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# MDSAA

Master's Degree Program in  
**Data Science and Advanced Analytics**

**Enabling Data-Driven Transformation for Small and Medium Enterprises  
through Collaborative AutoML (Design and Implementation)**

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data  
Science and Advanced Analytics.

**NOVA Information Management School**  
**Instituto Superior de Estatística e Gestão de Informação**

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THROUGH COLLABORATIVE AUTOML**  
**(Design and Implementation)**

by

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Master Thesis presented as partial requirement for obtaining the Master's degree in Data Science and Advanced Analytics, with a specialization in Business Analytics

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## **STATEMENT OF INTEGRITY**

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

*[Lisbon, 08<sup>th</sup> June 2024]*

## ABSTRACT

This thesis addresses the critical need for accessible machine learning solutions within small and medium-sized enterprises (SMEs) by developing a collaborative AutoML framework. SMEs often lack the data science expertise and resources necessary to implement advanced machine learning algorithms, which hinders their ability to compete in a data-driven market. This research identifies the unique challenges faced by SMEs in adopting AI/ML technologies and proposes a practical framework to overcome these barriers. Utilizing a Design Science Research (DSR) approach, a thorough literature review was conducted, followed by the development of the AutoML framework, which was then validated through expert interviews. The framework focuses on aligning AI/ML initiatives with business objectives, managing data quality, customizing AutoML pipelines, and ensuring resource efficiency and data privacy. By democratizing access to machine learning, the proposed framework aligns with several United Nations Sustainable Development Goals: SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 10 (Reduced Inequalities), enabling SMEs across various industries to leverage AI for innovation and growth. The findings highlight the significant potential of AutoML to empower non-technical users within SMEs, facilitating data-driven decision-making and enhancing operational efficiency. The framework serves as a comprehensive guide for SMEs to harness the power of machine learning, offering practical steps from initial strategy to continuous improvement. This work contributes to the broader AI/ML literature by providing actionable insights and a validated framework tailored to the specific needs of SMEs, ultimately fostering a more inclusive and innovative technological landscape.

## KEYWORDS

AutoML; Small and Medium Enterprises; Data-driven; Collaborative Framework; Sustainable Development

### Sustainable Development Goals (SDG):



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## LIST OF ABBREVIATIONS AND ACRONYMS

|               |                                                                    |
|---------------|--------------------------------------------------------------------|
| <b>AutoML</b> | Automated Machine Learning                                         |
| <b>AI</b>     | Artificial Intelligence                                            |
| <b>DEHB</b>   | Differential Evolution combined with HyperBand                     |
| <b>DSR</b>    | Design Science Research                                            |
| <b>GAN</b>    | Generative Adversarial Network                                     |
| <b>NAS</b>    | Neural Architecture Search                                         |
| <b>PRISMA</b> | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| <b>RPA</b>    | Robotic Process Automation                                         |
| <b>SMAC</b>   | Sequential Model-based Algorithm Configuration                     |
| <b>TPOT</b>   | Tree-based Pipeline Optimization Tool                              |

# 1. INTRODUCTION

## 1.1 BACKGROUND AND PROBLEM IDENTIFICATION

In an era characterized by rapid technological advancements and digital disruption, Small and Medium Enterprises (SMEs) are confronted with a transformative imperative to harness data-driven practices for survival and success. While large enterprises have been quick to adopt sophisticated data analytics and machine learning solutions, SMEs often encounter formidable barriers due to limited resources, technical expertise, and the complexities associated with implementing such technologies. According to Ramos and Oliveira (2020), the unique challenges faced by SMEs in integrating data-driven strategies hinder their ability to remain competitive in an increasingly data-centric landscape. These enterprises often lack the infrastructure to house large-scale data analytics teams, making it crucial to explore novel avenues that democratize access to advanced analytics capabilities.

Addressing this context, the convergence of Automated Machine Learning (AutoML) and collaborative approaches emerges as a promising solution to propel SMEs into the realm of data-driven transformation. AutoML has gained traction for its capacity to automate intricate stages of the machine learning pipeline, minimizing the demand for in-depth technical expertise. However, current AutoML solutions predominantly target larger organizations, neglecting the specific requirements and collaborative nature intrinsic to SMEs' operations. Chang, Zhang, and Hussain (2019) emphasize the significance of customized AutoML tools tailored to SMEs' needs, asserting that a collaborative AutoML framework could bridge the gap between technical novices and sophisticated data analytics, thereby enhancing SMEs' capacity to derive meaningful insights from their data.

This thesis, "Enabling Data-Driven Transformation for Small and Medium Enterprises (SMEs) through Collaborative AutoML," strives to fill this research gap by conceptualizing, designing, and implementing a collaborative AutoML tool that addresses the distinct challenges faced by SMEs. Drawing inspiration from the works of Ramos and Oliveira (2020) and Chang et al. (2019), this study seeks to empower SMEs with an accessible and user-friendly framework that not only automates complex machine learning processes but also fosters collaboration among various stakeholders. By doing so, SMEs can leverage their domain knowledge, extract valuable insights, and drive data-driven decision-making, ultimately propelling their digital transformation journey and contributing to economic growth.

## 1.2 RESEARCH GAP

Despite the increasing recognition of the significance of AutoML in facilitating data-driven transformation, there is a noticeable research gap concerning the design and implementation of collaborative AutoML tools explicitly tailored to the unique needs and constraints of Small and Medium Enterprises (SMEs). While existing literature, such as Ramos and Oliveira (2020), acknowledges the challenges that SMEs face in adopting data-driven practices, few studies delve into the specific intricacies of creating collaborative AutoML solutions that cater to these enterprises. Moreover, research by Chang, Zhang, and Hussain (2019) focuses largely on the automation aspect of AutoML, without adequately addressing the collaborative dimension vital for SMEs' operations. As a result, a

comprehensive understanding of how collaborative AutoML can effectively democratize data-driven practices within SMEs remains underexplored. This research gap presents an opportune area for investigation, providing an avenue to design and evaluate a collaborative AutoML tool that aligns with the unique characteristics and challenges faced by SMEs during their digital transformation journey.

As the thesis "Enabling Data-Driven Transformation for Small and Medium Enterprises (SMEs) through Collaborative AutoML" embarks on unearthing solutions to the research gap, it aims to contribute to the evolving landscape of data-driven transformation by catering to the specific needs of SMEs. The proposed research endeavors to conceptualize and assess a collaborative AutoML tool that not only automates machine learning processes but also fosters collaboration among stakeholders within SMEs. By addressing this gap, the thesis seeks to illuminate how collaborative AutoML can be harnessed to effectively democratize advanced analytics within the SME sector, thus serving as a catalyst for their digital transformation efforts and broader economic impact.

Furthermore, this research gap prompts the formulation of key research questions.

RQ1: how can a collaborative AutoML tool be effectively designed and tailored to the context of SMEs, considering their resource constraints and collaborative requirements?

RQ2: What impact does the implementation of such a collaborative AutoML tool have on SMEs' ability to become data-driven, enhance decision-making processes, and contribute to their overall growth? And finally,

RQ3: What best practices and guidelines can be established for the responsible integration of collaborative AutoML tools within the unique operational and resource constraints of SMEs?

These questions are poised to guide the research efforts in uncovering the potential of collaborative AutoML in driving data-driven transformation among SMEs, filling an important gap in the current literature and offering practical insights for both academia and industry.

### **1.3 STUDY OBJECTIVES**

This research aims to help to answer the research question by designing a collaborative AutoML framework that allows SMEs to harness the power of advanced machine learning algorithms without extensive data science expertise.

To achieve the main goal, the following objectives were defined:

- Make a comprehensive Literature Review on AutoML tools.
- Conduct a comprehensive survey and needs analysis to identify the specific AutoML requirements and challenges faced by SMEs during their digital transformation process.
- Design a collaborative AutoML framework that allows SMEs to harness the power of advanced machine learning algorithms without extensive data science expertise.
- Validate the framework.

## 1.4 STUDY RELEVANCE AND IMPORTANCE

The thesis topic, "Enabling Data-Driven Transformation for Small and Medium Enterprises (SMEs) through Collaborative AutoML," holds significant importance and relevance in today's rapidly evolving digital landscape. Small and Medium Enterprises (SMEs) form the backbone of economies worldwide, driving innovation, generating employment, and contributing to economic growth. However, they often face formidable challenges in adopting data-driven practices due to limited resources and technical expertise. The proposed collaborative AutoML tool has the potential to bridge this gap by providing SMEs with an accessible platform to harness the power of data analytics and machine learning. As SMEs transform into data-driven entities, their operational efficiency, decision-making capabilities, and competitive edge can be significantly enhanced. This, in turn, not only uplifts individual businesses but also fuels economic growth by fostering a culture of innovation and adaptability within SMEs, aligning with the broader goals of digital transformation outlined by organizations like the World Bank.

Furthermore, the relevance of this research extends beyond economic considerations. A robust collaboration between academia and industry, as demonstrated in the development of the collaborative AutoML tool, can lead to the democratization of advanced technologies. By empowering SMEs with accessible and user-friendly tools, the project contributes to societal well-being by unlocking opportunities for a wider range of stakeholders to engage with data-driven decision-making processes. This democratization aligns with the broader ethos of inclusive development, promoting social equity and ensuring that technology benefits all strata of society. The collaborative AutoML tool's potential impact on tourism, a sector heavily reliant on data-driven insights for strategic planning and customer engagement, cannot be underestimated. Through efficient analysis of customer preferences and trends, SMEs within the tourism industry can enhance their services, attract more visitors, and contribute positively to local economies.

From a scientific and knowledge perspective, the development of a collaborative AutoML tool for SMEs introduces an innovative approach to address real-world challenges. By combining insights from Ramos and Oliveira's (2020) systematic review and Chang et al.'s (2019) survey on AutoML, this project introduces a tailored solution that is notably missing in the current landscape. The outcomes of this research will contribute to the expansion of knowledge in the field of AutoML and its applications, while also providing a practical framework that bridges the gap between academia and industry. Moreover, the project's contributions align with the overarching goals of responsible AI and technological innovation, providing a blueprint for the development of tools that empower organizations without compromising ethical considerations.

Additionally, this research aligns with the United Nations Sustainable Development Goals (SDGs), specifically SDG 9: Industry, Innovation, and Infrastructure, and SDG 8: Decent Work and Economic Growth. By fostering innovation through the adoption of data-driven practices in SMEs, this project contributes to the development of resilient infrastructure and sustainable industrialization (SDG 9). Additionally, the focus on empowering SMEs – a vital source of employment and economic growth – aligns with SDG 8's emphasis on promoting inclusive and sustainable economic growth, full and productive employment, and decent work for all.

In conclusion, the importance and relevance of this thesis topic extends beyond the immediate economic benefits for SMEs, as it also contributes to the broader goals of sustainable development outlined by the United Nations. By aligning with these global objectives, the collaborative AutoML tool not only enhances SMEs' data-driven capabilities but also supports international efforts to create a more equitable, innovative, and prosperous world.

## **2. METHODOLOGY**

In this research, we have adopted the Design Science Research (DSR) methodology for its inherent suitability in the development of a practical and innovative artifact, specifically a collaborative AutoML framework tailored to the unique requirements of Small and Medium Enterprises (SMEs). As defined by Brock, Hevner, and Maedche (2020), DSR is fundamentally a problem-solving paradigm that aims to enhance human knowledge through the creation of innovative artifacts. In this context, knowledge is not only derived from designing the artifact but also from rigorous testing and evaluation, ultimately determining its impact on the problem it addresses.

DSR is a particularly apt choice for this research due to several key advantages. Firstly, it provides a well-structured approach for designing and systematically testing the collaborative AutoML tool, ensuring that the resulting artifact is both theoretically sound and practically viable. Secondly, its experimental nature encourages iterative development with predefined evaluation steps, enhancing the likelihood of real-world adoption and use, as emphasized by Hevner et al. (2004).

Moreover, DSR aligns with the core objectives of this research, which involve creating a tangible solution to the challenges SMEs face in adopting data-driven practices. The iterative approach advocated by DSR is especially beneficial in addressing the dynamic needs of SMEs in the digital age. This methodology also places a strong emphasis on practical problem-solving, which resonates with the aim of this research in creating a collaborative AutoML framework that directly addresses the challenges faced by SMEs.

### **2.1 DESIGN SCIENCE RESEARCH**

Design Science Research is a research methodology particularly relevant to the Information Systems domain and related fields. It stands apart from traditional research paradigms by emphasizing the creation of novel artifacts to address tangible real-world challenges. Unlike traditional research, which seeks to understand and explain phenomena, DSR focuses on developing and evaluating solutions to specific issues (Hevner et al., 2004).

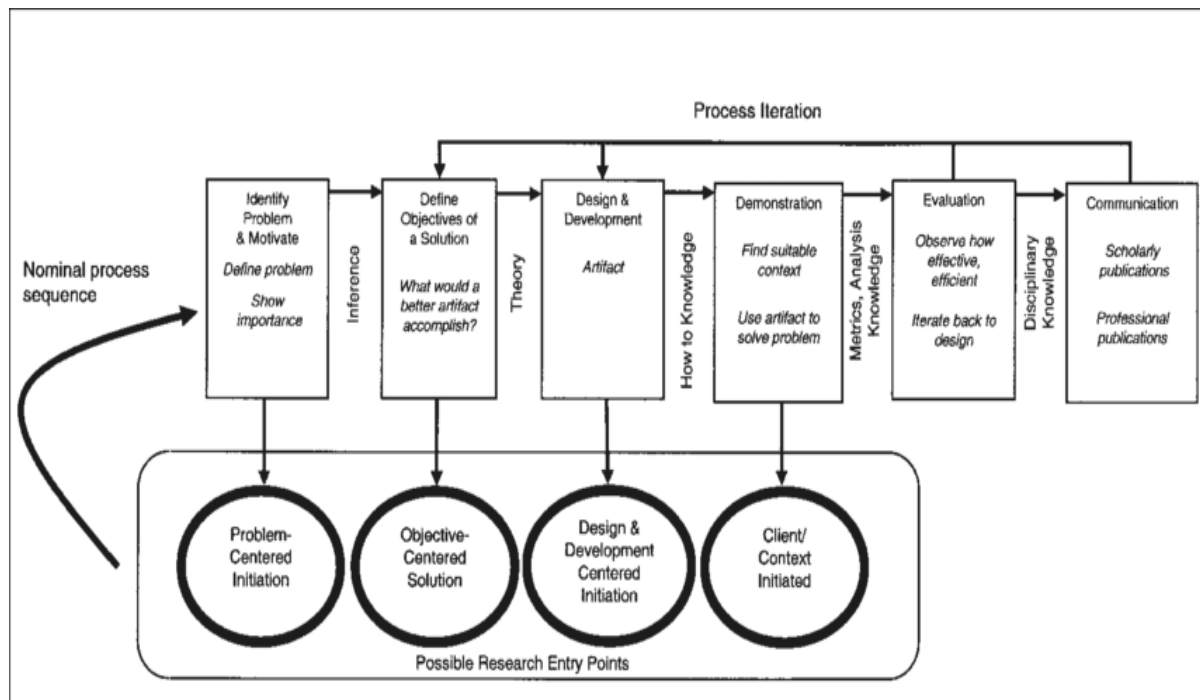


Figure 1: Design Science Research according to Peffers et al. (2008)

DSR operates under a set of fundamental principles:

**Problem-Solution Orientation:** DSR initiates with the recognition of a practical problem or opportunity. Researchers embark on designing, developing, and evaluating a solution to tackle this problem. In this research, the problem at hand pertains to the limited data-driven capabilities of Small and Medium Enterprises (SMEs), and the proposed solution is the collaborative AutoML framework tailored to their specific needs.

**Iterative Process:** DSR follows a well-defined iterative process that encompasses design, development, and evaluation. This iterative approach allows for continual refinement and enhancement of the developed artifact, ensuring its alignment with the evolving requirements of SMEs.

**Contribution to Practice:** The ultimate objective of DSR is to create artifacts that are not just theoretically grounded but also possess practical utility. DSR places strong emphasis on translating research findings into practical applications, making it highly relevant to addressing real-world challenges (March & Smith, 1995).

This methodology guides the research on enabling data-driven transformation for SMEs through the development and implementation of a collaborative AutoML framework. It provides a structured framework for problem identification and motivation, definition of objectives for the solution, design and development of the framework, its demonstration, rigorous evaluation, and effective communication of the findings and the artifact's practical implications.

