study based on (Ashish et al., 2018; Zadeh, 2015)

ANNs are simplified models of biological neural networks designed to mimic the features observed in the brain, such as learning to recognize patterns, decipher perceptions, classify data, and predict future events (J. Zhang et al., 2023). Countless studies have similarly described ANNs, as parallel computer modeling after the biological brain (Samek et al., 2021; W. Zhang et al., 2020). ANNs comprise layers of adaptive nonlinear processing elements called neurons or nodes. The basic structure consists of input and output layers sandwiched between one or more hidden layers. Each neuron is an elementary information processing unit that receives input signals via the input layer and sends the data to the next layer when activated. **Figure 3.2** below is a schematic representation of a neuron, showing the input signals X_1, X_2 and X_n, and the output signals W_1, W_2 and W_n.

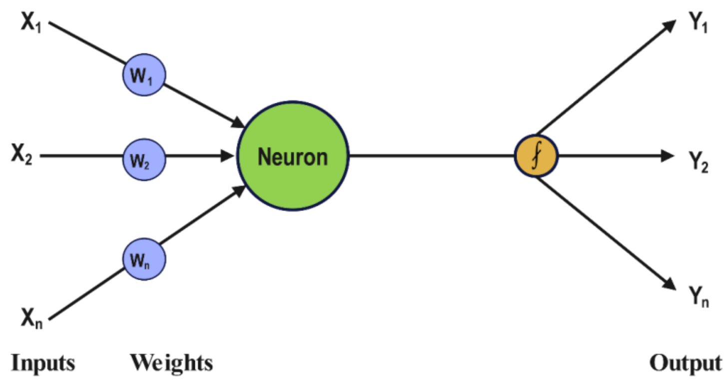

Figure 3.2. Neuron
Source: Own study based on (Anandakumar & Arulmurugan, 2019)

ANNs are classified into several groups depending on the network architecture. Three fundamental classes include single-layer feedforward networks, multilayer feedforward networks, and recurrent networks (Sharkawy, 2020). The single-layer feedforward network features input and output layers with no hidden layers in between, as illustrated by **Figure 3.3**. The input layer neurons receive and transmit the data to the output layer neurons via connections carrying weights. These networks are unidirectional, carrying signals from input to output layers and not vice-versa, hence the term feedforward. A Multilayer feedforward network consists of input and output layers and at least one or more hidden layers whose neurons help perform further computations before redirecting the input information to the output layers. Finally, recurrent networks feature at least one feedback loop.

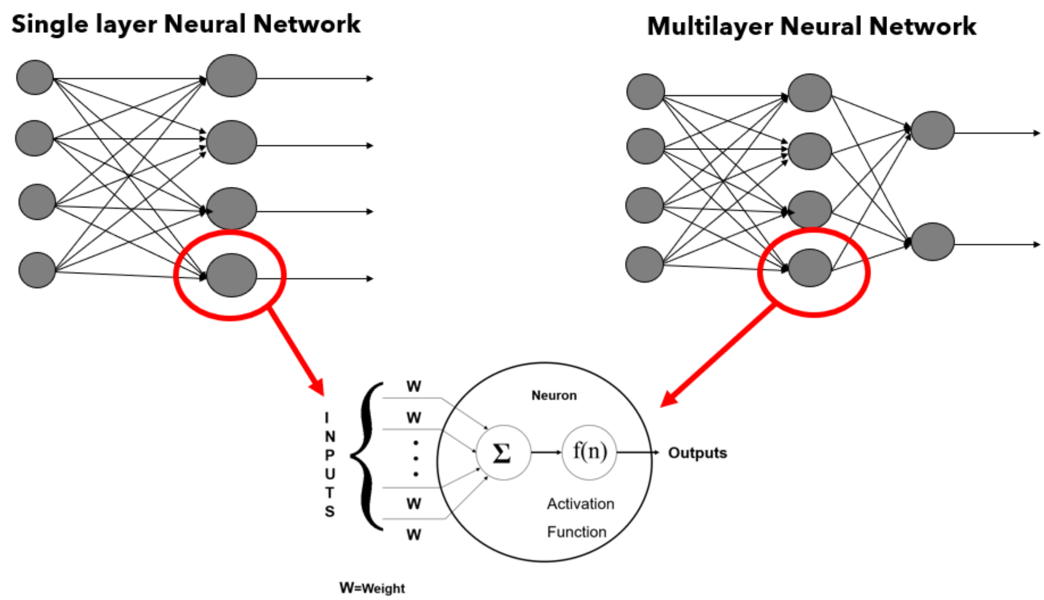

Figure 3.3. ANN architecture
Source: Own study based on (Anandakumar & Arulmurugan, 2019)

The learning paradigms for ANNs include supervised, unsupervised, and reinforcement (Anandakumar & Arulmurugan, 2019; F. A. Rodrigues, 2023). Supervised learning involves feeding the network with input and output training data samples (Anandakumar & Arulmurugan, 2019). Unsupervised learning consists of the adjustment of weights based on internal rules, and the network learns independently by discovering data structure through clustering and compression (Anandakumar & Arulmurugan, 2019). Reinforcement learning is similar to supervised learning, but weights are not modified based on the error values. Instead, the errors indicate whether the computed output is correct or incorrect. The training is output-based (Anandakumar & Arulmurugan, 2019). The learning paradigms for ANNs are shown in **Figure 3.4** below.

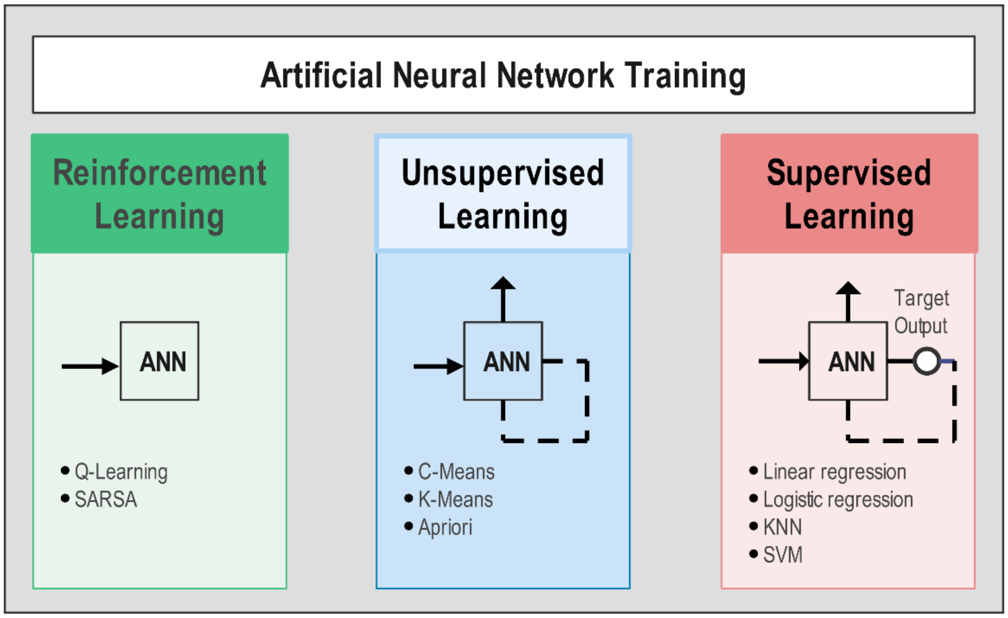

Figure 3.4. ANN learning paradigms
Source: Own study based on (Anandakumar & Arulmurugan, 2019)

ANNs are robust computing systems capable of modeling and solving complex nonlinear problems across disciplines. Recent studies reveal the increasing adoption of ANNs across different fields, including construction, where ANN models have been studied in cost estimation (Matel et al., 2022) and prediction of material properties (Asteris & Mokos, 2020; Ben Chaabene et al., 2020; D. C. Feng et al., 2020; I.-J. Han et al., 2019; Roshani et al., 2021) and the medical field for diagnosing and predicting diseases (Abdelaziz Ismael et al., 2020; Bharati et al., 2020; Kweik et al., 2020; Muhammad et al., 2019). ANN research has long been part of the manufacturing industry. Recent applications in manufacturing management of additive and advanced manufacturing processes and systems (Bajaj et al., 2019; T. Chen & Wang, 2016; Elhoone et al., 2020; Kłos & Patalas-Maliszewska, 2019; Mehrpouya et al., 2021; Pfrommer et al., 2018; Stathatos & Vosniakos, 2019; Y. Tang et al., 2023; Wahsh et al., 2018; Zhu et al., 2021). These studies indicate that applying intelligent methodologies to solve complex problems in manufacturing is an area of increasing research interest.

Genetic algorithms are well-known computerized search and optimization algorithms modeled after natural selection. Genetic algorithms were introduced in the 1960s and have grown to become one of the most popular methods for solving optimization problems (Jafari-Marandi & Smith, 2017). Like many other meta-heuristics, genetic algorithms are an evolutionary-based technique where the population of potential solutions to a given problem evolves throughout the optimization course, and solutions are encoded on chromosome-like structures (Jafari-Marandi & Smith, 2017). Training genetic algorithms involves several steps outlined in **Figure 3.5** below.

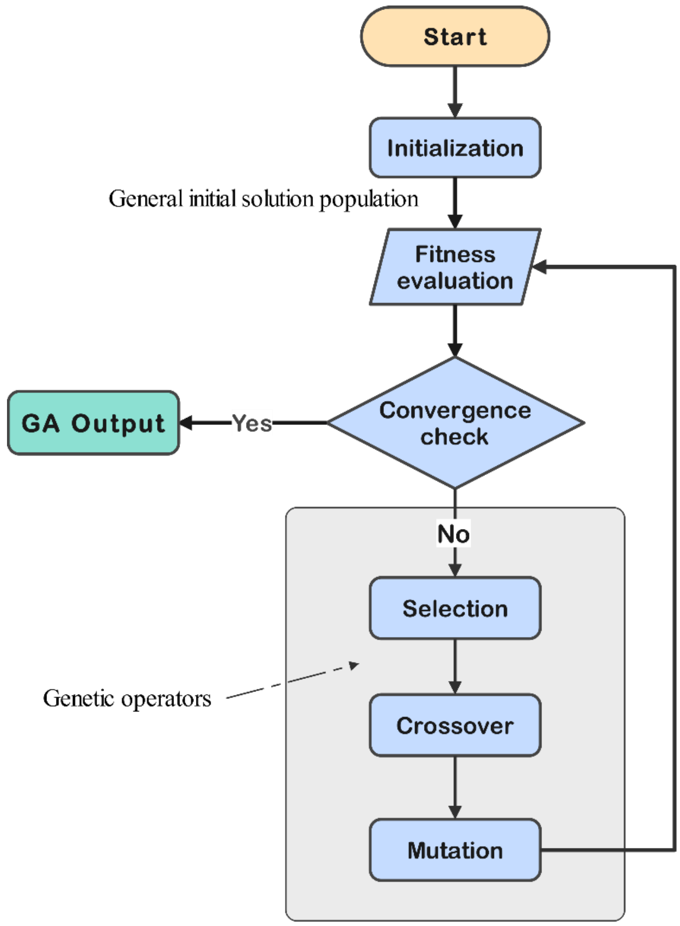

Figure 3.5. GA training flowchart
Source: Own study based on (Hassanat et al., 2019)

Genetic algorithms are a versatile and powerful tool for solving optimization problems and have contributed significantly to many areas of science and engineering (Alam et al., 2021; Jafari-Marandi & Smith, 2017; Katoch et al., 2021). Genetic algorithms are widely used in manufacturing to perform functions such as feature extraction, pattern recognition, and image processing to support decision-makers in optimizing manufacturing systems and processes (Castillo-Rivera et al., 2020; Drachal & Pawłowski, 2021; Egilmez et al., 2016; Grznár et al., 2021; Kordos et al., 2020; Kowalski et al., 2021; Kumar & Maji, 2020; Umam et al., 2022).

Genetic algorithms have also been studied in the construction industry to solve optimization problems (Abd Elrehim et al., 2019). Their ability to tackle complex optimization problems has rendered them indispensable in various intelligent solutions.

The Fuzzy Logic concept describes the non-linear representation of real-world problems that treat system variables in a gradient instead of binary logic. Fuzzy logic is the capability to communicate, reason, and make rational judgments and decisions in an imprecise, uncertain environment characterized by limited knowledge. Fuzzy logic allows the use of levels of truth assigned to values between 0 and 1, and as a result, it is well-suited for real-world problems across different disciplines. Fuzzy logic is a powerful tool that has found applications in a wide range of fields. Its ability to handle uncertainty, ambiguity, and imprecision makes it particularly useful in decision-making problems. Fuzzy logic-based methods have been successfully applied to control systems (Dumitrescu et al., 2021) and artificial intelligence. In the field of artificial intelligence, fuzzy logic has been used to model uncertainty and imprecision in reasoning and decision-making problems, such as the initial screening of manufacturing reshoring (Hilletofth et al., 2021) and risk assessment in additive manufacturing research (Moreno-Cabezali & Fernandez-Crehuet, 2020). Fuzzy logic-based expert systems have been developed to solve complex problems in medicine, finance, engineering, and other fields. Fuzzy logic-based decision support systems have also been developed to aid decision-making in complex and uncertain manufacturing environments (Raja Dhas & Francalanza et al., 2016; Tashtoush et al., 2020). In pattern recognition, fuzzy logic has been used to classify and cluster data with uncertainty and imprecision. Fuzzy logic-based clustering methods have been developed to group data into clusters based on their similarity. Fuzzy logic-based classification methods have also been proposed to classify data into different classes based on their attributes.

Neuro-fuzzy hybrid describes the combination of neural networks and fuzzy logic and constitutes one of the most researched hybrid methodologies for intelligent systems. Neural networks can effectively model non-linear and complex relationships and are well-suited for classification and pattern recognition problems (Elbaz et al., 2019). However, the precision of the output is often limited, and the performance largely depends on the quality of the selected data. By contrast, fuzzy logic is designed to work with imprecise inputs and outputs directly as they form fuzzy sets. Among the pioneering neuro-fuzzy hybrids is the NN-driven fuzzy reasoning proposed by Takagi and Hayashi (Yazid et al., 2019). Many studies have been conducted since then to improve the neuro-fuzzy hybrid methodology, such as a multi-staged fuzzy approximate reasoning integrating self-organizing feature map (SOFM) and fuzzy logic (S. Javaid et al., 2018), Adaptive-Network-based Fuzzy Inference System (ANFIS) (Olayode et al., 2023), and fuzzy ARTMAP that integrates fuzzy logic with adaptive resonance theory (ART) neural networks (Al-Andoli et al., 2023). Combining these two techniques, neuro-fuzzy systems provide more accurate and robust predictions in various domains, such as pattern recognition and decision-making. They are also often more interpretable, making understanding and interpreting the reasoning behind the system's decisions more manageable.

A neuro-genetic hybrid involves the integration of neural networks and genetic algorithms. Although neural networks can be trained to model complex non-linear relationships, recognize patterns, and perform classification, the elementary attributes of concern when designing them are problem-specific. For this reason, the optimization of the neural network design can benefit from computational processes. Genetic algorithms have provided excellent tools for optimizing parameters when designing neural networks. Several studies indicate the successful integration of neural networks and genetic algorithms. For instance, a genetic algorithm has been used to improve the learning process in artificial neural networks (Vakili et al., 2017). Studies have shown that the neural networks-genetic algorithms combination is more accurate than single neural networks (Alsaleh & Larabi-Marie-Sainte, 2021; Patra et al., 2017; D. K. Sharma et al., 2022; Vakili et al., 2017). Neuro-genetic systems are essential because they combine the strengths of neural networks and genetic algorithms to solve complex problems. Neural networks are good at learning from data, while genetic algorithms are good at optimizing solutions through natural selection. Therefore, this hybrid system is powerful for solving complex learning and optimization problems.

The fuzzy-genetic hybrid involves the combination of fuzzy logic and genetic algorithms. Fuzzy logic offers a way to deal with bias and uncertainty in problems where conventional methods are ineffective. Genetic algorithms, on the other hand, use the principles of natural selection and genetics to solve optimization problems. Combining these two methods has led to efficient hybrid tools to solve complex problems across different fields. The concept of a fuzzy genetic algorithm was first introduced in the late 1980s and early 1990s, and since then, many studies have been done to improve and optimize the method (Human et al., 2021; Malarvizhi et al., 2020). A fuzzy genetic approach helps find rules that define patterns in knowledge and has proven effective in dealing with uncertainties and uncertainties in data (Georgieva, 2018; Malarvizhi et al., 2020; Ponticelli et al., 2019). Since then, many researchers have explored using fuzzy-genetic algorithms in various applications such as pattern recognition, classification, clustering, and optimization. For instance, the fuzzy genetic model was developed for metal form manufacturing control, where genetic algorithms ensure the optimization of defined fuzzy members to consider uncertainties (Ponticelli et al., 2019). Further studies have been conducted on using fuzzy genetic hybrid systems to solve problems in manufacturing processes (Gojković et al., 2021). Thus, fuzzy genetic algorithms remain potent integrations that can solve bias and uncertainty in many problems. This method is beneficial in multi-objective optimization problems, rule extraction, feature selection, and extensive data analysis.

Artificial neural networks, fuzzy logic, and genetic algorithms have been combined to draw upon the strengths of each technique in developing more effective hybrid intelligent technologies. There are several reasons and ways neuro-fuzzy-genetic hybrids are created, for instance, to improve the performance of artificial neural networks by combining the learning and adaptation of fuzzy logic capabilities with the search optimization of genetic algorithms. Studies indicate the possibility of optimizing the degree of membership value in the neuro-fuzzy method using genetic algorithms (Fata et al., 2019). The performance of the neuro-fuzzy model is, thus, optimized using a genetic algorithm (Ashish et al., 2018). Several areas of application of neuro-fuzzy-genetic hybrid models include medical, manufacturing, and finance. In medicine, the model has been studied in disease diagnosis and management decisions (Ashish et al., 2018; Fata et al., 2019; Kaur et al., 2019; Omisore et al., 2017; Shokouhifar & Pilevari, 2022). In manufacturing and engineering, use cases generally range from increasing accuracy in robotic systems (El-Sherbiny et al., 2018) to solving process optimization problems (Saw et al., 2018). Thus, neuro-fuzzy-genetic hybrid methods are potent in building more capable intelligent systems.

3.2. Methodology for a systematic review of the intelligent support methodologies

3.2.1. Systematic review, question formulation, and study location

The broader context of this study is to apply an evidence-based investigation paradigm in exploring artificial intelligence-based techniques in intelligent support systems for manufacturing process selection. Systematic reviews provide researchers with a tool to identify, evaluate, and aggregate findings from relevant empirical studies to present objective evidence on particular issues. There are several approaches to conducting a systematic review, popularized by Joanna Briggs Institute and Cochrane to inform practice and policy across diverse fields (Munn et al., 2018). However, not all systematic review methods can be used in all fields. For instance, the Cochrane approach is suited for the medical field (Denyer & Tranfield, 2009), while the style promoted by Brereton et al. is well suited for conducting a review of software engineering (Brereton et al., 2007). According to Denyer and Tranfield, adopting the Cochrane systematic review style is insufficient and unsuitable for the wide range and richness of research design aims and use cases in management (Denyer & Tranfield, 2009). Denyer and Tranfield developed principles for effective systematic review based on transparency, inclusivity, explanation, and heuristics (Denyer & Tranfield, 2009). This review adopts revised principles for systematic reviews in management and organization studies, as recommended (Denyer & Tranfield, 2009), for the reasons behind each principle. Unlike the Cochrane style, reviews in management should not be focused on replication or eradicating bias, which often diminishes transparency. In addition, there needs to be more uniformity in research data collection and analysis methods within the management field, as studies rarely address identical research questions. Thus, a simple 5-stage style proposed by Denyer and Tranfield is adopted for this study, as shown in **Figure 3.6** below.

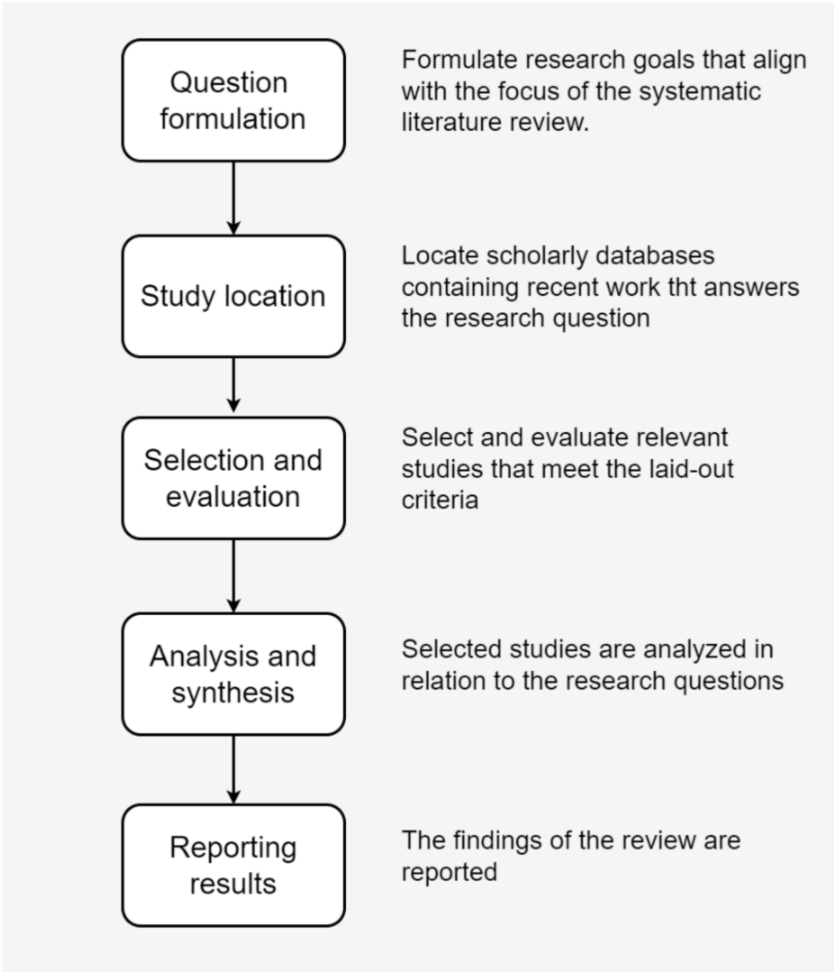

Figure 3.6. 5-stage systematic review style
Source: own study based on (Denyer & Tranfield, 2009)

Establishing the review's focus is essential and is accomplished by clearly formulating the research questions. According to Denyer and Tranfield, well-formulated questions become the basis for primary study inclusion (Denyer & Tranfield, 2009). Therefore, this review is guided by four research questions to delve deeper into the nuances of intelligent support systems, emphasizing the role of artificial neural networks, fuzzy logic, genetic algorithms, and their hybrid techniques in addressing the intricacies of manufacturing process selection. The research questions are outlined as follows:

Q1: What are the key trends in intelligent support for manufacturing process selection?

Q2: How do recent intelligent support methodologies address manufacturing selection complexities?

Q3: What are the challenges and limitations of intelligent support methodologies for manufacturing process selection?

Since a systematic literature review aims to select, appraise, and synthesize relevant studies, the location of the studies is the second step. The studies considered in this review are retrieved from Scopus, IEEE Xplore, Springer, and Web of Science. While other databases, such as Google Scholar, can be reliable sources, the four databases selected are much more robust, with high-quality and relevant published studies. The search terms for the selected databases are outlined in **Table 3.1** below.

Table 3.1: Search queries

Search database	Search terms
Web of Science	*Intelligent Support AND Manufacturing Process Selection AND (neural network OR genetic algorithm OR Fuzzy logic)*
Scopus	*(Manufacturing AND process AND selection) AND (Intelligent AND support) AND ((neural AND network) OR (fuzzy AND logic) OR (genetic AND algorithms))*
IEEE Xplore	*Intelligent Support AND Manufacturing Process Selection AND (neural network OR genetic algorithms OR Fuzzy logic)*
Springer Link	*Intelligent Support AND Manufacturing Process Selection AND (genetic algorithms OR neural network OR Fuzzy logic)*

Source: Own study

3.2.2. Study selection and evaluation

A selection criterion is developed to assess the relevance of the identified studies. The selected studies are evaluated to check if they address the review question (Denyer & Tranfield, 2009). An explicit selection criterion ensures the reviewer's decisions can be scrutinized (Denyer & Tranfield, 2009). **Table 3.2** below shows the search inclusion criteria used for this study.

Table 3.2: Inclusion criteria

No.	Criteria	Include value
1	Publication year	2014- 2024
2	Publication stage	Final
3	Language	English
4	Source type	Journal article and conference proceeding
5	Research type	Study on DSS for manufacturing process selection

Source: Own study

The selected publications were passed through a quality check to ensure the final selection consisted of quality studies published in high-ranking scientific journals. The quality checklist is summarized in **Table 3.3** below.

Table 3.3: Quality checklist

No.	Quality checklist item	Include
2	Not duplicate	✓
2	Abstracts available	✓
3	Source title outlined	✓
4	Author information provided	✓
5	The year of publication indicated	✓
6	Identifications such as DOI or serial identifiers indicated	✓
7	The title and abstract are relevant to the review objective	✓

Source: Own study

3.3. Results and discussions of the systematic literature review

3.3.1. Intelligent support selection of additive manufacturing processes

Execution of the search on the identified databases resulted in the retrieval of 44 papers from IEEE Xplore, 31 from Web of Science, 138 from Scopus, and 67 from Springer Link papers published between 2013 and 2023. The retrieved studies were trimmed down to 168 journal articles and conference proceeding papers. After checking the relevance, full-text availability, and correctness of data, including identifiers and removing duplicates, the final list comprises 93 papers, as illustrated by the study selection process in **Table 3.5** below.

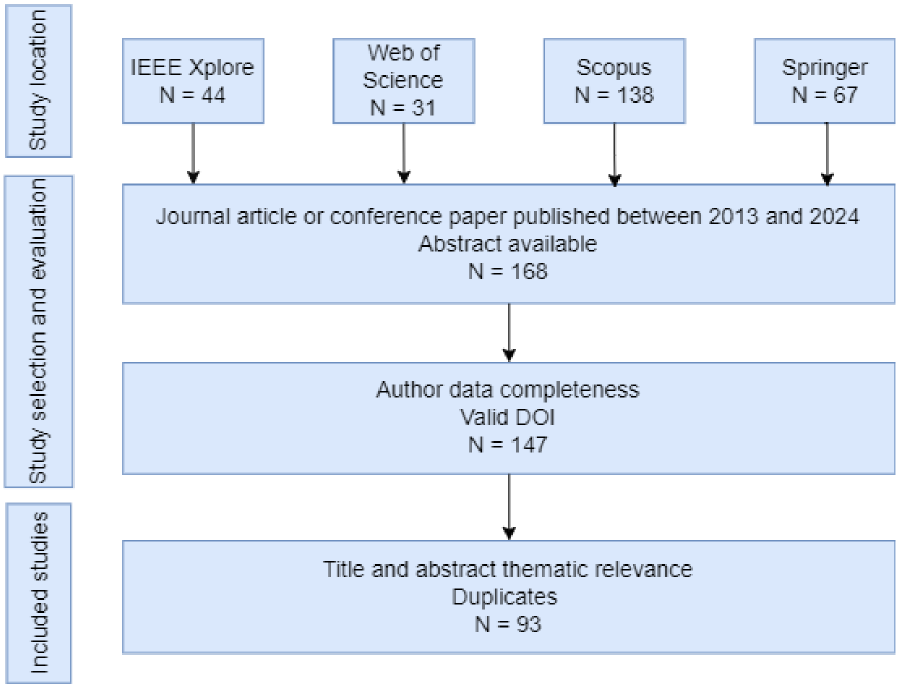

Figure 3.7. Study selection process
Source: Own study

As illustrated in **Figure 3.8**, the final selection consisted of 71 journal articles and 22 conference papers, accounting for 77% and 23% of the total, respectively.

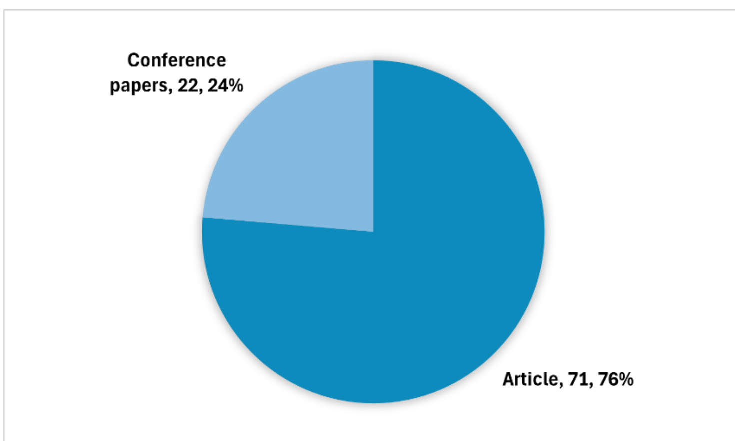

Figure 3.8. Publication types
Source: Own study

The distribution of the selected studies by the year of publication reveals a growing interest in decision support systems for the selection of manufacturing processes. The number of published studies rose steadily from 2013 to 2020, with a notable decline in 2021. Despite the setback in 2021, the number of publications appears to rise, as shown in **Figure 3.9** below.

