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Collaborative automated machine learning (AutoML) process framework

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Abstract: In the face of rapid technological advancements and digital disruption, Small and Medium Enterprises (SMEs) grapple with integrating data-driven practices essential for competitiveness and growth. Unlike large corporations, SMEs often lack the resources and technical expertise to implement sophisticated data analytics and machine learning solutions. This study addresses the identified gap by developing a Collaborative Automated Machine Learning (AutoML) Process Framework tailored to the unique needs of SMEs. Leveraging Design Science Research methodology, the research conceptualizes, designs, and validates an accessible AutoML tool that automates complex machine learning processes while fostering collaboration among stakeholders. The framework aims to democratize advanced analytics, enabling SMEs to harness domain knowledge and drive data-driven decision-making without extensive data science expertise. The findings demonstrate that the proposed collaborative AutoML framework significantly enhances SMEs' operational efficiency, decision-making capabilities, and competitive edge, thereby contributing to their digital transformation and broader economic growth. This research not only bridges the existing gap in AutoML applications for SMEs but also aligns with sustainable development goals by promoting inclusive innovation and economic resilience.
Keywords: *Automated machine learning (AutoML), Collaborative framework, Data-driven transformation, Design science research, Digital transformation, Small and medium enterprises (SMEs).*

1. Introduction

In today's rapidly evolving digital landscape, Small and Medium Enterprises (SMEs) are under immense pressure to adopt data-driven practices to sustain and enhance their competitiveness. While large enterprises swiftly integrate advanced data analytics and machine learning (ML) solutions, SMEs often face significant barriers, including limited financial resources, lack of technical expertise, and the complexities associated with implementing such technologies. Ramos and Oliveira (2020) highlight that these challenges impede SMEs' ability to remain competitive in an increasingly data-centric market. Without the necessary infrastructure and expertise, SMEs struggle to leverage large-scale data analytics, underscoring the need for innovative solutions that democratize access to advanced analytics.

Despite the recognized importance of Automated Machine Learning (AutoML) in facilitating data-driven transformation, there remains a substantial research gap concerning the development of collaborative AutoML tools specifically designed for SMEs. Existing studies, such as those by Ramos and Oliveira (2020), acknowledge the obstacles SMEs encounter in adopting data-driven strategies but seldom explore the intricacies of creating collaborative AutoML solutions tailored to their unique operational contexts. Furthermore, Chang, Zhang, and Hussain (2019) focus primarily on the automation aspects of AutoML, neglecting the collaborative elements essential for SME operations. This gap highlights the need for a comprehensive exploration of how collaborative AutoML can democratize data-driven practices within SMEs, providing a foundation for designing and evaluating tools that align with their specific challenges and requirements.

This research aims to address the aforementioned gap by designing a **Collaborative AutoML Framework** that empowers SMEs to utilize advanced machine learning algorithms without necessitating extensive data science expertise. The primary objectives of this study are:

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- Comprehensive Literature Review: Analyze existing AutoML tools to understand their functionalities, benefits, and limitations.
- Survey and Needs Analysis: Conduct surveys to identify the specific AutoML requirements and challenges faced by SMEs during their digital transformation journey.
- Framework Design: Develop a collaborative AutoML framework tailored to SMEs, facilitating the automation of machine learning processes while promoting stakeholder collaboration.
- Framework Validation: Evaluate the effectiveness of the proposed framework through empirical validation to ensure it meets the needs of SMEs.

The significance of this research lies in its potential to bridge the technological divide between large enterprises and SMEs, fostering an inclusive digital transformation landscape. SMEs are pivotal to global economies, driving innovation, creating employment, and contributing to economic growth. However, their limited resources and technical capabilities often hinder their adoption of data-driven practices. By developing a collaborative AutoML tool, this study provides SMEs with an accessible platform to harness data analytics and machine learning, enhancing their operational efficiency and decision-making processes.

Moreover, the research aligns with the United Nations Sustainable Development Goals (SDGs), particularly SDG 9: Industry, Innovation, and Infrastructure and SDG 8: Decent Work and Economic Growth. By enabling SMEs to adopt innovative data-driven strategies, the study promotes resilient infrastructure and sustainable industrialization, while also supporting inclusive economic growth and employment.

From a scientific perspective, the development of a collaborative AutoML framework introduces an innovative approach to addressing real-world challenges faced by SMEs. By integrating insights from existing literature and empirical data, this research contributes to the body of knowledge in AutoML applications and offers a practical solution that bridges the gap between academia and industry. Additionally, the collaborative nature of the proposed framework fosters a participatory approach, ensuring that the tool is user-centric and meets the diverse needs of SMEs.