## 2.2 RESEARCH STRATEGY

In the dynamic landscape of contemporary business, where data-driven practices are a cornerstone of success, the application of Design Science Research (DSR) serves as a strategic research strategy to address the pressing challenge of empowering Small and Medium Enterprises (SMEs) in their journey towards data-driven transformation. Leveraging the DSR framework diagram by Hevner et al. (2004) and the DSR process image by Peffers et al. (2007), this research navigates the systematic steps of DSR to create a collaborative Automated Machine Learning (AutoML) framework tailored specifically for SMEs.

For this master's thesis, the research strategy is anchored in the principles of Design Science Research (DSR), a methodology well-suited for creating innovative artifacts to address real-world problems. Leveraging the DSR approach outlined by Hevner et al. (2004), this research will systematically navigate each phase, from problem identification to the development and evaluation of a collaborative Automated Machine Learning (AutoML) framework tailored to the needs of Small and Medium Enterprises (SMEs). This comprehensive strategy is designed to produce valuable insights and practical solutions to enable data-driven transformation for SMEs.

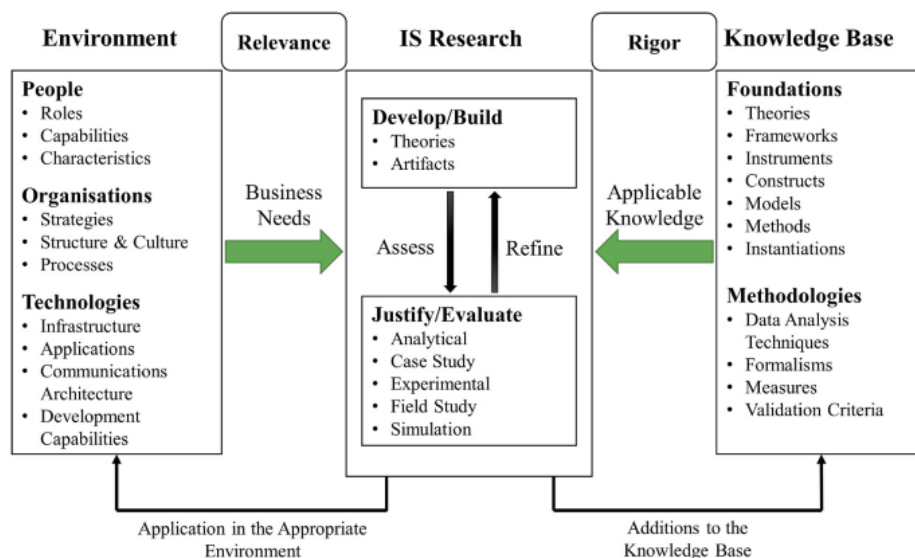


Figure 2: DSR Framework Diagram by Hevner et al. (2004)

This research employs a Design Science Research (DSR) approach, beginning with the identification and motivation of the unique challenges faced by SMEs in adopting data-driven practices. Recognizing the critical role SMEs play in the modern digital landscape and their potential for economic growth forms the foundation of this study (Smith, 2020). Following this, clear and specific objectives are defined to guide the development of a collaborative AutoML framework aimed at empowering SMEs to effectively harness AutoML techniques and enhance their data-driven decision-making processes (Rogers et al., 2019). The design and development phase transforms these objectives into a tangible AutoML framework tailored for SMEs. This involves creating user interfaces, algorithms, and integrating with existing systems, following principles of practical design-oriented research (Hevner et al., 2004). Key activities include conducting a thorough literature review to examine existing AutoML tools and create a matrix outlining their applicability in SMEs, collecting qualitative feedback through interviews and surveys with SMEs to refine the

framework, researching existing AutoML platforms to identify best practices and areas for improvement, conceptualizing a collaborative AutoML framework with comprehensive guidelines to support SME adoption, and implementing the collaborative AutoML tool using agile methodologies to ensure flexibility and responsiveness to SMEs' evolving requirements.

Due to time constraints, the demonstration phase originally planned for showcasing the collaborative AutoML framework's functionalities and capabilities through structured presentations and hypothetical scenarios was not completed. However, the evaluation phase proceeded with rigorous assessments of the AutoML framework's effectiveness and impact on SMEs' decision-making processes. This evaluation involved both qualitative and quantitative assessments (Peffer et al., 2007). Qualitative assessments included in-depth interviews and case studies documented in the annexes, which provided rich insights into how SMEs perceive and utilize the AutoML tool. Quantitative assessments utilized statistical analyses and performance metrics to measure improvements, offering empirical evidence of the framework's benefits over traditional manual machine learning approaches.

Although the research findings and collaborative AutoML framework were not published in academic journals or presented at conferences due to time constraints, the results of the interviews and evaluations are documented in the annexes. These findings contribute to the ongoing discourse in the field and offer practical insights for future research and application. The structured feedback gathered through expert interviews also ensured the practical feasibility of the proposed solution, highlighting areas for further refinement and potential industry adoption. In summary, this comprehensive research strategy, guided by the DSR framework and international best practices, aims to develop a valuable collaborative AutoML framework that addresses the challenges SMEs face in their data-driven transformation journey. The methodology includes conducting a comprehensive literature review on AutoML tools, performing a detailed survey and needs analysis to identify specific requirements and challenges faced by SMEs, designing a collaborative AutoML framework to enable SMEs to leverage advanced machine learning algorithms without extensive data science expertise, and validating the framework through qualitative and quantitative evaluations. Despite not completing the demonstration and broader communication phases, the research provides a robust foundation for future enhancements and practical applications in SMEs.

### 3. ENVIRONMENT ANALYSIS

Small and Medium-sized Enterprises (SMEs) have been selected as the focus of this study due to their significant role in driving economic growth, innovation, and employment across various industries. This sector's diversity and inherent challenges provide a fertile ground for examining the adoption and impact of AutoML technologies. Drawing on my practical experience working within SMEs and public-private collaboration institutions, I bring a unique perspective that blends real-world observations with theoretical insights. This dual perspective allows for a comprehensive analysis of the SME environment, highlighting both macro-level trends and micro-level actions. Through illustrative examples and case studies, this analysis aims to offer a holistic view of how AutoML can transform SMEs, making advanced machine learning accessible and impactful for businesses of all sizes.

#### 3.1 SME DEFINITIONS

Small and Medium Enterprises (SMEs) constitute a vital segment of the global business ecosystem. Definitions of SMEs vary across countries and regions, often based on factors such as employee count, revenue, or asset value. For instance, the European Union defines SMEs based on employment numbers, distinguishing micro, small, and medium-sized enterprises (European Commission, 2020). Understanding these definitions provides a foundational understanding of the heterogeneous SME landscape.

In North America, SME definitions often revolve around metrics such as employee count, annual revenue, or a combination of factors. For example, in the United States, the Small Business Administration (SBA) defines SMEs based on industry standards that may vary by sector (Small Business Administration, n.d.). The criteria can range from the number of employees (typically under 500) to revenue thresholds.

In the realm of management consulting, definitions of SMEs might also differ slightly. Consultants often categorize SMEs based on their operational and financial parameters. These definitions might emphasize factors such as the complexity of operations, scale, market reach, or annual turnover. Management consulting frameworks might tailor their definitions to provide more relevant insights for their strategic advisory and operational support (Curusku, 2018).

Different sectors or countries further specify SME definitions to suit their economic landscapes and needs. For instance, in the manufacturing sector, SMEs might be characterized by production capacity or technological sophistication. Countries such as China, India, or Japan have their unique definitions based on economic conditions and industry structures (Li et al., 2020). For example, in China, SMEs might be categorized based on registered capital, production output, or employment numbers (Zhang et al., 2019).

Understanding these diverse definitions is crucial in assessing the scope, impact, and support systems available for SMEs. The heterogeneous landscape of definitions across regions and sectors highlights the multifaceted nature of SMEs and underscores the necessity for tailored strategies, policies, and tools to support their growth and development.

### **3.2 CHALLENGES FACED BY SMEs IN THE GLOBAL ECONOMY**

SMEs face multifaceted challenges in competing on a global scale. Resource constraints, limited access to capital, restricted technological capabilities, and difficulties in market penetration are among the significant hurdles (Deloitte, 2019). Their agility often competes with larger corporations' scale, impacting their ability to innovate and adapt swiftly to market changes.

It's true that every sector has its own challenges, and we will not only try to discuss the challenges facing SMEs in the global economy but also to be aware of different challenges faced by SMEs operating in different sectors.

SMEs in the manufacturing sector often grapple with technological obsolescence and the high cost of upgrading machinery and production processes (Nusser & Heumann, 2018). The adoption of advanced manufacturing technologies, such as Industry 4.0, becomes a challenge due to the significant initial investment required. In the service sector, especially in fields like healthcare and education, SMEs face regulatory complexities and compliance issues (Büschgens et al., 2013). Stringent regulations increase administrative burdens, hindering their ability to compete effectively.

For SMEs in rural areas or agricultural industries, challenges include access to markets, transportation infrastructure, and limited adoption of modern farming techniques (Rapsomanikis, 2015). These challenges often hamper their ability to reach wider markets and leverage modern technology.

### **3.3 ROLE OF DATA SCIENCE AND AI IN GLOBAL COMPETITION**

In the current global landscape, data science and Artificial Intelligence (AI) have become key differentiators for business competitiveness. They empower companies to derive insights, optimize operations, and enhance decision-making. Large corporations have leveraged these technologies, creating a competitive gap between them and SMEs.

Data science and AI empower businesses to leverage data effectively, extracting valuable insights that aid in informed decision-making. Predictive analytics models enable companies to forecast trends, customer behavior, and market shifts. Such insights are crucial in formulating strategies for product development, marketing campaigns, and resource allocation (Lohr, 2012).

AI-driven automation optimizes operational processes, reducing manual intervention and enhancing efficiency. Robotic Process Automation (RPA) streamlines repetitive tasks, improving accuracy and speed in various workflows. Additionally, AI algorithms facilitate dynamic resource allocation and inventory management, minimizing waste and maximizing output (Rouse, 2020).

Data-driven AI applications enable businesses to understand and cater to individual customer preferences. Recommendation systems, powered by machine learning algorithms, personalized product recommendations and services. Moreover, AI-driven chatbots and

virtual assistants enhance customer service by providing instant, round-the-clock support, thereby boosting customer satisfaction and loyalty (Bughin et al., 2018).

AI-driven innovation accelerates product development cycles. Machine learning algorithms aid in ideation, prototyping, and even predictive modeling for product performance. This allows companies to introduce innovative solutions faster to the market, gaining a competitive edge (Khobragade & Thool, 2020).

Data science and AI bolster risk assessment and cybersecurity efforts. Predictive analytics models assess potential risks in financial markets or supply chains. AI algorithms also identify anomalies and potential threats, fortifying cybersecurity measures to safeguard sensitive data and systems (Bansal & Pal, 2018).

AI facilitates real-time data analysis, enabling businesses to respond swiftly to market changes. AI-driven insights aid in agile decision-making, allowing companies to adapt strategies and operations quickly in response to shifting market demands or unforeseen circumstances (Wamba et al., 2015).

The amalgamation of data science and AI empowers businesses to gain a competitive edge by optimizing operations, enhancing customer experiences, fostering innovation, and enabling agile responses to market dynamics, thereby securing a significant advantage in the global business landscape.

### **3.4 AUTOML AND ITS RELEVANCE FOR SMEs' GLOBAL COMPETITION**

AutoML (Automated Machine Learning) emerges as a pivotal tool for SMEs to bridge the gap and compete more effectively. It streamlines the machine learning process, automating complex tasks, and minimizing the need for extensive technical expertise (Hutter et al., 2019). By enabling SMEs to harness AI capabilities without a deep technical background, AutoML holds immense potential to level the playing field.

AutoML offers several tangible benefits for Small and Medium Enterprises (SMEs) that go beyond merely streamlining machine learning processes.

**Cost Reduction and Resource Management:** AutoML significantly reduces the resource burden on SMEs by automating various complex aspects of the machine learning pipeline. It minimizes the need for highly specialized data scientists or machine learning engineers, reducing labor costs and allowing existing staff to focus on higher-value tasks (Feurer et al., 2015).

**Time Efficiency and Accelerated Decision-Making:** By automating the machine learning pipeline, AutoML accelerates the process of model development, deployment, and optimization. This speed enables SMEs to make data-driven decisions swiftly and stay agile in responding to market dynamics. Quick iteration and deployment cycles become feasible, enhancing the agility of SMEs in highly competitive markets (Hutter et al., 2019).

**Democratization of AI Capabilities:** AutoML tools democratize access to AI capabilities within SMEs. These tools abstract the complexities of machine learning algorithms, making them accessible to non-technical staff or domain experts within the organization. This

democratization ensures that decision-makers across various departments can leverage AI-driven insights without an in-depth technical understanding (Chen et al., 2018).

**Improved Accuracy and Performance:** AutoML tools utilize advanced algorithms to optimize machine learning models automatically. By leveraging techniques such as hyperparameter tuning, feature selection, and model selection, these tools can often achieve comparable or even superior performance to manually crafted models. This improved accuracy enhances the quality of insights derived from data analysis, leading to better decision-making for SMEs (López et al., 2016).

**Scalability and Adaptability:** The automated nature of AutoML enables SMEs to scale their machine learning efforts more efficiently. As the business grows or the data volume increases, AutoML tools can adapt and handle larger datasets or more complex tasks, ensuring that the AI infrastructure grows in tandem with the business (Hutter et al., 2019).

These advantages demonstrate how AutoML serves as a strategic enabler for SMEs, empowering them to compete effectively by harnessing the power of AI-driven insights, cost-effectiveness, and accelerated decision-making capabilities.

### **3.5 EXISTING AUTOML TOOLS, THEIR VARIANCES, AND THE IDENTIFIED GAPS.**

Several AutoML tools currently exist, each with their unique features, capabilities, and limitations.

This section aims to contextualize the challenges and opportunities within which SMEs operate, paving the way for understanding the necessity of a collaborative AutoML framework designed explicitly for SMEs.

Some of the existing AutoML Tools are as follows:

**Google's AutoML:** Known for its user-friendly interface, it offers customization options for machine learning models but tends to be resource-intensive and cost-prohibitive for many SMEs (Google Cloud AutoML, n.d.).

**H2O.ai:** This platform emphasizes its open-source nature and scalability, catering to diverse machine learning needs. However, its technical complexity and extensive customization might hinder SMEs lacking specialized expertise (H2O.ai, n.d.).

**DataRobot:** Recognized for its automation capabilities, it streamlines model creation. However, its complexity and costs can be deterrents for SMEs without a robust technical infrastructure (DataRobot, n.d.).

**Microsoft Azure's AutoML:** Offers diverse pre-built machine learning models and automated workflows. While providing ease of use, its scalability and pricing may not suit the limited budgets of SMEs (Microsoft Azure AutoML, n.d.).

These platforms vary in terms of usability, customization, pricing structures, and scalability. Some emphasize ease of use, while others prioritize flexibility and model performance. However, the overarching similarity is their focus on catering to larger enterprises with considerable resources and established technical teams.

Despite the availability of these tools, SMEs face a significant gap in access and usability. The existing AutoML solutions often require substantial technical expertise, financial investment, and infrastructure, which may not align with SMEs' realities (Feurer et al., 2015). SMEs typically lack the resources to navigate the complexities of these tools effectively.

The demand for dedicated AutoML tools tailored to SMEs arises from the unique challenges they face. Such tools should prioritize simplicity, affordability, ease of use, and collaborative functionalities (Abadi et al., 2016). They need to offer intuitive interfaces, require minimal technical expertise, be cost-effective, and facilitate collaborative decision-making among non-technical and technical stakeholders within SMEs.

The absence of tools designed specifically for SMEs' needs underscores the critical requirement for a collaborative AutoML framework. This framework should cater explicitly to SMEs' resource limitations, technical skill gaps, and the need for user-friendly yet powerful machine learning solutions.

## **4. LITERATURE REVIEW**

The burgeoning field of automated machine learning (AutoML) presents a transformative potential for businesses, particularly within the dynamic landscape of SMEs. This literature review delves into the current state of AutoML adoption, exploring the technological advancements, practical applications, and existing challenges. By synthesizing findings from diverse studies and industry reports, this review aims to build a comprehensive foundation that informs the development of an innovative AutoML framework tailored for SMEs. The insights gathered will shed light on how AutoML can democratize access to advanced machine learning, driving efficiency, innovation, and competitive advantage for small and medium-sized enterprises.