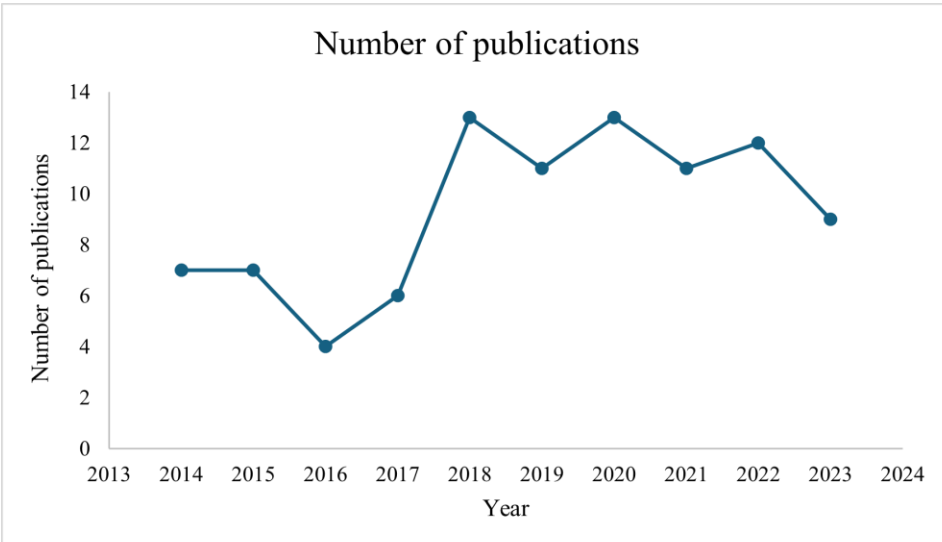

Figure 3.9. Distribution of included publications per year
Source: Own study

The selected papers have been cited 1789 times, indicating a significant impact and interest in applying intelligent support systems in manufacturing process selection. This high citation count reflects the growing recognition of the importance of advanced technologies such as artificial neural networks, fuzzy logic, and genetic algorithms in addressing the complexities associated with the selection of manufacturing processes. Researchers have extensively explored and validated these technologies, highlighting their potential to enhance decision-making, optimize processes, and improve overall efficiency in manufacturing. The diverse range of applications and the consistent acknowledgment in the literature underscores the growing relevance of intelligent support in the modern manufacturing landscape. **Figure 3.10** shows the distribution of citations by year of publication.

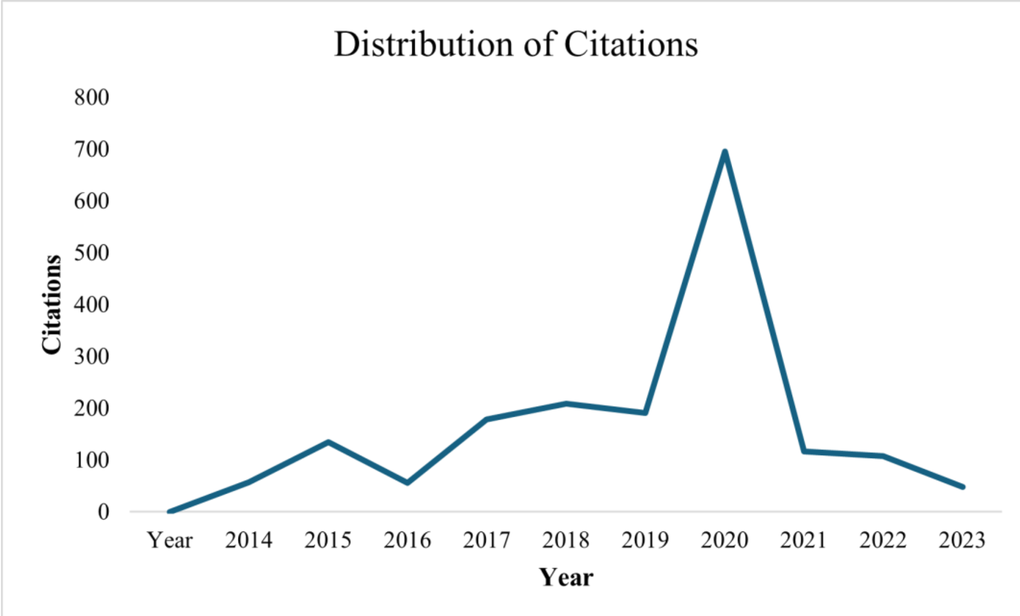

Figure 3.10. Distribution of citations by year of publication
Source: Own study

In this review, 93 papers were selected from 71 distinct sources, encompassing journal articles and conference papers. This selection highlights the specialized focus and diverse scope of the sources within the domain of artificial intelligence and its application in intelligent support for manufacturing process selection. The considerable number of unique sources underscores the interdisciplinary nature of the subject matter, reflecting the extensive and nuanced exploration necessary to advance understanding and application in this dynamically evolving field. This wide range of sources indicates the depth of research and the comprehensive approach required to address the complexities of integrating artificial intelligence within manufacturing processes. **Table 3.4** depicts the sources of the selected papers.

Table 3.4: Sources of included research papers

Source Title	Papers	Authors
2019 23rd International Conference on Mechatronics Technology, ICMT 2019	1	(Hagemann et al., 2019)
2021 Global Reliability and Prognostics and Health Management, PHM-Nanjing 2021	1	(J. Zhang et al., 2021)
2021 IEEE 8th International Conference on Industrial Engineering and Applications, ICIEA 2021	1	(Ransikarbum & Leksomboon, 2021)
23rd International Conference for Production Research, ICPR 2015	1	(Yurdakul & Iç, 2015)
Advances in Materials Science and Engineering	1	(Ghaleb et al., 2020)
Advances in Production Engineering And Management	1	(Lukic et al., 2017)
Applied Sciences (Switzerland)	1	[242]
Archives of Civil and Mechanical Engineering	1	(Kuziak et al., 2019)

Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AIEDAM	1	(Rojek, 2017)
CIRP Journal of Manufacturing Science and Technology	1	(Bak et al., 2021)
Composites and Advanced Materials Expo, CAMX 2021	1	(Klunker et al., 2021)
Decision Science Letters	1	(Pandey et al., 2014)
IEEE Open Journal of the Industrial Electronics Society	1	(Yousefi et al., 2023)
IEEE Transactions on Industrial Informatics	1	(Y. Zhang et al., 2023)
IEEE Transactions on Semiconductor Manufacturing	1	(J. Feng et al., 2019)
IEEE/CAA Journal of Automatica Sinica	1	(Ghahramani et al., 2020)
Informatica (Netherlands)	1	(Nouri et al., 2015)
Information Sciences	1	(A.-D. Li et al., 2023)
International Journal of Advanced Manufacturing Technology	8	(Bahadir & Bahadir, 2015; Gleadall et al., 2016; Kadkhoda-Ahmadi et al., 2019; Marini & Corney, 2020; Sadeghian & Sadeghian, 2016; Simeone et al., 2021; Temuçin et al., 2014; Q. Yi et al., 2023)
International Journal of Computer Integrated Manufacturing	1	(Hamouche & Loukaides, 2018)
International Journal of Fuzzy Systems	1	(K.-J. Wang et al., 2017)
International Journal of Industrial Engineering: Theory Applications and Practice	1	(de León-Delgado et al., 2022)
International Journal of Industrial Engineering and Production Research	1	(Zare Banadkouki et al., 2021)
International Journal of Logistics Systems and Management	1	(K. K. Mittal et al., 2018)
International Journal of Manufacturing Technology and Management	1	(P. L. Ramkumar & Kulkarni, 2014)
International Journal of Mechanical and Production Engineering Research and Development	1	(Ayshath Zaheera et al., 2018)
International Journal of Modeling, Simulation, and Scientific Computing	1	(C. Shi et al., 2017)
International Journal of Process Management and Benchmarking	1	(K. K. Mittal et al., 2019)
International Journal of Production Research	2	(Stanisavljevic et al., 2020; Tan et al., 2022)
International Journal of Reliability, Quality and Safety Engineering	1	(K.-S. Chen et al., 2019)
International Journal of Services and Operations Management	3	(Gothwal & Saha, 2015; Kiron & Kannan, 2018; Kodali et al., 2014)
International Journal on Interactive Design and Manufacturing	1	(Hodonou et al., 2020)
IOP Conference Series: Materials Science and Engineering	1	(Mohamed Noor et al., 2017)
Computer Integrated Manufacturing Systems, CIMS	1	(Lyu et al., 2020)
Journal of Advanced Manufacturing Systems	1	(Yurdakul & Iç, 2019)
Journal of Circuits, Systems and Computers	1	(J. Wang et al., 2016)
Journal of Engineering Design	1	(Saidi et al., 2018)
Journal of Industrial Engineering and Management	1	(Chang & Lin, 2015)
Journal of Intelligent Manufacturing	2	(Park et al., 2022; Z. Wang & Rosen, 2023)
Journal of Manufacturing Science and Engineering	1	(Roohnavazfar et al., 2014)
Journal of Manufacturing Systems	2	(D.-H. Lee et al., 2019; Yan & Melkote, 2023)
Journal of Manufacturing Technology Management	1	(Jenab et al., 2015)
Journal of Materials Engineering and Performance	2	(Kumar & Maji, 2020;

		Ransikarbum & Khamhong, 2021)
Journal of Testing and Evaluation	1	(C.-W. Wu et al., 2016)
Journal of The Institution of Engineers (Indi): Series C	1	(Saranya et al., 2018)
Control and Decision	1	(Pan & Yang, 2014)
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	1	(Z. H. Lim et al., 2019)
Lecture Notes in Information Systems and Organisation	1	(Ahmed & Lokhande, 2022)
Lecture Notes in Mechanical Engineering	1	(A. Malaga & Vinodh, 2023)
Management and Production Engineering Review	1	(Kotliar et al., 2020)
Materials Today: Proceedings	4	(Baswaraj et al., 2018; Jaisingh Sheoran & Kumar, 2020; A. K. Malaga et al., 2022; Teharia et al., 2022)
Mathematics	1	(Gojković et al., 2021)
Neural Processing Letters	1	
PLoS ONE	1	(Menekse et al., 2023)
Procedia CIRP	1	(Simeone et al., 2020)
Procedia Computer Science	1	(Aboelfotoh et al., 2018; Anghel et al., 2018)
Proceedings - 16th International Conference on Embedded and Ubiquitous Computing, EUC 2018	1	(Anghel et al., 2018)
Proceedings of International Design Conference, DESIGN	1	(Tuckwood et al., 2014)
Proceedings of the 2nd International Conference on Artificial Intelligence and Smart Energy, ICAIS 2022	1	(Ahmed & Lokhande, 2022)
Proceedings of the ASME Design Engineering Technical Conference	3	(H. Chen & Zhao, 2015; Nagarajan et al., 2018; Zhao & Melkote, 2022)
Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture	1	(Tlija & Al-Tamimi, 2023)
Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science	1	(Mehrvar et al., 2020)
Rapid Prototyping Journal	4	(Anand & Vinodh, 2018; Ren et al., 2022; Y. Wang et al., 2017, 2018)
RI2C 2019 - 2019 Research, Invention, and Innovation Congress	1	(Khamhong et al., 2019)
Robotics and Computer-Integrated Manufacturing	2	(C.-Y. Lee & Tsai, 2019; Qin et al., 2020)
Sadhana - Academy Proceedings in Engineering Sciences	1	(Raigar et al., 2020)
Scientific Programming	1	(Raja, John Rajan, Praveen Kumar, Rajeswari, Girija, Modak, Vinoth Kumar, Mammo, et al., 2022)
Surface Technology	1	(X. Zhang et al., 2022)
Sustainability (Switzerland)	1	(Lu, 2021)
Tehnicki Glasnik	1	(Krulčić et al., 2022)
Tehnicki Vjesnik	1	(Peko et al., 2018)

Source: Own study

While additive manufacturing has presented several benefits, such as freedom of design and increased customization capabilities, selecting the most suitable process for a given product design and application remains challenging (Muvunzi et al., 2022). The selection of an optimal additive manufacturing process can be subject to several uncertainties and complexities. One source of uncertainty and complexity is the large pool of additive manufacturing processes available for selection, each with its merits and demerits. These processes significantly differ in terms of compatible materials, tolerance, build volume, precision, cost, build time, and other parameters (Menekse et al., 2023). For this reason, selecting appropriate processes mandates a proper understanding of these parameters. Another source of uncertainty and complexity in additive manufacturing process selection is the high variability of input material and the process itself. Inherent material properties such as thermal conductivity, viscosity, and density can significantly improve the quality of the final product.

A manufacturing process can also introduce uncertainties such as distortion, warpage, and shrinkage, which can adversely impact the accuracy and quality of the final product. Therefore, decision-makers require intelligent tools to help reach acceptable solutions that consider all underlying factors, including parameters related to the material and geometric, technological, and post-processing operations. As such, deciding the proper process for a particular product is effortful and requires in-depth knowledge. These challenges are being addressed through the use of intelligent systems and modeling to reveal correlations between processes and parameters and optimize them for better and consistent quality (Y. Tang et al., 2023). **Table 3.5** shows some current literature on intelligent process selection of additive manufacturing processes.

Table 3.5: Current literature on the intelligent selection of additive manufacturing processes

Reference	Method	Application
(Menekse et al., 2023)	Fuzzy Logic	Assessing additive manufacturing alternatives
(A. Malaga & Vinodh, 2023)	Fuzzy Logic	Prioritizing additive manufacturing technologies
(Buechler et al., 2022)	Fuzzy Logic	Car part suitable manufacturing processes
(Hodonou et al., 2020)	Fuzzy Logic	Ranking manufacturing processes based on economic and environmental implications
(Qin et al., 2020)	Fuzzy Logic	Selecting the appropriate additive manufacturing process
(Marini & Corney, 2020)	Fuzzy Logic	Selection of near-net shape processes
(Büyüközkan & Göçer, 2020)	Fuzzy Logic	Selection and suitability analysis for 3D printing processes
(Khamhong et al., 2019)	Fuzzy Logic	Analysis of criteria for additive manufacturing processes
(Peko et al., 2018)	Fuzzy Logic	Selecting adequate additive manufacturing processes
(Anand & Vinodh, 2018)	Fuzzy Logic	Ranking additive manufacturing processes

(Zheng et al., 2017)	Fuzzy Logic	Selection of appropriate additive manufacturing processes

Source: Own study

Fuzzy logic has been widely used to address complexities and uncertainties in evaluating and selecting additive manufacturing processes. Plenty of existing studies reveal the ability of fuzzy logic to help engineers consider various parameters and their complexities and uncertainties in the decision-making process. For instance, the ability of fuzzy sets to handle ambiguity and uncertainty is exploited by designing an integrated fuzzy multi-criteria decision-making based on Pythagorean fuzzy sets for assessing alternative additive manufacturing processes for the automotive sector (Menekse et al., 2023). The existing body of literature reveals that the application of fuzzy logic in the selection of additive manufacturing is multifaceted, with specific use cases including solving ambiguity and uncertainty in multi-criteria decision-making methods (Menekse et al., 2023) and enriching the performance of other methods, such as AHP (Anand & Vinodh, 2018; A. Malaga & Vinodh, 2023). Other studies have combined fuzzy logic, AHP, and at least one more multi-criteria decision-making method, such as PROMETHEE and TOPSIS (Anand & Vinodh, 2018; Nouri et al., 2015; Peko et al., 2018). While a vast majority of studies focus on a general selection of manufacturing processes, a few involve the deployment of intelligent tools to support the decision with a focus on the specific output, such as the near-net shape (Kumar & Maji, 2020; Marini & Corney, 2020). In general, fuzzy logic is the most prevalent intelligent system technique in selecting additive manufacturing processes.

3.3.2. Intelligent selection of conventional manufacturing processes

Process selection in conventional manufacturing involves evaluating and determining the optimal method for a specified product. For this reason, the choice of appropriate manufacturing processes is highly influenced by many factors, such as flexibility, cost, efficiency, and quality. Intelligent system techniques such as neural networks, fuzzy logic, and genetic algorithms have been used to assist in the decision-making process for the selection of manufacturing processes. As already discussed, neural networks are intelligent system tools that can be modeled to predict and recognize patterns and cluster objects. Neural networks can analyze vast volumes of data to identify similarities and make accurate predictions. As such, neural networks are ideal for selecting optimal processes considering many variables and constraints.

Besides neural networks, fuzzy logic and genetic algorithms play an essential role in designing and developing intelligent systems in the manufacturing landscape. Fuzzy logic is a reasoning method that is especially useful in cases where the available data is uncertain or imprecise, as it allows linguistic variables and approximations in describing a problem. This has made fuzzy logic ideal for assigning weights to different parameters in manufacturing process selection, such as quality, cost, tolerance, and size, among others, based on their relative importance in decision-making. By contrast, genetic algorithms mimic natural selection processes to resolve optimization problems. They help search for optimal solutions among a population of alternatives. In the manufacturing process selection, genetic algorithms are used to search for the optimal combination of parameters for the best alternative. **Table 3.6** below summarizes recent studies involving neural networks, genetic algorithms, and fuzzy logic in manufacturing process selection.

Table 3.6: Artificial intelligence technologies in manufacturing process selection

Reference	Method	Application
(Yan & Melkote, 2023)	Artificial Neural Networks	Simulation of the manufacturing process
(Z. Wang & Rosen, 2022)	Artificial Neural Networks	Classification of manufacturing processes
(Z. Wang & Rosen, 2023)	Artificial Neural Networks	Manufacturing process classification
(de León-Delgado et al., 2022)	Artificial Neural Networks and Genetic Algorithms	Planning, optimization, simulation, and decision-making in manufacturing process selection
(Hamouche & Loukaides, 2018)	Artificial Neural Networks	Automating manufacturing process selection
(Sadeghian & Sadeghian, 2016)	Artificial Neural Networks and Fuzzy Logic	Manufacturing system selection
(Lu, 2021)	Fuzzy Logic	Selection of advanced manufacturing processes
(Mastrocinque et al., 2016)	Fuzzy Logic	Selection of manufacturing technology
(Nouri et al., 2015)	Fuzzy Logic	Manufacturing technology selection

Source: Own study

Several use cases of neural networks related to manufacturing processes have been studied. For instance, Siamese Neural Network (SNN) is integrated into deep generative models of machining operations to automate manufacturability analysis and machining process selection (Yan & Melkote, 2023). The proposed Autoencoder and Siamese Neural Network (AE-SNN) achieves a class-average process selection accuracy of 89%, and a manufacturability analysis accuracy of 100%, outperforming a discriminative model trained on the same dataset (Yan & Melkote, 2023). Neural networks have also been studied to develop solutions to the problem of classification and identification of manufacturing processes suitable for specified part designs. CNN has been used to improve the classification accuracy of manufacturing processes based on part shapes (Z. Wang & Rosen, 2022). Manufacturing process classification has also been enhanced using invariant shape descriptors and CNN for better accuracy in the selection of appropriate processes (Z. Wang & Rosen, 2023). Researchers have also proposed an improved method for selecting a Radial Basis Function Neural Network that is more accurate in describing manufacturing process parameters, which incorporates a genetic algorithm proposed (de León-Delgado et al., 2022). Using neural network-based intelligent decision support has been lauded as a crucial step between design and manufacturing through manufacturing process selection (Hamouche & Loukaides, 2018). Therefore, it is likely that neural networks will continue to be integral to research from academia and business in manufacturing processes.

While conventional manufacturing processes are generally well understood compared to additive manufacturing processes, fuzzy logic has also been used as a standalone soft computing technology and in combination with neural networks to develop intelligent support capabilities that address complexities and uncertainties in selecting appropriate manufacturing processes. Several intelligent decision support systems for aiding manufacturing systems and process selection have been studied based on neuro-fuzzy methodologies (Sadeghian & Sadeghian, 2016). Fuzzy logic has also been incorporated into multi-criteria decision-making methods such as the AHP, TOPSIS, DEA, and Analytic Network Process (ANP) (Lu, 2021; Mastrocinque et al., 2016; Nouri et al., 201). The combination of fuzzy logic and neural networks in conventional manufacturing has been explored in cases such as the selection of manufacturing systems (Sadeghian & Sadeghian, 2016), selection of plastic manufacturing processes using an intelligent Self-Organizing Map and fuzzy logic-based model (Pei et al., 2023). Fuzzy logic has been used to improve the accuracy of training neural networks for manufacturing process selection. Genetic algorithms have also been used in conventional manufacturing process selection, with their application mainly in resolving optimization problems (Fallahpour et al., 2017; Georgieva, 2018; Kordos et al., 2020). Intelligent support based on techniques such as neural networks, fuzzy logic, and genetic algorithms in the selection of manufacturing processes is a powerful tool that can improve the accuracy and efficiency of the process.

3.3.3. Complexity and uncertainty in additive and conventional manufacturing

While additive manufacturing is a relatively new and rapidly evolving field, conventional manufacturing has existed longer, and most of its processes are well-established and understood. Different additive manufacturing processes and technologies are categorized into seven groups: vat photo-polymerization, material extrusion, material jetting, binder jetting, directed energy deposition, powder bed fusion, and sheet lamination. Each process has its own set of unique and inherent constraints and considerations. There is often a limited or total lack of well-established knowledge and expertise on process parameters, including their complexities, as reported by several studies (M. M. Mabkhot et al., 2019; White et al., 2022). The degree of complexity and uncertainty in additive manufacturing is generally higher than in conventional manufacturing as the former involves building products or components layer by layer, which can lead to the introduction of a range of issues, such as poor adhesion between layers, low-quality surface finish, and material defects. Additionally, predicting the quality of the final product is generally tricky in additive manufacturing as it is highly dependent on the material and specific process parameters involved. However, conventional manufacturing processes are also becoming complex due to technological advances and increasing pressure to reduce environmental impact and improve sustainability in manufacturing. The complexity arises from various new considerations, such as reducing the environmental footprint, sustainable use of raw materials, and product lifecycles.

Consequently, the selection of manufacturing processes in both conventional and additive manufacturing involves a degree of uncertainty and complexity depending on the specific product requirements. However, the nature of their challenges differs somewhat. Each manufacturing approach has flaws and strengths, and selecting a suitable process depends on particular requirements and parameters. As a result, neural networks, genetic algorithms, and fuzzy logic methods are used to address the specific problem within the selected manufacturing approach.

3.3.4. Limitation of current intelligent methodologies

The existing literature shows more research interest in using fuzzy logic in selecting additive manufacturing processes than in neural networks and genetic algorithms. This phenomenon can be explained firstly by the fact that additive manufacturing processes are still being developed.

As such, there is insufficient established knowledge and expertise around their selection due to uncertain and imprecise data. In contrast, conventional manufacturing involves thousands of well-known alloys to choose from. Research shows that additive manufacturing has only fully matured. As a result, it has a limited number of metal alloys and lacks decades of understood knowledge and experience offered by traditional manufacturing (Gradl et al., 2022). Unlike neural networks and genetic algorithms, fuzzy logic is more capable of handling uncertain and imprecise data. Therefore, it is well-suited for the complexity and uncertainty surrounding the selection of additive manufacturing processes. Secondly, additive manufacturing often involves using novel materials that require new and complex approaches to selection and processing involving a wide range of selection criteria, including but not limited to product requirements, inherent material properties, and process parameters. Finally, additive manufacturing processes are generally more flexible and well-suited for customization; hence, their selection involves more variables and constraints. Fuzzy logic is especially effective at handling many variables, which makes it an ideal choice for solving process selection in additive manufacturing.

The analyzed literature reveals that neural networks are commonly used in designing intelligent systems for handling different problems related to the selection of conventional manufacturing processes (Hamouche & Loukaides, 2018; Z. Wang & Rosen, 2022, 2023; Yan & Melkote, 2023). This can be attributed to the large amounts of data available for training since conventional manufacturing processes have a long history and are well-understood. In manufacturing processes, neural networks involve algorithms that can learn from available data and make predictions or perform classification based on that learning, primarily based on historical data. Paradoxically, data availability is the major challenge of neural networks for manufacturing process selection, as historical data may be incomplete, limited, or of poor quality, affecting the neural network's accuracy and performance. Additionally, training neural networks on large datasets with high computational power may be time-consuming.

Despite these limitations, neural networks remain highly significant for improving the selection of conventional manufacturing processes. By analyzing the input data and identifying patterns, neural networks can help improve decision-making in process selection and limit waste generation by selecting less costly and environmentally sound processes among the alternatives. As conventional manufacturing continues to face pressure for climate-change-conscious and sustainable practices, neural networks can play a significant role in analyzing and identifying environmentally friendly manufacturing processes. For instance, energy use and waste generation data can be added to the input parameters to help select optimal processes with minimal adverse environmental impacts and a low carbon footprint.

Genetic algorithms are sparingly used in the selection of manufacturing processes, and their application is limited to supporting other methods, such as neural networks through variable optimization. Genetic algorithms can handle complex optimization problems with many variables. Genetic algorithms have inherent capabilities to identify optimal solutions that may not be apparent and can simultaneously optimize multiple criteria. However, they have limitations, such as being computationally intensive, having the propensity to converge on sub-optimal solutions in the case of a poorly defined search space, and requiring many simulations to perform well. Consequently, genetic algorithms are expensive and not ideal, especially when the goal is to reduce manufacturing costs.

3.3.5. Proposed Generalized Matrix Learning Vector Quantization

Given the growing complexity and uncertainty surrounding the manufacturing process selection, we propose using GMLVQ neural networks to overcome the limitations of current approaches. GMLVQ is an advanced machine-learning algorithm that builds upon the original LVQ and its prior variants. GMLVQ was developed to handle high-dimensional data sets, where noise can accumulate and interfere with classification, and heterogeneous data sets exhibit different scaling and correlations among dimensions. Schneider, Biehl, and Hammer sought to create a consistent statistical framework for prototype and metric adaptation in discriminative prototype-based classifiers, introducing a matrix adaptation scheme for GLVQ based on an intuitive, heuristic cost function. In contrast to the squared Euclidean distance, a generalized distance metric utilizing the entire matrix was proposed.

In GMLVQ, each prototype vector is linked with a transformation matrix, enabling more flexible and robust data modeling. The distance measure in GMLVQ employs a fully adaptive matrix that is adjusted during training along with the prototypes. Recent research indicates that by weighing each pair of features, GMLVQ can account for correlations between dimensions through implicit scaling and rotation of the data, resulting in more reliable performance (Van Veen et al., 2022). GMLVQ, based on distance and prototypes, incorporates a comprehensive relevance matrix into the distance metric. This allows it to consider correlations between dimensions and rotations within the feature space. Therefore, GMLVQ is a robust prototype-based classification algorithm enhanced by integrating a full matrix. This provides several benefits, including increased flexibility, adaptability, and improved capability to manage complex datasets (Biehl et al., 2015).

Existing research has shown that GMLVQ outperforms peer classifiers such as support vector machines and decision trees, SSM/PCA (Mudali, Biehl, Leenders, & Roerdink, 2016; Veen et al., 2018). Recent research has investigated hybrid algorithms and techniques for GMLVQ, comparing their performance and applicability (LeKander et al., 2017). The studies demonstrate how various methods create GMLVQ models that achieve superior performance during validation and better fit the training dataset (LeKander et al., 2017). Novel techniques are emerging for training the GMLVQ model for classification, leveraging data from multiple, sometimes uncalibrated sources, without explicit transfer learning (Ravichandran et al., 2022; Villmann et al., 2022). GMLVQ boasts of enhanced feature relevance learning using the relevance matrix, which allows the algorithm to understand the importance of each feature in the dataset. Furthermore, the matrix-based approach allows for a more adaptable representation of data, making it suitable for many applications, including those with high-dimensional and heterogeneous data(Schleif et al., 2015; Straat et al., 2017). In addition, GMLVQ adapts a generalized distance metric during training, which is more flexible and can be tailored to various data types (Huai et al., 2022; Song et al., 2022). This metric learning aspect allows GMLVQ to perform well with complex, non-linearly separable datasets.