In conclusion, this study not only enhances the data-driven capabilities of SMEs but also supports broader economic and societal goals by promoting inclusive innovation and sustainable growth. The collaborative AutoML framework serves as a catalyst for SMEs' digital transformation, enabling them to thrive in a competitive, data-centric economy and contributing to overall economic resilience and growth.

2. Background

The application of Automated Machine Learning (AutoML) within small and medium-sized enterprises (SMEs) has garnered significant attention due to its potential to democratize machine learning (ML). AutoML enables businesses, particularly those with limited technical expertise and resources, to implement advanced ML techniques without requiring in-depth data science knowledge. By automating critical processes such as feature engineering, model selection, and hyperparameter tuning, AutoML reduces the complexity of deploying machine learning models, making it highly appealing for SMEs that wish to leverage data-driven insights to improve decision-making and operations. This literature review synthesizes research on the use of AutoML in SMEs, highlighting relevant studies that address the benefits, challenges, and current status of AutoML adoption in this sector.

Research on AutoML has intensified over recent years, particularly as its benefits for SMEs have become clearer. One major area of focus is how AutoML can be tailored to meet the specific needs of SMEs, which typically lack the resources and technical staff to manage complex ML workflows. Studies emphasize the importance of developing user-friendly platforms that enable SMEs to harness the power of ML without needing to invest heavily in technical expertise or infrastructure. Several frameworks have been proposed to facilitate AutoML adoption, emphasizing ease of use and scalability, which are crucial for SMEs operating in dynamic environments. Research also highlights the growing number of SMEs adopting AutoML for various applications, such as customer segmentation, sales forecasting, and anomaly detection. These tools allow businesses to gain a competitive edge by making data-driven decisions that optimize operations and drive growth.

2.1. Techniques and Applications of AutoML in SMEs

The use of AutoML techniques in SMEs is increasingly directed toward predictive modeling tasks that align with business priorities. These include applications such as customer behavior analysis, inventory management, and demand forecasting, which are essential for improving operational efficiency and competitiveness. AutoML tools have proven especially valuable in areas where SMEs traditionally struggle due to limited access to large datasets or advanced computing power. AutoML platforms like Google Cloud's AutoML and Microsoft's Azure AutoML offer SMEs access to powerful AI capabilities without the need for bespoke models or advanced in-house expertise.

Deep learning, a subset of AutoML, has also seen a surge in adoption among SMEs, particularly for tasks involving image recognition, natural language processing, and time-series analysis. While deep learning models are typically more complex and resource-intensive, AutoML simplifies their implementation, allowing SMEs to integrate these innovative technologies into their business operations. Studies consistently show that SMEs using AutoML for deep learning are able to extract valuable insights from their data, improving their ability to innovate and stay competitive.

2.2. Advantages of Applying AutoML in SMEs

The integration of AutoML into SMEs offers numerous advantages, with enhanced decision-making being one of the most notable. By analyzing large datasets, AutoML models can uncover patterns and trends that would otherwise remain hidden, empowering SMEs to make more informed business decisions. This is particularly valuable in areas like marketing, where understanding customer preferences can lead to more effective campaigns, or in operations, where supply chain optimization can result in significant cost savings.

Moreover, AutoML contributes to increased efficiency by automating routine tasks such as data entry, fraud detection, and customer service interactions. Automation allows SMEs to reallocate human resources to higher-value activities, enhancing productivity and operational efficiency. The ability to scale ML models as a business grows is another advantage, providing SMEs with the flexibility to adapt their ML solutions as their data volumes and operational needs expand.

2.3. Challenges and Issues in AutoML Adoption

Despite its advantages, the adoption of AutoML in SMEs is not without challenges. One of the primary issues is the lack of high-quality data. Effective ML models depend on large, clean, and well-structured datasets, but SMEs often face difficulties in accessing such data. This limitation can significantly undermine the performance of AutoML models, as smaller or noisier datasets may lead to less accurate predictions or insights.

Another major hurdle is the technical expertise required to implement and manage AutoML systems. While AutoML platforms simplify many processes, SMEs still need a basic understanding of machine learning concepts to effectively deploy these tools. This presents a barrier for businesses without dedicated data science teams. Additionally, the talent gap in the data science and AI fields further complicates recruitment and retention efforts for SMEs seeking to build in-house expertise.

The interpretability and transparency of AutoML models pose further challenges. Many AutoML solutions, particularly those involving deep learning, operate as "black boxes," where the decision-making process is not easily understood by users. This lack of transparency can lead to concerns about the fairness, bias, and accountability of the models, especially in industries where regulatory compliance and ethical considerations are paramount.

Scalability also presents a challenge for SMEs using AutoML. As businesses grow, so do their data and computational requirements. Scaling AutoML solutions to accommodate these demands can be costly, particularly when SMEs must invest in cloud infrastructure or other advanced technologies. Moreover, while AutoML helps reduce the need for custom coding or manual model building, it may not always offer the flexibility required to address highly specific or unique business problems.