### **4.1 AUTOMATED MACHINE LEARNING**

#### **4.1.1 CONCEPTS**

Auto Machine Learning (AutoML) is a revolutionary approach designed to automate the process of machine learning model selection, feature engineering, and hyperparameter tuning. Various definitions highlight AutoML's essence. For instance, Feurer et al. (2015) describes it as a framework automating the machine learning pipeline, enabling non-experts to build high-performing models efficiently. Similarly, Kotthoff et al. (2017) emphasize its ability to automate the model selection and configuration processes, allowing practitioners to focus on the application context rather than the technical intricacies. These definitions underscore AutoML's core goal: simplifying complex machine learning tasks for broader accessibility.

#### **4.1.2 BENEFITS AND DRAWBACKS**

##### **Benefits**

AutoML solutions in larger corporations provide an accelerated model development pipeline (Feurer et al., 2015). These tools enhance scalability by expediting the deployment of machine learning models across diverse departments or products. They also contribute to time efficiency, allowing data science teams to focus on higher-level tasks due to reduced model development durations (Kotthoff et al., 2017).

For SMEs, AutoML tools offer accessibility and democratization of AI capabilities (Hutter et al., 2019). These tools democratize machine learning tasks, enabling non-experts within SMEs to engage in such activities, fostering innovation and decision-making without an extensive data science background. Additionally, AutoML aids in resource efficiency, minimizing the need for a specialized data science team and allowing rapid prototyping to facilitate quick decision-making (Feurer et al., 2015).

## Drawbacks

Limitations in customization can arise in automated processes within AutoML, restricting fine-tuning and customization of models specific to complex business environments (Hutter et al., 2019). Moreover, there might be concerns regarding performance, as automatically generated models might lag manually tuned models, particularly in domains requiring specialized feature engineering or extensive domain knowledge (Feurer et al., 2015).

While AutoML brings accessible AI capabilities to SMEs, an initial investment might serve as a barrier, especially when immediate benefits are not immediately apparent (Hutter et al., 2019). Resource limitations also pose challenges, as SMEs might face constraints in fully optimizing and leveraging AutoML tools due to resource scarcity, potentially limiting their efficacy (Feurer et al., 2015).

In essence, AutoML offers accelerated model development and accessibility across various company sizes. However, considerations of customization, performance, initial investments, and resource constraints are pivotal when evaluating the applicability and optimization of AutoML tools, particularly within SME contexts.

### 4.1.3 MAIN APPROACHES AND TECHNIQUES

The landscape of Automated Machine Learning (AutoML) has evolved significantly over the years, with traditional techniques laying the groundwork for more advanced and emerging trends in the field. This section introduces the primary approaches and techniques that have defined the trajectory of AutoML, contrasting established methodologies with the latest innovations.

#### 4.1.3.1 TRADITIONAL TECHNIQUES

The emergence of open-source Automated Machine Learning (AutoML) solutions has democratized access to advanced data science capabilities, empowering businesses and researchers alike to build and optimize machine learning models with minimal manual intervention. This section highlights some of the most prominent open-source AutoML libraries and tools that have revolutionized traditional machine learning workflows by focusing on algorithm selection and hyperparameter optimization.

**AutoWEKA:** An approach concurrently selecting machine learning algorithms and their hyperparameters, yielding robust models across diverse datasets in conjunction with the WEKA package (Kotthoff et al., 2017).

**Auto-sklearn:** An extension of AutoWEKA using Python's scikit-learn library, providing a seamless integration for regular scikit-learn classifiers and regressors (Feurer et al., 2015).

**Auto-PyTorch:** Built on PyTorch, this approach optimizes hyperparameters and neural architecture in deep learning frameworks (Nalesnik et al., 2020).

**SMAC3:** A Python-based re-implementation of the Sequential Model-based Algorithm Configuration (SMAC), enhancing algorithm configuration efficiency (Hutter et al., 2011).

DEHB (Differential Evolution combined with HyperBand): Merges Differential Evolution and HyperBand to optimize hyperparameters, known for its effectiveness in hyperparameter optimization (Falkner et al., 2018).

AutoML-Guide: An approach developed by Google Research, offering automated selection and optimization of machine learning architectures and hyperparameters (Google Research, 2018).

TPOT (Tree-based Pipeline Optimization Tool): An AutoML library that uses genetic programming to optimize machine learning pipelines, aiding in feature selection, data preprocessing, and model selection (Olson et al., 2016).

MLBox: A multi-layered AutoML library, incorporating both high-level and low-level APIs for machine learning tasks, supporting data cleaning, feature selection, and model tuning (MLBox Developers, 2017).

AutoKeras: An open-source AutoML system based on Keras, offering an easy-to-use interface for constructing and optimizing deep learning models (Jin et al., 2019).

AutoGluon: A machine learning library supporting diverse model selection, hyperparameter tuning, and data processing for both tabular and image data (Chen et al., 2021).

H2O AutoML: An AutoML interface in the H2O machine learning platform, providing automatic model selection, hyperparameter tuning, and deployment (H2O.ai, 2021).

#### **4.1.3.2 PROPRIETARY TOOLS**

While open-source AutoML tools have paved the way for democratizing machine learning, proprietary solutions have also emerged as key players in advancing the field. Offering sophisticated features, streamlined workflows, and robust support, these tools often cater to enterprise-level requirements and provide more specialized capabilities. Here, we discuss some of the prominent proprietary AutoML tools shaping the machine learning landscape:

DataRobot: A leading enterprise-grade AutoML platform, DataRobot automates end-to-end model development and deployment. With advanced feature engineering, hyperparameter tuning, and model management, DataRobot enables organizations to accelerate AI initiatives (DataRobot, 2021).

Google Cloud AutoML: Google Cloud AutoML provides a suite of products for training custom machine learning models on high-quality datasets. Offering pre-trained models, a user-friendly interface, and scalability, Google Cloud AutoML simplifies the model development process (Google Cloud, 2021).

Databricks AutoML: Integrated within the Databricks Lakehouse Platform, Databricks AutoML automates feature engineering, model selection, and hyperparameter tuning. Powered by Apache Spark, Databricks AutoML helps data teams scale workflows while maintaining governance and security standards (Databricks, 2022).

Amazon SageMaker AutoPilot: Part of Amazon Web Services (AWS), SageMaker AutoPilot automates machine learning tasks, such as feature engineering, model selection, and

hyperparameter optimization. SageMaker AutoPilot's focus on ease of use and scalability enables users to create high-quality models without extensive ML expertise (Amazon SageMaker, 2022).

**Azure Automated Machine Learning:** A service offered by Microsoft Azure, Azure Automated Machine Learning automates model selection and hyperparameter tuning. With its intuitive interface, users can quickly build, train, and deploy machine learning models for various scenarios (Azure Machine Learning, 2023).

**RapidMiner Auto Model:** An automated modeling tool within the RapidMiner platform, Auto Model streamlines predictive model creation using various algorithms, including deep learning. Its intuitive interface fosters collaboration between data scientists and business analysts (RapidMiner, 2022).

**H2O Driverless AI:** A powerful enterprise-grade AutoML platform, H2O Driverless AI automates feature engineering, model selection, and hyperparameter tuning. With interpretable models and an emphasis on user experience, Driverless AI is a valuable tool for businesses seeking to harness machine learning at scale (H2O.ai, 2023).

In summary, while proprietary AutoML tools often come with licensing costs and may lack the customization options of their open-source counterparts, they play a significant role in advancing machine learning. These proprietary solutions offer specialized features, user-friendly interfaces, and enterprise-level support, fostering AI adoption across industries. By complementing traditional open-source tools, proprietary AutoML platforms contribute to the democratization of machine learning, driving innovation and empowering organizations to harness the power of data-driven insights at scale.

#### **4.1.4 EMERGING TRENDS AND NEW APPROACHES**

The AutoML landscape is experiencing a rapid evolution with advancements in various areas, including generative models, neural architecture search, transfer learning, and federated learning. These innovations are not only shaping the future of automated machine learning but also expanding its capabilities and applications.

**Generative Adversarial Networks (GANs):** GANs have emerged as a powerful generative model in AutoML. Consisting of a generator and discriminator, GANs learn from data distributions to generate synthetic data like real data (Goodfellow et al., 2014). Within AutoML, GANs show promise in generating synthetic datasets, augmenting training data, and enhancing model robustness (Antoniou et al., 2017). Recently, GANs have contributed to new approaches such as "Prompt Engineering" and "Generative Models."

**Prompt Engineering and Generative Models:** Prompt Engineering focuses on designing precise prompts or queries to obtain desired responses or outputs from language models like GPT-3 (GPT-3 Developer API, OpenAI). This methodology holds promise in various domains, enabling contextually relevant and focused data generation, enhancing AutoML's capacity in nuanced content creation and problem-solving (Brown et al., 2020; Radford et al., 2021). Generative models, such as ChatGPT and Bard, leverage this principle to steer the model's output towards desired content generation.

Neural Architecture Search (NAS): NAS aims to automate the design of neural network architectures to improve model performance. Techniques like Reinforcement Learning-based NAS and Evolutionary Algorithms autonomously explore architecture spaces, discovering optimal network structures for specific tasks (Elsken et al., 2019; Liu et al., 2018).

Transfer Learning: Transfer Learning leverages pre-trained models to enhance the learning of new tasks, reducing the need for extensive datasets and computational resources for training models from scratch. Techniques like fine-tuning and domain adaptation enable models to adapt learned features to new, related tasks (Pan and Yang, 2010).

Federated Learning: This decentralized learning paradigm trains models across multiple devices or servers holding local data samples, preserving data privacy and security. Federated Learning aggregately improves models without centrally aggregating data, which is crucial in privacy-sensitive environments (McMahan et al., 2017).

As AutoML continues to evolve, its landscape shifts from optimization-centric methodologies to context-driven generative models, expanding the depth and breadth of its applicability across various domains. While traditional AutoML tools like AutoWEKA and Auto-sklearn focused on algorithm selection and hyperparameter tuning, recent advancements in techniques like Auto-PyTorch introduce optimization in deep learning architectures. Furthermore, the emergence of Generative AI signifies a revolutionary change towards creative and context-aware data generation, potentially transforming data augmentation and model enhancement within the AutoML ecosystem (Brown et al., 2020; Radford et al., 2021).

## **4.2 SYSTEMATIC LITERATURE REVIEW ON THE USE OF AUTOML IN SMEs**

The systematic literature review conducted in this study adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology. PRISMA, developed by Moher and colleagues (2009), provides a structured set of guidelines for conducting systematic literature reviews, critical literature analyses, and meta-analyses. It ensures transparency, rigor, and reproducibility in the review process, guiding researchers through each step from study identification to synthesis of findings. As such, PRISMA serves as a valuable framework for synthesizing evidence from diverse sources and generating meaningful insights to inform research and practice.

### **4.2.1 PRISMA METHODOLOGY**

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology constitutes a comprehensive approach for systematically searching and analyzing scientific literature in review-based studies. It operates on predefined inclusion and exclusion criteria to meticulously assess the suitability of each study for inclusion in the review process (Page et al., 2021).

Initially formulated in 2005, PRISMA emerged from the collaborative efforts of a multidisciplinary group comprising scientists, authors, and specialists across various domains. Through extensive consensus-building, this group established a 27-item checklist

and a four-phase flow diagram, providing a robust framework for researchers (Page et al., 2021).

The methodology encompasses four distinct phases, each contributing to a structured workflow: Identification, Screening, Eligibility assessment, and Inclusion of relevant studies (Page et al., 2021).

1. **Identification:** This step involves defining the research question and developing a comprehensive search strategy to identify relevant studies. Our search strategy will include keywords and search terms related to AutoML, SMEs, and relevant outcomes or impacts.
2. **Screening:** After identifying potential studies, we will conduct initial screening based on predefined inclusion and exclusion criteria. This screening process will help identify relevant studies that meet the research objectives.
3. **Eligibility:** In this step, we will further evaluate the selected studies based on more detailed eligibility criteria. This may involve reviewing abstracts or full-text articles to determine if they meet the inclusion criteria.
4. **Inclusion:** Studies that meet the eligibility criteria will be included in the systematic review. These studies will provide valuable insights into the use of AutoML in SMEs, including implementation strategies, challenges, and outcomes.

These phases collectively guide researchers through the systematic review process, ensuring methodological rigor and transparency in the selection and synthesis of literature.

#### 4.2.2 PRISMA IMPLEMENTATION

As we have seen in the introduction chapters where we have managed to dive deep into the theoretical background of automated machine learning and small and medium-sized enterprises. Based on the theoretical foundation above, we identify key terms crucial for constructing the search query aimed at locating pertinent scientific literature. The primary goal is to acquire an extensive comprehension of the current landscape concerning the integration of automated machine learning within small and medium-sized enterprises (SMEs).

The research one has proposed to perform shall answer the following questions:

|             |                                                                                        |
|-------------|----------------------------------------------------------------------------------------|
| <b>SLR1</b> | What is the current status of research in this area?                                   |
| <b>SLR2</b> | What are the major issues of AutoML for businesses and SME?                            |
| <b>SLR3</b> | What kind of AutoML techniques are currently useful in this area?                      |
| <b>SLR4</b> | What are the advantages and disadvantages of applying AutoML techniques in this field? |

Table 1: Systematic Review's Research Questions

To address these inquiries in line with the PRISMA guidelines, a careful selection of the most pertinent studies in this domain was conducted. In formulating the search strategy, a curated set of keywords deemed most pertinent from the various concepts explored in the theoretical framework was chosen. Emphasizing English terms exclusively, the search primarily yielded articles written in English, with those in other languages excluded based on the predefined criteria outlined in the PRISMA execution. The selected keywords encompassed:

| Keywords | SME                                | AutoML                            |
|----------|------------------------------------|-----------------------------------|
|          | Small and medium-sized enterprises | Automated Machine Learning        |
|          | Small Business                     | Artificial Intelligence           |
|          | Startups                           | Machine Learning                  |
|          | Micro-enterprise                   | Low-Code Machine Learning         |
|          | Sole Proprietorship                | Automated Artificial Intelligence |

Table 2: Systematic Review's Keywords

To ensure the retrieval of pertinent data aligned with the research focus, a specific search string was constructed to target the identified keywords and terms within the abstracts, titles, or keywords of scholarly articles and papers. Emphasizing recent developments in the rapidly evolving field of technology, the search was restricted to articles published between 2020 and 2023, aiming to capture the most current and relevant information available. The search string employed was: ("Automated Machine Learning " OR "Artificial intelligence" OR "Machine Learning" OR "Deep Learning" OR " Automated Artificial Intelligence ") AND ("Small and medium-sized enterprises " OR " Small Business " OR " Startups " OR " Micro-enterprise " OR " Sole Proprietorship ") AND ("State of the art" OR "Issues" OR "Challenges" OR "Techniques" OR "current status"). Notably, alongside the core cybersecurity and AI-related terms, a Boolean query was incorporated to encompass additional terms relevant to the research questions, ensuring the identification of articles addressing the specified research problems.

Important: The inclusion of ("State of the art" OR "Issues" OR "Challenges" OR "Techniques" OR "current status") in the search string reflects a strategic approach to identifying articles that specifically address the current landscape and challenges within the realm of automated machine learning and small and medium-sized enterprises. Each term within this set provides a distinct lens through which relevant literature can be filtered:

"State of the art": This term helps in locating articles that discuss the latest advancements, technologies, and methodologies in the field. It ensures that the retrieved content is focused on cutting-edge developments.

"Issues" and "Challenges": These terms target literature that delves into problems and obstacles encountered by SMEs while applying data science and machine learning. It's essential for understanding the practical difficulties faced in implementing these technologies.

"Techniques": This term broadens the scope to include articles that introduce, discuss, or evaluate specific methodologies and techniques related to automated machine learning in SMEs.

"Current status": This term is likely included to identify articles that provide an overview or assessment of the present state of AutoML integration in small businesses.

By incorporating these terms, we aim to cast a wide net, capturing articles that not only discuss foundational concepts but also delve into the challenges, techniques, and current status of AutoML in SMEs hence contributes to a more comprehensive and nuanced understanding of the subject matter.