3.3.6. GMLVQ and the limitations of current intelligent methods

The review findings show that the current intelligent support methods based on neural networks require large amounts of high-quality and significant computational resources for training. By contrast, GMLVQ inherently and effectively manages high-dimensional data using an adaptive matrix during exercise, allowing it to identify and account for relevant features and reducing dependency on large, high-quality datasets. Fuzzy logic excels at managing uncertainty and imprecision but may struggle with high-dimensional data. GMLVQ, on the other hand, combines the strengths of prototype-based learning with an adaptive distance metric, enabling it to handle complex, uncertain, and imprecise data with greater flexibility and robustness. Neural networks and fuzzy logic have been shown to fail to account for correlations and different scaling among features when used in manufacturing process selection. GMLVQ can solve this limitation since it utilizes a generalized distance metric that incorporates a relevance matrix, allowing it to capture correlations between features and adjust for different scaling, enhancing model accuracy and reliability. While robust for optimization, the review of the genetic algorithm shows that it can be computationally intensive and prone to converging on sub-optimal solutions. GMLVQ is more efficient in training due to its prototype-based approach and adaptive metric, which reduces the computational burden and accelerates the learning process. Thus, GMLVQ can address the limitations of current intelligent support methodologies in manufacturing process selection in both additive and conventional manufacturing contexts.

3.3.7. Future perspectives on manufacturing process selection and conclusion

Additive manufacturing processes are increasingly being adopted, and the trend will continue across different industries. The development of new manufacturing materials is likely to be a significant trend as more and more industries continue to incorporate additive manufacturing approaches. New materials will be developed to produce components with improved chemical, thermal, and mechanical properties. For instance, using metal powder with high thermal properties will be critical in producing high-performance components in the aerospace sector and bio-based materials to facilitate the manufacturing of sustainable and biodegradable products. As a result, selecting an appropriate manufacturing process will become even more complex and uncertain and will depend on many factors, including the material properties and precision levels required. Moreover, developing new technologies for handling different products and components will likely impact the uncertainty and complexity of manufacturing process selection. New technologies are likely to expand the flexibility and capabilities of manufacturing processes, leading to increased demand for customized solutions that meet specific standards. However, selecting the proper process will become even more challenging and require more than expert knowledge and experience.

The interest in the selection of conventional manufacturing processes is poised to grow. Although traditional manufacturing processes are well understood, they evolve and become more complex as new materials are discovered. The growing pressure for sustainable manufacturing puts pressure on industries to minimize or eliminate the environmental impact of manufacturing. For this reason, there is likely to be increased research on evaluating and selecting energy-efficient processes with minimal waste generation and the potential for manufactured products and components to be recycled. The use of advanced technologies and data analytics to optimize manufacturing processes will continue to grow, with artificial intelligence likely to play a leading role in handling the challenges of developing advanced process selection and control methods to handle complexity and uncertainty and enable sustainable manufacturing of high-quality components at low costs.

Future research on robust, dynamic, and flexible intelligent methodologies, such as the GMLVQ and its hybrids, should be conducted to enhance sustainable, efficient, and cost-effective manufacturing. Given the rapid advances in manufacturing, the growing complexity, and the voluminous amounts of data generated, GMLVQ holds great potential in advancing intelligent decision-making in the selection and management of manufacturing processes. Future trends in artificial intelligence capabilities, including machine learning and data processing, underscore the growing importance of robust pattern recognition and classification algorithms like GMLVQ. There is an increasing demand for cost-effective and sustainable machine-learning models with minimal computational requirements (Dunn et al., 2020). Therefore, more comparative studies are needed to pit GMLVQ against other classification algorithms across various metrics and domains to better understand its relative performance and applicability in manufacturing process selection.

This review has explored the current state of intelligent support in manufacturing process selection, focusing on artificial neural networks, genetic algorithms, and fuzzy logic. The manufacturing process selection continues to grow in complexity as the field evolves and new materials and technologies emerge. The phenomenon is driving the interest in research on soft computing technologies for developing intelligent support systems to aid in evaluating and selecting optimal manufacturing processes as manufacturers strive to meet customer needs while ensuring sustainable use of resources. There has been a significant interest in research on using fuzzy logic, neural networks, and genetic algorithms and their pivotal role in developing intelligent systems capable of handling different complexities in manufacturing process selection and optimization. However, a close look at current studies reveals a disproportionately high interest in fuzzy logic adoption in intelligent selection of additive manufacturing processes compared to neural networks and genetic algorithms. By contrast, artificial neural networks are more favored when selecting conventional manufacturing processes. The use of genetic algorithms is not prevalent in both additive and traditional manufacturing.

The limitations of the current methods include the inability to handle high-dimensional data by artificial neural network-based and fuzzy logic-based intelligent support systems. Uncertain and imprecise data also pose performance risks, as artificial neural networks' performance relies on the availability of high-quality datasets. Genetic algorithms are hampered because they are computationally intensive and prone to converging on sub-optimal solutions. Based on these limitations, this study proposes using GMLVQ in intelligent manufacturing process selection because of its inherent flexibility, adaptability, and efficiency. GMLVQ provides greater interpretability through its prototype-based classification, allowing for a more precise understanding and explanation of the selection process. Therefore, this review affirms artificial intelligence's growing importance and transformative impact in developing intelligent support methodologies for manufacturing process selection.

4. Generalized Matrix Learning Vector Quantization

This chapter focuses on how the increasing complexity and uncertainty in data across domains continue to drive the demand for more robust, efficient, and accurate computational methods, including machine learning algorithms for pattern recognition and classification problems, particularly the Generalized Matrix Learning Vector Quantization (GMLVQ). The chapter begins with a reflection on how Kohonen's Learning Vector Quantization (LVQ) algorithms have been integral to classification algorithms for decades and the development of even better performing variants primarily the GMLVQ, that has emerged as highly promising and capable computational models for analyzing complex patterns in high-dimensional and noisy datasets with increased performance. The chapter uses a systematic literature approach to comprehensively examine recent studies on GMLVQ algorithms, focusing on algorithmic enhancements and variations, inherent features like feature relevance and metric learning, application domains, and performance. Using the Denyer and Tranfield 5-stage systematic literature review method, 61 studies published between 2015 and 2024 are selected for analysis from Scopus, Web of Science, IEEE, and Springer. The findings reveal significant advancements and applications of the GMLVQ across sectors, including healthcare, bioinformatics, and agriculture. The analyzed empirical studies highlight the algorithm's adaptability to various classification problems and enhanced performance. While the cross-disciplinary potential for GMLVQ is well documented, the review identifies gaps in the literature, particularly in the manufacturing domain. Given the rapid advances in manufacturing and the voluminous amounts of data generated, GMLVQ holds great potential to advance intelligent decision-making across the domain, such as in the selection and management of manufacturing processes.

4.1. Background on the GMLVQ algorithm

GMLVQ is a powerful and sophisticated variant of Learning Vector Quantization (LVQ) introduced in 2009 by Schneider, Biehl, and Hammer (Van Veen et al., 2020). LVQ is among the popular algorithms in classification and pattern recognition of machine learning introduced by Kohonen in the 1980s (Horbiichuk et al., 2020; Parini et al., 2018). It uses a prototype-based learning approach where prototypes denote classes in the dataset, each representing a point in the feature space. Unknown data points are assigned to the nearest prototype based on a defined Euclidean distance. GMLVQ was introduced as an extension of Generalized Learning Vector

Quantization (GRLVQ), a variant of LVQ proposed by Sato and Yamada (Cruz-Vega & Escalante, 2017). LVQ is inherently a fast and straightforward learning algorithm and has long been studied to optimize reference vectors.

The classification error in standard LVQ algorithms is heuristically optimized due to the distribution of the prototypes. However, the reference vector has a high tendency for divergence, leading to the loss of pattern recognition ability. This problem was solved by introducing GLVQ, which involves minimizing the cost function to ensure continuous approximation of the classes based on a stochastic gradient descent mechanism. Thus, prototype learning is performed by the stochastic gradient of the cost function (Kastner et al., 2012). Despite the improvements achieved in GLVQ, the algorithm still relies on predefined metrics that implicitly assume that prototypes are isotropic and, as such, perform poorly on high-dimensional data (Schneider et al., 2009). GMLVQ was, therefore, proposed to manage the problem of noise accumulation in high-dimensional data and improve its performance. The distinguishing features of GMLVQ include a complete matrix-based generalized distance metric instead of the squared Euclidean distance, relevance learning through the integration of distance metric parameters and the prototype, and the lack of explicit occurrence of input space dimensionality.

GMLVQ is an advanced machine-learning algorithm that extends the original LVQ and subsequent variants, such as GLVQ. For this reason, it offers several advantages in terms of flexibility, adaptability, and enhanced ability to handle complex datasets (Biehl et al., 2015). GMLVQ boasts of enhanced feature relevance learning using the relevance matrix, which allows the algorithm to learn the importance of each feature in the dataset. Furthermore, the matrix-based approach allows for a more adaptable representation of data, making it suitable for many applications, including those with high-dimensional and heterogeneous data (Schleif et al., 2015; Straat et al., 2017). In addition, GMLVQ adapts a generalized distance metric during training, which is more flexible and can be tailored to various data types (Huai et al., 2022; Song et al., 2022). This metric learning aspect allows GMLVQ to perform well with complex, non-linearly separable datasets.

Future trends in machine learning, data processing, and application underscore the growing importance of robust pattern recognition and classification algorithms like GMLVQ. There is an increasing demand for cost-effective and sustainable machine-learning models with minimal computational requirements (Dunn et al., 2020; Mumali & Kałkowska, 2024). GMLVQ has efficient feature relevance learning and is robust in handling overfitting and noise. As a result, the algorithm stands out as a promising solution in scenarios where computation resources are limited or energy efficiency is a priority (Mumali & Kałkowska, 2024). Its flexibility and adaptability make GMLVQ suitable for various engineering applications, including bioinformatics, image and speech recognition, and financial analysis. This broad applicability ensures its continued relevance in different research and industry fields. The robustness of GMLVQ to noise and its ability to handle overfitting are crucial for real-world applications where data quality and overfitting are common concerns. Additionally, the interpretability of GMLVQ models, owing to the relevance matrix, is a significant advantage.

Additionally, the exponential growth in data complexity and volume presents significant challenges. GMLVQ's ability to handle increasingly complex and high-dimensional datasets makes it an invaluable tool for extracting meaningful insights from such data. Its adaptability and precision in feature selection and classification are critical in managing the deluge of information generated by modern data sources. The rise of online and streaming data environments, characterized by dynamic, high-dimensional datasets, necessitates algorithms capable of real-time analysis and adaptation. Recent studies show an increased interest in computational algorithms capable of handling streaming data (Ahmad et al., 2017; Eskandari & Seifaddini, 2023; Hiriotappa et al., 2017; D. Wu et al., 2022; Yang et al., 2023). GMLVQ's potential in these environments lies in its capability for iterative learning and quick adaptation to evolving data patterns. As such, GMLVQ is particularly relevant for applications in IoT, real-time monitoring systems, and other areas where immediate data processing is essential. Therefore, the unique strengths of GMLVQ position it as a highly relevant and potent tool in addressing some of the key challenges and trends in the future landscape of data science and machine learning.

There is a wealth of existing literature on GMLVQ and its uses. However, a comprehensive evaluation that covers the algorithm's processes, enhancements, and range of applications is still lacking. A thorough analysis that synthesizes these various applications and contrasts the effectiveness of GMLVQ with alternative vector quantization techniques is still required. To our knowledge, GMLVQ, an improved prototype-based pattern recognition algorithm, has never been the subject of a systematic review. The objective of this review is to provide a comprehensive understanding of the algorithm's unique capabilities, opportunities for application in emerging machine learning fields, limitations, and potential areas for future research by methodically going over the existing literature and comparative studies with an emphasis on the development, mechanisms, and applications of GMLVQ. This review is significant because it can bring together disparate knowledge regarding GMLVQ, providing researchers and practitioners in sectors where sophisticated pattern recognition techniques are essential with clarity and guidance.

GMLVQ is an extension of the LVQ algorithm, incorporating a matrix-based distance metric (Ravichandran et al., 2022). LVQ is a widely used pattern recognition algorithm developed by Kohonen in the 1980s. LVQ is a supervised learning algorithm for statistical classification that defines class regions inside the input data space. The LVQ algorithm remains a top choice among machine learning experts for its noteworthy effectiveness, efficiency, and simplicity in tackling classification problems in numerous domains, including image and sound recognition, natural language processing, and pattern recognition in fields such as fraud detection (Jiang et al., 2022; Nahar et al., 2016). Additionally, LVQ algorithms stand out for their user-friendly approach and built-in functionalities for managing large datasets, handling incomplete and noisy data, and exceptional resilience regarding outliers and irrelevant attribute space. Despite their robustness, LVQ algorithms are marred by degraded recognition ability that raises the cost function. Consequently, several attempts to create variants that improve LVQ algorithms have been successfully made to manage the cost function and stability. Among the proposed improvements are generalized learning vector quantization (GLVQ), relevance learning vector quantization (RLVQ), robust soft learning vector quantization, and generalized relevance learning vector quantization (GRLVQ), which formed the basis for GMLVQ.

The GLVQ algorithm was designed to solve the reference vector divergence problem in the original LVQ algorithms. LVQ 2.1 is based on the idea of differential shifting towards Bayes limits with no consideration for the location of the reference vector. LVQ3 is an improvement to ensure reference vectors continue approximating the class distributions. However, assigning only one reference vector to each class invalidates self-stabilization in LVQ3, making it the same as LVQ2.1, which leaves the problem of reference vector divergence unsolved. GLVQ was, thus, proposed as an improvement with a new learning method based on minimizing the cost function. The algorithm addressed some limitations of previous LVQ variants by introducing a general cost function based on differentiable distance measures. The algorithm is derived based on the assumption that m_i is the nearest reference vector that belongs to the same class, x, while m_j is the closest reference vector belonging to a separate class with a relative distance difference:

$$\mu(x) = \frac{d_i - d_j}{d_i + d_j} \qquad (3.1)$$

where d_i and d_j are distance of x from m_i and m_j respectively. The value of relative distance μ(x) will range from -1 and $+1$, with negative and positive signs indicating current and incorrect classification, respectively. To improve the cost function or error rate, μ(x) should decrease for all input vectors. For this reason, GLVQ introduced the cost function: -

$$S = \sum_{i=1}^{N} f\ (\mu\ (x_i)) \qquad (3.2)$$

where f(μ) is a monotonically increasing function, and N is the number of input vectors. To minimize the cost function, weight vectors m_i and $m_j$are updated based on the descent method with a slight positive learning rate constant α. Using the squared Euclidean distance $d_i = |x - w_i|^2$, GLVQ's learning equations are:

$$w_i = w_i + \alpha \frac{\partial f}{\partial \mu} \frac{d_j}{d_i + d_j} (x - w_i) \rightarrow w_i \qquad (3.31)$$

$$w_j = w_j - \alpha \frac{\partial f}{\partial \mu} \frac{d_j}{d_i + d_j} \left(x - w_j\right) \rightarrow w_j \qquad (3.4)$$

Relevance Learning Vector Quantization (RLVQ) was introduced to automatically determine the relevance of input dimensions of LVQ architecture during training(Bojer et al., 2001b). RLVQ introduced weighting factors of input dimensions that are automatically adapted to the specific problem, drawing inspiration from Hebbian learning. RLVQ assumes that dimensions are roughly proportionally sized and of equal importance. Before training, data are therefore pre-processed and scaled accordingly. According to research, estimating the relevance of input dimensions may necessitate problem-specific expert knowledge, posing a formidable obstacle for specific learning tasks. Because different data dimensions are ranked equally, LVQ fails if dimensions are not scaled appropriately. Assuming X and w_i. are the training set and weight vectors, respectively, a new input weight function allows for different scaling of input dimensions substitutes Euclidian metric |x – y| by the following equation:

$$|x - y|_w^2 = \sum_{i=1}^{n} w(x_i - y_i)^2 \qquad (3.25)$$

The equations for the RLVQ algorithm are as follows:

$$w_j(t+1) = w_j(t) + \alpha(t)\Lambda(t)\left(x - w_j(t)\right), \quad (3.6)$$

if w_j is the winning prototype and belongs to the same class as x and

$$\Lambda(t+1) = \Lambda(t) - \beta(t)\left(d_i{}^2(x) - d_j{}^2(x)\right)\left(x - w_i(t)\right) \otimes \left(x - w_i(t)\right) \qquad (3.7)$$

where Λ is the incorporated adaptive relevance matrix.

To improve classification performance in noisy environments, Robust Soft Learning Vector Quantization (RSLVQ) implemented a soft decision rule based on the statistical modeling of class-conditional densities. Assuming P_y (l | x) and P (l | x) are assignment probabilities, RSLVQ is derived as follows:

$$P_y(l \mid x) = \frac{p(l)\, exp\, f(x,\theta_l)}{\sum_{\{j:\, cj=y\}} p(j)\, exp\, f(x,\theta_j)} \qquad (3.8)$$

$$P(l \mid x) = \frac{p(l)\, exp\, f(x,\theta_l)}{\sum_{j=1}^{m} p(j)\, exp\, f(x,\theta_j)} \qquad (3.3)$$

P (l | x) is the (posterior) probability that the data point x is assigned to the component l of the complete mixture when all classes are considered. Using stochastic gradient ascent, the following is the learning rule:

$$\theta_l(t+1) = \theta_l(t) + \alpha(t)\frac{\partial}{\partial\theta_l}\left[log\frac{p(x,y|\tau)}{p(x|\tau)}\right], \qquad (3.40)$$

where $\alpha(t)$ is the learning rate of the algorithm. Therefore, the ultimate learning rule for RSLVQ is as follows:

$$\theta_l(t+1) = \theta_l(t) + \alpha(t)f(x) = \begin{cases} P_y\,(l \mid x)\left[\frac{\partial f(x,\theta_l)}{\partial \theta_l}\right],\ if\ \ c_l = y, \\ -P_{\bar{y}}\,(l \mid x)\left[\frac{\partial f(x,\theta_l)}{\partial \theta_l}\right],\ if\ \ c_l \neq y. \end{cases} \qquad (3.11)$$

RSLVQ provided a better alternative involving a robust optimization scheme derived from maximizing the likelihood ratio of the probability of correct classification to the total probability in a Gaussian mixture model. Therefore, RSLVQ is an alternative discrete LVQ scheme in which prototypes are modified based solely on misclassifications. All underlying model assumptions are stated explicitly in the statistical formulation and can be easily modified as required by the application scenario, making RSLVQ an attractive model. Considering equation:

$$S = \sum_{i=1}^{N} f\ (\mu\ (x_i)) \qquad (3.2)\ ,$$

which is used to minimize the cost function in GLVQ via stochastic gradient descent and the learning rules $w_i = w_i + \alpha \frac{\partial f}{\partial \mu} \frac{d_j}{d_i + d_j}(x - w_i) \rightarrow w_i$ (3.31) and $w_j = w_j - \alpha \frac{\partial f}{\partial \mu} \frac{d_j}{d_i + d_j}(x - w_j) \rightarrow w_j$ (3.4) GLVQ's success relies on the Euclidian metric being suitable for the data and the input dimensions being approximately equally scaled and weighted. Hammer and Villmann introduced input weights $\lambda = (\lambda_1 \ldots, \lambda_n), \lambda_i \geq 0$ and substituted Euclidean metric $||x - y||$ by its scaled variant as follows:

$$||x - y||_{\lambda}^{2} = \Sigma_{i=j}^{n} \lambda_i\ (x_i - y_i)^2 \qquad (3.12)$$

Replacing the receptive field of prototype w^i in the cost function leads to an adaptive metric as the weighting of input dimensions changes. Additionally, stochastic gradient descent automates the determination of the weighting factor λ, leading to the integration of the relevance factor λ_i in the RLVQ learning rule. An updated learning rule involving relevance factors λ_i of the metric applied to GLVQ yields GRLVQ, a novel, robust method for automatically adapting the Euclidian metric used for clustering to the data, determining the relevance of multiple input dimensions for the overall classifier, and estimating the intrinsic extent of data.

GMLVQ was introduced by Schneider, Biehl, and Hammer in 2009 to enhance the performance of all previous LVQ improvements. Even though variants such as GLVQ and RSLVQ are vastly superior to the original LVQ variants, classification is based on a predefined metric. The variants rely on Euclidean distance, analogous to the implicit assumption that clusters are isotropic. As a result, these models perform well only if the data exhibits Euclidean properties. Therefore, GMLVQ was created to manage high-dimensional data sets where noise accumulates and disrupts classification or heterogeneous data sets where different scaling and correlations can be observed between the dimensions. Schneider, Biehl, and Hammer aimed to develop a uniform statistical formulation for prototype and metric adaptation in discriminative prototype-based classifiers and a matrix adaptation scheme for GLVQ based on a heuristic but intuitive cost function. Unlike the squared Euclidean distance, a generalized distance metric was proposed using the full matrix. The general form is as follows:

$$d_{\Lambda}(\varepsilon, w) = (\varepsilon - w)^T (\varepsilon - w), \quad (3.13)$$

where Λ is an $\mathrm{N} \times \mathrm{N}$ matrix restricted to positive-definite forms to guarantee metricity, which is achieved using $\Lambda = \Omega^{\mathrm{T}}\Omega$ where $\Omega \in \mathbb{R}^{\mathrm{M} \times \mathrm{N}}$. Significantly, Λ must be normalized after each learning step to stop the algorithm from degenerating. GMLVQ extends the cost function in GLVQ using the general metric and adapts matrix parameters Ω_{ij} together with the prototypes utilizing a stochastic gradient descent, resulting in the following learning rules:

$$\Delta w_j = \alpha_1 . \acute{\Phi}\big(\mu(\varepsilon)\big) . \mu^{+}(\varepsilon) . \Lambda . \big(\varepsilon - w_j\big), \quad (3.14)$$

$$\Delta w_k = -\alpha_1 . \acute{\Phi}\big(\mu(\varepsilon)\big) . \mu^{-}(\varepsilon) . \Lambda . (\varepsilon - w_k), \quad (3.15)$$

$$\Delta\Omega_{lm} = -\alpha_2 . \acute{\Phi}\big(\mu(\varepsilon)\big) . \Big(\mu^{+}(\varepsilon) . \Big(\big(\varepsilon_m - w_{J,m}\big) . \big[\Omega\big(\varepsilon - w_J\big)\big]_l\Big) - \mu^{-}(\varepsilon) . \Big(\big(\varepsilon_m - w_{K,m}\big) . [\Omega(\varepsilon - w_K)]_l\Big)\Big) \quad (3.16)$$

In GMLVQ, each prototype vector is associated with a transformation matrix, allowing for more flexible and powerful data modeling. The distance measure GMLVQ uses a full adaptive matrix tuned during training and the prototypes. Recent studies show that by weighing every pair of features, GMLVQ could account for correlations of dimensions via implicit scaling and rotation of the data, leading to more reliable performance (Van Veen et al., 2022). The distance and prototype-based GMLVQ includes a complete relevance matrix in the distance metric, allowing it to account for dimension correlations and feature space rotations. GMLVQ is, thus, a robust prototype-based classification algorithm strengthened by a full matrix integration.

Existing research has shown that GMLVQ outperforms peer classifiers such as support vector machines and decision trees in comparable diagnostic situations involving Parkinsonian disorders and SSM/PCA (Mudali, Biehl, Leenders, & Roerdink, 2016; Veen et al., 2018). Recent studies have explored hybrid algorithms and methods for GMLVQ, comparing performance and their applicability (LeKander et al., 2017). The studies show how different methods generate GMLVQ models that perform better in validation and how well they fit the training set of data (LeKander et al., 2017). New techniques are emerging for training the GMLVQ model for classification, utilizing data from several, sometimes uncalibrated, sources without explicit transfer learning (Ravichandran et al., 2022; Villmann et al., 2022). The transfer learning is accomplished using a Siamese-like GMLVQ architecture consisting of distinct prototypes for target categorization and source separation learning. Parallel to the classification task learning, a linear map is learned in the mapping space using GMLVQ for source distinction(Villmann et al., 2022). The related null-space projection provides a consistent data representation of the various source data for classification learning.

Due to its effectiveness, GMLVQ has received multiple applications in different fields. Multiple studies have demonstrated the efficacy of GMLVQ in neuroimaging applications. GMLVQ was successfully integrated with FDG-PET imaging to classify neurodegenerative diseases and reveal idiopathic REM sleep behavior disorder trajectories(Van Veen et al., 2022; Veen et al., 2018). These studies provide strong evidence for the utility of GMLVQ in assisting accurate disease classification in neuroimaging. Similarly, recent research has utilized an interpretable classification model based on GMLVQ to study early folding residues during protein folding (Bittrich et al., 2019). The findings highlighted the potential of GMLVQ in improving the understanding of protein folding processes. By employing GMLVQ, researchers gained insights into the essential features and patterns associated with early folding residues, contributing to protein folding analysis. GMLVQ has also shown promising results in astronomy, with the algorithm integrated with explainable AI techniques to detect extragalactic Ultra-compact dwarfs and Globular Clusters (Mohammadi et al., 2022).

As outlined in this background section, the evolution and performance of GMLVQ as a computational method for intelligent decision support underscores its significance in the field. However, despite its potential, there is a noticeable gap in the literature regarding a comprehensive and systematic review of GMLVQ, focusing on its algorithmic development, improvements, applications, and future directions. Thus, the need for this systematic review is evident, as it will not only consolidate existing knowledge but also highlight areas for future research, ultimately contributing to the advancement of intelligent decision support systems.

4.2. Systematic literature review on GMLVQ and results

The broader context of this review is to apply an evidence-based investigation paradigm in exploring GMLVQ's algorithmic development, variations, mechanisms, adoption of feature relevance and metric learning, and application domains, comparisons, and limitations, as presented in the literature of a selected number of studies published between 2015 and 2024. A systematic literature review is preferred to achieve this objective as it inherently provides a tool to identify, evaluate, and aggregate results from selected empirical studies and to provide objective evidence on a given issue. Several approaches to conducting systematic reviews have been popularized to inform practice and enrich policy based on evidence in various domains (Munn et al., 2018). However, not all fields can equally benefit from a particular approach. Notably, the Cochrane systematic review method is well-suited for the medical field (Denyer & Tranfield, 2009), while Kitchenham's approach befits the software engineering domain. According to Denyer and Tranfield, Cochrane's systematic review style is insufficient and unsuitable for wide-ranging research designs (Denyer & Tranfield, 2009). The Denyer and Tranfield 5-stage systematic literature review method is used for this review, as shown in **Figure 4.1** below.

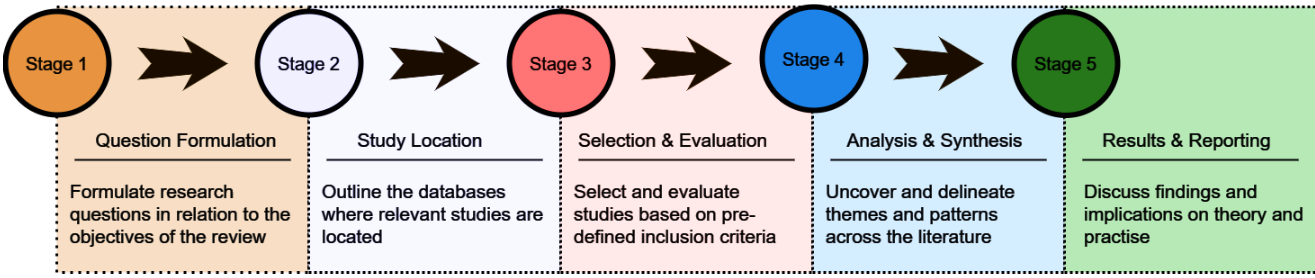

Figure 4.1. Denyer and Tranfield's 5-stage systematic literature review method
Source: Own study based on (Denyer & Tranfield, 2009)

Based on the adopted systematic review methodology, the first stage is the formulation of research questions, which establishes the focus of the study. Given the aim of this systematic review, 6 research questions are formulated as follows:

Q1: What algorithmic enhancements and variations or improvements are made to the original GMVQ?

Q2: What insights have been reported regarding the impacts of feature relevance and metric learning on GMLVQ's performance?

Q3: In what application domains have GMLVQ been utilized, and how can these be categorized and summarized?

Q4: What novel or particularly effective uses of GMLVQ are reported in the literature?

Q5: What are the observed trends in the performance of GMLVQ across different studies? How does it compare to other algorithms in terms of performance and application, as presented in the studies?

Q6: What limitations or challenges associated with using GMLVQ have been noted in existing studies?

Study location is the next step following the formulation of research questions. The studies considered for this systematic review are sourced from Scopus, IEEE Xplore, Web of Science, and Springer Link. Given the broad scope of this study, the search terms used to locate relevant studies were "*GMLVQ*" and "*Generalized Matrix Learning Vector Quantization*." Both "and" and "or" operators combined the search terms on all four databases, targeting titles, abstracts, keywords, and full text where applicable. The results were filtered by the year of publication, with 2015 to 2024 as the preferred range since computational methods and neural networks are rapidly evolving, and the papers published in the last 10 years are more likely to contain the most up-to-date and relevant information. Relevant studies were selected based on pre-determined selection criteria presented in the **Table 4.1** below.