2.4. Ethical and Practical Considerations

Beyond the technical challenges, ethical considerations are becoming increasingly important as AutoML systems are integrated into business operations. Data privacy, algorithmic bias, and the potential unintended consequences of automated decision-making are significant concerns for SMEs. For instance, biased training data can lead to discriminatory practices in customer service or hiring processes, raising both legal and reputational risks for SMEs. Ensuring transparency and accountability in AI-driven systems is essential for building trust among customers and stakeholders, which is crucial for SMEs operating in competitive markets.

In conclusion, while AutoML holds great promise for SMEs, its implementation comes with a set of challenges that must be carefully managed. By addressing issues such as data quality, technical expertise, scalability, and ethical concerns, SMEs can fully harness the benefits of AutoML to drive innovation and competitiveness. Ongoing research and development in this field are expected to further simplify AutoML platforms, making them more accessible and user-friendly for businesses of all sizes.

3. Methodology

This research adopts the Design Science Research (DSR) methodology, which is well-suited for developing innovative solutions to real-world problems, particularly within the context of Small and Medium Enterprises (SMEs). The aim is to design and evaluate a collaborative Automated Machine Learning (AutoML) framework tailored specifically to the needs of SMEs. DSR is particularly appropriate for this project due to its focus on creating artifacts that address practical challenges and its iterative nature, which allows for ongoing refinement of the proposed solution based on continuous feedback and evaluation. This section details the research design, data collection methods, and analysis techniques used in the study.

3.1. Research Design

The research follows the DSR methodology, which emphasizes both the creation of innovative artifacts and the generation of knowledge through the evaluation of those artifacts. In this study, the artifact is a collaborative AutoML framework designed to support SMEs in adopting machine learning practices. The DSR approach ensures that the framework is not only theoretically grounded but also useful for SMEs that often lack in-house expertise in data science.

The iterative process of DSR involves several key steps: identifying the problem, defining objectives, designing, and developing the artifact, evaluating the artifact, and refining it based on feedback. These phases are central to our approach:

1. **Problem Identification and Motivation:** The research begins by identifying the specific challenges SMEs face in adopting data-driven practices, such as limited access to technical expertise and resources. SMEs often struggle to implement machine learning techniques that require specialized knowledge, making AutoML a promising solution. Understanding these challenges guides the design of the collaborative AutoML framework.
2. **Objective Definition for the Solution:** Based on the identified problem, the objectives for the AutoML framework are defined. These include creating a tool that is user-friendly, scalable, and capable of providing SMEs with data-driven insights without requiring extensive machine learning expertise. The framework must also be flexible enough to adapt to the evolving needs of SMEs.
3. **Design and Development:** The design phase involves creating a collaborative AutoML framework that addresses the specific needs of SMEs. This includes developing user interfaces that simplify interaction with machine learning models, integrating the framework with existing SME systems, and ensuring it supports collaboration between users with varying levels of technical expertise.
4. **Evaluation and Refinement:** The framework is rigorously evaluated through both qualitative and quantitative methods. Based on the feedback gathered from SMEs, the artifact is refined to better meet their needs. This iterative process ensures that the framework evolves into a practical tool that can be effectively used by SMEs.

3.2. Data Collection Methods

To design and evaluate the AutoML framework, data collection was conducted through multiple methods, ensuring a comprehensive understanding of the challenges SMEs face and the effectiveness of the proposed solution. The research employs a combination of primary and secondary data sources.

1. **Literature Review:** A thorough review of existing literature on AutoML tools and SME data-driven practices was conducted. This review helped identify the current limitations of AutoML platforms for SMEs and informed the design of the framework by highlighting best practices and areas for improvement.
2. **Surveys and Interviews with SMEs:** Qualitative data was collected through structured interviews and surveys with SMEs across different sectors. The aim was to gather insights into their data needs, the specific challenges they face in adopting machine learning, and their expectations for an AutoML solution. This feedback directly influenced the design of the framework, ensuring that it aligns with the practical needs of SMEs. The interviews also helped identify key areas where existing AutoML tools fall short in supporting SMEs.
3. **Expert Feedback:** To further refine the framework, input was gathered from data science professionals and AutoML experts. Their feedback helped ensure that the tool incorporates innovative machine learning techniques while remaining accessible to non-experts. The combination of expert feedback and SME input ensured a balanced approach that combines technical sophistication with practical usability.
4. **Case Studies:** To provide deeper insights into how the AutoML framework could be used in practice, case studies of specific SMEs were conducted. These case studies involved an in-depth analysis of the challenges faced by the SMEs and how the AutoML framework could address those challenges. This method provided practical examples of the framework's potential impact.

3.3. Analysis Techniques

The data collected was analyzed using both qualitative and quantitative methods to evaluate the effectiveness of the AutoML framework and to identify areas for further improvement.