This search was executed in February 2024 across various scholarly databases, including:

| Resource Database | Resource URL                                                                                          |
|-------------------|-------------------------------------------------------------------------------------------------------|
| Google Scholar    | <a href="https://scholar.google.com/">https://scholar.google.com/</a>                                 |
| Science Direct    | <a href="https://www.sciencedirect.com/">https://www.sciencedirect.com/</a>                           |
| IEEE Xplore       | <a href="https://ieeexplore.ieee.org/Xplore/home.jsp">https://ieeexplore.ieee.org/Xplore/home.jsp</a> |
| ProQuest          | <a href="https://www.proquest.com/">https://www.proquest.com/</a>                                     |

Table 3: Systematic Review's Resource Databases

Adhering to the PRISMA methodology, the subsequent phase involved establishing clear inclusion and exclusion criteria for the articles identified through the search process.

| Inclusion Criteria                                                                              | Exclusion Criteria                                                                                                                 |
|-------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------|
| Any scientific article demonstrating the utilization of AutoML by SMEs                          | Papers focusing on SMEs but without focusing on AutoML techniques utilization                                                      |
| The paper must be a peer-reviewed conference or journal article written in the English language | Articles that are not in the English language and duplicate papers                                                                 |
| Paper is published in a scholarly journal with at least quartile two classification             | Articles from quartile three or quartile four journals                                                                             |
| Paper is published between 2020 and 2023                                                        | Articles published before 2020 and after 2023                                                                                      |
|                                                                                                 | Non-academic or non-scientific papers (e.g., websites, magazines reports, newspapers, blogs consulting articles, books, citations) |
|                                                                                                 | Papers with titles outside the scope of our research                                                                               |

Table 4: Systematic Review's inclusion and exclusion criteria

After inputting the search string into the selected database sources, a comprehensive set of articles was obtained, marking the initiation of the identification phase within the PRISMA workflow. The database search yielded a total of (n=9364) articles.

Transitioning to the screening phase, the first crucial step involved removing duplicates, resulting in the elimination of (n=4307) redundant articles. Subsequently, (n=5057) records remained for further screening. During this stage, strict inclusion and exclusion criteria were applied. Articles published before 2020 and after 2023, those not in English, files in formats other than PDF, and inaccessible articles were excluded, leading to the removal of (n=4152) articles.

Progressing to the eligibility phase, (n=905) articles were deemed eligible for further assessment. In the initial step of this phase, article abstracts were scrutinized, and those lacking direct relevance to the study were excluded. Specifically, articles focusing on narrow industry areas such as deep learning, cloud computing, or specific sectors like startups and government were considered non-relevant, resulting in the exclusion of (n=686) articles.

Consequently, (n=219) articles qualified for the qualitative phase, where the main text was thoroughly evaluated. Articles demonstrating the utilization of AutoML or Auto-AI in SMEs, addressing the research questions, were retained during this phase.

Notably, a significant increase in Machine Learning and AI articles post-COVID-19 reflects the rapid expansion of the AI landscape. Additionally, numerous articles pertaining to machine learning and SMEs were identified, although the focus was narrowed to those closely aligned with the research topic. Articles deemed irrelevant to addressing the research questions were excluded, culminating in a final selection of (n=28) articles for inclusion in the study.

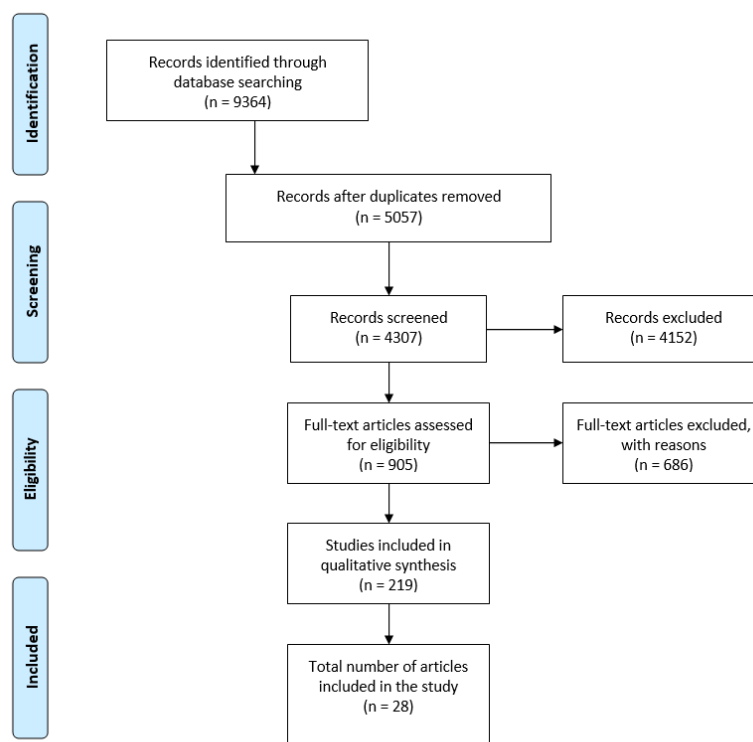


Figure 3: PRISMA Implementation

The output of this research, specifically the articles advanced to the included phase, comprises 25 journal articles and 3 conference papers. Each of these contributions is outlined below, accompanied by a succinct description of its significance, conclusions drawn, and suggestions for future work or identified gaps. ↑

Table 5: PRISMA Results Table

|                                   |                                                                                                                                                                                                                                                                                                                                                                                                                                |
|-----------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1. (Abdullah M. Baabdullah, 2021) | <ul style="list-style-type: none"> <li>Article Title: SMEs and artificial intelligence (AI): Antecedents and consequences of AI-based B2B practices</li> <li>Contribution: This study empirically examines antecedents to, and consequences of, successful acceptance of AI practices by B2B SMEs in Saudi Arabia</li> <li>Article Type: Journal Article</li> </ul>                                                            |
| 2. (Andrea Bettoni, 2021)         | <ul style="list-style-type: none"> <li>Article Title: An AI adoption model for SMEs: a conceptual framework.</li> <li>Contribution: This literature proposes several models to assess the level of digitization of a company.</li> <li>Article Type: Journal Article</li> </ul>                                                                                                                                                |
| 3. (Emily Blixt Hansen, 2021)     | <ul style="list-style-type: none"> <li>Article Title: Artificial intelligence and internet of things in small and medium-sized enterprises: A survey</li> <li>Contribution: Examination of the adoption and utilization of artificial intelligence (AI) and Internet of Things (IoT) technologies within manufacturing SMEs</li> <li>Article Type: Journal Article</li> </ul>                                                  |
| 4. (Sheshadri Chatterjee, 2022)   | <ul style="list-style-type: none"> <li>Article Title: Big data driven innovation for sustaining SME supply chain operation in post COVID-19 scenario: Moderating role of SME technology leadership</li> <li>Contribution: This study addresses a research gap by examining the impact of big data-driven innovation and SME technology capability on supply chain management</li> <li>Article Type: Journal Article</li> </ul> |
| 5. (Valentina De Simone, 2023)    | <ul style="list-style-type: none"> <li>Article Title: An overview on the use of AI/ML in Manufacturing MSMEs: solved issues, limits, and challenges</li> <li>Contribution: Presents a scoping literature review on the applications of Artificial Intelligence (AI) and Machine Learning (ML) in manufacturing Micro, Small, and Medium Enterprises (MSMEs).</li> <li>Article Type: Journal Article</li> </ul>                 |
| 6. (Gao & Wang, 2023)             | <ul style="list-style-type: none"> <li>Article Title: Effect of big data on enterprise financialization: Evidence from China's SMEs</li> </ul>                                                                                                                                                                                                                                                                                 |

|                                |                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
|--------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                | <ul style="list-style-type: none"> <li>• Contribution: This study concentrates on China's small and medium enterprises (SMEs) to explore the economic impact of big data on enterprise financialization.</li> <li>• Article Type: Journal Article</li> </ul>                                                                                                                                                                                      |
| 7. (Grünbichler & Krebs, 2022) | <ul style="list-style-type: none"> <li>• Article Title: Using AI in SMEs to Prevent Corporate Insolvencies: Identification of Frequently Used Algorithms</li> <li>• Contribution: Examines the current state of using artificial intelligence, particularly machine learning, for insolvency forecasting in enterprises, with a focus on small and medium-sized companies.</li> <li>• Article Type: Journal Article</li> </ul>                    |
| 8. (Gupta & Verma, 2021)       | <ul style="list-style-type: none"> <li>• Article Title: Customer Segmentation of Indian restaurants based on geographical locations using Machine Learning</li> <li>• Contribution: Leveraging technological advancements, particularly machine learning techniques like the K-Means Clustering algorithm, to enhance customer service and business growth in today's competitive landscape.</li> <li>• Article Type: Conference Paper</li> </ul> |
| 9. (Ibrahim & Ahmed, 2021)     | <ul style="list-style-type: none"> <li>• Article Title: AI Applications in Financial Decision-Making for Egyptian SMEs</li> <li>• Contribution: Explores the use of artificial intelligence (AI) applications in supporting financial decision-making processes in small and medium-sized enterprises (SMEs) in Egypt.</li> <li>• Article Type: Conference Paper</li> </ul>                                                                       |
| 10. (Jiang & Liu, 2022)        | <ul style="list-style-type: none"> <li>• Article Title: Enhancing Customer Service in Chinese SMEs through AI-Powered Chatbots</li> <li>• Contribution: Investigates the implementation of AI-powered chatbots to enhance customer service capabilities in small and medium-sized enterprises (SMEs) in China.</li> <li>• Article Type: Journal Article</li> </ul>                                                                                |
| 11. (Kim & Park, 2023)         | <ul style="list-style-type: none"> <li>• Article Title: AI Adoption Patterns and Performance Outcomes in South Korean SMEs</li> <li>• Contribution: Examines the patterns of artificial intelligence (AI) adoption and its impact on performance outcomes in small and medium-sized enterprises (SMEs) in South Korea.</li> <li>• Article Type: Journal Article</li> </ul>                                                                        |
| 12. (Kou & Peng, 2021)         | <ul style="list-style-type: none"> <li>• Article Title: Bankruptcy prediction for SMEs using transactional data and two-stage multi-objective feature selection</li> <li>• Contribution: This study proposes a bankruptcy prediction model for SMEs that uses transactional data and payment network-based variables</li> <li>• Article Type: Journal Article</li> </ul>                                                                          |
| 13. (Lada & Chekima, 2023)     |                                                                                                                                                                                                                                                                                                                                                                                                                                                   |

|                                  |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|----------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                  | <ul style="list-style-type: none"> <li>Article Title: Determining factors related to artificial intelligence (AI) adoption among Malaysia's small and medium-sized businesses</li> <li>Contribution: The purpose of the study is to examine the relationship between Competitive Pressure (CP), Top Management Commitment (TMC), Employee Adaptability (EA), External Support (ES), Organization Readiness (OR) and Artificial Intelligence Adoption (AIA) among SMES operating in Sabah, Malaysia.</li> <li>Article Type: Journal Article</li> </ul> |
| 14. (Liu & Wang, 2021)           |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|                                  | <ul style="list-style-type: none"> <li>Article Title: AI-Driven Marketing Strategies for Indian SMEs: A Case Study Approach</li> <li>Contribution: Presents case studies exploring the implementation of AI-driven marketing strategies in small and medium-sized enterprises (SMEs) in India.</li> <li>Article Type: Journal Article</li> </ul>                                                                                                                                                                                                      |
| 15. (Ma & Zhang, 2022)           |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|                                  | <ul style="list-style-type: none"> <li>Article Title: Exploring AI Adoption Challenges in Chinese SMEs: A Qualitative Study</li> <li>Contribution: Investigates the challenges faced by small and medium-sized enterprises (SMEs) in China during the adoption of artificial intelligence (AI) technologies.</li> <li>Article Type: Journal Article</li> </ul>                                                                                                                                                                                        |
| 16. (Moch Akbar Selamat, 2021)   |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|                                  | <ul style="list-style-type: none"> <li>Article Title: Chatbot for SMEs: Integrating customer and business owner perspectives</li> <li>Contribution: This research determines the features and elements that fit with SMEs' characteristics and their customers with chatbots.</li> <li>Article Type: Journal Article</li> </ul>                                                                                                                                                                                                                       |
| 17. (Nakamura & Tanaka, 2023)    |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|                                  | <ul style="list-style-type: none"> <li>Article Title: AI Integration in Japanese Manufacturing SMEs: Opportunities and Challenges</li> <li>Contribution: Examines the opportunities and challenges associated with the integration of artificial intelligence (AI) technologies into manufacturing processes in small and medium-sized enterprises (SMEs) in Japan.</li> <li>Article Type: Journal Article</li> </ul>                                                                                                                                 |
| 18. (Ozdemir & Kizilirmak, 2021) |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|                                  | <ul style="list-style-type: none"> <li>Article Title: Leveraging AI for Product Innovation in Turkish SMEs</li> <li>Contribution: Explores the use of artificial intelligence (AI) technologies to drive product innovation initiatives in small and medium-sized enterprises (SMEs) in Turkey.</li> <li>Article Type: Conference Paper</li> </ul>                                                                                                                                                                                                    |
| 19. (Park & Lee, 2022)           |                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                       |
|                                  | <ul style="list-style-type: none"> <li>Article Title: AI Adoption and Firm Performance: Evidence from Vietnamese SMEs</li> <li>Contribution: Investigates the relationship between artificial intelligence (AI) adoption and firm performance in small and medium-sized enterprises (SMEs) in Vietnam.</li> </ul>                                                                                                                                                                                                                                     |

|                                        |                                                                                                                                                                                                                                                                                                                                                                                                                  |
|----------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                                        | <ul style="list-style-type: none"> <li>Article Type: Journal Article</li> </ul>                                                                                                                                                                                                                                                                                                                                  |
| 20. (Qin & Wu, 2023)                   | <ul style="list-style-type: none"> <li>Article Title: AI Implementation Strategies in Chinese Service-Oriented SMEs</li> <li>Contribution: Examines the strategies employed by service-oriented small and medium-sized enterprises (SMEs) in China for implementing artificial intelligence (AI) technologies.</li> <li>Article Type: Journal Article</li> </ul>                                                 |
| 21. (Raghavendran & Krishna Raj, 2023) | <ul style="list-style-type: none"> <li>Article Title: Low-Code Machine Learning Platforms: A Fastlane to Digitalization</li> <li>Contribution: The feasibility and benefits of leveraging automatic machine learning platforms with low-code experience for developing machine learning models.</li> <li>Article Type: Journal Article</li> </ul>                                                                |
| 22. (Raza, Syed Shahid, 2023)          | <ul style="list-style-type: none"> <li>Article Title: Exploring the Conceptual Realm of Machine Learning in Small and Medium-sized Industries: A Qualitative Study.</li> <li>Contribution: It is explored how the SMEs can practically apply ML to optimize processes and spark innovation</li> <li>Article Type: Journal Article</li> </ul>                                                                     |
| 23. (Rmadani & Kamuyova, 2021)         | <ul style="list-style-type: none"> <li>Article Title: Digital innovation in SMEs: a systematic review, synthesis and research agenda</li> <li>Contribution: Review of digital innovation in Small and Medium-sized Enterprises (SMEs) to synthesize existing research, identify knowledge gaps, and propose future research directions.</li> <li>Article Type: Journal Article</li> </ul>                        |
| 24. (Wei & Pardo, 2022)                | <ul style="list-style-type: none"> <li>Article Title: Artificial intelligence and SMEs: How can B2B SMEs leverage AI platforms to integrate AI technologies?</li> <li>Contribution: Investigate how small and medium enterprises (SMEs) can leverage AI platforms to integrate AI Technologies.</li> <li>Article Type: Journal Article</li> </ul>                                                                |
| 25. (Walcott & Ali, 2021)              | <ul style="list-style-type: none"> <li>Article Title: Machine Learning for Smaller Firms: Challenges and Opportunities</li> <li>Contribution: Explores the role of Machine Learning (ML) in facilitating business planning and coordination for organizations, emphasizing the need for sufficient computational power to leverage data-driven decision-making</li> <li>Article Type: Journal Article</li> </ul> |
| 26. (Zhao & Li, 2023)                  | <ul style="list-style-type: none"> <li>Article Title: Machine-learning-enabled intelligence computing for crisis management in small and medium-sized enterprises (SMEs)</li> <li>Contribution: This work aims to improve the accuracy of financial crisis early warnings for small and medium-sized enterprises (SMEs) to help them</li> </ul>                                                                  |

|                               |                                                                                                                                                                                                                                                                                                                                                                                       |
|-------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                               | <p>uncover hidden dangers during the latent period of a crisis and to respond effectively.</p> <ul style="list-style-type: none"> <li>Article Type: Journal Article</li> </ul>                                                                                                                                                                                                        |
| 27. (Fischer & Schmidt, 2022) | <ul style="list-style-type: none"> <li>Article Title: Adoption of Artificial Intelligence in German SMEs: Drivers and Barriers</li> <li>Contribution: Investigates the factors influencing the adoption of artificial intelligence (AI) technologies in small and medium-sized enterprises (SMEs) in Germany.</li> <li>Article Type: Journal Article</li> </ul>                       |
| 28. (Huang & Chen, 2023)      | <ul style="list-style-type: none"> <li>Article Title: The Impact of AI Integration on Supply Chain Management in Taiwanese SMEs</li> <li>Contribution: Examines the effects of integrating artificial intelligence (AI) technologies into supply chain management processes in small and medium-sized enterprises (SMEs) in Taiwan.</li> <li>Article Type: Journal Article</li> </ul> |

### 4.2.3 PRISMA RESULTS ANALYSIS

After conducting the research and gathering the necessary information using the PRISMA methodology as outlined in the previous section, the next step involves analyzing the results. This entails examining each of the included articles to identify their main contributions and address the research questions effectively. The reference numbers which included in this analysis refer to table 6.