Table 4.1. Study inclusion and exclusion criteria

No.	Inclusion	Exclusion
1	Published between 2015 and 2024	Published before 2015
2	Journal article or conference paper	Neither journal article nor conference paper
3	Abstract available	Abstract not available
4	Author details available	Missing author details
5	The paper title and abstract are aligned with the review objectives.	The title and abstract are not aligned with the review objectives.
6	GMLVQ algorithm or its variants predominantly featured	Does not predominantly feature GMLVQ or its variants
7	Clear research objectives	Unclear research objectives
8	Correct identification details such as DOI and serial numbers	Missing DOI and other essential identification details

Source: Own study

Analysis and synthesis of the selected studies are done in two steps. First, bibliometric and general characteristics of the studies are performed using descriptive analysis methodologies to capture the picture of research in GMLVQ over the past decade. This step involves several aspects of the selected studies, such as sources, publishers, and document type. The second step of analysis and synthesis focuses on distributing and comparing thematic and contextual data extracted from the selected studies. The thematic and contextual data is extracted based on the research questions to present proposed GMLVQ models, developments, variations, and study improvements.

The findings are reported following the analysis and synthesis approach. First, an overview of the characteristics, trends, and bibliometric distribution of the selected studies is reported. Next, a detailed report of thematic trends and insights, including algorithmic development and variations, key performance metrics, implications of feature relevance and metric learning, application domains, and drawbacks of GMLVQ algorithms, as identified from the studies, is performed. A detailed report of the results paves the way for interpretation and discussion of the findings.

4.2.1. Overview of included studies

The study selection process resulted in 64 journal articles and conference papers published between 2015 and 2024, as shown in **Table 4.2** below.

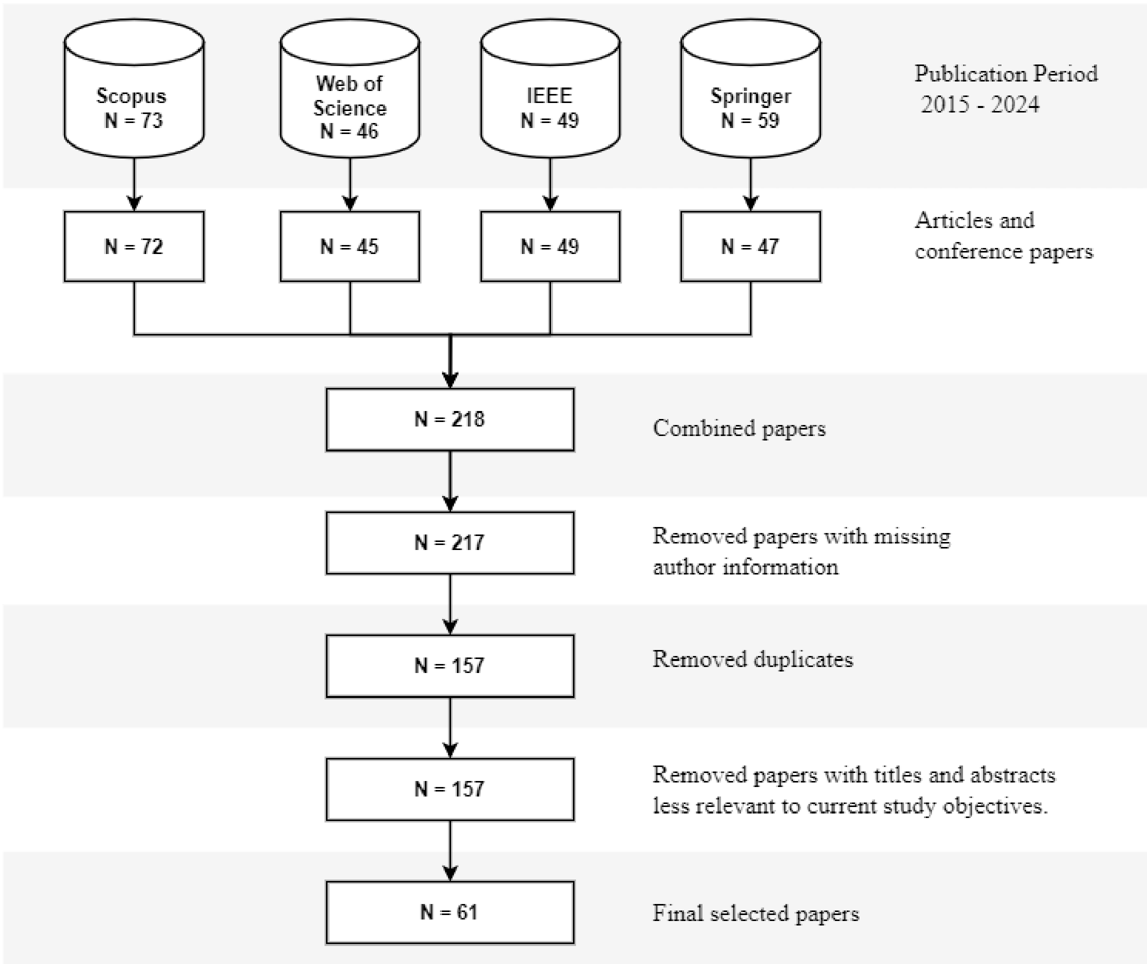

Figure 4.2. Study selection
Source: Own study

The systematic literature review was conducted across four prominent databases: Scopus, Web of Science, IEEE Xplore, and Springer, focusing on the period from 2015 to 2024. This timeframe was chosen to capture the most recent advancements in the rapidly evolving field of computational methods and their applications in engineering. The papers published during this period provide the most current and pertinent information, facilitating a comprehensive understanding of the field's state-of-the-art, emerging trends and progressions. Furthermore, confining the study to the past decade ensures comparability among the papers, as they were produced under analogous technological and scientific constraints. An initial pool of 218 journal articles and conference papers was identified for potential inclusion. However, documents with incomplete author information, duplicates, and those whose titles and abstracts were deemed insufficiently relevant to the review's objectives were excluded. Following this rigorous screening process, a final selection of 64 papers was retained for detailed evaluation.

The distribution of papers selected for the systematic review over the years exhibits a somewhat irregular pattern. The number of papers peaked in 2016 and 2017, with 10 published yearly. This trend was followed by a decrease in 2018 to 6 papers and a further drop to 4 papers in 2019. The number of papers then increased to 8 in 2020 before decreasing slightly to 6 in 2021 and then increasing again to 7 in 2022. The number of papers decreased to 5 in 2023 and remained relatively stable, with 4 in 2024.

This fluctuating trend could indicate the field's varying research interest and output over the years. The peaks in 2016 and 2017 suggest a heightened focus on the topic during these years, possibly due to breakthroughs or significant advancements in the field. The subsequent decrease could be due to a shift in research focus or the field's maturation, with fewer novel aspects to explore. The distribution of papers over the years, as shown in the **Figure 4.3** below, provides valuable insights into the progression of the algorithm and can help identify periods of significant research activity. However, the quantity of papers does not necessarily equate to the quality or impact of the research conducted during that period. A more in-depth analysis of the content and implications of these papers is presented in the following sections, providing a more comprehensive understanding of the progression of GMLVQ algorithms.

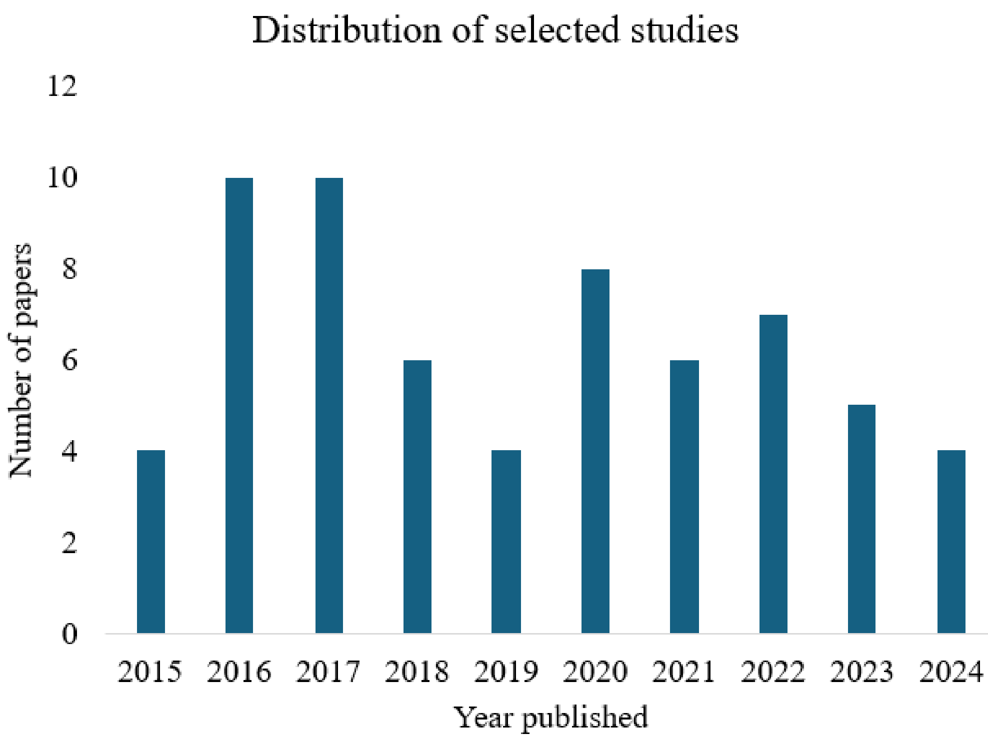

Figure 4.3. Distribution of the number of selected studies by year of publication
Source: Own study

The systematic review revealed a fluctuating trend in the number of citations over the years, as shown in **Figure 4.4** below. 2016 saw the highest number of citations at 72, followed closely by 2021 with 63 citations. 2015 and 2017 also had a substantial number of citations, with 49 and 59, respectively. However, there was a noticeable drop in citations in 2018, with only 15. The number of citations rebounded in 2019 and 2020, with 39 and 61 citations, respectively. A decline was observed in the subsequent years, with 28 citations in 2022 and a significant drop to 4 in 2023. As of 2024, no citations have been recorded. This trend could indicate the evolving interest and research focus on the field.

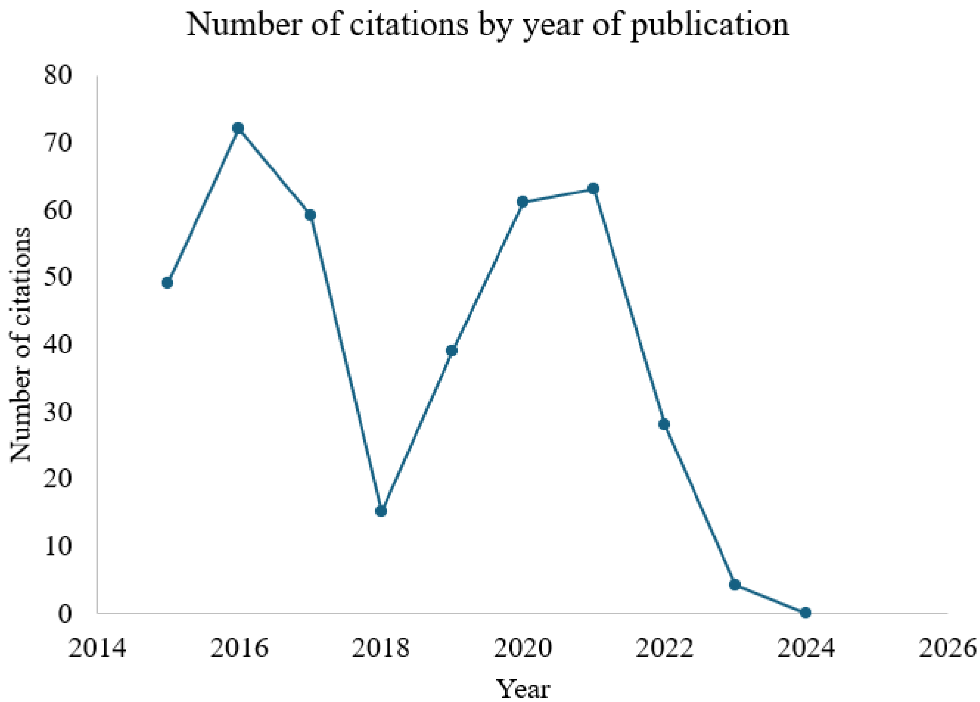

Figure 4.4. Distribution of citations by year of publication
Source: Own study

4.2.2. Distribution of selected papers by source

The distribution of the 64 selected papers on GMLVQ across various source titles suggests a broad interest in the GMLVQ algorithm across different fields. The papers are spread across a diverse range of 36 source titles, including conference proceedings and journals, as shown in **Table 4.2** below. This diversity indicates that the GMLVQ algorithm is not confined to a specific domain but is being explored and utilized in various research areas.

Table 4.2: Distribution of selected studies by source title

Source Title	No. of Studies
12th International Workshop on Self-Organizing Maps and Learning Vector Quantization, Clustering and Data Visualization, WSOM 2017 - Proceedings	4
2016 IEEE Congress on Evolutionary Computation, CEC 2016	1
2017 IEEE 19th International Conference on e-Health Networking, Applications and Services, Healthcom 2017	1
23rd European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2015 - Proceedings	1
ACM International Conference Proceeding Series	1
Advances in Intelligent Systems and Computing	5
Alimentary Pharmacology and Therapeutics	1
Arabian Journal for Science and Engineering	1
Artificial Intelligence in Medicine	1
Astronomy and Computing	1

BioData Mining	1
BMJ Open	1
Communications in Computer and Information Science	1
Computer Methods and Programs in Biomedicine	2
Current Directions in Biomedical Engineering	1
Development and Psychopathology	1
ESANN 2018 - Proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning	2
Frontiers in Artificial Intelligence	1
Frontiers in Artificial Intelligence and Applications	1
Frontiers in Computational Neuroscience	1
IAENG International Journal of Computer Science	1
IEEE Access	2
IEEE International Conference on Data Mining Workshops, ICDMW	1
IEEE Transactions on Cybernetics	1
IEEE Transactions on Knowledge and Data Engineering	1
IEEE Transactions on Neural Networks and Learning Systems	1
Journal of Machine Learning Research	1
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	7
Lecture Notes in Networks and Systems	1
Nature Communications	1
Neural Computing and Applications	2
Neural Networks	1
Neurocomputing	3
Pattern Recognition	1
Proceedings of the International Joint Conference on Neural Networks	5
Progress in Biomedical Optics and Imaging - Proceedings of SPIE	3

Source: Own study

The source title with the highest number of studies is "*Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*" with 7 papers, followed by "*Advances in Intelligent Systems and Computing*" and "*Proceedings of the International Joint Conference on Neural Networks*" both with 5 papers respectively. These sources are well-regarded in the field of computational intelligence, further emphasizing the significance of GMLVQ in this domain.

Moreover, the presence of GMLVQ-related papers in high-impact journals such as "*Nature Communications*" and "*IEEE Transactions on Neural Networks and Learning Systems*" underscores the relevance and impact of this algorithm in the scientific community. The wide distribution of GMLVQ-related papers across various source titles and their presence in high-impact journals attests to the algorithm's versatility and growing recognition in diverse research fields. This trend is likely to continue as more applications of the GMLVQ algorithm are discovered and explored.

4.2.3. Thematic scope and systematic review research questions

The selected papers provide a comprehensive overview of the developments and applications of Generalized Matrix Learning Vector Quantization (GMLVQ).

Q1: Several improvements and variations to the original GMLVQ have been reported, including the integration of adaptive tangent distance learning, the use of a more suitable and natural cost function for ordinal regression problems, and the incorporation of an enhanced feature selection objective via L1-regularization.

Q2: Various studies have highlighted the impact of feature relevance and metric learning on GMLVQ's performance. For instance, using matrix relevance learning for high-dimensional data and applying localized generalized matrix learning vector quantization for handling imbalanced classes have enhanced GMLVQ's performance.

Q3: GMLVQ has been utilized in various application domains, including healthcare, psychology, astronomy, edge computing, agriculture, cybersecurity, and more. These applications range from diagnosing diseases, analyzing biomedical data, classifying galaxy catalogs, and detecting sleep positions.

Q4: Novel uses of GMLVQ reported in the literature include the classification of time-series and functional data, the analysis of brain activities from resting-state functional MRI (fMRI) data, and the development of a computer-aided diagnosis system for early detection of glaucoma.

Q5: The performance of GMLVQ across different studies has been generally positive, with several studies reporting that GMLVQ outperforms other algorithms in terms of accuracy and computational efficiency. However, the performance can vary depending on the specific application and the nature of the data.

Q6: Some challenges associated with using GMLVQ have been noted, such as the susceptibility of Generalized Matrix LVQ to adversarial attacks and the tendency of relevance matrices to become singular with only one or very few non-zero eigenvalues. Despite these challenges, the ongoing research and development in this field continue to enhance the robustness and applicability of GMLVQ. **Table 4.3** below shows the findings from all selected studies concerning the research questions.

Table 4.3: Selected studies and findings

Source	GMLVQ application	Empirical study	GMLVQ enhanced	Feature relevance and metric learning	Improved performance	Application field
(Ravichandran et al., 2020)	Stability estimation in neural networks	✓	✓	✓	✓	Remote sensing.
(Bittrich et al., 2019)	Early folding residue prediction in proteins	✓		✓	✓	Bioinformatics
(Baciu et al., 2022)	Non-fatty liver disease fibrotic stages prediction		✓	✓	✓	Bioinformatics
(Villmann et al., 2022)	Classification of non-calibrated data	✓	✓	✓		
(Straat et al., 2020)	Time series and functional data classification	✓	✓	✓		Healthcare
(Golz et al., 2020)	EEG data classification	✓		✓		Healthcare
(Van Veen et al., 2024)	Neurodegenerative diseases classification using FDG-PET data	✓	✓	✓	✓	Healthcare
(Neocleous et al., 2017)	Early detection of fetal chromosomal abnormalities	✓		✓	✓	Healthcare
(Van Veen et al., 2018)	Alzheimer’s and Parkinson’s disease diagnosis using FDG-PET data	✓	✓	✓	✓	Healthcare.
(Nova & Estévez, 2017)	Overfitting prevention in GMLVQ algorithm	✓	✓	✓	✓	
(Straat et al., 2017)	Texture classification considering color or channel information	✓	✓	✓		
(Shumska & Bunte, 2023)	Distance-based classification of functional data	✓	✓	✓	✓	Healthcare
(Melchert et al., 2016)	Resting-state fMRI data classification	✓	✓	✓	✓	
(DSouza et al., 2017)	Early dementia diagnosis based on cognitive skills	✓		✓	✓	Healthcare
(Alahmadi et al., 2016)	NAQI evaluation in digital mammography	✓	✓	✓	✓	Healthcare
(Costa et al., 2019)	Performance improvement of SSM/PCA in neurodegenerative disease diagnosis	✓		✓	✓	Healthcare
(Van Veen et al., 2020)	EEG data classification for motor imagery tasks	✓	✓	✓		Healthcare
(F. Tang et al., 2021)	Model parameters optimization in gradient-based training	✓	✓	✓	✓	Healthcare
(LeKander et al., 2017)	Investigation of convex and non-convex regularization effects	✓	✓	✓	✓	
(Biehl et al., 2016)	Privacy-preserving data analysis tasks	✓		✓	✓	Healthcare
(Nova & Estévez, 2016)	Matrix Relevance Learning for high-dimensional data	✓	✓	✓	✓	
(Brinkrolf et al., 2018)	Automated diagnosis of crop diseases in cassava plants	✓	✓	✓		Data privacy
(Schleif et al., 2015)	Early detection of glaucoma using fundus photography	✓	✓	✓	✓	Life sciences
(Mwebaze & Biehl, 2016)	Bar-like structures delineation	✓		✓	✓	Agriculture
(Guo et al., 2019)	Early recurrence of disease identification in patients	✓		✓	✓	Healthcare
(Strisciuglio et al., 2015)	Feature relevances analysis in classification problems	✓		✓	✓	Healthcare
(Mukherjee et al., 2016)	Early detection of crop disease in cassava crops	✓		✓	✓	Healthcare
(Lövdal & Biehl, 2024)	Cassava diseases diagnosis	✓	✓	✓	✓	
(Owomugisha et	Disease-related brain patterns	✓	✓	✓	✓	Agriculture

al., 2020)	identification in neurodegenerative disorders					
(Ahishakiye et al., 2023)	Improved classification accuracies for Parkinsonian syndromes	✓	✓	✓	✓	Agriculture
(Van Veen et al., 2022)	Non-invasive biomarker strategy to stage NAFLD	✓	✓	✓	✓	Healthcare
(Mudali, Biehl, Leenders, & Roerdink, 2016)	Open-source Python implementation of LVQ algorithms	✓	✓	✓	✓	Healthcare
(Moolla et al., 2020)	Stability estimation in neural networks	✓	✓	✓	✓	Healthcare
(Biehl et al., 2016)	Early folding residue prediction in proteins	✓	✓	✓	✓	
(Van Veen et al., 2021)	Non-fatty liver disease fibrotic stages prediction	✓	✓			Software Development
(H. Miller et al., 2024)	NAFLD severity staging	✓	✓	✓		Healthcare
(Krishnan & Shrinath, 2024)	IoT network attack identification	✓	✓	✓	✓	Cybersecurity
(F. Tang et al., 2023)	Classification of data on Riemannian manifold	✓	✓	✓	✓	
(Lian et al., 2023)	Efficient graph analytics	✓	✓	✓	✓	Information Networks
(M. Fan et al., 2023)	High-dimensional data projection	✓	✓	✓	✓	
(M. L. Fan et al., 2022)	Covariance matrix data handling	✓	✓	✓	✓	
(Giorgio et al., 2022)	Future tau accumulation prediction in AD	✓		✓		Healthcare
(Mohammadi et al., 2022)	Compact stellar systems separation	✓	✓	✓	✓	Astronomy
(Shobha & Nalini, 2022)	Data fusion		✓			Data Science
(Pauli et al., 2021)	Youth classification into TD or CD	✓	✓	✓	✓	Psychology
(Diao et al., 2021)	Efficiency improvement of ML algorithms on edge devices	✓	✓		✓	Edge Computing
(Owomugisha et al., 2021)	Cassava diseases diagnosis	✓	✓	✓		Agriculture
(Saralajew et al., 2020)	Robustness evaluation of LVQ models	✓	✓		✓	Cybersecurity
(Nolte et al., 2019)	Labeled galaxy catalog analysis	✓	✓	✓		Astronomy
(Nolte et al., 2018)	Labeled galaxy catalog data analysis	✓	✓	✓		Astronomy
(Lischke et al., 2018)	High-dimensional data model learning	✓	✓	✓	✓	Psychology
(DSouza et al., 2018)	Regional self-influence patterns characterization	✓	✓	✓	✓	Healthcare
(Fallmann et al., 2017)	Eight sleep positions detection	✓	✓		✓	Lifestyle
(F. Tang & Tiňo, 2017)	Ordinal regression problem-solving	✓	✓		✓	
(Miyajima et al., 2017)	Learning of fuzzy inference systems	✓	✓			
(Biehl, 2017)	Biomedical data analysis			✓		Biomedical
(Saralajew & Villmann, 2016)	Prototype-based classification learning	✓	✓			
(Miyajima et al., 2016)	Fuzzy inference systems learning	✓	✓		✓	
(Biehl et al.,	LVQ theoretical analysis		✓	✓		

2015)				
(Fischer et al., 2015)	Online, incremental learning tasks	✓	✓	✓

Source: Own study

4.3. GMLVQ systematic literature review discussion

4.3.1. Algorithmic enhancement and variations

Based on the findings from the reviewed studies, it is evident that the evolution and diversification of the GMLVQ algorithm as a computational method have been notable in recent research. The algorithm was initially designed to improve upon its predecessors, including the original Kohonen’s LVQ variants, addressing their limitations and enhancing their strengths. However, the selected studies show considerable adaptations, enhancements, and variations in GMLVQ. These modifications to the GMLVQ algorithm have increased its computational efficiency and broadened its applicability across various domains, demonstrating its flexibility and potential for intelligent decision-making. These improvements enable the algorithm to better adjust to various data types and application scenarios, resulting in more accurate and efficient outcomes.

The GMLVQ algorithm has significantly enhanced its adaptability and performance, particularly in complex data landscapes. One of the critical modifications introduced is the incorporation of non-linear activation functions (Ravichandran et al., 2020). Non-linear activation functions are mathematical equations that determine the output of a neural network. The output is then used as input for the next layer in the model. These functions are termed ‘non-linear’ because they introduce non-linearity into the output of a neuron. A recent literature review reveals empirical studies involving the reformulation of GMLVQ based on a multi-layer network approach, making it possible to consider different activation functions, including non-linear ones in the mapping layer (Ravichandran et al., 2020). This enhancement is crucial as most real-world data is non-linear and cannot be separated or classified via a simple linear model. From the reviewed studies, a non-linear activation function has been introduced to the GMLVQ to enhance its adaptability and performance (Ravichandran et al., 2020). This is evidently in line with current research trends, where the role of activation functions is increasingly becoming important (Bawa & Kumar, 2019; Dubey et al., 2022; Khan et al., 2022; Parisi et al., 2024). As noted in a recent study, activation functions are essential in building deep neural networks’ discriminative capabilities (Bawa & Kumar, 2019). The non-linear activation functions allow for a more nuanced mapping of input features, enhancing the model's ability to learn and emphasizing the most relevant features for classification tasks. The uncovered incorporation of the non-linear activation function in GMLVQ is part of recent trends where non-linear activation functions have gained more popularity (Dubey et al., 2022; H. Li et al., 2023; B. Liu et al., 2023; Pappas et al., 2023; H. Zhang et al., 2024). Xiao proposed using a non-linear activation function to solve time-varying non-linear equations (Xiao, 2016). This study highlights the significance of employing non-linear activation functions in GMLVQ, especially considering the algorithm's capability to manage complex non-linear datasets, including those in online or streaming environments. This advancement represents an important step in enhancing GMLVQ's effectiveness in handling dynamic and intricate data scenarios.

From the review findings, the GMLVQ algorithm has been integrated with various machine learning models, including Random Forest, SVM, and kNN, demonstrating its versatility and improved performance through collaborative model utilization (Baciu et al., 2022). The integration of GMLVQ with other ML models is reported to enhance performance significantly (Mudali, Biehl, Leenders, Roerdink, et al., 2016). Such integration improves classification accuracy and ensures more reliable and consistent results across various datasets and application scenarios. Furthermore, the exploration of iterative and ensemble approaches has allowed for the leveraging of GMLVQ's strengths in conjunction with other models and techniques, such as SSM/PCA, PCA, SVM, and various spectroscopy methods (Biehl et al., 2016; Lövdal & Biehl, 2024; Moolla et al., 2020; Mudali, Biehl, Leenders, & Roerdink, 2016; Owomugisha et al., 2020; Van Veen et al., 2022). Our review reveals a study aiming to utilize a combination of FDG-PET, SSM/PCA, and GMLVQ to accurately discriminate between healthy controls and individuals with Alzheimer's disease, Parkinson's disease, and Dementia with Lewy Bodies (Van Veen et al., 2022). The authors adopt SSM/PCA and GMLVQ as classifiers on FDG-PET, with the results indicating significant performance in identifying neurodegenerative disorder patterns and successful FDG-PET data quantification (Van Veen et al., 2022). A similar study combines GMLVQ and SVM classifiers to detect patterns for Parkinsonian syndrome in FDG-PET brain data, with the results indicating improved performance in classification (Mudali, Biehl, Leenders, & Roerdink, 2016). Impressive performance has been reported using GMLVQ with dimension reduction using PCA in early plant disease detection (Owomugisha et al., 2020).

The combination of GMLVQ with other classifiers, such as SSM/PCA and SVM, has demonstrated the algorithm's capability to enhance classification accuracy and robustness, leveraging the strengths of each method to handle complex and high-dimensional data effectively. These adaptations have broadened the algorithm's applicability across diverse domains and bolstered its robustness and classification performance, underscoring the potential of GMLVQ as a computation method with immense potential in intelligent decision-making.

This review reveals that integrating innovative architecture into the GMLVQ model, such as adopting a Siamese-like structure, has significantly developed in the field (Villmann et al., 2022). This structure facilitates the simultaneous learning of multiple sets of prototypes, thereby enhancing classification accuracy and source separation, as reported by the authors (Villmann et al., 2022). This approach indicates a shift towards more sophisticated model designs catering to intricate classification scenarios. The Siamese-like GMLVQ architecture is particularly effective when dealing with data from several potentially non-calibrated sources. The effectiveness of these approaches is achieved without the need for explicit transfer learning, which presents a significant advantage by reducing computational complexity and enhancing generalization capabilities (Villmann et al., 2022). Siamese networks are a type of neural network that share weights and are designed to process paired data (Oinar et al., 2023). Existing literature shows that the Siamese network architecture is commonly used in algorithms that rely on contrastive learning (Oinar et al., 2023). Several studies have shown improved performance in computational methods integrating Siamese networks (Z. Han et al., 2021; Yan & Melkote, 2023; Zeng et al., 2019). For instance, integrating Siamese networks has been shown to enhance accuracy and robustness in various tasks, including image recognition, face verification, and one-shot learning. These networks excel in scenarios where distinguishing between similar yet distinct data points is crucial. Siamese networks have also emerged as a dominant paradigm in tracking applications, showing significant progress in object-tracking tasks (Hayale et al., 2023; Javed et al., 2023). They have been widely adopted due to their ability to maintain consistency in feature representation across frames, which is essential for reliable tracking performance. Therefore, the variation of GMLVQ to incorporate Siamese-like architecture presents a significant advancement in machine learning, particularly in classification tasks. It extends the model's utility across domains and enhances its robustness and classification performance. As such, the Siamese-like GMLVQ architecture represents a promising direction for future research and application of GMLVQ in designing intelligent support systems involving complex data landscapes. Thus, we can deduce that integrating GMLVQ with innovative architectures such as Siamese networks make it a powerful tool in advancing computation methods for intelligent decision support systems.

Our review reveals that adapting the GMLVQ model for complex-valued data through Wirtinger calculus has expanded avenues for the model's application (Straat et al., 2017, 2020). This adaptation allows the model to handle complex numerical data efficiently, addressing a significant need in machine learning. The use of the Wirtinger calculus in the GMLVQ model allows for the formulation of gradient-based update rules within the framework of cost-function-based GMLVQ (Straat et al., 2020). This observation provides a fresh perspective on these updated rules and their applicability in different contexts, expanding the model's utility. The variation has proved effective in classifying time series and similar functional data. This data can be represented in complex Fourier and wavelet coefficient space, further illustrating the versatility of the GMLVQ model (Straat et al., 2017). As established in the findings, applying the method in combination with wavelet-space features for heartbeat classification underscores the model's potential in real-world applications (Straat et al., 2020). Thus, the review shows how innovative adaptations and enhancements can effectively utilize the GMLVQ model in various domains, from time-series analysis to healthcare.

The review results have unveiled specific variations related to relevance learning in the context of the GMLVQ model. One of the key advancements in this area is the introduction of a 'relevance space' and correction matrices (Biehl, 2017; Biehl et al., 2012; Owomugisha et al., 2021; Van Veen et al., 2024). Recent research has shown that prototype-based systems can be significantly enhanced through the data-driven optimization of adaptive distance measures (Biehl, 2017). Implementing relevance learning within this framework greatly increases the flexibility of these approaches, offering valuable insights into the importance of the features being analyzed (Biehl, 2017). This strategic development aims to minimize center-dependent variation, refining the classification process by focusing on essential features (Van Veen et al., 2024). In machine learning, data often originates from various sources and combining them can introduce extraneous variation that impacts both generalization and interpretability. Awo-step approach has been proposed (Van Veen et al., 2024). Firstly, a GMLVQ model is trained on control data to identify a 'relevance space' that distinguishes between centers (Van Veen et al., 2024). Secondly, this space is used to construct a correction matrix restricting a second GMLVQ system's training on the problem (Van Veen et al., 2024). Further research reveals that utilizing local and global relevance matrices in the GMLVQ model demonstrates its capability to distinguish between complex health conditions such as Parkinson's and Alzheimer's diseases (Van Veen et al., 2018). However, it has been shown that cross-center classification can be problematic due to potential center-specific characteristics of the available data (Van Veen et al., 2018). Nevertheless, these variations extend the GMLVQ's utility across domains and enhance its robustness and classification performance. As pointed out, the application of GMLVQ as a prototype and distance-based classification in the biomedical domain represents significant progress in computation methods for intelligent decision support (Biehl, 2017). As such, the continuous refinement and integration of relevance learning in GMLVQ enhances its computational efficiency and expands its applicability, paving the way for more accurate and reliable decision-making processes in complex biomedical scenarios.

The review findings show that the GMLVQ model has seen significant advancements, including a nuclear norm as a regularization method, enhancing the model's generalization and robustness. This method prevents oversimplification, overfitting, and oscillatory behavior of small eigenvalues of the positive semi-definite relevance matrix, leading to lower classification error and better interpretability of the relevance matrix (Nova & Estévez, 2017). The model's applicability in image processing has also been enhanced by using a particular matrix format for multi-channel images and extending the parametrized angle dissimilarity measure, improving its robustness against variations in lighting conditions (Shumska & Bunte, 2023). This approach is convenient in texture classification, playing a significant role in healthcare, agriculture, and industry. Furthermore, the employment of functional expansions, such as the truncated Chebyshev series, leverages the functional nature of data, providing a nuanced approach to data representation and classification (Melchert et al., 2016). This method, applied in the space of expansion coefficients, can significantly improve classification performance, opening new avenues for applying GMLVQ in diverse data environments. Further enhancements include transitioning to accommodate data in Riemannian manifolds by modifying the distance metric within the GMLVQ framework, introducing a novel classification approach for complex data structures, and expanding the model's applicability (Adaptive Basis Functions for Prototype-Based Classification of Functional Data, 2020). Additionally, employing adaptive functional bases for data expansion and integrating various regularization techniques for sparsity reflect ongoing efforts to enhance model efficiency and interpretability (LeKander et al., 2017; Nova & Estévez, 2016). These advancements contribute to a more versatile and robust GMLVQ framework capable of handling a wide range of complex data environments with improved precision and interpretability, thereby broadening its potential applications across various scientific and industrial domains.

The algorithmic development and variations in the GMLVQ algorithm indicate a dynamic evolution geared toward addressing various data classification and analysis challenges. This evolution is characterized by continuously integrating innovative techniques and methodologies within the GMLVQ framework. From the incorporation of non-linear activation functions and the use of a nuclear norm as a regularization method to the introduction of a Siamese-like structure and the employment of functional expansions such as the truncated Chebyshev series, each modification and enhancement has significantly expanded the model's utility and performance. Furthermore, the model's adaptability is evident in its ability to handle complex numerical data, multi-channel images, and diverse health conditions. Integrating other machine learning models, such as Random Forest, SVM, and kNN, further illustrates its versatility and collaborative model utilization. These developments demonstrate the GMLVQ model's potential for future research and application and underscore its role in facilitating intelligent decision-making processes.

4.3.2. Feature relevance and metric learning

Based on the analysis of selected studies, this review shows that the GMLVQ model has seen significant advancements in integrating feature relevance and metric learning, enhancing its efficacy in classification tasks through nuanced mapping of input features. The extension of GMLVQ includes non-linear activation functions, and the use of DropConnect underlines a refined approach toward emphasizing the most relevant features for classification tasks (Ravichandran et al., 2020). This adaptation enables a more nuanced feature mapping, aligning with metric learning principles to maintain classification stability under various conditions. The integration of comprehensive visualization capabilities allows for a more detailed interpretation of data, suggesting the algorithm's inherent focus on feature relevance and metric learning (Bittrich et al., 2019). These improvements highlight the GMLVQ model's capability to adapt to complex datasets while ensuring robust performance. Consequently, the model's enhanced interpretability and precision make it a powerful tool for intelligent decision-making across diverse applications.

The examined studies reveal that combining multi-omics data with regular clinical parameters in GMLVQ enhances AI model performance, indicating the significant role of metric learning in handling complex datasets (Baciu et al., 2022). The algorithm's approach to training a linear map for source distinction further exemplifies the application of metric learning in parallel to classification tasks (Villmann et al., 2022). This approach employs a Siamese-inspired GMLVQ architecture featuring distinct prototypes for target classification and source separation learning. Within this framework, a linear map is concurrently trained via GMLVQ for distinguishing sources in the mapping space while simultaneously learning the classification task (Villmann et al., 2022). Feature relevance and metric learning are highlighted by several examined studies focusing on the classification of time-domain representations (Straat et al., 2017, 2020). Using gradient-based update rules within the cost-function-based framework of GMLVQ highlights the continuous focus on metric learning, suggesting an inherent involvement in enhancing feature relevance (Straat et al., 2017, 2020). In addition to the potential for enhancing classification accuracy, this method can significantly reduce the dimensionality of feature vectors (Straat et al., 2017). Given that the number of parameters in GMLVQ, which pertain to feature relevance, increases quadratically with the number of dimensions, this reduction can substantially decrease the computational effort required during the training phase, thereby enhancing the model's efficiency and focus on the most pertinent features (Straat et al., 2020). Further research indicates that training directly on complex-valued data with GMLVQ, utilizing learning rules derived from Wirtinger calculus, provides the advantage of effectively managing complex dimensions, thereby ensuring a mathematically robust formulation (Straat et al., 2020). The simultaneous adaptation of prototype vectors and weight matrices during training further underscores the emphasis on metric learning (Golz et al., 2020). Given its fluctuating nature, the authors investigate whether the relatively new method, GMLVQ, offers a distinct advantage in analyzing EEG data (Golz et al., 2020). This method features a learning rule for an adaptive metric, which may enable it to outperform other methods that use fixed metrics (Golz et al., 2020). However, the research indicates poor performance and suggests that the weight matrix adaptation may require more sophisticated regularization techniques to achieve better results.

Identifying a “relevance space” exemplifies the algorithm’s ability to distinguish between varying centers by focusing on the most pertinent features indicative of metric learning’s impact (Van Veen et al., 2024). The GMLVQ’s application in identifying relevant markers from clinical examinations showcases the direct application of feature relevance principles, demonstrating its effectiveness in practical healthcare settings (Neocleous et al., 2017). Additionally, incorporating regularization methods and dissimilarity measures into the GMLVQ model aligns with metric learning objectives, aiming to refine feature selection and improve classification accuracy by reducing overfitting and enhancing generalizability (Nova & Estévez, 2017; Shumska & Bunte, 2023). The use of prototypes and relevance matrices, transformed back to original data spaces, illustrates the practical application of metric learning principles in real-world scenarios, including early detection of neurodegenerative conditions such as Parkinson’s disease (Van Veen et al., 2020). These enhancements underscore the flexibility and robustness of GMLVQ and highlight its potential in various domains, including bioinformatics, where precise feature relevance can lead to significant advancements in understanding complex biological data. Furthermore, these techniques' continuous development and integration into GMLVQ reflect ongoing efforts to enhance its performance and applicability, ensuring it remains a significant computation method in machine learning and data analysis.

Adopting Riemannian metrics and applying algorithms to diverse data types, such as SPD matrices or functional expansions, demonstrate the extensive integration of feature relevance and metric learning across various domains and data structures (Adaptive Basis Functions for Prototype-Based Classification of Functional Data, 2020; M. Fan et al., 2023; Mudali, Biehl, Leenders, & Roerdink, 2016; F. Tang et al., 2021, 2023). These include the classification of EEG, where GMLVQ has demonstrated superior accuracy in distinguishing between different mental states by effectively handling the fluctuating nature of EEG signals (Golz et al., 2020). Additionally, the method has been applied to symmetric positive definite (SPD) matrices, providing robust solutions in scenarios where maintaining the geometric structure of the data is crucial, such as in medical imaging and computer vision tasks (F. Tang et al., 2021). Furthermore, GMLVQ has proven effective in analyzing both spectral data and time series, showcasing its versatility in capturing essential patterns across diverse datasets, thereby improving predictive performance in fields ranging from finance to environmental monitoring (Adaptive Basis Functions for Prototype-Based Classification of Functional Data, 2020). These applications underscore the algorithm’s adaptability and robustness across complex data environments. Furthermore, the application of GMLVQ in analyzing complex biological, clinical, and astronomical data showcases its versatility and the critical role of feature relevance and metric learning in achieving precise classifications and interpretations (Biehl, 2017; H. Miller et al., 2024; Moolla et al., 2020; Mudali, Biehl, Leenders, & Roerdink, 2016; Nolte et al., 2018, 2019; Owomugisha et al., 2021). As noted by the authors, GMLVQ is selected for analysis of morphological features in labeled catalogues from the galaxy and mass assembly because of its capability to provide classification boundaries, class-representative prototypes, and feature relevance (Nolte et al., 2019). This research extends to a previous one that similarly applied GMLVQ to investigate whether the morphological classification can be reproduced (Nolte et al., 2018, 2019). The generalized Euclidean distances, parameterized by a matrix of adaptive relevance parameters, highlight the continual evolution of metric learning strategies within GMLVQ, aiming to enhance the interpretability and effectiveness of classification models (Biehl et al., 2015). As noted by Moolla et al., the distance metric in GMLVQ is adaptive and optimized alongside the prototypes during the data-driven training process (Moolla et al., 2020). This metric is defined by a matrix of adjustable parameters known as the relevance matrix. The authors further note that diagonal elements of this matrix represent the significance of individual steroids in the classification scheme (Moolla et al., 2020). These advancements underscore GMLVQ's significant potential for providing robust, interpretable, and efficient solutions for complex classification tasks across various domains.

Integrating feature relevance and metric learning within the GMLVQ model signifies a paradigm shift in machine learning, marking a substantial advancement in how models can adaptively and intelligently learn from data. This integration allows for a more nuanced understanding of the importance of individual features, which enhances the model's ability to provide accurate and insightful classifications. The continuous evolution and refinement of these methodologies, as evidenced by the studies reviewed, underscore the transformative potential of the GMLVQ model, highlighting its capacity to evolve alongside advancements in the field. Its ability to handle complex numerical data, multi-channel images, and diverse health conditions, among others, speaks volumes about its robustness and precision. For instance, in the medical field, GMLVQ has shown remarkable success in accurately diagnosing diseases by analyzing intricate patterns in clinical data, proving its effectiveness in real-world applications (Biehl et al., 2016; Golz et al., 2020; H. Miller et al., 2024). Furthermore, its application in various domains, from biological and clinical data analysis to astronomical data interpretation, showcases its broad-spectrum applicability and critical role in the quest for knowledge and understanding of computational methods for intelligent decision-making. The versatility of GMLVQ in adapting to different types of data environments and its capacity to provide clear, interpretable results make it a valuable tool in both scientific research and practical applications. Integrating advanced regularization techniques and adaptive metrics within GMLVQ improves its performance and ensures that the model remains relevant and practical as new challenges and datasets emerge. This continued innovation and adaptability highlights GMLVQ's essential role in pushing the boundaries of what is possible in the computational engineering domain.

4.3.3. Novel use-cases and application areas

The application of GMLVQ spans various fields, reflecting its adaptability and efficacy in addressing diverse challenges. This section delves into the range of application areas identified in the selected studies shown in **Figure 4.5** below, illustrating the breadth of GMLVQ’s utilization.

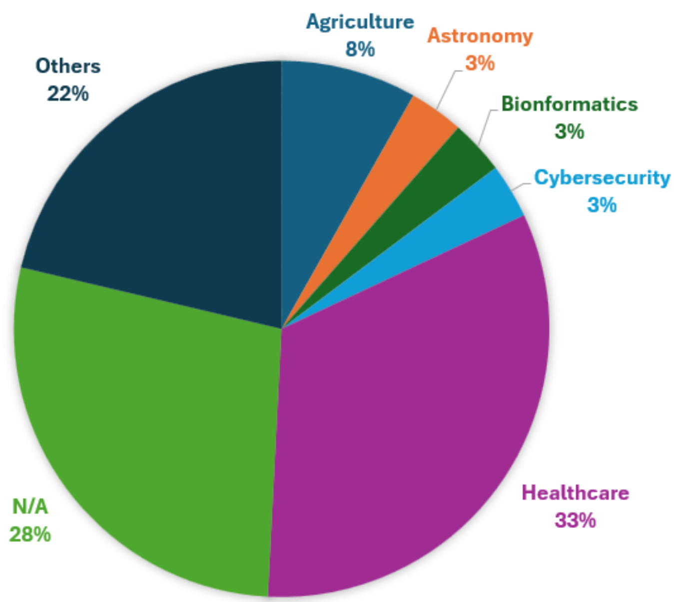

Figure 4.5. Distribution of GMLVQ algorithm application areas
Source: Own study

Predominantly, GMLVQ finds extensive application in the healthcare sector, addressing various aspects ranging from neurodegenerative disorders, Parkinsonian syndromes, and Non-

Alcoholic Fatty Liver Disease (NAFLD) to the specific challenge of renal cell carcinoma. This widespread use within healthcare, including general applications and targeted medical conditions, underscores GMLVQ's significance in improving diagnostic accuracy, patient stratification, and disease understanding (Baciu et al., 2022; Biehl et al., 2016; Costa et al., 2019; DSouza et al., 2017; Golz et al., 2020; H. Miller et al., 2024; Moolla et al., 2020; Mudali, Biehl, Leenders, & Roerdink, 2016; Mukherjee et al., 2016; Van Veen et al., 2018; Van Veen et al., 2020, 2022, 2024). The GMLVQ model is also heavily utilized in bioinformatics, showcasing its capacity to handle complex biological data, assist in genomic studies, and contribute to the broader life sciences field (Baciu et al., 2022; Biehl, 2017; Bittrich et al., 2019). The review findings are consistent with the general trends in the field, as noted from related reviews, which directly address algorithms and computational methods being adopted in healthcare and bioinformatics. For instance, a review on using machine learning to forecast Diabetes Type-2 notes the significance of using advanced computational methods for pattern identification and clustering to identify high-risk individuals (Nimmagadda et al., 2024). The authors discuss various computational techniques, including SVM, KNN, and RF, and their application in diabetes detection, noting their good accuracy, specificity, and sensitivity in identifying individuals at risk (Nimmagadda et al., 2024). This study shows that adopting these techniques enhances the performance of GMLVQ as a pattern recognition algorithm. Similar reviews have attempted to discuss related algorithms and machine learning techniques and their use in healthcare, including identifying skin diseases, predicting respiratory conditions, and analyzing cardiovascular issues (Kayaalp Ata, 2023; Koul et al., 2024; Singh et al., 2024). These insights underscore the critical role of integrating advanced machine learning methodologies, like GMLVQ, in improving diagnostic accuracy and patient outcomes across various medical domains.

This review reveals the role of GMLVQ in agriculture, where the algorithm is adopted to aid in crop disease detection and management, showcasing its utility in ensuring food security and agricultural productivity. The method's application extends to solving problems related to cassava diseases and analyzing agricultural data to enhance yield and disease resistance (Ahishakiye et al., 2023; Mwebaze & Biehl, 2016; Owomugisha et al., 2021). These findings are also consistent with the general trends, where computational algorithms are increasingly adopted in agriculture to optimize yields by minimizing constraints such as diseases. Recent empirical studies show the effective use of different machine-learning algorithms in plant disease and weed detection (Dayang & Kouyim Meli, 2021; Ruigrok et al., 2020) and in predicting plant diseases, enabling mitigation measures (Dayang & Kouyim Meli, 2021). Therefore, GMLVQ holds great potential in agriculture, so further research into enhancements and variations for specific problems is warranted. Continued advancements in GMLVQ could lead to even more precise and efficient disease detection systems, significantly reducing crop losses and improving food security. Integrating GMLVQ with other emerging technologies, such as remote sensing and IoT, could further revolutionize agricultural practices, given its ability to handle complex datasets, including online and streaming environments. As such, investing in research and development in this area is crucial for the future of sustainable agriculture.

Another notable application area is astronomy, where GMLVQ is employed in analyzing galaxy catalogs and compact stellar systems, facilitating the study of celestial objects and phenomena (Mohammadi et al., 2022; Nolte et al., 2018, 2019). The adoption of GMLVQ in edge computing indicates its relevance in computational advancements and the development of efficient computing solutions (Diao et al., 2021), which enables complex research such as classification and pattern recognition in data collected from deep space. Recent studies argue that the rapid expansion of space engineering and its technology has enabled data collection from distant galaxies, and computational algorithms are at the forefront of analyzing such voluminous data to provide meaningful information (Tyagi et al., 2023). As the astronomical field continues to advance, computational methods, including GMLVQ and their hybridizations, will play critical roles in understanding and advancing space exploration. Consequently, the integration of GMLVQ in astronomical research represents a significant step forward in handling and interpreting the vast amounts of data generated by modern telescopes and space missions. Future developments in this area will likely enhance our understanding of the universe, unlocking new discoveries and insights.

This review shows that GMLVQ contributes to enhancing privacy and tackling cybersecurity challenges, particularly in IoT networks and against adversarial attacks, reflecting its relevance in securing data and networks against emerging threats (Brinkrolf et al., 2018; Krishnan & Shrinath, 2024; Saralajew et al., 2020). The technique's application in information networks illustrates its capability to handle network data, optimize information retrieval, and understand network dynamics (Lian et al., 2023). GMLVQ can significantly mitigate the problem of high dimensionality while improving classification accuracy and interpretability. As such, it will continue to play a crucial role in astronomy alongside other computational methods. The versatility of GMLVQ in addressing diverse security issues underlines its potential as a foundational tool in developing robust cybersecurity frameworks. Ongoing advancements and research in GMLVQ will be pivotal in fortifying defenses against evolving cyber threats and ensuring the integrity and safety of critical information systems.

Beyond these primary areas, GMLVQ is applied in diverse fields, such as speech-based emotion recognition and sleep position tracking (Fallmann et al., 2017; Lischke et al., 2018). This study also reveals the algorithm's relevance in psychology, particularly in studying conduct disorder and parenting behavior. It highlights its potential in social sciences to analyze behavioral data and understand complex human behaviors (Pauli et al., 2021). GMLVQ is also involved in specialized domains such as fuzzy modeling, fuzzy inference systems, and ordinal regression, which underlines its expanding reach into areas requiring nuanced data interpretation and decision-making frameworks (Miyajima et al., 2016, 2017; F. Tang & Tiňo, 2017). These applications demonstrate the algorithm's flexibility and ability to contribute to various research areas and practical challenges. GMLVQ's broad applicability across these diverse fields underscores its robustness and adaptability in handling different types of data. Its success in these areas indicates its potential for future innovations and improvements in machine learning techniques. Continued exploration and refinement of GMLVQ will likely yield more versatile and powerful tools for academic research and practical applications.

As observed, the application areas of GMLVQ highlight its versatility and effectiveness across a broad spectrum of disciplines. The novel use cases of GMLVQ presented in the literature reveal its versatility and adaptability across various domains and challenges. From healthcare and bioinformatics to agriculture, astronomy, and beyond, GMLVQ's contributions are pivotal in advancing research, enhancing decision-making processes, and addressing domain-specific challenges. This diversity underscores the method's adaptability and its potential for continued evolution and application in new and emerging fields. The novel use of GMLVQ's enhancements and variations highlights the dynamic and expanding applications of GMLVQ, demonstrating its flexibility and potential in addressing a wide range of real-world problems. The continuous exploration and integration of GMLVQ in different domains advances its methodological development and contributes to the broader field of intelligent decision-making and data analysis.

4.3.4. Performance improvement

The enhancements in GMLVQ models have demonstrated substantial performance improvements across various domains, illustrating their superiority to conventional LVQ algorithms. These improvements stem from the refined feature relevance, metric learning, algorithmic enhancements, and novel use cases reported in the selected studies. For instance, This review reveals that including information-theoretic measures and stability estimations in neural networks has shown significant potential in evaluating and enhancing the robustness and performance of GMLVQ models (Ravichandran et al., 2020). Such measures allow for a more refined analysis of the algorithm's stability, leading to better generalization capabilities. These advancements highlight the continuous evolution of GMLVQ, positioning it as a powerful tool in machine learning. Consequently, ongoing research and development in this area will unlock even greater potential and applicability in diverse fields.

The literature review shows that the application of GMLVQ in bioinformatics demonstrates comparable performance to state-of-the-art classifiers, with improvements notably in integrating multi-omics data and clinical parameters, which led to an impressive increase in performance from 87% to 99% (Bittrich et al., 2019). Thus, GMLVQ and its variations hold the potential to handle complex biological data efficiently. Similarly, in healthcare, GMLVQ applications have achieved considerable success. For instance, in neuroimaging and disease classification, the GMLVQ models have facilitated the development of machine learning systems with reduced bias, allowing for more informative relevance profiles that medical experts can interpret (Van Veen et al., 2024). The algorithm's application to EEG data classification and FDG-PET data for neurodegenerative diseases showcases its utility in handling varied healthcare data, often achieving classification accuracy that outperforms traditional methods and offering more interpretable results (Biehl et al., 2016; Golz et al., 2020; Mudali, Biehl, Leenders, & Roerdink, 2016; Van Veen et al., 2018; Van Veen et al., 2022). Further performance improvements are noted in the industry, where GMLVQ has been adapted to enhance texture classification, offering better generalization and robustness against varying conditions, which is essential in these dynamic fields (Shumska & Bunte, 2023), and in agriculture, where the algorithm variations perform efficiently in disease detection. Thus, these findings demonstrate the algorithm's versatility and effectiveness beyond the medical domain.

Performance enhancements are not just limited to classification accuracy but also include better interpretability of relevance matrices, reduced computational effort, and improved generalization abilities (Melchert et al., 2016; Nova & Estévez, 2017). For example, GMLVQ achieved state-of-the-art results in speech-based emotion recognition, which indicates its effectiveness in processing and classifying complex emotional speech data (Lischke et al., 2018). Additionally, in more specialized applications such as sleep position tracking and fuzzy inference systems, GMLVQ models have shown remarkable accuracy, outperformed conventional methods, and illustrated the adaptability and efficiency of GMLVQ in diverse application areas (Fallmann et al., 2017; Miyajima et al., 2016, 2017). GMLVQ presents a notable advancement over traditional LVQ due to its incorporation of metric and relevance learning, allowing for more nuanced feature weighting and adaptation. Thus, metric and relevance teaching leads to a more refined classification that is particularly beneficial in complex data landscapes where traditional methods may falter due to the lack of these sophisticated mechanisms.

The performance improvements documented across various studies demonstrate the effectiveness of the GMLVQ enhancements and highlight the importance of continuous algorithmic development to meet the evolving needs of different domains. This advancement in performance, coupled with increased interpretability and adaptability, solidifies GMLVQ's superiority over conventional LVQ models and establishes it as a valuable tool in the arsenal of machine-learning methodologies for intelligent decision-making. Integrating advanced features, such as adaptive metrics and relevance learning, ensures that GMLVQ remains at the forefront of machine learning innovations. Furthermore, its versatility across diverse applications, from healthcare to astronomy, underscores its robust potential. As research continues to push the boundaries of GMLVQ, it promises to deliver even more impactful solutions, driving progress in various scientific and industrial fields.

4.4. Implications, limitations, and future research direction

This systematic literature review of GMLVQ models has yielded significant theoretical implications, expanding the understanding of classification algorithms and their application in various fields. This review highlights GMLVQ's adaptability through its enhancements and variations to accommodate different data types and structures, such as complex-valued data and time series. This observation underscores a theoretical advancement in the adaptability of machine learning models to varied data landscapes, pushing the boundaries beyond traditional classification methods. Furthermore, incorporating relevance learning and metric optimization within GMLVQ models exemplifies how these advancements can lead to more precise and interpretable outcomes. The versatility of GMLVQ in addressing domain-specific challenges, from healthcare diagnostics to astronomical data analysis, showcases its broad applicability and robustness. Additionally, the continuous evolution of GMLVQ underscores the importance of ongoing research and innovation in the field, ensuring that machine learning models remain relevant and practical. Overall, this review not only highlights the current strengths of GMLVQ but also paves the way for future explorations and enhancements in machine learning methodologies.

Integrating metric learning within GMLVQ models, allowing for dynamic weighing and selecting relevant features, contributes to the theoretical understanding of distance metrics' importance in classification tasks. In GMLVQ, adaptive metric learning considers the structural knowledge about the data's functional characteristics, proposed to allow for efficient processing of functional data, such as time series and hyper-spectra, synonymous with streaming environments (Villmann et al., 2014). Metric learning is particularly critical in healthcare and bioinformatics, where feature relevance can significantly influence diagnosis accuracy. Metric learning is already a significant area of active research, with several studies exploring its effectiveness in different contexts and domains (Huai et al., 2022; Song et al., 2022). As research continues to delve into the intricacies of metric learning, its integration within GMLVQ models promises to yield even more sophisticated and effective classification algorithms. Consequently, these advancements will likely drive significant improvements in various fields, from medical diagnostics to real-time data processing and intelligent decision-making applications.

As observed in the selected studies, applying regularization methods and relevance learning in GMLVQ demonstrates theoretical progress in addressing overfitting and improving model generalization. This study has revealed the enhancement of feature selection via the L1, spectral, and both convex and non-convex regularization techniques (Lischke et al., 2018; Nova & Estévez, 2016, 2017). Regularization is a critical aspect of machine learning theory, as it ensures that models remain effective and reliable when applied to new, unseen data. Incorporating these techniques within GMLVQ models highlights their ability to maintain high performance across different datasets and reduce the risk of overfitting. This advancement strengthens the model's robustness and practical applicability in real-world scenarios. Ultimately, the continuous improvement and integration of regularization methods within GMLVQ underline its potential to set new benchmarks in machine learning.