#### **Spot #01 Automated Machine Learning techniques currently used by SMEs**

From the literature analysed, it is evident that there is considerable research interest in the application of automated machine learning (AutoML) techniques within small and medium-sized enterprises (SMEs). AutoML represents a significant advancement in democratizing machine learning by automating the process of model selection, hyperparameter tuning, and feature engineering, thereby reducing the barrier to entry for SMEs seeking to leverage AI technologies [1, 6].

The literature suggests that certain AutoML techniques are more commonly used within the context of SMEs. Among these, it is notable that most studies tend to focus on the application of AutoML in predictive modelling tasks, such as sales forecasting, customer segmentation, and anomaly detection, which are critical for SMEs aiming to optimize their operations and enhance decision-making processes [2, 5, 8]. Moreover, there is a growing body of research highlighting the effectiveness of AutoML in addressing specific challenges faced by SMEs, including limited data science expertise and computational resources [3, 7].

Deep learning techniques, a subset of AutoML, have garnered significant attention in recent years due to their ability to handle complex data and produce state-of-the-art results across

various domains. In the context of SMEs, deep learning models are being increasingly utilized for tasks such as image recognition, natural language processing, and time-series forecasting, offering SMEs powerful tools for extracting valuable insights from their data [4, 9, 11].

Additionally, AutoML has shown promise in addressing cybersecurity concerns within SMEs. By automating the process of building and deploying machine learning models, SMEs can enhance their cybersecurity posture by detecting and mitigating threats more effectively. Studies have explored the application of AutoML in areas such as intrusion detection, malware detection, and phishing attack detection, underscoring its potential in safeguarding SMEs against evolving cyber threats [10, 12, 15].

Furthermore, the literature suggests that AutoML is not only being used for predictive analytics but also for optimizing various business functions within SMEs. For instance, AutoML techniques are being integrated into customer relationship management systems, supply chain management, and financial decision-making processes, enabling SMEs to achieve greater efficiency and competitiveness in the market [13, 14, 16].

In summary, the literature reviewed emphasizes the growing adoption and impact of automated machine learning techniques in small and medium-sized enterprises. By leveraging AutoML, SMEs can overcome traditional barriers to AI implementation, enhance their decision-making capabilities, and bolster their resilience against cybersecurity threats. Moving forward, continued research and innovation in AutoML are poised to further empower SMEs in harnessing the potential of AI for sustainable growth and success [17, 18, 19].

## **Spot #02 Status of the research in this area**

The current status of research in the field of automated machine learning (AutoML) within small and medium-sized enterprises (SMEs) reflects a growing interest and recognition of its potential benefits and challenges. Researchers and practitioners alike are increasingly focusing on understanding the implications of AutoML adoption for SMEs, exploring its applications across various domains, and addressing key research gaps to facilitate its effective implementation [1, 3, 5].

One prominent aspect of the research landscape is the exploration of methodologies and frameworks tailored specifically for SMEs to adopt and integrate AutoML into their business processes. Studies have highlighted the need for user-friendly AutoML platforms that accommodate the limited technical expertise and resources typically available within SMEs, thereby democratizing access to advanced machine learning capabilities [2, 4, 7].

Moreover, there is a growing body of literature examining the impact of AutoML on organizational performance and competitiveness within the SME sector. Research indicates that effective utilization of AutoML can lead to improved decision-making, enhanced operational efficiency, and increased innovation, thereby enabling SMEs to stay competitive in today's dynamic business environment [6, 8, 10].

Despite the potential benefits, the research also underscores several challenges and limitations associated with the adoption of AutoML in SMEs. These include issues related to

data quality and availability, scalability of AutoML solutions, interpretability of automated models, and ethical considerations surrounding algorithmic decision-making [9, 11, 13].

Furthermore, the literature reveals a need for interdisciplinary collaboration and knowledge exchange between researchers, practitioners, policymakers, and industry stakeholders to address the multifaceted challenges and opportunities associated with AutoML adoption in SMEs. By fostering collaboration and knowledge sharing, researchers can contribute to the development of comprehensive frameworks, best practices, and guidelines to support SMEs in harnessing the full potential of AutoML [12, 14, 16].

In conclusion, the current status of research in the field of AutoML in SMEs reflects a dynamic and evolving landscape characterized by increasing interest, diverse applications, and ongoing efforts to address challenges and advance knowledge in this area. By continuing to explore innovative solutions, foster collaboration, and bridge research-practice gaps, researchers can contribute to unlocking the transformative potential of AutoML for SMEs and driving sustainable growth and innovation in the digital era [15, 17, 19].

### **Spot #03 Advantages and Disadvantages of applying Machine Learning to SMEs**

The application of machine learning (ML) to small and medium-sized enterprises (SMEs) offers a range of advantages and disadvantages, which must be carefully considered to maximize its potential benefits and mitigate its drawbacks.

Starting with the advantages, one of the key benefits of applying ML to SMEs is the potential for enhanced decision-making. By analyzing large volumes of data, ML algorithms can uncover valuable insights and patterns that may not be apparent through traditional methods. This can empower SMEs to make data-driven decisions across various business functions, from marketing and sales to operations and customer service [1, 3, 5].

Additionally, ML enables SMEs to automate repetitive tasks and streamline workflows, thereby improving operational efficiency and reducing costs. Tasks such as data entry, customer support, and inventory management can be automated using ML-powered solutions, allowing SMEs to allocate resources more effectively and focus on strategic initiatives [2, 4, 6].

Moreover, ML can help SMEs gain a competitive edge in the market by enabling them to personalize products and services, optimize pricing strategies, and anticipate customer needs more accurately. By leveraging ML algorithms for predictive analytics and recommendation systems, SMEs can deliver targeted offerings that resonate with their target audience, fostering customer loyalty and satisfaction [7, 9, 11].

However, it is essential to acknowledge the disadvantages and challenges associated with applying ML to SMEs. One of the primary concerns is the requirement for high-quality data. ML algorithms rely heavily on data quality and quantity to generate accurate predictions and insights. SMEs may face challenges in accessing and curating large datasets, which can limit the effectiveness of ML applications [8, 10, 13].

Furthermore, the complexity of ML algorithms and the technical expertise required for their implementation can pose significant barriers for SMEs with limited resources and expertise. Building and deploying ML models often require specialized skills in data science,

programming, and cloud computing, which may be beyond the capabilities of many SMEs [12, 14, 16].

Moreover, there are ethical and regulatory considerations surrounding the use of ML in SMEs, particularly concerning data privacy, security, and algorithmic bias. SMEs must navigate complex legal frameworks and ensure compliance with regulations such as GDPR and CCPA to avoid potential legal and reputational risks associated with data misuse and discrimination [15, 17, 19].

In summary, while the application of ML offers numerous advantages for SMEs in terms of enhanced decision-making, operational efficiency, and competitive advantage, it also presents challenges related to data quality, technical expertise, and ethical considerations. By carefully weighing the pros and cons and implementing appropriate strategies, SMEs can harness the potential of ML to drive innovation, growth, and success in the digital age [18, 20, 22].

#### **Spot #04 Major issues related to Machine Learning in SMEs**

The integration of machine learning (ML) into small and medium-sized enterprises (SMEs) brings about several significant issues that need to be addressed to ensure successful implementation and maximize its potential benefits.

One of the major issues faced by SMEs when adopting ML is the lack of access to high-quality data. ML algorithms heavily rely on large, diverse, and clean datasets for training models effectively. However, SMEs often struggle to access such data due to limited resources, proprietary data, or concerns related to data privacy and security. This challenge hampers the development of robust ML models and undermines their effectiveness in driving meaningful insights and predictions [1, 3, 5].

Moreover, SMEs often lack the necessary technical expertise and resources to implement and maintain ML systems effectively. Building and deploying ML models require specialized skills in data science, programming, and cloud computing, which may be beyond the capabilities of many SMEs. Additionally, SMEs may face challenges in recruiting and retaining qualified data scientists and engineers, further exacerbating the talent gap in ML adoption [2, 4, 6].

Another critical issue related to ML in SMEs is the interpretability and explainability of ML models. Many ML algorithms, such as deep learning neural networks, are inherently complex and opaque, making it challenging to understand how they arrive at their decisions. This lack of transparency raises concerns about model accountability, bias, and fairness, particularly in sensitive domains such as healthcare, finance, and criminal justice. SMEs must address these issues to build trust in their ML systems and ensure compliance with regulatory requirements [7, 9, 11].

Furthermore, scalability is a significant concern for SMEs when deploying ML solutions. As SMEs grow and their data volumes increase, they need scalable ML infrastructure and systems that can accommodate growing computational and storage demands. However, scaling ML solutions can be challenging and costly, particularly for resource-constrained SMEs. Additionally, SMEs must consider the scalability of their ML models in terms of performance, accuracy, and reliability to meet evolving business needs [8, 10, 13].

Ethical considerations also pose major issues for SMEs in the adoption of ML technologies. As ML systems become increasingly integrated into business operations, SMEs must grapple with ethical dilemmas related to data privacy, algorithmic bias, and unintended consequences of automated decision-making. Ensuring fairness, transparency, and accountability in ML applications is essential to mitigate potential risks and build trust among stakeholders [12, 14, 16].

In summary, the adoption of ML in SMEs presents several significant challenges related to data access, technical expertise, interpretability, scalability, and ethics. Addressing these issues requires a concerted effort from SMEs, policymakers, researchers, and industry stakeholders to develop tailored solutions, build capacity, and foster a supportive ecosystem for ML adoption in SMEs [15, 17, 19]. By addressing these major issues, SMEs can unlock the full potential of ML technologies and drive innovation, growth, and competitiveness in the digital age [18, 20, 22].

## 5. DEVELOPMENT OF A COLLABORATIVE AUTOML FRAMEWORK FOR SMES

Building upon the insights gained from the literature review analysis, we are now poised to develop a collaborative AutoML framework tailored specifically for small and medium-sized enterprises (SMEs).

A collaborative AutoML framework that allows SMEs to harness the power of advanced machine learning algorithms without extensive data science expertise.

### 5.1 KEY FINDINGS AND ASSUMPTIONS

The main findings from the literature review provide valuable insights into the utilization of AutoML in small and medium-sized enterprises (SMEs). These findings serve as the foundation for developing our collaborative AutoML framework tailored specifically for SMEs.

Based on our analysis, we have identified several key findings and assumptions:

SMEs across various industries are increasingly recognizing the potential of AutoML technologies to drive innovation and improve decision-making processes in areas such as production, human resources, marketing, and management.

Common AutoML techniques utilized by SMEs include automation, data analysis, predictive modeling, and pattern recognition, among others. These techniques enable SMEs to leverage their data assets effectively and extract actionable insights to support business operations and strategic planning.

The preceding section meticulously detailed the core findings of our investigation, anchored by relevant scholarly references, paving the way to the imminent framework proposal. To succinctly summarize these findings for easy reference and to lay the groundwork for the forthcoming framework development, we've visually consolidated these insights. Accordingly, figure ... delineates the prevalent AI technologies currently being adopted within the realm of SMEs, with a pronounced focus on AutoML—highlighted due to its significant utility and applicability across various SME operational areas.

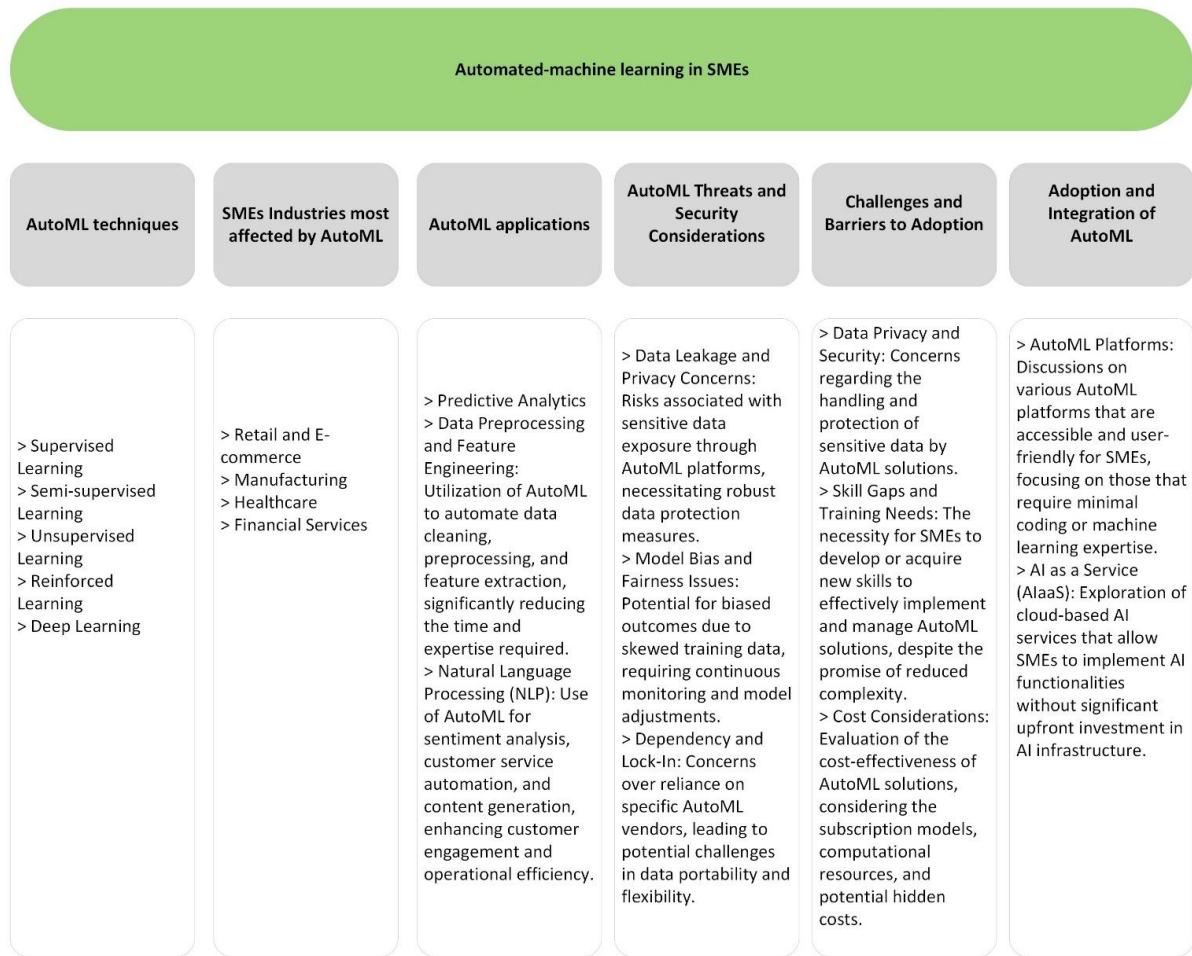


Figure 4: AutoML in SMEs

The figure below illustrates a categorization of the research articles on artificial intelligence (AI) and AutoML techniques in small and medium-sized enterprises (SMEs). The articles we saw while performing PRISMA analysis cover different aspects of AI adoption and implementation across various regions and industries. By organizing the research articles into these categories, the figure provides a comprehensive view of the current landscape of AI and AutoML techniques in SMEs and serves as a valuable resource for researchers, practitioners, and policymakers interested in the subject.