Similarly, this review has several practical implications. The significant success of GMLVQ models in healthcare, from neurodegenerative disease classification to medical imaging, showcases their practical usefulness in diagnosing and understanding complex medical conditions. Such success has real-world implications, potentially improving diagnostic accuracy and patient outcomes. Moreover, the application of GMLVQ in agriculture for disease detection in crops and bioinformatics for analyzing biological data highlights the model's practical relevance in addressing food security and understanding biological processes. GMLVQ's role in cybersecurity, specifically in IoT networks, and its application in data privacy illustrate its practical benefits in protecting digital information and infrastructure, an increasingly important concern in this digital age. In addition, the review demonstrates GMLVQ's application across various domains, suggesting its potential in other areas that require complex decision-making and classification, such as environmental monitoring, finance, and social media analytics. Furthermore, in the context of intelligent decision-making or decision support systems for manufacturing process selection, GMLVQ offers significant advantages. The model's ability to adaptively learn and identify the most relevant features can be leveraged to optimize manufacturing processes by selecting the most efficient and cost-effective methods.

Recent studies have noted the significance of intelligent support methodologies, such as artificial neural networks, in manufacturing process selection (Mumali & Kałkowska, 2024). By integrating GMLVQ into decision support systems, manufacturers can enhance operational efficiency, reduce production costs, and improve overall product quality. The use of GMLVQ in this manner underscores its versatility and practical utility, making it a valuable tool in both strategic and operational decision-making processes within the manufacturing industry. Overall, the diverse applications of GMLVQ across multiple fields demonstrate its broad utility and potential to drive innovation and efficiency in various sectors. As such, continued research and development in GMLVQ can further extend its practical implications, solidifying its role as a cornerstone in intelligent decision support systems.

While this review provides comprehensive insights into GMLVQ models, it is not without limitations. First, the scope of review is limited to articles and conference papers from leading journals, potentially omitting relevant studies from other sources or grey literature that could provide additional insights. Second, the selected studies show a heavy concentration of GMLVQ applications in healthcare and bioinformatics, which may skew the understanding of the model's versatility and effectiveness in other fields. The review lacks a systematic comparative analysis between GMLVQ and other classification models across all domains, which could provide a clearer picture of its relative strengths and weaknesses.

The findings from this review suggest several future research directions for GMLVQ, notably the expansion of its research into the manufacturing domain. This review shows the GMLVQ algorithm's success in healthcare and limited application in manufacturing. Existing reviews on artificial neural network-based decision support in manufacturing processes highlight the growing interest in using machine learning algorithms to handle complex decisions in product and process design (Mumali, 2022; Mumali & Kałkowska, 2024). The author further notes that computational methods, including artificial neural networks, are used in product and process design within the manufacturing domain to simplify decision-making by predicting time-series events, analyzing complex variables, and simulating different scenarios (Mumali, 2022). The rapidly increasing complexity and uncertainty in manufacturing necessitate decision support systems capable of handling more complex data (Mumali, 2022; Mumali & Kałkowska, 2024).

The manufacturing landscape is experiencing increased complexity, uncertainty, and streaming environments, whereby large volumes of complex data are streamed in real time, for example, from IoT devices. The effectiveness of decision support systems in manufacturing is enhanced when combined with intelligent computational methods such as artificial neural networks and genetic algorithms (Mumali & Kałkowska, 2020). The combination leads to robust and comprehensive capabilities for managing manufacturing processes. GMLVQ holds great potential in the realm of manufacturing processes. The relevance learning and feature selection capabilities of GMLVQ are ideal for analyzing data in a streaming environment (Klingner et al., 2014). As noted in their application in astronomy, GMLVQ algorithms effectively handle high-dimensional data (Mohammadi et al., 2022; Nolte et al., 2019). As such, there is a significant opportunity to explore using the GMLVQ algorithm in managing manufacturing processes, including selection, design, and control. Research could focus on adapting GMLVQ to the specific challenges and data types found in manufacturing settings, such as the selection of optimal manufacturing processes for a given product, considering a multitude of constraints, including sustainability goals, material properties, design requirements, time, cost, and safety, among others.

In addition, there is a need for more comparative studies that pit GMLVQ against other classification algorithms across various metrics and domains to understand its relative performance and applicability better. Further research should also explore leveraging GMLVQ in interdisciplinary research. Combining insights from healthcare, bioinformatics, and other fields could lead to novel applications and enhancements of the model. For instance, integrating GMLVQ with emerging technologies, such as blockchain for data privacy, edge computing for real-time analytics, and augmented reality for enhanced data visualization, could open new avenues for application and research. By addressing these future research directions, the field can further improve the theoretical understanding and practical applications of GMLVQ models, contributing to their evolution and effectiveness in addressing complex classification challenges.

5. Methodology for Intelligent Support in Manufacturing Process Selection

This chapter introduces the use of GMLVQ algorithms to optimize manufacturing process selection. The proposed method is exemplified in selecting the optimal polymer processing method in the prevailing conditions of technological capabilities, domain expert knowledge, and sustainability goals. The chapter begins with a problem description and introduces GMLVQ as and its capabilities in handling complex and high-dimensional data typically of today's complex manufacturing landscapes. The chapter devolves into GMLVQ-based methodology for intelligent selection of polymer processing methods, showcasing critical components including data collection and preprocessing, model training, and output evaluation. The methodology's performance is compared with Support Vector Machine, a comparable peer methodology for intelligent selection of manufacturing processes that similarly handles non-linear complex data. The chapter describes an experimental setup that involves hyperparameter optimization to identify the optimal activation function and regularization techniques. The chapter shows that the application of GMLVQ for manufacturing process selection demonstrates substantial promise, particularly in its ability to achieve high accuracy and efficient prototype learning of the complex selection parameters. The model's robust performance, highlighted by 100% accuracy in the tested dataset, emphasizes its potential to effectively classify complex manufacturing processes, especially when coupled with advanced solver techniques such as BFGS optimization, Swish activation function, and Elastic-Net regularization. The chapter includes limitations of the study and future research directions.

5.1. Problem description and the GMLVQ algorithm

Process selection is essential to modern manufacturing systems, with far-reaching consequences for productivity, product quality, and competitiveness. Producers have to contend with complex process options for specific material properties, design requirements, and production quantities in the diversified industrial environment of the modern era. While such choices have been based on specialized experience and expertise in the past, the heightened complexity of manufacturing environments now demands more systematic and data-based methods. As manufacturing technologies continue to develop with high-speed innovation in traditional and additive processes, the capability to quantitatively assess and choose the best process has grown more critical. This problem is compounded by the dynamic interplay between human consideration factors in decision-making and technical variables, suggesting the need for intelligent, adaptive multiple information source decision support systems to base process selection decisions.

Recent developments in artificial intelligence provide promising solutions for this problem, and machine learning algorithms have played an essential role in developing decision support systems. GMLVQ is one of those algorithms that has excelled because it can learn and weigh the importance of different features adaptively. This capability is crucial in manufacturing environments where decisions must consider the many interrelated factors and uncertainties inherent in high-dimensional data. GMLVQ extends the classical Learning Vector Quantization framework by incorporating a relevance matrix that transforms the feature space (Mumali & Kałkowska, 2025). This extension of metric learning effectively captures correlation and similarity on varying scales of multiple process parameters. It thus offers a strong foundation for manufacturing process classification and optimum selection. Such a feature is especially beneficial in polymer processing, where subtle differences in material behavior or production conditions can significantly impact the final product.

This study presents a new decision aid that utilizes GMLVQ's capability to select the appropriate processing technology of a chosen plastic that best suits blow molding, injection molding, or rotation molding. By fusing large-scale information processing and knowledge related to specialties, our GMLVQ-based system attempts to overcome some of the constraints of conventional selection techniques. The proposed method can make decision-making more precise, optimized, effective, and efficient, and lead to high-quality, sustainable production processes.

The choice of polymer processing techniques exemplifies the suggested model. Various processing technologies characterize the polymer production environment, each with its own product needs and production objectives to achieve. Blow, injection, and rotational molding stand out by their distinctive features and extensive industrial use. However, selecting the most suitable approach is a complex decision-making issue that directly influences production efficiency, product quality, and cost-effectiveness. There are some benefits and inherent limitations to all these polymer processing processes. Blow molding is well adapted to producing hollow products and containers, injection molding to manufacture complex parts with high reproducibility for large-volume production, and rotational molding to achieve design flexibility and economy for medium-volume production runs. The selection process must, therefore, weigh a set of competing considerations that include material properties, design complexity, production volume, and cost factors.

The combination of technical and subjective human parameters makes the task even more complex. The traditional decision-making methods that are used universally across most disciplines and industries depend, to a large extent, on the recommendations and analysis provided by specialists, or they may also adhere to naive and often ill-informed rules of thumb. This very particular type of methodology is susceptible to significant errors and illusions due to frequently disregarding the widespread and complex range of factors present in decision-making. These factors have high levels of heterogeneity with complex technical information that could require specialized knowledge and prevalent cognitive biases that distort human judgment. These factors can collectively lead to inefficient decision-making that fails to reflect the best possible line of action. Considering such deficits, it is clear that a paradigm shift to embracing more systematic and fact-based decision-making is critical to dealing with such issues effectively. Such a shift would allow decision-making with adequate regard to the wide-ranging expertise in concerned areas, coupled with the input of a detailed objective evaluation of all concerned variables.

The systematic review in section 4 unveiled that GMLVQ uses a full matrix incorporating pairwise correlations of used dimensions with the following form:

$$d^{\Lambda}\,(\boldsymbol{w},\xi) \;=\; (\xi\, - \boldsymbol{w})^{T}\,\Lambda\,(\xi\, - \boldsymbol{w}) \qquad (5.1)$$

In the metric equation 5.1 above, Λ is an $N \times N$ matrix, ξ is a data point, $\boldsymbol{w}$ denotes the weight space. In LVQ, a cost minimization function serves as the learning approach as depicted by equation 5.2 below:

$$\sum_i \Phi\left(\frac{d_J^{\lambda} - d_K^{\lambda}}{d_J^{\lambda} + d_K^{\lambda}}\right) \qquad (5.2)$$

In the equation 5.2 above, Φ represents a monotonically increasing function, while the distance of the data point ξ_i from the nearest prototype $\boldsymbol{w}_K$ with a similar class label y_i is denoted by d_J^{λ}, which equals to $d^{\lambda}(\boldsymbol{w_J}, \xi)$. By contrast, the distance of the data point ξ_i from the nearest prototype $\boldsymbol{w}_K$ with a different class label than y_i is denoted by d_K^{λ}, which equals to $d^{\lambda}(\boldsymbol{w_K}, \xi)$. The similarity measure in the metric form shown by equation 5.2 above holds if Λ is positive, which can be achieved by substitution Λ with $\Omega\Omega^T$. An assumption is made that Ω is symmetric, given the symmetric square root of Λ equals Ω^2 exists. The equation for GMLVQ is, therefore, derived by computing the derivatives of the cost minimization function of LVQ with respect to $\boldsymbol{w}$ and Ω.

$$\Delta \mathbf{w}_\mathrm{J} = \alpha_1 . \acute{\Phi}\big(\mu(\xi)\big). \mu^+(\xi). \Lambda. \big(\xi - \mathbf{w}_\mathrm{J}\big) \qquad (5.3)$$

$$\Delta \mathbf{w}_\mathrm{K} = \alpha_1 . \acute{\Phi}\big(\mu(\xi)\big). \mu^+(\xi). \Lambda. (\xi - \mathbf{w}_\mathrm{K}) \qquad (5.4.)$$

$$\Delta\Omega_{lm} = -\alpha_2 . \acute{\Phi}\big(\mu(\xi)\big). \Big(\mu^+(\xi). \Big([\Omega\big(\xi_m - w_{J,m}\big). \big[\Omega\big(\xi - w_J\big)\big]_l\Big) - \mu^-(\xi). \Big(\big(\xi_m - w_{K,m}\big). [\Omega(\xi - w_K)]_l\Big)\Big) \qquad (5.5)$$

Figure 5.1 below is the proposed methodology for selecting manufacturing processes based on GMLVQ algorithms.

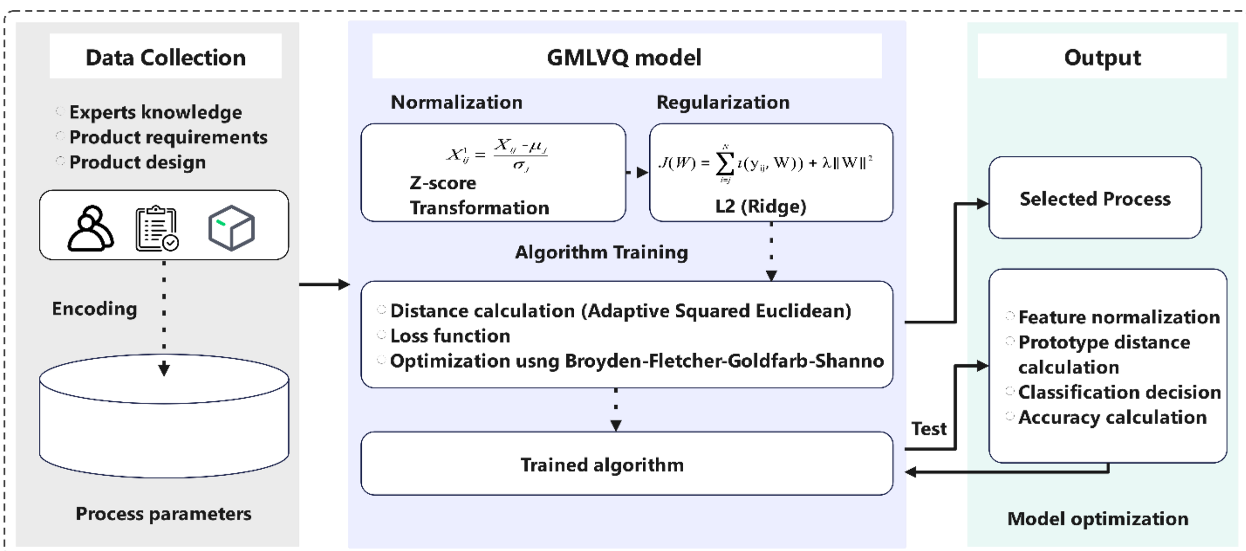

Figure 5.1. Methodology for manufacturing process selection based on GMLVQ
Source: Own study

As shown in **Figure 5.1** above, the proposed methodology uses a three-tier system to operationalize the GMLVQ algorithm. In the data collection section, a vector of process selection parameters is constructed from heterogeneous data sources, including domain expert knowledge, formalized product requirements and specifications, and product design, taking into consideration environmental impact. These parameters are normalized and regularized in the GMLVQ model section before algorithm training. The GMLVQ algorithm training involves quantification of the pairwise relations via an adaptive squared-Euclidean metric whose relevance matrix is iteratively refined by minimizing the GMLVQ cost function; the optimization proceeds with a quasi-Newton Broyden-Fletcher-Goldfarb-Shanno (BFGS) solver technique that jointly adapts prototypes and the metric to converge toward class-separating manifolds. The converged model feeds the output section, wherein unseen feature vectors are normalized, their prototype distances computed in the learned metric space, and subsequently assigned to manufacturing process classes. Metrics such as overall accuracy, confusion-matrix statistics, and guide a final hyper-parameter optimization to provide a rigorously optimized, interpretable classifier that differentiates the optimal polymer process selection recommendation.

5.2. Experimental setup for GMLVQ-based intelligent decision support

5.2.1. Dataset description and preprocessing

This study uses a dataset containing historical data on four polymer processing methods for manufacturing cylindrical and cubic plastic containers using thermoplastics. The four processes include blow molding, injection molding, rotational molding, and thermoforming. The dataset contains 200 samples involving the four processing methods and a total of 14 parameters, including size (m^3), surface finish (R), tolerance, wall thickness, cycle time (s), precision, processing rate, labor cost, suitability for large runs, suitability for small runs, scrap generation, scrap recycling, and energy use. The list of selection parameters is not exhaustive. However, for this study, only 13 parameters are considered, as shown in the **Figure 5.2** below.

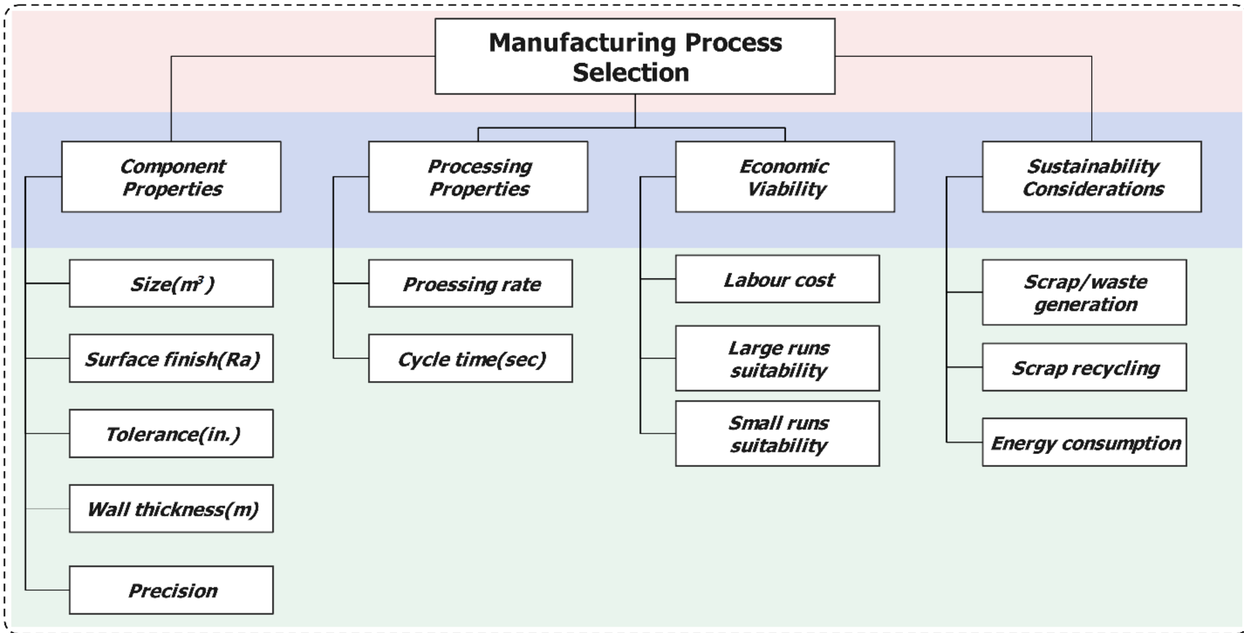

Figure 5.2. Process selection criteria/parameters
Source: Own study

The dataset features a mix of numerical, ordinal, and categorical values. Size, surface finish, tolerance, wall thickness, and cycle time are numerical. Ordinals include precision, processing rate, labor cost, scrap generation, and energy use. Binary categorical parameters include large runs suitability, small runs suitability, and scrap recyclability. **Table 5.1** below shows data types for the various parameters used.

Table 5.1. Manufacturing process selection parameters

	Parameter	**Type**	**Values**
1	Size	Numerical	
2	Surface finish	Numerical	
3	Tolerance	Numerical	
4	Wall thickness	Numerical	
5	Precision	Ordinal	High/Moderate/Low
6	Processing rate	Ordinal	High/Moderate/Low
7	Cycle time	Numerical	
8	Labor cost	Ordinal	High/Moderate/Low
9	Large runs suitability	Binary categorical	Yes/No
10	Small runs suitability	Binary categorical	Yes/No
11	Scrap generation	Ordinal	High/Moderate/Low
12	Scrap recyclability	Binary categorical	Yes/No
13	Energy use	Ordinal	High/Medium/Low

Source: Own study

Preliminary data reprocessing was necessary to adjust several parameters to ensure compatibility with the GMLVQ model and the comparable algorithms. The dataset contained a mix of categorical, ordinal, and numerical variables, requiring transformation into a format suitable for machine learning models. Binary categorical variables (*Large runs, Small runs, Scrap recycle*) were encoded using binary assignment **Yes = 1**and **N = 0**. Ordinal variables (*Precision, Processing rate, Scrap generation, Energy use)* were encoded as: **High = 3**, **Moderate/Medium = 2,** and **Low = 1**. Encoding ordinal variables ensured the classification models respect the inherent ranking relationships between levels. In addition, a target encoding was performed whereby the four polymer processing methods (*Blow Molding, Injection Molding, Rotational Molding, Thermoforming*) were mapped to numerical labels **0, 1, 2,** and **3**, respectively. Using 0-based indexing ensures that models can efficiently handle classification without unnecessary shifts in numerical space. Once encoded, the dataset, now consisting of numerical variables, was standardized using the Z-score normalization, computed as $X' = \frac{X-\mu}{\sigma}$ where X' is the standardized feature, μ is the mean, and σ is the standard deviation. Standardization is necessary to ensure all parameters contribute to model learning and prevent dominance by high-magnitude variables like cycle time in seconds. The dataset was split into 75% training and the remaining 25% portion for testing throughout the experiment.

5.2.2. Tools and evaluation metrics

The algorithm training and testing were conducted on a Lenovo ThinkPad P4s Generation 5 laptop with an AMD Ryzen 7 PRO 8840HS processor, Radeon 780M Graphics, 3301 MHz, 8 cores, and 16 logical processors. Python programming language version 3.13.2 was used to run normalization, regularization, and training and testing algorithms using Jupyter Lab version 4.3.5.

A total of 7 evaluation metrics were adopted for the model, including classification metrics, discriminative projection, feature distribution visualization, class-wise feature importance, relevance matrix, decision boundary, and execution time. The classification metrics used include accuracy as the primary performance metric and a confusion matrix to help visualize true and predicted class assignments and detect misclassification across the polymer processing methods. Classification metrics also include precision, recall, and F1-score to understand class imbalance. A discriminative projection was plotted using the first two eigenvectors of the GMLVQ-transformed data. The class separation was visualized, with GMLVQ prototypes highlighted to show decision boundaries. Feature distribution before and after standardization was used to showcase the spread and skewness in both cases. The GMLVQ relevance matrix (λ) was analyzed per class, highlighting the most discriminative features for each polymer processing method. A bar chart per class was generated, showing which features were most influential in decision-making. The diagonal of the GMLVQ relevance matrix was plotted to show the model's weighted different features and indicate redundant features with low weights. The final trained model's decision boundary was plotted using the transformed data to show how well the model classifies different polymer processing methods. The execution time served as an evaluation metric during optimization to find the best activation function, regularization method, and solver type for the GMLVQ model.

5.2.3. Model fit, optimization, and comparative models

The Z-score normalization was implemented to ensure that all features had a mean of zero and a standard deviation of one, enhancing numerical stability and preventing the model from being biased toward high-magnitude variables. This preprocessing step was necessary to ensure each feature contributed equally to the distance calculations in the GMLVQ model. Different regularization strategies were explored to enhance generalization further and prevent overfitting, including L1 (Lasso), L2 (Ridge), and Elastic-Net. L2 regularization was the most effective in balancing feature weights, particularly in cases where strong correlations were present, ensuring that no single feature dominated the learning process.

Hyperparameter tuning was performed using a grid search approach to determine the optimal configuration for the model. The selection of solvers was a key aspect of this process, as different solvers impact both computational efficiency and classification accuracy. Three solvers were evaluated: Waypoint-Gradient Descent, Adaptive-Moment Estimation (Adam), and Broyden-Fletcher-Goldfarb-Shanno (BFGS). The solver that achieved the best balance between accuracy and execution time was chosen for the final model. The activation function was also crucial in determining how feature transformations were applied within the model. Two activation types were assessed: Swish Activation, known for its smooth, non-monotonic properties that allow better gradient flow, and Sigmoid Activation, a traditional bounded function that ensures stable updates during classification.

Finally, the Relevance Matrix Regularization process was used to fine-tune feature importance weights, ensuring that the model effectively learned the most discriminative features. The optimal regularization method, whether L1, L2, or Elastic-Net, was selected based on classification accuracy and computational efficiency. This comprehensive approach to model optimization allowed the GMLVQ model to achieve high performance while maintaining interpretability and efficiency. To validate the effectiveness of the GMLVQ model, it was compared against the Support Vector Machine (SVM). SVM was used as a baseline model for classification using Radio Basis Function (RBF) kernel due to its ability to handle non-linearly separable data. L2 Regularization was applied to prevent overfitting and control model complexity. SVM's accuracy and execution time were compared to the performance of GMLVQ.

5.3. Results and analysis

5.3.1. Correlation matrix, training, and hyperparameter optimization

The correlation matrix provides a statistical overview of the relationship between different variables. Each value in the matrix depicts the Pearson correlation coefficient, which measures the linear association between a pair of parameters. The correlation values range from -1 to 1, where 1 signifies a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 implies a lack of correlation. **Table 5.3** shows the correlation heatmap.

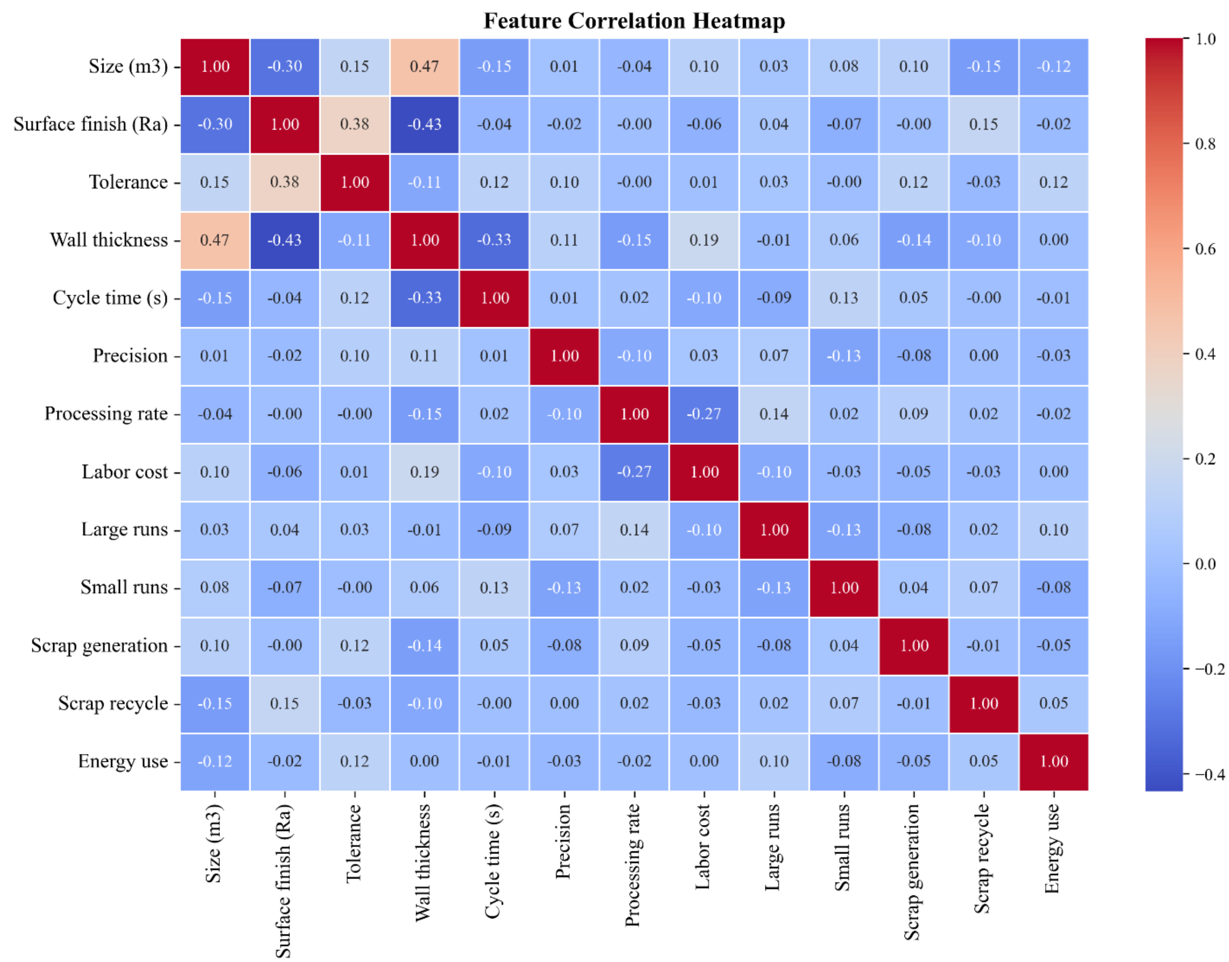

Figure 5.3. Process selection parameters correlation heatmap
Source: Own study

Based on the results depicted by the correlation heatmap in **Figure 5.3** above, surface finish and wall thickness exhibit a strong negative correlation (-0.4336), indicating that one of these features might be redundant or that their relationship needs to be accounted for during model training. A strong positive correlation (0.4687) between size and wall thickness is exhibited. A moderate correlation is observed between surface finish and tolerance (0.3776). By contrast, cycle time and scrap generation show a weaker correlation (0.0459, indicating they hold independent discriminative power. Similarly, scrap recycling and processing time have a near-zero correlation, suggesting that other factors likely drive them.

The objective function used by the model is the generalized learning objective to learn the prototype's position alongside the relevance matrix adopted in the distance function. Rather than using the conventional squared Euclidean distance, GMLVQ uses the modified version:

$$d^{\Lambda}(w,x) = (x-w)^T \Lambda (x-w)$$

where Λ is a positive semi-definite matrix, w the prototype and x the sample. To optimize hyperparameters, this study evaluated three solver types, including waypoint gradient descent, Adam, and BFGS, against two activation functions, namely Sigmoid $f(x) = \frac{1}{e^{-\beta.x}+1}$ and Swish $f(x) = \frac{X}{1+ e^{-\beta.x}}$, which previous research shows performs better over typical $ReLU$(Villmann et al., 2020). Three regularization techniques, L1, L2, and Elastic-Net, were also included to select the optimal combination. Both Adam and BFGS reached an accuracy of 100%, while waypoint gradient descent reached 93% accuracy across the activation functions. Comparing execution time, the best-performing combination using waypoint gradient descent used sigmoid activation and elastic-net regularization with 93% accuracy. For this reason, waypoint gradient descent was dropped in favor of Adam and BFGS, which registered a 94% to 100% range. The execution time for the two algorithms was evaluated for the activation function and regularization type combination. Because of the slight variation in execution times, 3 iterations were performed, and the results are as shown in **Figure 5.4**, **Figure 5.5**, and **Figure 5.6** below.

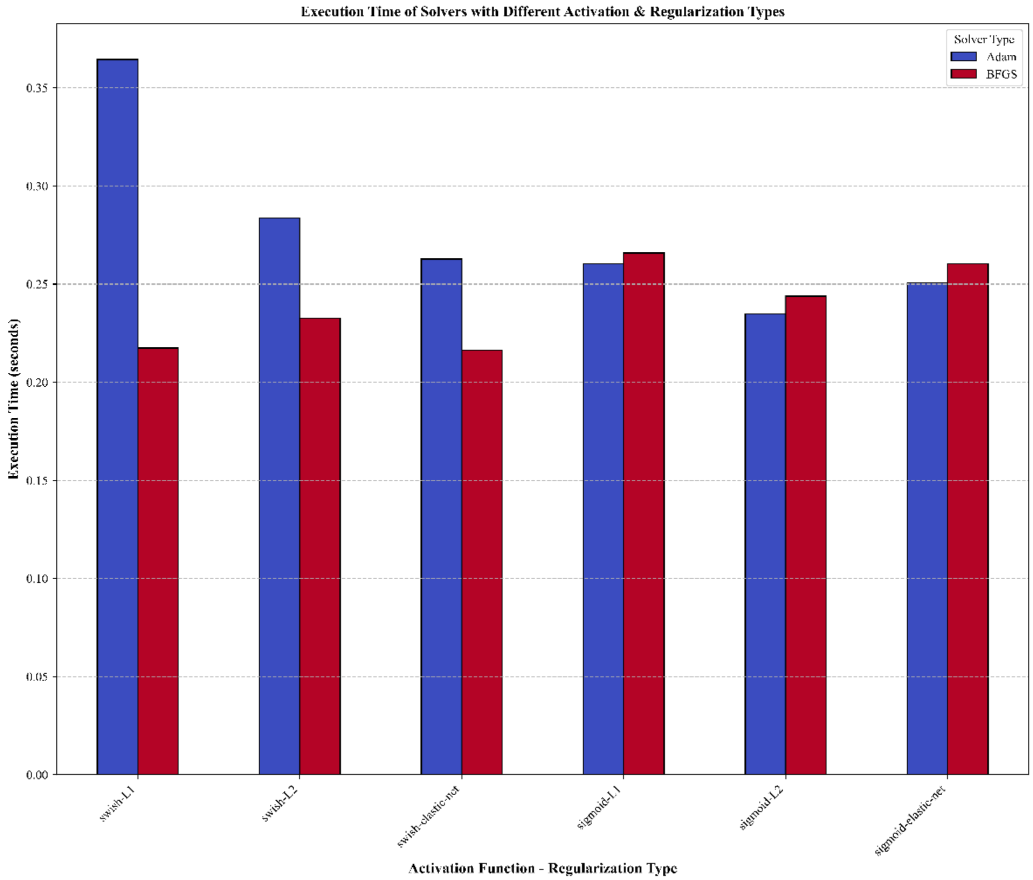

Figure 5.4. Iteration 1 of the Solver-Activation-Regularization combination
Source: Own study

As shown in **Figure 5.4** above, Adam takes the longest execution time for Swish and Sigmoid activation functions in combination with L1, L2, and elastic net regularization. By contrast, BFGS takes the least execution time in similar settings. The best performance is, however, seen in BFGS solver in combination with Swish activation function and elastic net regularization.

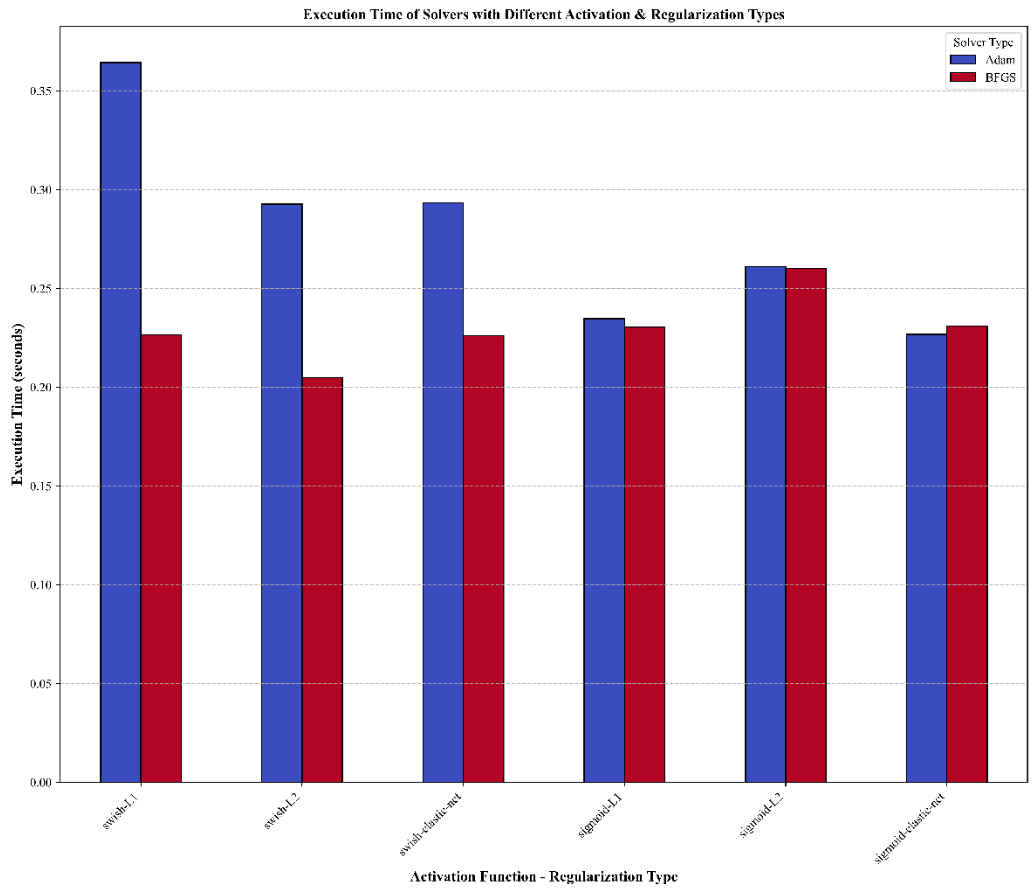

Figure 5.5. Iteration 2 of the Solver-Activation-Regularization combination
Source: Own study

Similarly, the second iteration as shown by **Figure 5.2** above shows that Adam takes the longest execution time for Swish and Sigmoid activation functions in combination with L1, L2, and elastic net regularization. On the other hand, BFGS takes the least execution time in similar settings. The best performance is again observed in the BFGS-Swish-Elastic net combination.

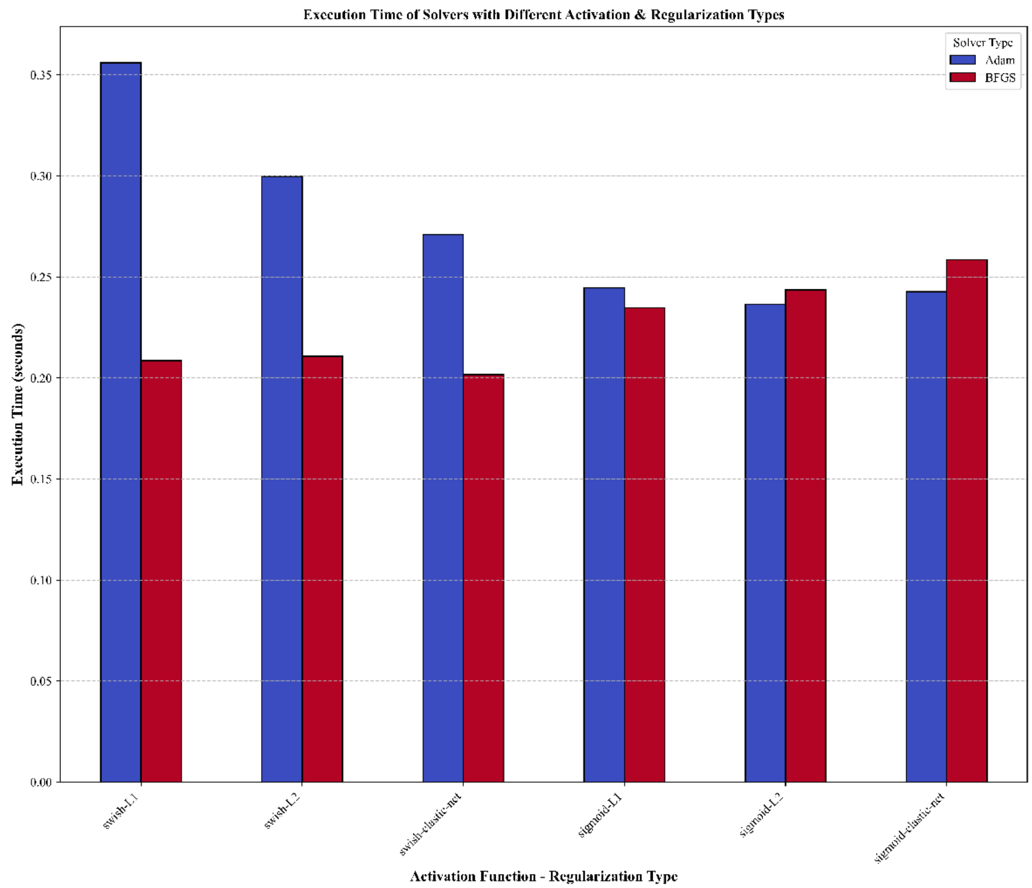

Figure 5.6. Iteration 3 of the Solver-Activation-Regularization combination
Source: Own study

The third iteration, as shown in **Figure 5.6** above yielded a similar trend to the first two iterations. The average execution time for the 3 iterations was computed, and as shown by **Table 5.2** below, which indicates the BFGS-Swish-Elastic-net as the winning combination of GMLVQ parameters.

Table 5.2: Accuracy and execution time for solver-activation-regularization combination

Solver	Activation	Regularization	Accuracy	Iteration 1	Iteration 2	Iteration 3	Average
				Time (sec)	Time (sec)	Time (sec)	Time (sec)
Adam	Swish	L1	94%	0.3645	0.3643	0.356	0.3616
Adam	Swish	L2	94%	0.2838	0.2927	0.2998	0.2921
Adam	Swish	Elastic-net	94%	0.2627	0.2933	0.2709	0.2756
Adam	Sigmoid	L1	96%	0.2604	0.2347	0.2445	0.2465
Adam	Sigmoid	L2	96%	0.2348	0.2611	0.2365	0.2441
Adam	Sigmoid	Elastic-net	96%	0.2507	0.2267	0.2426	0.2400
BFGS	Swish	L1	100%	0.2175	0.2264	0.2086	0.2175
BFGS	Swish	L2	100%	0.2325	0.2049	0.2107	0.2160
BFGS	Swish	Elastic-net	100%	0.2163	0.2261	0.2017	0.2147
BFGS	Sigmoid	L1	100%	0.2659	0.2304	0.2348	0.2437
BFGS	Sigmoid	L2	100%	0.2438	0.2601	0.2436	0.2492
BFGS	Sigmoid	Elastic-net	100%	0.2604	0.2308	0.2585	0.2499

Source: Own study

Based on the results in **Table 5.2** above, further analysis is performed using the optimized hyperparameters, and the confusion matrix is obtained as shown in the **Figure 5.7** below.

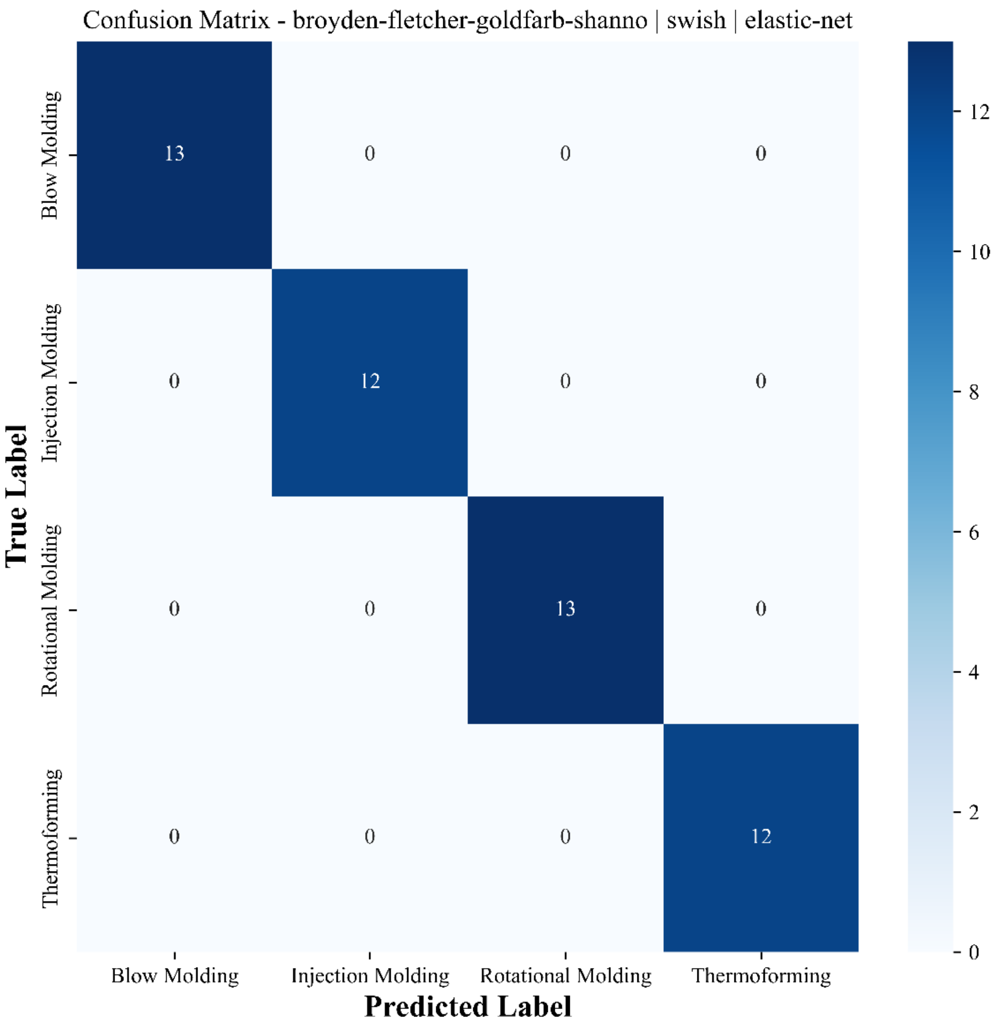

Figure 5.7. Confusion matrix
Source: Own study

As shown in **Figure 5.7** above, the 4 × 4 confusion matrix reveals a perfectly diagonal outcome: all 50 test observations were assigned to their correct manufacturing process class, thermoforming with a score of 12/12, rotational molding with a score of 13/13, injection molding with a score of 12/12 and blow molding with a score of 13/13, and zero off-diagonal entries. As a result, every standard performance metric reaches its theoretical optimum with an overall accuracy of 100%, macro-averaged precision of 100%, macro-averaged recall of 100%, macro-averaged F_1 of 100, and Cohen's κ constat of = 1.000.

The BFGS-Swish-Elastic-net combination produced a feature importance heatmap show in and **Figure 5.8** below.

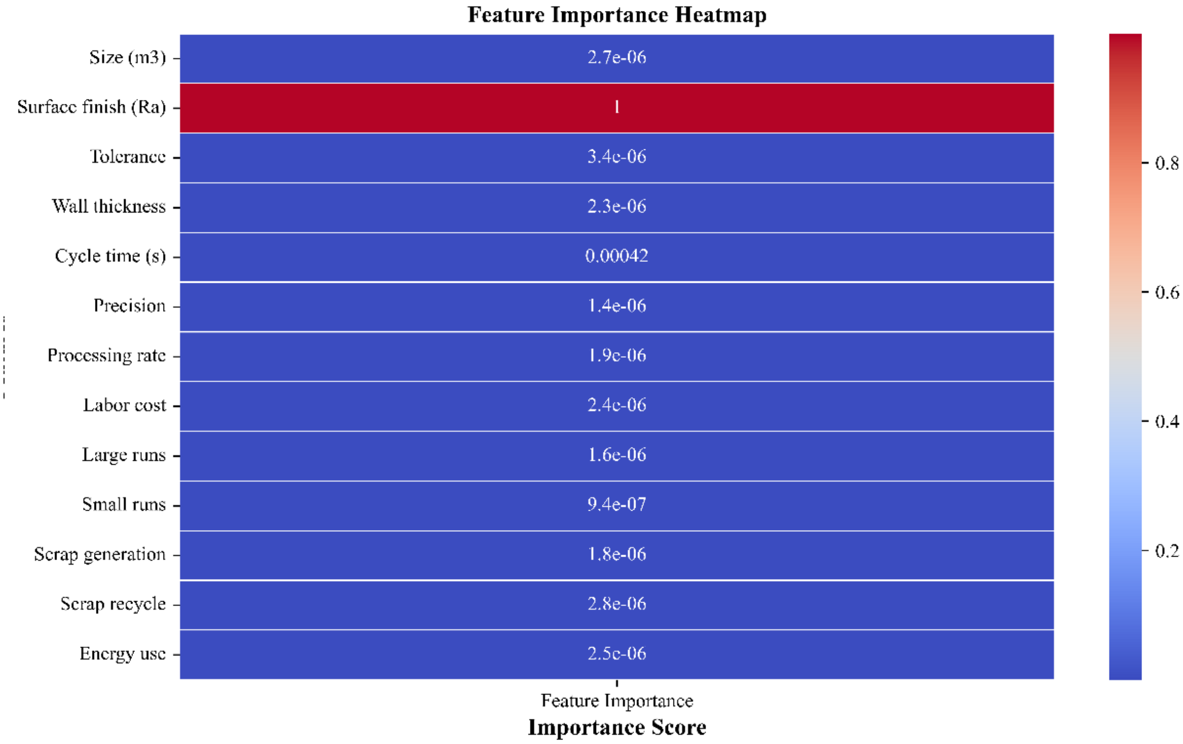

Figure 5.8. Feature importance heatmap
Source: Own study

The feature-relevance heatmap produced by the GMLVQ relevance matrix is strikingly unimodal, as shown in **Figure 5.8** above. Surface finish (Ra) dominates with a normalized importance of 1.0, whereas every other attribute, even cycle time(s), which is the next most relevant, is at 4.2×10^{-4}, a value more than three orders of magnitude below it. The remaining features are clustered in the 10^{-6} to 10^{-7} range. Because all inputs were z–score–standardized before training, these relevance values directly express how strongly the adaptive squared-Euclidean metric must stretch or compress each axis to achieve perfect class separation.

The unscaled five-number summaries reveal two distinct groups of features. Continuous, wide-range variables (Size, Surface finish, Tolerance, Wall thickness, and Cycle time) are highly right-skewed. For instance, Cycle time stretches from 24.6 s to an extreme 1194s, with its upper quartile already four times the median, indicating a long-tail of unusually slow cycles. *Size* shows a similar pattern: while half the parts fall below 4 m^3, the largest part (18.7 m^3) is nearly five times the 75th-percentile, suggesting occasional out-of-scale products that could dominate distance-based learning if left unstandardized. Surface finish (Ra) spans more than an order of magnitude (16 µm–500 µm) and, with a median (105 µm) well above the lower quartile (49 µm), reflects an asymmetric distribution skewed toward rougher surfaces. Tolerance and wall thickness exhibit milder but still noticeable skew; maxima are roughly three and two times their respective upper quartiles, showing that a few precision-sensitive or thick-walled parts sit at the fringes of the dataset. The remaining eight variables are coarse, ordinal indicators (values 0 - 3) whose interquartile ranges collapse to single integers. For Precision, Processing rate, Labor cost, Scrap generation, and Energy use, the first quartile equals the minimum, signaling that at least 25 % of observations occupy the base level. At the same time, medians lie at level 2, implying a symmetric climb to “moderate” values. Large runs and Small runs reveal a classic dummy-variable split: both have zeros at Q_1 and ones at Q_3, confirming binary usage. Finally, Scrap recycling stands out with a hard floor of zero and a Q_3 of one, indicating that three-quarters of records report no recycling at all. These disparate scales and skewed distributions underscore why standardization is essential before feeding the data into metric-based algorithms such as GMLVQ. The feature distribution before and after standardization is summarized by **Figure 5.9** below.

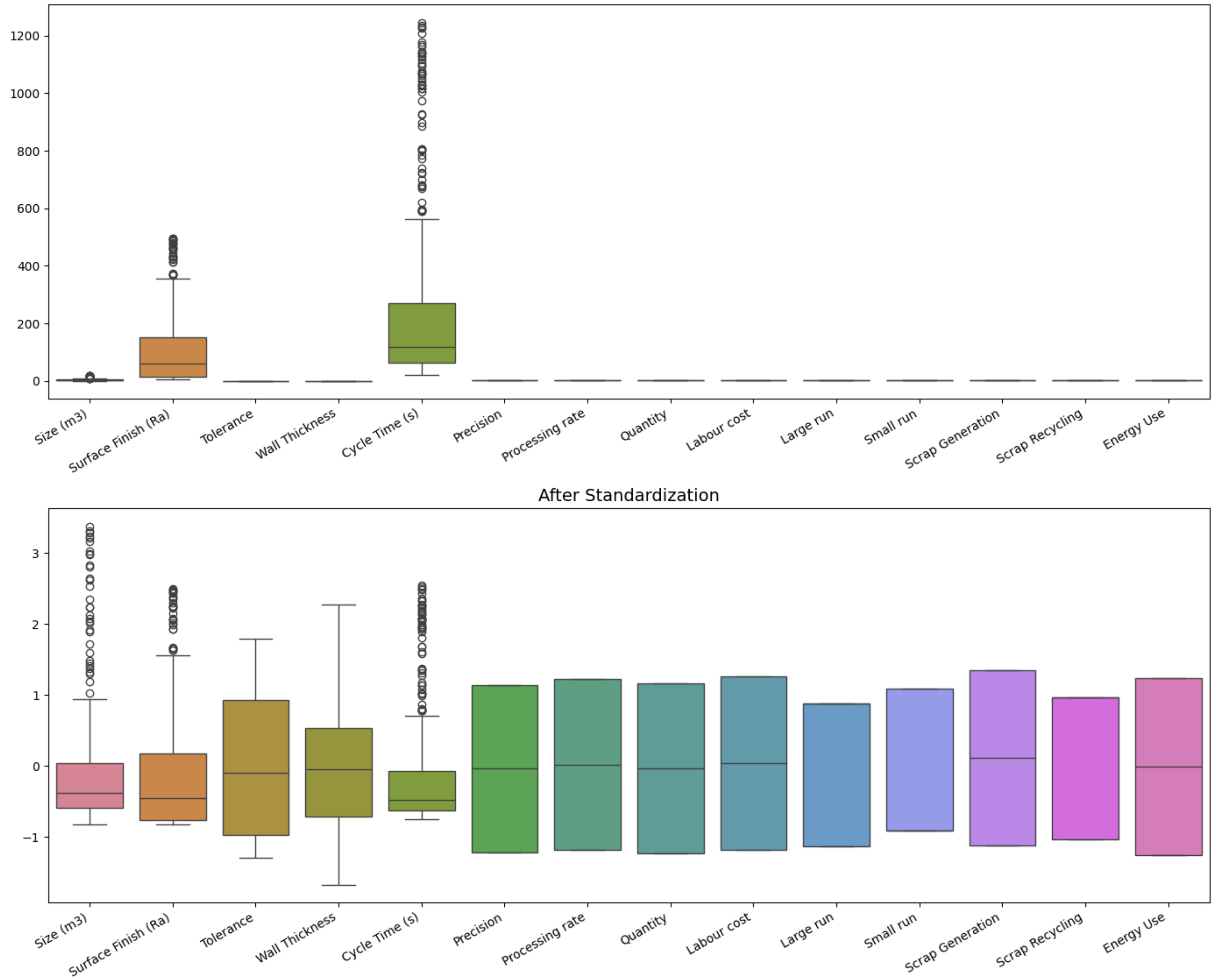

Figure 5.9. Feature distribution before and after standardization
Source: Own study

As shown by **Figure 5.9** above, every feature oscillates within a comparable, unit-free band of roughly ± 3 standard deviations after z-scoring, erasing the multi-order-of-magnitude disparities seen in the raw data while preserving each attribute's intrinsic shape. The heavy-tailed continuous variables (Size, Surface finish, Tolerance, Wall thickness, and Cycle time) all show medians clustered modestly below the grand mean (-0.15 σ to -0.47 σ) with lower whiskers extending to about $-1.6\ \sigma$ and upper extremes reaching between +1.7 σ (Surface finish) and +3.4 σ (Size), confirming that a handful of particularly large or slow-cycle parts still register as outliers but no longer dominate the numeric scale. The ordinal, 0 - 3 process indicators now occupy symmetric, integer-like positions: their first quartiles lie at either

−1.01 σ or −1.42 σ (encoding the modal "0" category), their medians hover within ±0.13 σ (reflecting a mid-level "1" or "2"), and their upper quartiles reach +0.99 σ to +1.29 σ, mirror images of the lower tails, thereby retaining categorical structure yet fitting neatly into the same variance budget as the metric features. In short, standardization equalizes feature influence for distance-based learning while still flagging rare, extreme observations through moderate positive or negative z-scores rather than overwhelming raw magnitudes.

The BFGS solver, Swish activation function, and elastic-net regularization combination achieve 100% classification with the GMLVQ model. This result indicates that the learned prototypes and relevance matrix carve out decision regions that perfectly separate the four manufacturing-process classes on the held-out test set. The BFGS optimizer accelerates convergence toward a local optimum of the GMLVQ cost, and Swish's smooth, non-monotonic activation furnishes additional curvature that helps fine-tune prototype positions. The elastic-net regularization, meanwhile, keeps individual relevance weights from exploding while still allowing sparsity. Combined, these choices extracted a metric space where every test instance lies closest to the correct class prototype. The optimized model accuracy is as shown by **Figure 5.10** below.

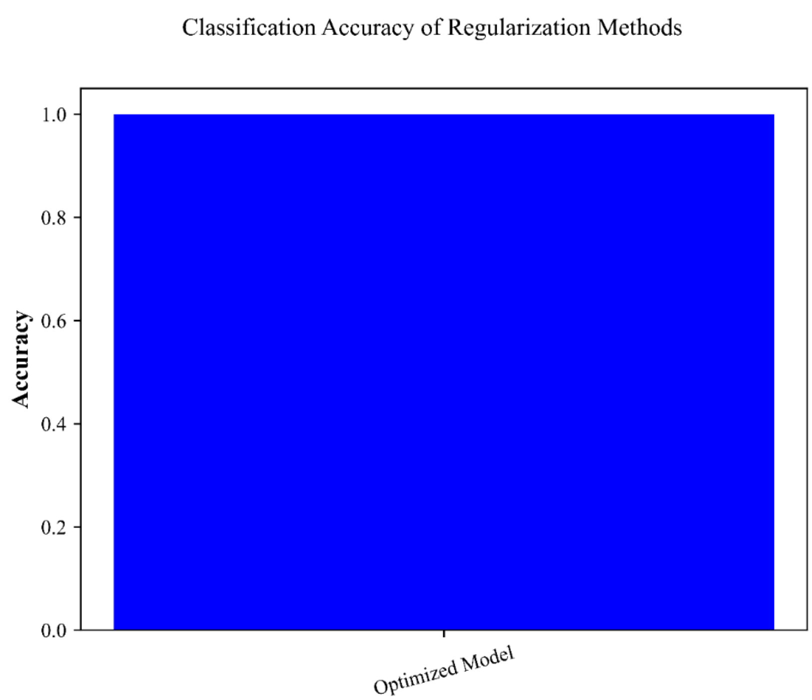

Figure 5.10. Optimized model accuracy
Source: Own study

The diagonal of the learned relevance matrix is almost singularly dominated by surface finish (Ra), whose weight (0.9996) dwarfs every other attribute by at least three orders of magnitude. The only secondary signal the model retains is a faint trace for cycle time (4.2×10^{-4}), while the remaining eleven features, including geometric measures such as size, wall thickness and tolerance, as well as all cost-, volume- and sustainability-related indicators, sit in the 10^{-6} range and are therefore functionally ignored when the adaptive squared-Euclidean metric computes distances.