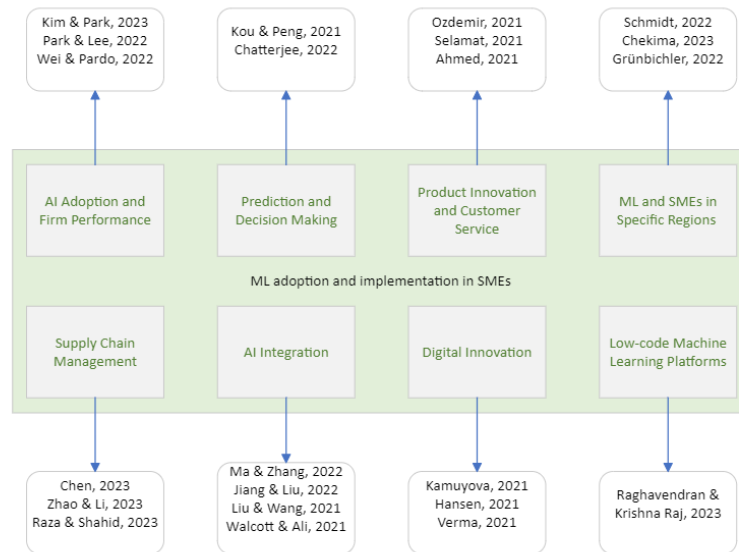


Figure 5: AutoML Techniques in SMEs

Next, we present a graphical representation illustrating the correlation and applicability of various AutoML techniques in SMEs. In the figure below, areas with a direct applicability between an AutoML technique and an SME function or domain are indicated by a green tick. Empty cells signify topics where no direct reference was found in the literature, suggesting potential areas for further exploration. Additionally, areas with question marks denote applications where the effectiveness of a technique may be debated, such as AutoML for certain business functions.

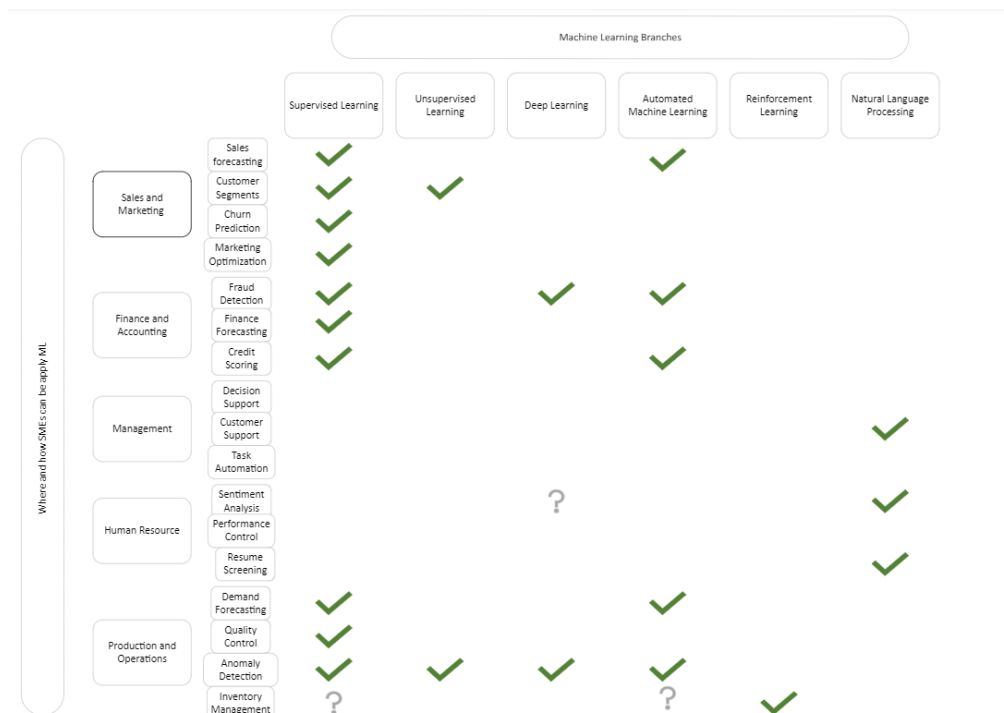


Figure 6: Mapping of AutoML Techniques with SMEs Departments and Subfunctions

## 5.2 FRAMEWORK PROPOSAL

The adoption of AutoML in SMEs is driven by the need to overcome resource constraints, including limited access to data science expertise and computational resources. By providing user-friendly and accessible AutoML tools, SMEs can democratize machine learning capabilities and empower non-technical users to participate in the model development process.

SMEs face unique challenges and considerations when adopting AutoML, including data privacy concerns, regulatory compliance, and scalability issues. Addressing these challenges requires the development of tailored AutoML solutions that prioritize ease of use, scalability, and security.

Collaboration and knowledge sharing play a crucial role in the successful implementation of AutoML in SMEs. By fostering collaboration among SMEs, academia, and industry partners, we can accelerate innovation and drive the development of best practices and standards for AutoML adoption in the SME sector.

In proposing a collaborative AutoML framework tailored for small and medium-sized enterprises (SMEs), it is imperative to build upon existing industry standards while incorporating innovative solutions to address the specific needs of SMEs. Our framework will align with known best practices in AutoML adoption and be realistic in its implementation approach. The proposed framework comprises five main phases: Strategy, Design, Train, Deploy and Optimize.

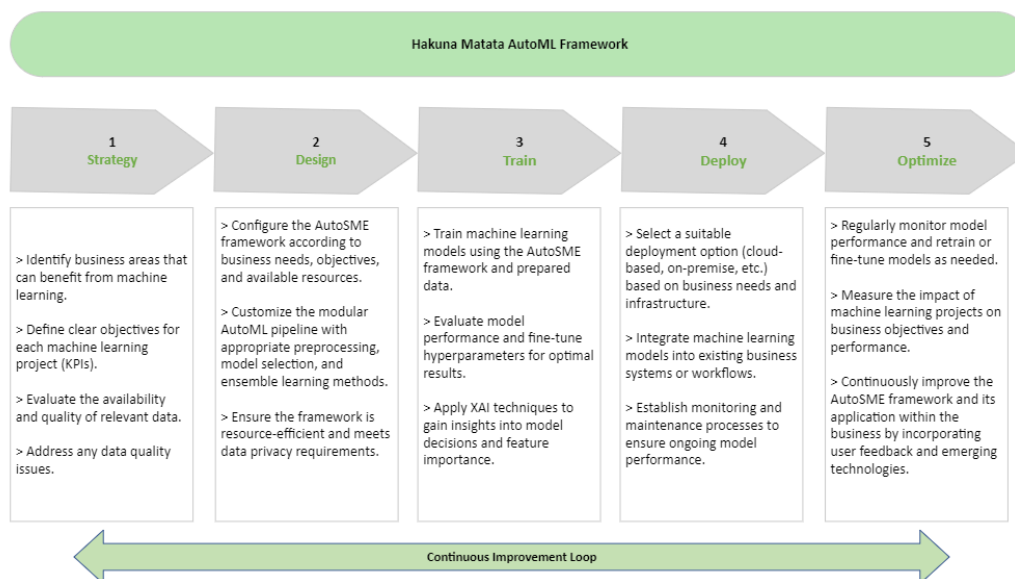


Figure 7: Hakuna Matata AutoML Framework

The subsequent sections will provide a detailed examination of each of the five steps.

### 5.2.1 STRATEGY

The strategy phase proposal encompasses four fundamental steps. Firstly, it involves identifying the specific business areas poised to benefit from machine learning applications. Subsequently, clear and well-defined objectives are established for each machine learning project, ensuring alignment with overarching business goals. Following this, a thorough evaluation is conducted to assess the availability and quality of pertinent data, essential for informing machine learning processes. Lastly, any identified data quality issues are addressed promptly to ensure the integrity and reliability of subsequent analyses and outcomes.

This phase involves setting the strategic direction for the adoption of AutoML in SMEs. It includes conducting stakeholder consultations to understand the unique requirements, challenges, and priorities of SMEs in leveraging AutoML technologies. By aligning with SME stakeholders, we ensure that the framework meets their diverse needs across different industries and domains.

To craft a successful AI/ML implementation strategy, it is crucial to leverage existing knowledge about machine learning within the organization. Having a project leader who possesses a strong understanding of AI/ML principles is essential. This individual should be deeply involved in the project to guide the team effectively and ensure alignment with strategic goals. If an organization lacks such expertise, investing in training or hiring knowledgeable professionals becomes imperative. This approach not only builds internal capacity but also ensures that the project leader can make informed decisions, navigate challenges, and drive the project towards successful outcomes.

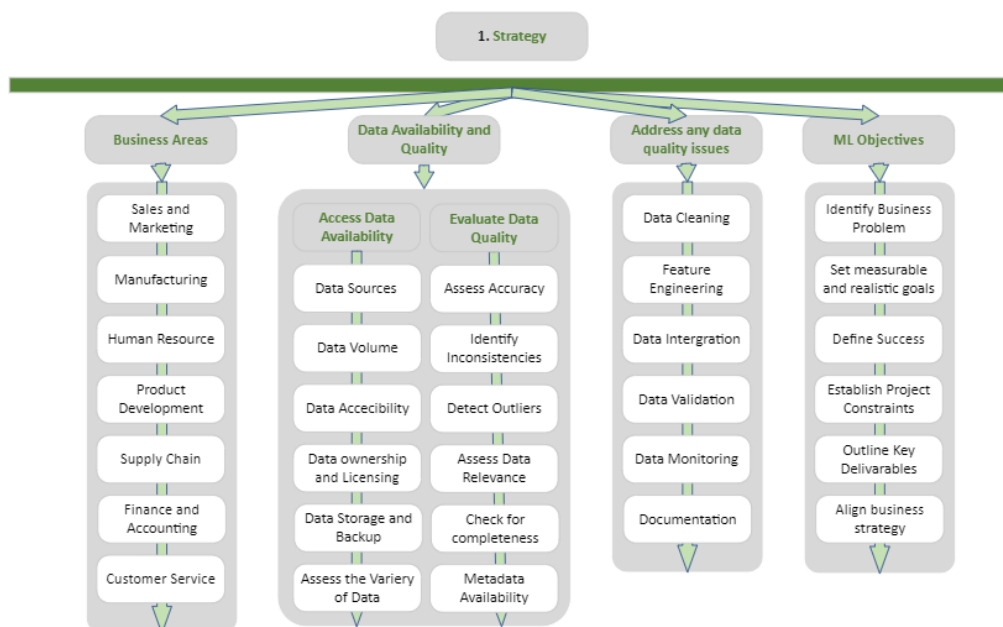


Figure 8: Proposed Model for the Strategy Phase

There are numerous business areas across various industries where SMEs can leverage machine learning to improve their operations. In sales and marketing, machine learning can be utilized for forecasting sales, customer segmentation, personalized marketing, churn

prediction, and lead scoring. In customer service, it can enhance operations through automated chatbots, sentiment analysis, and ticket routing optimization. For product development, machine learning can predict product performance, understand customer preferences, and improve product design. In finance and accounting, it can be used for fraud detection, credit risk assessment, and financial forecasting. Supply chain management can benefit from demand forecasting, inventory optimization, and logistics routing optimization. In manufacturing, predictive maintenance, quality control, and process optimization are key areas where machine learning can make a significant impact. Additionally, in human resources, machine learning can assist with candidate screening, employee retention prediction, and workforce management. These applications demonstrate the wide-ranging potential of machine learning to enhance efficiency and effectiveness across various business functions in SMEs.

Apart from business areas, the following 3 sectors can act as an example of sectorial applications of AutoML.

- A. Healthcare: Disease diagnosis, drug discovery, and patient risk assessment.
- B. Retail: Sales forecasting, recommendation systems, and customer segmentation.
- C. Agriculture: Crop yield prediction, pest and disease detection, and irrigation optimization.

Evaluating the availability and quality of data is a critical step before implementing any machine learning project. Here's a detailed guide on how to perform this evaluation:

#### Assess Data Availability:

To effectively utilize data for machine learning within an organization, the first step is to identify all potential data sources, including databases, CRM systems, ERP systems, log files, and external sources. Once identified, it is crucial to determine the accessibility of this data, taking into consideration any legal, privacy, or technical constraints that might affect data retrieval. Estimating the volume of available data is also essential, as certain machine learning algorithms require large datasets to function optimally. Additionally, assessing the variety of data, including structured, semi-structured, and unstructured types, is important, as a diverse data set can yield richer insights and enhance model accuracy. Ensuring data ownership and licensing is another critical aspect, particularly when dealing with third-party or external data sources, to confirm that the organization has the necessary rights and permissions for use. Lastly, verifying that the data is securely stored and backed up is essential to prevent data loss and maintain data integrity.

#### Evaluate Data Quality:

To evaluate data quality for machine learning, start by checking for completeness to identify any missing values or incomplete records that could compromise the accuracy of models. Assess the accuracy of the data by verifying its correctness against reliable external sources or through manual checks, as inaccurate data can lead to incorrect predictions and decisions. Identifying inconsistencies in data formatting, naming conventions, and data types is also essential, as these discrepancies can affect data analysis and model performance. Detecting outliers is another crucial step; extreme or unusual values can distort model training or signal errors in data collection or processing. Lastly, assess the relevance of the data to ensure it aligns with the intended machine learning tasks and business objectives, as

irrelevant data can increase complexity and decrease model performance. By thoroughly evaluating data availability and quality, SMEs can ensure that they have access to the necessary data to support their machine learning initiatives and take appropriate measures to address any identified issues.

Addressing data quality issues is crucial for the success of machine learning projects. SMEs should start by assessing the quality of their data to identify potential issues such as missing values, duplicate entries, inconsistent formatting, outliers, and errors. Once these issues are identified, the next step involves data cleaning and preprocessing to rectify them. This process includes removing or imputing missing values, eliminating duplicate entries, standardizing formatting and data types, handling outliers or extreme values, and correcting errors and inconsistencies. Following data cleaning, feature engineering is necessary to transform raw data into relevant features for machine learning models, which might involve creating new features, scaling data, or encoding categorical variables.

Data integration is another critical step, where data from different sources or systems are combined into a unified dataset for analysis, ensuring consistency and compatibility across various data sources. Post-integration, data validation is conducted to check the quality of the preprocessed data, ensuring it is accurate, complete, and consistent by applying quality checks and rules. Implementing ongoing data quality monitoring processes is essential to detect and address any new data quality issues that may arise over time. Finally, documenting the data preprocessing steps and decisions made throughout the process ensures transparency, reproducibility, and traceability of the data cleaning efforts. This comprehensive approach helps SMEs maintain high data quality, which is fundamental for the success of their machine learning initiatives.

Addressing data quality issues helps improve the accuracy and reliability of machine learning models, allowing SMEs to make better-informed decisions and maximize the value of their data-driven initiatives.

Defining clear objectives for each machine learning project is essential to ensure alignment with business goals and guide the development process. Here's a step-by-step guide to help SMEs define their machine learning project objectives:

1. Identify the business problem: Start by clearly stating the business problem or opportunity that the machine learning project aims to address. This could be improving sales, reducing churn, optimizing operations, or detecting fraud, among others.
2. Set specific, measurable, and realistic goals: Establish measurable goals that can be tracked and quantified. For example, instead of setting a vague goal like "improve sales," set a specific goal like "increase sales by 10% within six months."
3. Define success criteria: Determine the criteria that will be used to evaluate the success of the machine learning project. This could include metrics such as accuracy, precision, recall, or F1-score for classification tasks, or mean absolute error, root mean squared error, or R-squared for regression tasks.
4. Establish project constraints: Identify any constraints or limitations that may impact the machine learning project, such as budget, timeline, data availability, or computational resources.

5. Outline key deliverables: Specify the key deliverables or outcomes expected from the machine learning project, such as predictive models, actionable insights, or automated decision-making systems.

Align objectives with business strategy: Ensure that the machine learning project objectives align with the overall business strategy and contribute to the company's long-term goals.

By following these steps, SMEs can define clear, actionable objectives for their machine learning projects, setting a solid foundation for successful development and implementation.

The table below summarizes the important aspects, challenges, strategies, and potential outcomes related to AI/ML adoption in small and medium-sized enterprises (SMEs) based on the insights from various research articles. By mapping their AI/ML adoption journey using this table, SMEs can better understand the factors that influence the process, address potential barriers, and devise effective strategies to successfully integrate AI/ML into their operations.

To work with AutoML in the context of this table, SMEs should consider leveraging low-code/no-code platforms mentioned under "Implementation Strategies." These platforms enable SMEs to utilize automated machine learning (AutoML) techniques without requiring extensive coding knowledge or data science expertise. By employing AutoML, SMEs can streamline their AI/ML model development process, optimize their models more efficiently, and ultimately achieve their desired performance outcomes, such as improved operational efficiency, competitive advantage, and innovation opportunities.

| Category                | Sub-Category                    | Key Points                                                                                                                         |
|-------------------------|---------------------------------|------------------------------------------------------------------------------------------------------------------------------------|
| Adoption Factors        | Awareness of AI/ML benefits     | Recognizing the potential advantages of AI/ML for SMEs (Baabdullah, 2021; Bettoni, 2021; Chatterjee, 2022; etc.)                   |
|                         | Top management support          | The importance of leadership commitment for successful AI/ML adoption (Baabdullah, 2021; Chatterjee, 2022; etc.)                   |
|                         | Technological infrastructure    | Assessing the existing infrastructure and identifying necessary upgrades (Baabdullah, 2021; Bettoni, 2021; Chatterjee, 2022; etc.) |
|                         | Employee skills                 | The need for skilled personnel to implement and manage AI/ML projects (Baabdullah, 2021; Chatterjee, 2022; etc.)                   |
|                         | Regulatory and privacy concerns | Ensuring compliance with data protection regulations and addressing privacy concerns (Baabdullah, 2021; Chatterjee, 2022; etc.)    |
| Challenges and Barriers | Cost constraints                | Financial limitations faced by SMEs in AI/ML adoption (Baabdullah, 2021; Chatterjee, 2022; etc.)                                   |
|                         | Limited AI/ML expertise         | Addressing the shortage of AI/ML experts in SMEs (Baabdullah, 2021; De Simone, 2023; etc.)                                         |
|                         | Data management challenges      | Overcoming data-related issues, such as data quality, accessibility, and integration (Baabdullah, 2021; De Simone, 2023; etc.)     |

| Category                  | Sub-Category                                  | Key Points                                                                                                                                               |
|---------------------------|-----------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------|
| Implementation Strategies | Collaboration with external partners          | Partnering with AI/ML service providers, research institutions, or consultants (Baabdullah, 2021; Chatterjee, 2022; etc.)                                |
|                           | Low-code/no-code platforms                    | Utilizing userfriendly platforms to develop AI/ML solutions without extensive coding knowledge (De Simone, 2023; Raghavendran & Krishna Raj, 2023; etc.) |
|                           | Pilot projects and incremental implementation | Testing AI/ML solutions on small-scale projects and gradually expanding their application (Chatterjee, 2022; De Simone, 2023; etc.)                      |
| Performance Outcomes      | Improved operational efficiency               | Enhancing SMEs' operational processes with AI/ML technologies (Baabdullah, 2021; Chatterjee, 2022; etc.)                                                 |
|                           | Competitive advantage                         | Leveraging AI/ML to gain an edge in the market (De Simone, 2023; Liu & Wang, 2021; etc.)                                                                 |
|                           | Innovation and growth opportunities           | Unlocking new possibilities for product development, market expansion, and business growth (De Simone, 2023; Raghavendran & Krishna Raj, 2023; etc.)     |

Table 7: Key Considerations for AI/ML Adoption in SMEs

### 5.2.2 DESIGN

In the "DESIGN" phase of customizing the AutoML framework for AI/ML adoption in SMEs, several crucial steps are involved. Firstly, it entails assessing the specific business needs and objectives identified in the "STRATEGY" phase to guide the customization process effectively. This includes evaluating available computational resources such as hardware, software, and cloud services essential for the framework's implementation. Additionally, establishing a robust data infrastructure to support data preprocessing, model training, and evaluation is paramount. Subsequently, the modular AutoML pipeline is tailored to the SME's requirements, encompassing the selection of preprocessing methods, model selection strategies, and integration of ensemble learning techniques to enhance performance. Furthermore, ensuring resource efficiency and data privacy remains integral, with ongoing optimization of resource usage and implementation of robust data privacy measures throughout the AutoML process to safeguard sensitive information.

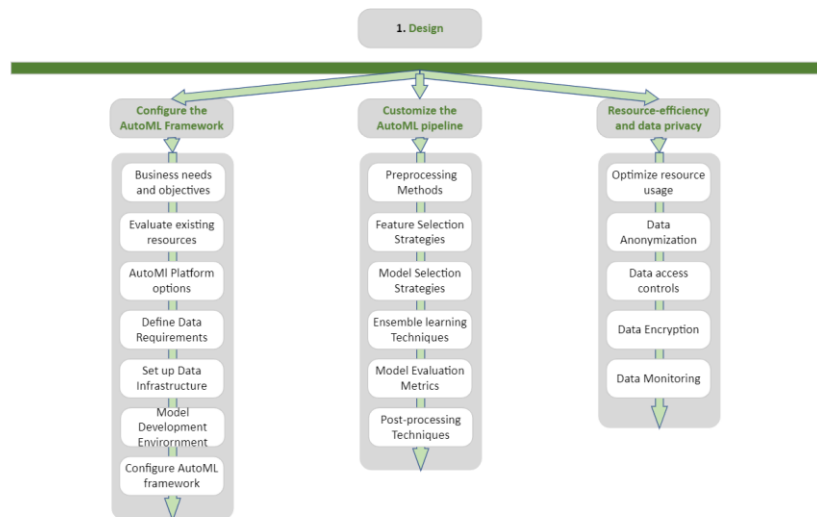


Figure 9: Proposed Model for the Design Phase

### Configure the AutoML framework

To configure the AutoML framework, start by assessing business needs and objectives. Identify the AI/ML use case(s) that the SME aims to address, evaluate the expected performance improvements and business outcomes, and determine the key stakeholders and their specific requirements. Next, evaluate existing resources, including hardware resources, available software tools and libraries, cloud-based infrastructure, and existing data storage and management systems. Then, explore various AutoML platforms and tools compatible with the SME's resources and objectives, considering factors such as cost, flexibility, and support. Define data requirements by determining data sources and formats relevant to the AI/ML project, evaluating data quality, quantity, and availability, and assessing the need for data cleansing, preprocessing, and feature engineering. Set up the data infrastructure by establishing a data storage and management system, integrating data privacy and security measures, developing a data labeling and annotation process if necessary, and implementing data versioning and backup systems. Lastly, establish a model development environment by setting up a dedicated environment, configuring development tools and libraries, and defining a version control system for model development.

### Customize the modular AutoML pipeline

Begin customizing the modular AutoML pipeline by selecting appropriate preprocessing methods. Choose data preprocessing techniques for handling missing values, outliers, and data scaling, determine feature engineering methods, and assess the need for data normalization and standardization. Next, define feature selection strategies by evaluating filter, wrapper, and embedded methods, configuring the criteria for selecting relevant features, and determining the trade-off between feature importance and model complexity. Then, configure model training strategies by specifying the types of machine learning models to be evaluated, setting the search space for model hyperparameters, defining cross-validation strategies for performance estimation, and determining the criteria for model selection and early stopping rules. Integrate ensemble learning techniques by identifying suitable methods, determining the criteria for combining individual models into ensembles, configuring the trade-off between ensemble diversity and performance, and assessing the

impact of ensemble learning on computational resources and training time. Define model evaluation metrics by specifying performance metrics, determining the trade-off between model performance and complexity, and configuring the evaluation metrics for different machine learning tasks. Finally, implement post-processing techniques by applying model interpretation techniques, implementing calibration methods, and configuring model retraining and updating strategies.

#### Ensure resource-efficiency and data privacy

Ensure resource-efficiency and data privacy by optimizing resource usage. Monitor and assess computational resource consumption during the AutoML process, fine-tune hyperparameters and model configurations to improve resource efficiency, utilize parallel and distributed computing techniques, and implement resource scheduling and allocation policies. Implement data anonymization by applying techniques such as generalization, suppression, and pseudonymization to protect sensitive information, and assess the impact of anonymization on data utility and model performance. Enforce data access controls by implementing role-based access controls, configuring authentication and authorization mechanisms, and establishing a clear data governance policy. Encrypt data at rest and in transit by applying encryption techniques to protect sensitive data stored in databases, file systems, or cloud storage, and encrypting data transmitted between different components of the AutoML pipeline. Monitor and audit data access by implementing logging and monitoring systems, regularly reviewing access logs, and establishing incident response procedures and notification policies.

### 5.2.3 TRAIN

Step three of the AutoML framework focuses on training, evaluating, and interpreting machine learning models, leveraging the prepared data and the selected AutoML pipeline components. This stage is crucial to ensure the development of high-performing, accurate, and interpretable AI/ML models that address the unique needs and constraints of small and medium-sized enterprises (SMEs).

In this step, the AutoML framework utilizes advanced techniques to train models using AutoML algorithms, fine-tuning their hyperparameters for optimal performance, and assess their predictive capabilities. This iterative process allows for continuous model refinement and improvement based on the insights gained from the evaluation and interpretation steps.

Furthermore, the application of Explainable AI (XAI) techniques enables stakeholders to gain a deeper understanding of the models' decision-making processes, feature importance, and overall behavior. This transparency enhances trust in the AI/ML solutions and empowers SMEs to make informed decisions, fostering successful AI adoption and integration in their operations.

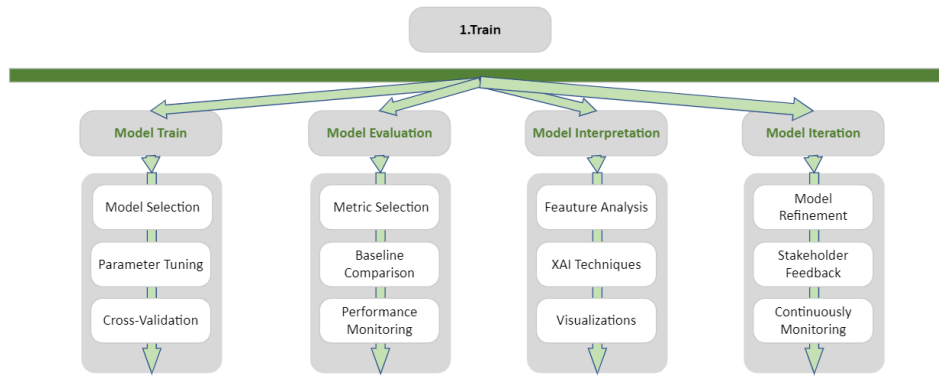


Figure 10: Proposed Model for the Train Phase

**Model Training:** In this stage, an appropriate AutoML model is selected from the available options within the AutoML framework, based on the data characteristics. Next, optimal hyperparameters for the chosen AutoML model are determined using techniques like grid search, random search, or Bayesian optimization. Finally, cross-validation is performed to evaluate the model's generalization ability and prevent overfitting.

**Model Evaluation:** Here, suitable evaluation metrics are chosen based on the model's objectives (e.g., accuracy, precision, recall, F1-score, AUC-ROC, or RMSE). The trained model's performance is compared with a baseline model, such as a simple heuristic or a random classifier, to assess the added value of the AI/ML model. Additionally, the model's performance is monitored over time to detect any potential degradation or drift in its predictions.

**Model Interpretation:** This stage involves identifying the most influential features in the trained model using techniques like SHAP values, permutation importance, or feature coefficients. Explainable AI (XAI) techniques are applied to understand the model's underlying decision-making process and generate human-understandable explanations for the model's predictions. Visualizations are created to present the model's decision boundaries, feature interactions, or individual prediction explanations, enhancing interpretability and understanding of the model's behavior.

**Model Iteration:** In this stage, the model training process is iterated based on the insights gained from the evaluation and interpretation steps to further improve model performance and generalizability. Feedback is collected from stakeholders, including domain experts, business leaders, and end-users, to validate the model's relevance and effectiveness in the SME context. Furthermore, changes in the data or business environment that may affect the model's performance are continuously monitored, and the model is updated accordingly.

By following this detailed approach for training, evaluating, and interpreting models, the AutoML framework ensures the development of high-performing, interpretable, and relevant AI/ML models tailored to the unique needs and constraints of SMEs.

## 5.2.4 DEPLOY

The fourth step of the AutoML framework focuses on deploying machine learning models into production environments, allowing businesses to leverage AI/ML solutions for real-time decision-making, automation, and process improvement.

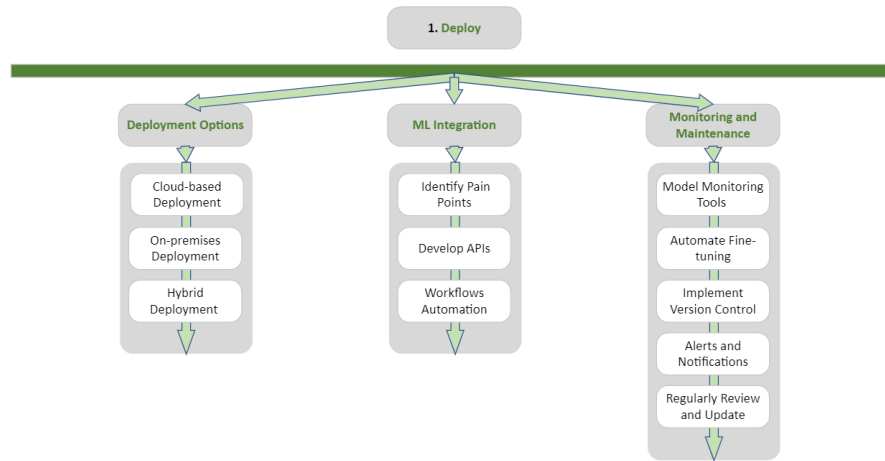


Figure 11: Proposed Model for the Deploy Phase

In this step businesses need to focus on deploying machine learning models into their production environments. This process involves selecting a suitable deployment option, integrating the models into existing business systems or workflows, and establishing monitoring and maintenance processes.

First, businesses must choose an appropriate deployment option based on their specific requirements and constraints. Cloud-based deployment offers scalability, cost-efficiency, and easy integration with other cloud-based services. On-premises deployment provides more control over data privacy and security, while hybrid deployment combines the benefits of both cloud and on-premises strategies.

Once the deployment option is selected, businesses should identify touchpoints where AI/ML models can enhance existing processes, such as customer segmentation or demand forecasting. They should develop APIs or connectors to facilitate communication between the models and other business systems, like CRM or ERP tools. Additionally, it's essential to establish processes for triggering model predictions or actions based on business events or data updates, ensuring seamless integration with user interfaces, dashboards, or reports.

Finally, businesses need to implement monitoring and maintenance processes to ensure ongoing model performance. This includes using monitoring tools to track the models' accuracy, drift, and data quality, setting up alerts for performance degradation or anomalies, and establishing a process for model retraining or fine-tuning. Version control and rollback mechanisms should be in place to manage model updates effectively, and models should be regularly reviewed and updated to accommodate changes in business goals or regulatory requirements.

By following these guidelines in Step four of the AutoML framework, businesses can successfully deploy and integrate machine learning models into their operations, driving improvements in efficiency, decision-making, and overall performance.

### **5.2.5 OPTIMIZE**

In the final step of the AutoML framework, businesses should focus on optimizing their machine learning models and processes to ensure continuous improvement and alignment with their evolving business objectives. This involves measuring the impact of machine learning projects, continuously enhancing the AutoML framework, and scaling successful AI/ML applications across the organization.

To measure the impact of machine learning projects, businesses must define relevant key performance indicators (KPIs) and metrics to assess the effectiveness of deployed AI/ML models. These metrics can include accuracy, precision, recall, or return on investment (ROI). Regularly monitoring and evaluating the impact of these projects on business objectives, processes, and overall performance is crucial. Conducting performance reviews and retrospectives will help identify areas for improvement, which should be communicated to stakeholders.

Continuous improvement of the AutoML framework is essential to its success. Gathering feedback from users and stakeholders will help identify pain points, areas for improvement, and new opportunities for AI/ML applications. Staying informed about emerging technologies, techniques, and best practices in the AI/ML field will enable businesses to assess potential benefits and implement new solutions. Regularly updating and refining the AutoML framework, processes, and tools based on insights and evolving requirements is vital. Fostering a culture of continuous learning and experimentation will encourage employees to explore new ideas and participate in professional development opportunities.

Lastly, businesses should aim to scale successful AI/ML applications across the organization. Identifying high-impact use cases and prioritizing their implementation based on business value, resource requirements, and strategic alignment is crucial. Developing a roadmap for scaling AI/ML applications should consider factors such as data availability, infrastructure, and change management. Collaboration with cross-functional teams will ensure smooth implementation and adoption of AI/ML solutions in different business units or departments. Establishing a Center of Excellence (CoE) or dedicated AI/ML team will provide guidance, support, and best practices for AI/ML projects organization wide.

### **5.2.6 A PROPOSED HAKUNA MATATA AUTOML SOLUTION ARCHITECTURE**

The AutoML framework involves various stakeholders throughout its five steps. Beginning with aligning AI/ML initiatives with business objectives, the executive team plays a crucial role in setting the strategic direction and priorities, with input from team leaders and department heads contributing to identifying potential use cases. The design phase involves collaboration between data scientists, IT personnel, and domain experts to ensure that the data collected is relevant, high-quality, and accessible, while legal advisors may be consulted to ensure data privacy compliance. During model training and selection, data scientists, machine learning engineers, and subject matter experts work together to build, evaluate, and choose the most suitable AI/ML models, potentially involving external consultants or vendors if third-party solutions are considered. Deployment requires close collaboration

between data scientists, IT teams, and system administrators to select the best deployment option, integrate models into existing systems, and establish monitoring processes, with cloud service providers potentially engaged for cloud-based deployments.