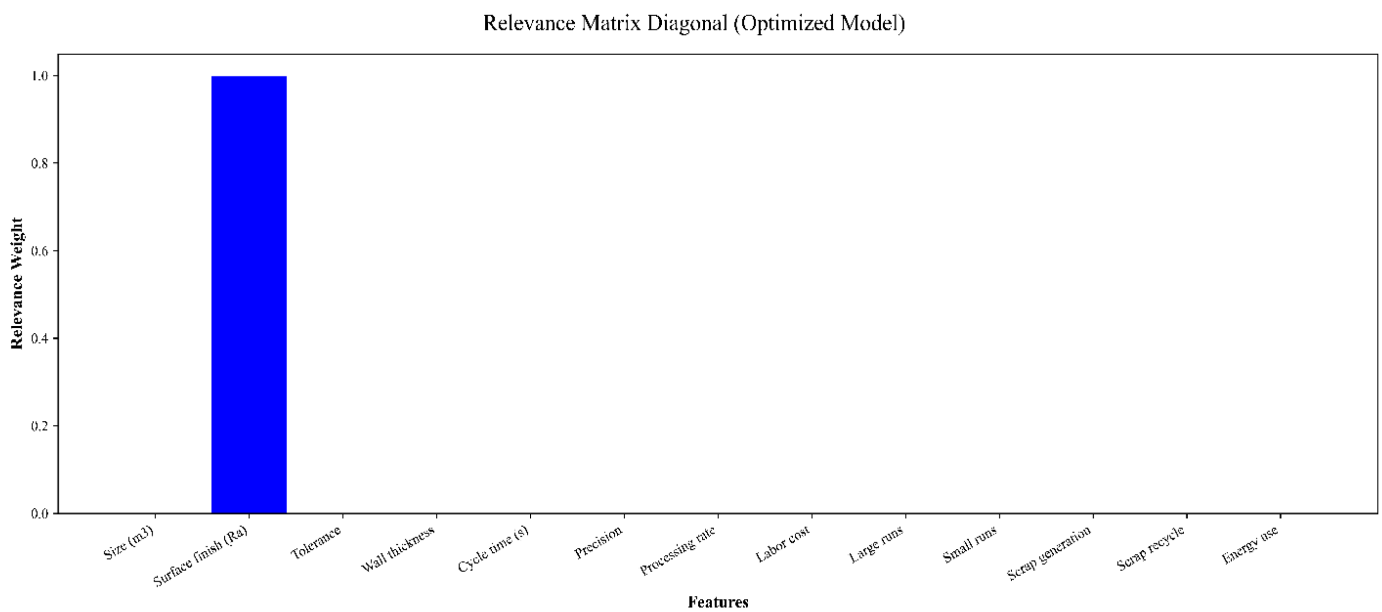

Figure 5.11. Relevance matrix diagonal
Source: Own study

5.3.2. Comparison with Support Vector Machines (SVM)

SVM and GMLVQ are supervised machine learning algorithms for pattern recognition and classification tasks. They are designed to identify the decision boundaries that best separate classes in the feature space based on labeled data. This study involved comparing the accuracy obtained on the same dataset using a similar normalization approach and applying regularization. **Table 5.3** and **Table 5.4** below shows the accuracy of the two algorithms.

Table 5.3: SVM accuracy

	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	0.80	1.00	0.89	12
2	1.00	0.77	0.87	13
3	1.00	1.00	1.00	13
accuracy			0.94	50
macro avg	0.95	0.94	0.94	50
weighted avg	0.95	0.94	0.94	50
SVM Accuracy:	94%			

Source: Own study

As indicated in **Table 5.3** above, the support for each class is evenly distributed (12 -13 parts per class), so the overall accuracy of 94 % (47/50 correct) reflects only three misclassifications. The SVM is flawless on the two extreme classes, classes 0 (Blow Molding) and 3 (Thermoforming), where precision, recall, and F_1 all equal 1.00, indicating that these categories have well-separated margins in the kernel space. The errors are confined to the middle pair. For class 1, Injection Molding, the model never misses a true instance (recall = 1.00) but occasionally over-predicts the label (precision = 0.80), implying that a few parts from other processes sit just inside the class-1 decision boundary. Class 2, Rotational Molding, shows perfect precision (1.00) yet reduced recall (0.77), meaning three true rotational cases were absorbed by neighboring classes, most likely by the more inclusive class 1, given its false-positive pattern. Macro- and weighted-average metrics (precision ≈ 0.95, recall ≈ 0.94) mirror the overall accuracy, confirming that class imbalance is negligible. In short, the SVM captures the gross structure of the data but struggles to carve a clean separating surface between the two mid-spectrum polymer processing methods, hinting at feature overlap that could be mitigated by additional discriminators or a more flexible kernel.

Table 5.4: GMLVQ accuracy

	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	1.00	1.00	1.00	12

2	1.00	1.00	1.00	13
3	1.00	1.00	1.00	13
accuracy			1.00	50
macro avg	1.00	1.00	1.00	50
weighted avg	1.00	1.00	1.00	50
GMLVQ Accuracy:	100%			

Source: Own study

The classification report in **Table 5.4** shows a perfect score for all test samples on a class-by-class basis. All the polymer processing methods were assigned to their correct category, yielding precision = recall = F_1 = 1.00 for every class and an overall accuracy of 100%. The result indicates that the GMLVQ model constructed prototypes, and the adaptive metric separated all four classes without a single overlap in the test fold.

5.4. Discussion and summary

5.4.1. Interpretation and analysis of the results

The correlation matrix presented above outlines the relationships between various process parameters. The correlations influence the suitability of the data for the GMLVQ algorithm and its ability to provide valuable insights for classification and pattern recognition. The correlation analysis, as depicted in **Figure 5.3**, indicates that the data was well-suited for the GMLVQ. The results showed several strong or moderate correlations, particularly between size and wall thickness and surface finish and tolerance, which provide a strong foundation for prototype learning in GMLVQ. Given GMLVQ's ability to take advantage of the relevance matrix to assign appropriate weights to the features based on their correlation with class boundaries, parameters such as size, wall thickness, surface finish, and tolerance were well aligned with the model's ability to distinguish classes on their features. Weakly correlated parameters such as precision and energy use could not significantly impact the prototype learning but could still be used in determining the decision boundaries. The data was highly suitable for GMLVQ, with clear patterns that the model could learn. The relationships between parameters guide the learning process, effectively allowing GMLVQ to separate classes based on their most relevant inherent features.

The hyperparameter optimization results indicated higher performance using Swish than Sigmoid activation function. Both Swish and Sigmoid achieved 100% accuracy with Adam and BFGS solver types. However, Swish registered the lowest execution time. This result is in line with previous research that demonstrated the superiority of Swish over Sigmoid and ReLU as activation functions for GLVQ (Villmann et al., 2020). Swish was shown to outperform ReLU and sigmoid, achieving higher accuracy for appropriate parameter choice, especially about convergence performance (Villmann et al., 2020). The Swish function's non-monotonic nature allows it to preserve information flow better by controlling the amount of non-linearity dictated by the dataset and the algorithm complexity, thus avoiding the vanishing gradient problem (Dubey et al., 2022). Additionally, it tends to converge faster than sigmoid, especially in more complex scenarios, and has been used extensively in recent studies (Alhassan & Zainon, 2021; Allu & Padmanabhuni, 2022, 2023; Fatima & Pethe, 2022; Jinsakul et al., 2019; Mercioni & Holban, 2020). Therefore, Swish provided a better learning dynamic for the GMLVQ model by addressing the vanishing gradient problem that could be problematic with the sigmoid.

Furthermore, the hyperparameter optimization results revealed that Adam and BFGS optimizers achieved 100% accuracy across all activation functions. Previous studies describe Adam as a stochastic optimizer that dynamically adjusts learning rates while adapting the parameters in real time for excellent results (Kingma & B, 2015; D. Yi et al., 2020). On the other hand, BFGS is described as a quasi-Newton method that demonstrates superior performance by ensuring convergence to an optimal solution (Ibrahim et al., 2014; J. Y. Wu et al., 2020). Based on the observation revealed from hyperparameter optimization, Adam and BFGS are well-suited for the classification task. Both solver types can handle the complexity of the GMLVQ model and produce high-accuracy solutions. However, introducing execution time as an evaluation metric saw BFGS considered as the sole solver type for the model, given its high accuracy coupled with low execution time.

Regularization is significant when training machine learning models and algorithms such as the GMLVQ, as it allows for good generalization on unseen data. Three regularization techniques, including L1, L2, and Elastic-Net (Friedman et al., 2010; Santos & Papa, 2022), were used during hyperparameter optimization. L1 regularization focuses on feature selection by setting some coefficients to 0, while L2 reduces the magnitude of coefficients without setting them to zero, improving generalization (Friedman et al., 2010). Elastic-net regularization combines the advantages of L1 and L2 and is described as a compromise between L1 and L2 penalties (Friedman et al., 2010). The hyperparameter optimization results indicated the best accuracy and execution time with the model parameters.

BFGS solver type is one of the most powerful algorithms for solving unconstrained optimization problems (Guerrout et al., 2018). Existing literature points out that BFGS has the advantages of meeting the requirements for conjugate direction and being the most numerically stable quais-Newton algorithm (Xue et al., 2022). In this study, BFGS is preferred for its fast convergence and little iteration, which are inherent features ideal for efficiently processing large amounts of high-dimensional data. Being a variation of the Quasi Newton optimization method, BFGS approximates the inverse of the Hessian matrix, leading to quicker convergence than the traditional gradient descent methods. As a result, the model can better traverse in the solution space, reducing the number of iterations to solve the optimal solution. The GMLVQ model seeks to optimize prototypes and the relevance matrix to minimize classification error. The speed and robustness of BFGS are especially useful in the case of intricate interdependencies among features and classes. This efficiency in optimizing the learning process directly contributes to the 100% accuracy achieved.

The Swish activation function is a key contributor to the improved performance of the GMLVQ model, particularly in non-linearity and gradient flow. Swish introduces a smooth, non-monotonic nature that enhances the model's ability to learn complex decision boundaries. In contrast to common activation functions such as sigmoid or ReLU, Swish addresses the constraints of the vanishing gradient issue and the dying ReLU issue, offering uninterrupted gradient propagation, which aids the model in learning optimally, particularly within the prototype learning stage of GMLVQ. This smooth gradient flow is essential to GMLVQ's prototype-based learning. It updates the relevance matrix and prototypes better, with better class separation and improved convergence. Swish also accelerates learning because it gives smoother gradients than sigmoid, which results in faster convergence and ultimately produces 100% accuracy in the model. By allowing the model to handle non-linear class boundaries more effectively, Swish allows GMLVQ to learn highly accurate and well-separated prototypes, such that the model generalizes well on unseen data.

The Elastic-Net regularization combines the best of both the L1 and L2 regularization techniques and, therefore, is highly effective in preventing overfitting without compromising feature selection and shrinking coefficient values. For the GMLVQ model, Elastic-Net helps to find a compromise between feature selection with L1 regularization and shrinkage with L2 regularization so that the model can retain only the most beneficial features and not get unduly bogged down by useless ones. This is particularly crucial in GMLVQ, where correct prototypes and a proper distance metric are very important for appropriate classification performance. Elastic-Net, through the use of L1 and L2 regularization, effectively controls the complexity of the model by properly optimizing the relevance matrix and prototypes without overfitting noisy samples. Also, this balanced regularization allows GMLVQ to generalize well so that the learned prototypes are not over-specific to the training data but capture the actual class structure. This ability to generalize is among the reasons why Elastic-Net is to be blamed for the model's 100% accuracy. It prevents the model from memorizing non-useful information and focuses on the underlying relationships in the data. The combination of BFGS, Swish, and Elastic-Net regularization has proven to be a highly efficient optimization framework for the GMLVQ model, with 100% accuracy and best performance.

The BFGS solver accelerates convergence, enabling the model to optimize prototypes and the relevance matrix effectively and quickly, even in high-dimensional, complex data. The Swish activation function enhances the optimization process by enabling smooth gradient flow, avoiding the vanishing gradient issue, and enabling the model to better learn non-linear boundaries between classes. Swish's smooth, non-monotonic nature enables quicker convergence and ensures the model can produce highly precise class separations. Lastly, Elastic-Net regularization prevents overfitting by combining L1 and L2 regularization so that GMLVQ can focus on the most valuable features while ensuring that the learned prototypes can be generalized to new data. These components work synergistically to construct a robust, effective, and accurate GMLVQ model capable of handling prototype-based classification tasks. This is a perfect solution to solving complex pattern recognition and classification problems. The feature importance values and outputs of the confusion matrix provide a clear image of the performance and action of the GMLVQ model. The confusion matrix demonstrates a perfect classification with 13 accurate predictions for each class (Blow Molding, Injection Molding, Rotational Molding, and Thermoforming) and 0 misclassifications for each class, providing a perfect accuracy rate of 100%.

This outcome confirms that the model successfully separated the classes using the identified prototypes, which efficiently captured patterns in the data without confusion or conflict between different classes. Alternatively, the feature importance values give insight into the direction of the attention of the model during training. Significantly, the surface finish is the top-ranked feature at 0.9995571, which indicates its key role in class discrimination. This aligns with its high level of importance in manufacturing operations, where surface quality is often a prime discriminator. The other features, such as size, tolerance, wall thickness, and precision, have extremely low feature importance values ranging from 3.4e-06 to 2.7e-06, signifying that these variables were less critical in class boundary specification in this dataset. The relatively low importance values of parameters like cycle time, Processing rate, Labor cost, and others once again validate that even though they contribute to the model, they are not as loaded in classifying the data as surface finish. These findings show the model's ability to classify the data accurately. It highlights the paramount role of surface finish in decision-making, presenting informative information regarding which characteristics are most significant in effective class separation for this manufacturing process.

5.4.2. Comparison with SVM and theoretical and practical implications

GMLVQ and SVM are two supervised pattern recognition and classification algorithms of learning. Based on labeled inputs, they must design the best decision boundaries for class separation in the feature space. The two methods differ in solving classification issues based on alternate principles, learning mechanisms, and mathematical bases. While GMLVQ is a prototype-based learning classifier that learns prototypes of every class as a function of the distance between an instance and such prototypes, SVM is a boundary-based learning classifier and strives to learn the optimal hyperplane that separates instances from disparate classes in feature space. The optimal hyperplane is regarded as maximizing the margin, or the separation between the closest points of the two classes, the so-called support vectors. The difference between SVM and GMLVQ provides adequate explanations concerning the advantages and disadvantages of the two models for classification performance.

The SVM model has 100% accuracy, which is superior to that of GMLVQ in terms of total accuracy. The class 0 and class 3 precision, recall, and F1-scores are all perfect (1.00) in both models, but SVM is imperfect in class 1, with a precision of 0.80 and an F1-score of 0.89. This outcome indicates that while SVM is strong in most cases, it is not as strong in handling class 1 and thus results in some misclassifications. On the other hand, GMLVQ achieves perfect performance on all classes with a 1.00 precision, recall, and f1-score for each class, giving a total accuracy of 1.00, indicating that GMLVQ would perfectly classify all instances. The weighted average and macro average of GMLVQ also show its consistency by having F1-scores of 1.00 for all classes, proving its ability to generalize perfectly to unseen data. As such, the GMLVQ is better equipped to handle class imbalances or uncertain class boundaries because it fared better even when it had a class that SVM did not handle well. GMLVQ's capability via prototype-based learning and relevance matrix adjustment also made its classification error-free. For SVM, although it was correct in all aspects except precision on class 1, this shows its inability to optimize all classes uniformly. Lastly, while SVM is an effective classifier, GMLVQ offers a superior and optimally generalized solution, especially in complicated or fine-grained class separability cases.

The theoretical value of this study lies in the comparative analysis of the GMLVQ model and SVM, both machine learning models, in classification problems. The study underscores the importance of prototype-based learning in recognizing complex, non-linear relationships in high-dimensional data. With the addition of BFGS optimization, Swish activation, and Elastic-Net regularization, GMLVQ is shown to have more extraordinary adaptability and generalization performance with a 100% accuracy rate across all classes, against SVM's 94% accuracy. This observation suggests that GMLVQ with adaptive prototypes using relevance matrices can better deal with class imbalance and intricate decision boundaries. As such, the model can be more stable in some cases. Theoretical also provides more understanding of why it is beneficial to have Swish activation being non-monotonic and smooth to enhance learning in prototype-based approaches by preventing gradient vanishing issues and enhancing learning rate and convergence. Furthermore, the research highlights the necessity of Elastic-Net regularization in striking a balance between feature shrinkage and selection so that the model is not overfitted but still preserves the importance of salient features. These findings are contrary to the traditional application of boundary-based learners like SVM, and they offer a theoretical explanation for enhancing prototype-based models capable of handling non-linear decision boundaries and complex datasets.

Practically, the findings of this study are of great potential value to industries and applications wherein the accuracy of classification and generalizability are paramount. The fact that GMLVQ can attain perfect accuracy over all classes in this research demonstrates that it can be used for applications such as classifying data and pattern recognition, whose classifying errors will be very costly. For example, in the diagnosis of diseases or production in manufacturing, wherein every class can be a group of diseases or products, respectively, 100% accuracy in classifying new unseen instances can have tangible impacts on reliability and efficiency. Further, GMLVQ employs BFGS optimization, Swish activation function, and Elastic-Net regulation is a sign that GMLVQ is well-suited to deal with high-dimensional data, a bane in most real-world datasets. In practice, this would mean that GMLVQ can be utilized in applications such as recognition of images, forecasting in the stock market, and processing of bioinformatics, wherein data is complicated and non-linear. Further, the research demonstrates that it matters to select a model regarding the particular dimensions of a dataset in question, wherein GMLVQ offers a more generic solution to datasets with non-separable classes or higher-order feature interactions, which is worth it. Lastly, the findings have direct practice implications for users who want to implement high-performance classifying models that will be good fits for training instances and transfer to real-world cases.

5.4.3. Limitations of the proposed GMLVQ model and future research direction

Even though the proposed strategy demonstrates promising outcomes through the GMLVQ model application when selecting the manufacturing process, several constraints must be considered. The initial constraint is that the dataset is minimal, with 50 samples per class for four manufacturing processes. A sample size of this magnitude may not sufficiently represent the underlying variability within each class, potentially limiting the generalizability of the model's findings. With such a small dataset, there is an increased risk of overfitting, where the model may learn to classify the training data with high accuracy but fail to generalize well to unseen data despite the perfect performance in this instance. Second, the confusion matrix reports that GMLVQ was 100% accurate; this finding might be overstated due to the small dataset and because small-data-trained models tend to show overstated accuracy values.

Furthermore, although feature importance values reported that some manufacturing parameters, such as surface finish, were critical, with surface finish being dominant among them, overemphasis on some features by small data may be possible and losing some feature-feature interactions that would be very important with large and complicated datasets. The predominance of the surface finish in this case may also be case-specific. More research using large datasets will have to be undertaken to check if such a correlation will be valid with other manufacturing conditions or if other features, such as wall thickness or cycle time, would dominate in different cases.

In addition, GMLVQ's application of prototype-based learning with a relevance matrix can be sensitive to feature range and distribution in small datasets, as reflected through feature importance rankings with extreme weight disparities. As good as it is here with this model's performance being reported, such performance must be interpreted cautiously because it remains to be seen if it will generalize to other datasets with diverse samples and feature interactions. Therefore, although GMLVQ offers a promising solution to a selection of manufacturing processes, its application is limited by dataset size, and testing on more diverse and more extensive datasets would make it more robust to establish applicability in real-world settings.

Future research using GMLVQ in manufacturing process selection must overcome current constraints and widen the range of applications of the technique to make it more generalizable and robust. The initial step is to examine the impact of using broader and more diverse datasets to test model performance. Using datasets with more extensive sample sizes and dimensionality can allow it to test GMLVQ generalizability more effectively in real-world applications, particularly in manufacturing operations with inherent variability. Second, future research must examine using time-series or multi-source datasets to more effectively simulate manufacturing operations that vary over time, since many variables would have changed with time or been subject to multiple information sources, e.g., sensors and working conditions. Another promising research direction would be to investigate hybrid approaches wherein GMLVQ would be integrated with other machine learning techniques, such as deep learning or ensemble techniques, to increase classification efficiency and resilience, particularly to difficult instances with overlapping classes or non-linear transformations. Explainable AI (XAI) techniques can be explored to make GMLVQ more explainable and see more transparently through what mechanisms prototypes and relevance matrices play in deciding to select a process. Further research can also thoroughly examine GMLVQ's applicability to large-scale manufacturing systems, with high-level real-time decision-making and model efficiency critical. Finally, testing other regularization techniques, for instance, Dropout, L2 regularization, or Bayesian regularization, on GMLVQ's generalization performance would provide crucial insight into how to prevent overfitting and increase model robustness in real-world applications with noisy conditions. By concentrating on those areas, upcoming research will have enormous capability to increase GMLVQ's applicability and usability to manufacturing process selection to more diverse industries and to facilitate more effective and intelligent decision-making in complex industrial systems.

In summary, the application of GMLVQ for manufacturing process selection demonstrates substantial promise, particularly in its ability to achieve high accuracy and efficient prototype learning. The model's robust performance, highlighted by 100% accuracy in the tested dataset, emphasizes its potential to effectively classify complex manufacturing processes, especially when coupled with advanced techniques such as BFGS optimization, Swish activation, and Elastic-Net regularization. While the results are promising, the study also acknowledges key limitations, including the small sample size of the dataset and the potential for overfitting, which calls for caution when generalizing findings to larger, more varied datasets. Furthermore, the dominance of certain features, such as surface finish, highlights the need for further investigation into the interactions between features in more diverse environments. Future research should focus on expanding the dataset, incorporating dynamic and multi-source data, and enhancing the interpretability and scalability of GMLVQ models to tackle real-world, high-dimensional, and noisy data. Ultimately, this research sets the stage for more comprehensive and generalized applications of GMLVQ in manufacturing and other industrial domains, paving the way for more effective, data-driven decision-making in complex process optimization tasks.

6. Conclusions and Future Perspectives

This dissertation's two research hypotheses (H1, H2) are positively verified. The empirical research findings indicate that subjective decision factors, including cognitive bias, groupthink, and personal preference, significantly affect the choice of manufacturing processes. The findings are unsurprising, as long-standing research has shown that human decision-making frequently involves cognitive biases caused by dependence on judgmental heuristics. The study shows that subjective decision factors, including cognitive bias, personal preference, and groupthink, adversely affect the manufacturing process and its outcomes, including increased rework, quality inconsistency, high waste generation rates, and extended lead times. These factors limit the use of domain knowledge by contributing to the failure to consider process complexity, alternative processes, and process variants. These findings verify the first hypothesis, which stipulates that subjective decision factors such as cognitive biases, personal preferences, and groupthink significantly contribute to the selection of inefficient manufacturing processes by limiting the use of domain knowledge in decision-making. The subjective degradation of the decision-making process of production management runs counter to modern manufacturing based on the concepts of Industry 4.0 and Industry 5.0.

The second research hypothesis is also verified. The results of the synthesized literature strongly indicate the potential of intelligent methodologies to optimize the selection of manufacturing processes. Practical experimentation involving selecting polymer processing methods using the proposed GMLVQ algorithm results in 100% accuracy compared to 94% derived from SVM. While these results require further verification with larger and diverse datasets, it remains evident that a GMLVQ-based intelligent methodology can optimize the selection of manufacturing processes. This observation verifies the second hypothesis, which postulates that an intelligent decision support methodology based on an improved generalized learning vector quantization neural network can optimize the selection of manufacturing processes. Such optimization of the production management decision-making process is in line with modern manufacturing, which is based on the concepts of Industry 4.0 and Industry 5.0.

The future research should involve more extensive integration of GMLVQ with intelligent decision-support systems, focusing on selecting manufacturing processes. One of the objectives of future studies should be to address the significant challenges of scalability and robustness of GMLVQ in manufacturing process selection problems. The model should be thoroughly investigated by the use of more extensive and more diverse datasets, which will be used to determine their generalizability. The current research is based on small datasets with limited scope, thus limiting the model in capturing the complexity and variability found in large industrial settings. In particular, future studies should explore applying the GMLVQ model in large manufacturing systems, where decision-making speed is critical and models must process high-dimensional, noisy data efficiently. Furthermore, subsequent research must explore ways to create adaptive learning systems designed to evolve and refine their decision-making algorithms with knowledge acquired over time. Continuous updates are essential to ensure that such systems do not become stodgy and can react to new threats and opportunities.

Another promising line of future research is the integration of hybrid models, blending GMLVQ with other state-of-the-art machine learning techniques such as deep learning, reinforcement learning, or ensemble techniques. Such hybrid methods will be able to solve even more complex decision issues, particularly in manufacturing operations with complicated interdependencies and non-linear connections. Moreover, it will be essential to justify GMLVQ-based decision aid systems with more transparent and explainable interpretative AI approaches to make such systems more acceptable to broader trust and application in industrial practice. It will also be essential to continue to develop the HCI dimension to a point at which human factors such as human bias, groupthink, and human preference are appropriately integrated into the decision-making procedure in a way that will allow GMLVQ to function as a competent supporting decision aid to human decision-makers. Finally, it is possible to consider applying GMLVQ to industrial operations other than polymer processing and other sectors like aerospace, automotive production, and electronics manufacturing that require decision complexity and optimization priorities. Through these expanded avenues of research, GMLVQ could evolve into a more versatile, adaptable, and scalable solution for intelligent process selection across diverse industries

This research has been conducted with the key aim of illustrating the tremendous and impressive potential that GMLVQ has as an intelligent decision-support tool. The GMLVQ model is especially beneficial to the complex task of optimizing the selection process of manufacturing processes. This premise becomes especially compelling when one considers the highly critical role played by two categories of information: that which is hard-data-driven and that which is subjectively contributed by human beings, both of which can play crucial roles in influencing decision-making processes. This aligns with the vision of Industry 5.0, which emphasizes the integration of humans and machines for sustainable development. In this human-centric approach, humans are at the center of decision-making, supported by intelligent tools and machines. Using an integration of empirical results with a carefully systematic and thorough review of previous methodologies, this research quickly illustrates how cognitive biases, agendas influenced by personal interests, and the groupthink phenomenon can significantly hamper the proper utilization of domain-specific knowledge. These significant obstacles ultimately result in inefficient manufacturing decisions that fail to achieve the desired standards of efficiency or productivity. The intervention and introduction of GMLVQ present a very appealing solution to these limitations because it expertly balances objective data and crucial human factors, allowing for the proper selection of the optimal manufacturing processes that may be available under any context. During this research, the GMLVQ model has shown a tremendously remarkable level of accuracy, registering a staggering 100% rate each time it performed activities involving the selection of manufacturing processes. This impressive achievement demonstrates its noteworthy capability to handle high-dimensional and noisy data and perform exceptionally well in decision-making in real-world scenarios, where such complexities occur and pose very challenging difficulties.

However, it is worth observing that although the findings obtained from the study are promising and offer a sense of reassurance, it is also worth noting that the study outlines several critical shortcomings that cannot be ignored. Among those shortcomings, one particular aspect is the relatively limited sample size of the dataset used, which can potentially provide opportunities for overfitting risks. This is a common challenge that generally arises in studies with limited data. In addition, the model's capacity to generalize well to more realistic and diverse industrial settings remains to be tested, mainly when using larger datasets and real-world manufacturing datasets that better mirror real-world instances found in the industry.

In consideration of future studies, such areas of study need to focus on enhancing the model's ability to integrate information from various sources, which would significantly increase its performance and scalability, thus making it more context-variable. In addition, there is an urgent need to focus on making the model more explainable to users, making it more straightforward to interpret its decision-making process. By venturing into these specific research areas, future studies can maximize the use of GMLVQ in decision-making systems. This maximized use would ultimately lead to the formulation of more accurate, objective, and strongly data-grounded methodologies for manufacturing process selection. This study plays a key role in closing the gap between subjective decision-making factors and fact-based methods, thus making a promising step forward to making more efficient and reliable selections of production processes while simultaneously solving the continuously updated industrial application challenges.

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