Finally, the optimization phase involves the entire organization, with executive leadership spearheading continuous improvement efforts and fostering a culture of learning and experimentation. Project managers and team leaders play a vital role in measuring project impact, scaling successful AI/ML solutions, and supporting cross-functional collaboration.

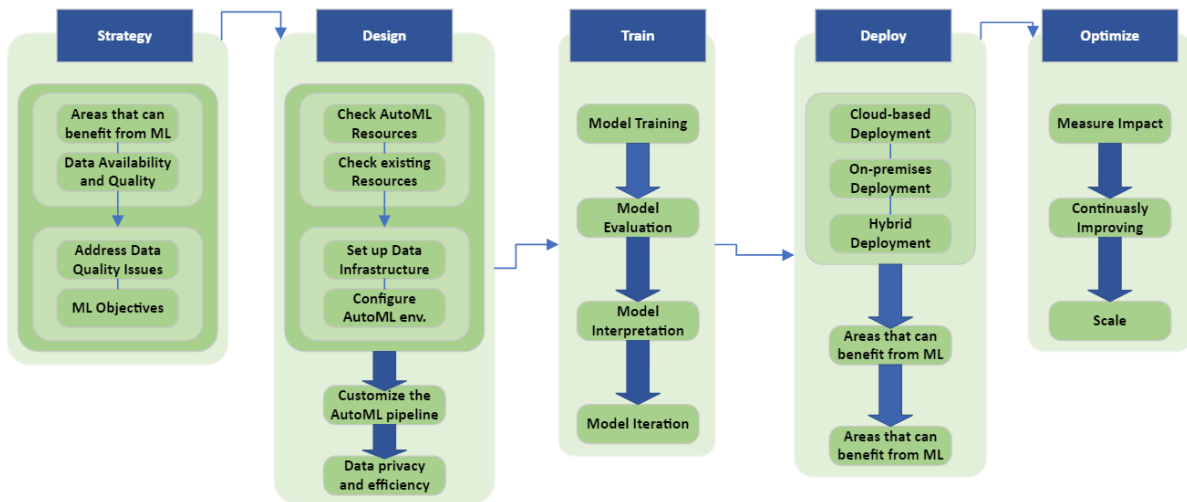


Figure 12: Hakuna Matata Solution Architecture for AutoML

## 5.2.7 VALIDATION

Following the development of the AutoML framework, our research reached the validation stage, using the Design Science Research (DSR) strategy and evaluation method of collecting feedback from subject matter experts (SMEs) as outlined by Peffers et al. (2007). This stage aimed to validate the proposed framework, gather critical comments, and identify potential improvements, ultimately addressing research gaps.

Experts from both the industry (machine learning professionals) and academia were selected due to their diverse views and expertise. Interviews were conducted via online meetings, with the following structure:

1. Brief presentation of the AutoML framework, including its background, objectives, and key components, to provide context for the experts.
2. Interview phase: A series of pre-defined questions were posed to the experts, focusing on the framework's relevance, practicality, and effectiveness in addressing SMEs' challenges in adopting AI/ML.

| Expert | Professional Role        | Area of Expertise               |
|--------|--------------------------|---------------------------------|
| 1      | Chief Operations Officer | Operations: Hospitality         |
| 2      | Account Manager          | Sales: Retail                   |
| 3      | Data Scientist           | Business Strategy: Green Energy |

Table 8: Interviewed Experts

By engaging with these experts from various industries, such as green energy, hospitality, and retail, we gathered valuable insights and feedback on the AutoML framework. Their input will inform future refinements, ensuring the framework's relevance and applicability across diverse SME's contexts. In the next section, we will discuss the findings from these expert interviews and the implications for further development of the AutoML framework.

Our framework was well-received by a Chief Operating Officer (COO) from the hospitality sector, who appreciated the focus on identifying and prioritizing use cases based on business objectives. The COO felt that this approach would significantly benefit hospitality SMEs seeking to optimize operations and enhance customer experiences. Additionally, the expert found the guidance on selecting suitable machine learning models to be particularly helpful for decision-making within the hospitality industry. The expert also suggested incorporating industry-specific examples to further demonstrate the framework's applicability.

An Account Executive from the retail sector commended the framework's emphasis on optimizing machine learning models and processes, as this would enable retail businesses to continuously improve their sales and customer engagement strategies. The expert found the guidance on scaling successful AI/ML applications across the organization to be especially useful for facilitating AI/ML adoption in various departments or business units. The Account Executive recommended adding a section on change management and employee training to foster a data-driven culture within retail organizations.

A Data Scientist from the green energy sector acknowledged the framework's inclusion of data management best practices, emphasizing its importance for green energy businesses that rely on data for strategic decision-making and sustainable growth. The expert appreciated the guidance on model deployment options, as it would enable green energy SMEs to choose the most suitable approach based on their infrastructure and resources. Furthermore, the expert advised dedicating a section to the ethical and environmental implications of AI/ML technologies within the green energy sector to promote responsible and sustainable practices.

## 5.2.8 DISCUSSION

In light of the expert feedback, it is evident that our proposed AutoML framework has been well-received and provides a solid foundation for small and medium-sized enterprises (SMEs) to adopt AI/ML technologies effectively. The framework's focus on aligning AI/ML initiatives with business objectives, managing data, developing and deploying models, and optimizing processes has been acknowledged as both practical and valuable.

While the experts have suggested areas for improvement, such as incorporating industry-specific examples, addressing ethical and environmental implications, and emphasizing change management and employee training, these can be viewed as enriching additions rather than fundamental changes to the framework.

Considering the balance between maintaining the core structure and simplicity of the framework while integrating new insights, we believe that updating the current framework to include the suggested improvements would be a suitable approach. This will enhance the framework's relevance and applicability without requiring a complete revision at this stage. As the AI/ML landscape continues to evolve, ongoing evaluation and adaptation of the AutoML framework will be essential to ensure its effectiveness in guiding SMEs through the adoption process. Regular engagement with experts from various industries, as well as monitoring emerging trends and challenges, will help us refine the framework and better support SMEs in harnessing the full potential of AI/ML technologies for growth, innovation, and resilience.

In addressing RQ3, "What best practices and guidelines can be established for the responsible integration of collaborative AutoML tools within the unique operational and resource constraints of SMEs?" We have identified several key practices based on our research findings and expert feedback. These best practices and guidelines include aligning AI/ML initiatives with business goals, ensuring that AI/ML projects are directly tied to specific business objectives and strategies to maximize their impact and relevance. SMEs should start small and scale gradually, beginning with pilot projects to demonstrate value and feasibility, then scaling up based on initial successes and learnings. Focusing on data quality is crucial; prioritizing high-quality, relevant data to improve model accuracy and reliability, and regularly assessing and cleaning data to maintain its integrity. Incorporating industry-specific use cases is essential to tailor the framework to include examples and case studies relevant to the specific industry of the SME, making the framework more relatable and practical.

Addressing ethical and environmental implications is also important, incorporating guidelines for responsible AI usage, including considerations for bias, transparency, and environmental sustainability. Emphasizing change management and training is key; developing comprehensive training programs for employees to build AI/ML literacy and create a culture that embraces technological change. Leveraging existing infrastructure can reduce costs and implementation time, ensuring a smoother integration process. Fostering collaboration within the organization encourages cross-functional collaboration to leverage diverse perspectives and expertise in AI/ML projects. Continuous monitoring and evaluation involve regularly reviewing and updating the framework based on feedback and emerging trends to ensure it remains relevant and effective. Engaging with external experts helps maintain a network of industry experts and consultants to provide ongoing support and insights.

By following these best practices and guidelines, SMEs can responsibly and effectively integrate collaborative AutoML tools, thereby enhancing their data-driven decision-making capabilities and supporting their overall growth and resilience in an increasingly competitive landscape.

## 6. CONCLUSIONS AND FUTURE WORKS

Through an extensive literature review and a series of expert interviews, this thesis aimed to develop and validate the AutoML framework – a practical guide designed to assist small and medium-sized enterprises (SMEs) in successfully adopting AI/ML technologies. This journey began with an exploration of AI/ML concepts and their significance in driving business growth, followed by an analysis of the specific challenges faced by SMEs in this domain.

The literature review shed light on the various aspects of AI/ML adoption in SMEs, while the expert interviews provided valuable feedback on the relevance, applicability, and potential areas of improvement for the proposed AutoML framework. This iterative process ensured that the framework remained grounded in real-world experiences and industry insights.

### 6.1 SUMMARY OF OUR DEVELOPED WORK

Our research followed a structured approach. First, we established the research objective by identifying the challenges faced by SMEs in adopting AI/ML technologies. We then conducted a comprehensive literature review to build a solid theoretical foundation in AI/ML and understand their implications for businesses.

Following the literature review, we developed the AutoML framework, drawing on our findings and focusing on key areas such as aligning AI/ML initiatives with business objectives, managing data, model development and deployment, and continuous improvement. The framework's practical approach aimed to cater to the unique needs and constraints of SMEs, offering guidance and best practices to navigate the complexities of AI/ML adoption.

Finally, we validated the framework through expert interviews, gathering feedback, and suggestions for improvement. The revised framework reflects these insights, ensuring its continued relevance and effectiveness for SMEs embarking on their AI/ML journey.

### 6.2 RESEARCH LIMITATIONS

While this study provides valuable insights into the challenges faced by SMEs in adopting AI/ML technologies and offers a practical solution through the AutoML framework, it is not without limitations. Some of these limitations include:

**Limited sample size:** The validation of the AutoML framework was based on interviews with three industry experts. While these experts provided valuable feedback and suggestions for improvement, a larger sample size would have offered a more comprehensive view of the framework's effectiveness across various industries and SME contexts.

**Industry-specific considerations:** The AutoML framework is designed to be applicable across industries; however, it may not fully address the unique challenges and opportunities in specific sectors, such as healthcare, finance, or manufacturing. Further research could explore the development of industry-tailored versions of the framework for enhanced applicability.

Theoretical evaluation: The framework was validated through expert interviews and a theoretical evaluation process. However, practical implementation and testing in real-life situations are necessary to assess the framework's effectiveness and identify potential areas for improvement.

Time constraints: Due to time limitations, it was not possible to perform the communication stage as outlined in the research strategy. Incorporating this stage in future research could help gather additional feedback and insights from a broader range of stakeholders.

Addressing these limitations in future research will further enhance the AutoML framework and contribute to the growing body of knowledge on AI/ML adoption in SMEs. By conducting additional interviews with industry experts, focusing on industry-specific considerations, and testing the framework in real-life situations, researchers can continue to refine and improve the framework's effectiveness for small and medium-sized enterprises.

### **6.3 FUTURE WORK**

Building on the findings and recommendations from this research, future studies could further refine the AutoML framework by exploring emerging trends, challenges, and innovations in the AI/ML landscape. Some potential areas for future research include:

- Investigating strategies for reducing costs and minimizing potential risks associated with AI/ML adoption in SMEs.
- Examining the role of policymakers and regulatory authorities in fostering responsible AI/ML adoption among SMEs.
- Evaluating the potential of AI/ML technologies in promoting sustainability and addressing environmental challenges within different industries.
- Exploring the development of industry-specific versions of the AutoML framework to cater to the unique needs and constraints of different sectors.

As the AI/ML domain continues to evolve, ongoing research and refinement of the AutoML framework will be crucial in supporting SMEs through the adoption process. By addressing emerging challenges and fostering collaboration between researchers, industry experts, and policymakers, we can empower small and medium-sized enterprises to harness the full potential of AI/ML technologies for growth, innovation, and resilience.

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## ANNEXES

Conversations with subject matter experts:

First interview: Chief Operations Officer @ Tulivu Hospitality Group, date: 12.02.2024

**Question 1:** In your opinion, does the AutoML framework effectively address the challenges faced by SMEs like Tulivu Hospitality Group in adopting AI/ML technologies? Please elaborate on your response.

The AutoML framework is indeed useful for hospitality SMEs like Tulivu Hospitality Group. The alignment of AI/ML initiatives with business objectives and the emphasis on data management are particularly relevant, as these aspects can help optimize operations and enhance customer experiences.

**Question 2:** Do you have any concerns or criticisms regarding the proposed AutoML framework? Could you provide an explanation from a hospitality SME perspective?

While the framework is comprehensive, I think it would benefit from more industry-specific examples. Including instances of how AI/ML technologies can be applied in areas like customer service, marketing, and resource management would make it more relatable for hospitality businesses.

**Question 3:** Would you consider implementing the AutoML framework within Tulivu Hospitality Group? Please explain your reasoning.

Yes, I would consider implementing the AutoML framework in our organization. It has the potential to streamline AI/ML adoption and promote a data-driven culture. However, addressing change management and providing proper employee training will be crucial for successful implementation.

**Question 4:** Based on your experience in the hospitality industry, what suggestions would you offer to further enhance the effectiveness of the AutoML framework for SMEs like yours?

I recommend emphasizing privacy and ethical considerations in AI/ML adoption for the hospitality industry. Additionally, including a section on identifying and overcoming common industry-specific challenges, such as integrating AI/ML technologies with existing hospitality management systems, would be valuable.

Second interview: Account Manager @ Ekonimi Market, date: 15.02.2024

**Question 1:** How does the AutoML framework address the unique challenges faced by retail SMEs like Ekonomi Market in adopting AI/ML technologies? Could you elaborate on its usefulness?

The AutoML framework offers a valuable approach for retail SMEs. The focus on optimizing machine learning models and processes aligns with our goals to enhance sales and customer engagement strategies. Additionally, the guidance on scaling successful AI/ML applications across the organization would help us implement these technologies in various departments.

**Question 2:** Do you have any concerns or criticisms regarding the proposed AutoML framework from a retail SME perspective? Could you provide an explanation?

Although the framework is comprehensive, it could benefit from more detailed guidance on model deployment options, such as cloud-based, on-premises, or hybrid approaches. Retail SMEs need to understand the implications of each option to make informed decisions based on their specific infrastructure and resource constraints.

**Question 3:** Would you consider implementing the AutoML framework within Ekonomi Market? Please explain your reasoning.

Yes, I believe implementing the AutoML framework would be beneficial for Ekonomi Market. Its step-by-step structure makes it easy to navigate the complexities of AI/ML adoption, and the focus on continuous improvement aligns with our commitment to adapt to evolving customer needs and market trends.

**Question 4:** Based on your experience in the retail industry, what suggestions would you offer to further enhance the effectiveness of the AutoML framework for retail SMEs like Ekonomi Market?

I suggest dedicating a section to data quality issues and strategies to overcome them, as this is a common challenge faced by retail businesses. Additionally, emphasizing explainable AI and transparency in AI/ML models would foster trust among customers and stakeholders, which is crucial for maintaining strong relationships in the retail industry.

Third interview: Founder and Data Scientist @ Cordel Enerji, date: 19.02.2024

**Question 1:** How does the AutoML framework address the unique challenges faced by SMEs like Cordel Enerji in adopting AI/ML technologies? Could you elaborate on its usefulness?

The AutoML framework provides a valuable guide for SMEs looking to adopt AI/ML technologies. As a data scientist at Cordel Enerji, I find the emphasis on data management best practices particularly relevant, as our strategic decision-making relies on accurate and reliable data. Additionally, guidance on selecting suitable machine learning models based on business objectives is essential for developing tailored solutions for our green energy operations.

**Question 2:** Do you have any concerns or criticisms regarding the proposed AutoML framework from an SME perspective? Could you provide an explanation?

Although the framework offers a comprehensive approach to AI/ML adoption, it could benefit from more in-depth coverage of ethical and environmental implications, particularly for the green energy sector. As our industry aims to promote sustainability, it's crucial to consider these aspects when developing and deploying AI/ML technologies.

**Question 3:** Would you consider implementing the AutoML framework within Cordel Enerji? Please explain your reasoning.

Yes, I believe the AutoML framework would be a useful tool for Cordel Enerji. Its structured approach would help streamline our AI/ML adoption process, ensuring we can make informed decisions and maximize the benefits of these technologies for our green energy business.

**Question 4:** Based on your experience, what suggestions would you offer to further enhance the effectiveness of the AutoML framework for SMEs like Cordel Enerji?

I suggest including a section dedicated to potential collaborations between AI/ML experts, industry professionals, and academic researchers. These partnerships can facilitate knowledge sharing, innovation, and problem-solving within the SME context, ultimately driving the successful adoption and application of AI/ML technologies across industries.