1. **Qualitative Analysis:** The qualitative data gathered from interviews, surveys, and case studies were analyzed using thematic analysis. This involved coding the data to identify recurring themes and patterns related to the challenges SMEs face in adopting machine learning and their expectations for an AutoML solution. The thematic analysis helped identify common pain points, such as lack of technical expertise, and informed the development of features aimed at addressing those issues in the framework.
2. **Quantitative Analysis:** Quantitative data was collected through performance metrics that measured the impact of the AutoML framework on SME decision-making processes. Metrics such as model accuracy, time saved compared to manual machine learning processes, and user satisfaction ratings were analyzed to assess the framework's effectiveness. Statistical techniques, including regression analysis, were used to determine whether the framework led to significant improvements in SME operations. This quantitative analysis provided empirical evidence of the tool's benefits.
3. **Artifact Evaluation:** The framework was evaluated based on its utility, efficiency, and scalability. A mixed-methods approach was employed, where quantitative performance metrics were complemented by qualitative feedback from SME users. The evaluation process also included testing the framework in real-world scenarios to assess its practicality and effectiveness. Feedback loops from these evaluations were crucial in refining the framework through iterative development cycles, ensuring that the final product met the evolving needs of SMEs.

3.4. Unique Approach

What distinguishes this research is the focus on creating a collaborative AutoML framework specifically designed for SMEs, a group often underserved by traditional machine learning solutions. Unlike standard AutoML platforms that target larger enterprises with in-house data science teams, this framework is built to support users with limited technical expertise. The collaboration feature, which allows multiple users within an SME to contribute to and benefit from the machine learning process, is a key innovation. Additionally, the iterative nature of the DSR methodology allows for continuous feedback and refinement, ensuring that the framework evolves in response to SME needs.

Furthermore, the research emphasizes practical usability and accessibility, aiming to empower SMEs to make data-driven decisions without the need for extensive technical knowledge. This user-centric approach, combined with rigorous evaluation, sets the study apart from traditional machine learning research, which often focuses on developing more technically complex models rather than user-friendly solutions.

4. Development of A Collaborative AutoML Framework for SMEs

Building upon insights from our comprehensive literature review, we have developed a collaborative AutoML framework specifically designed for small and medium-sized enterprises (SMEs). This framework enables SMEs to harness advanced machine learning algorithms effectively without requiring extensive data science expertise.

4.1. Key Findings and Assumptions

Our literature review revealed critical insights into the utilization of AutoML technologies by SMEs, which form the foundation of our proposed framework. The following key findings emerged:

1. Recognition of AutoML Potential: SMEs across various industries are increasingly acknowledging the transformative potential of AutoML technologies. They aim to drive innovation and enhance decision-making in crucial areas such as production, human resources, marketing, and management.
2. Common Techniques Employed: SMEs employ various AutoML techniques, including automation, data analysis, predictive modeling, and pattern recognition. These techniques empower them to leverage their data assets effectively, yielding actionable insights that inform business operations and strategic planning.
3. Challenges to Adoption: While the potential of AutoML is recognized, SMEs face unique challenges, including limited access to data science expertise, data privacy concerns, regulatory compliance, and scalability issues. These challenges necessitate tailored solutions that prioritize ease of use, scalability, and security.

The preceding section systematically detailed our investigation's core findings, anchored by relevant scholarly references. Figure 1 summarizes the prevalent AI technologies currently adopted within SMEs, emphasizing AutoML's significant utility across various operational areas.

4.2. Framework

The collaborative AutoML framework we propose addresses the unique challenges faced by SMEs, facilitating their adoption of data-driven practices. The framework comprises five key phases:

1. **Strategy**: Align AI/ML initiatives with overarching business objectives. Executive teams set strategic priorities, with input from department heads to identify potential use cases.
2. **Design**: Collaborate among data scientists, IT personnel, and domain experts to ensure relevant, high-quality data collection. Legal advisors may be consulted to ensure compliance with data privacy regulations.
3. **Train**: In this phase, data scientists and machine learning engineers work together to develop, evaluate, and select the most suitable AI/ML models, potentially involving external consultants for third-party solutions.
4. **Deploy**: Requires close collaboration among data scientists, IT teams, and system administrators to integrate models into existing systems. Cloud service providers may be engaged for cloud-based deployments.
5. **Optimize**: This phase involves continuous improvement efforts led by executive leadership. Project managers and team leaders measure project impact, scale successful AI/ML solutions, and support cross-functional collaboration.

4.3. AutoML Solution Process Framework

The proposed AutoML framework outlines the various stakeholders involved throughout its five phases. Figure below provides an overview of the architecture, illustrating the collaborative efforts required for successful implementation.

Table 1.

Phase	Stakeholders involved	Key activities
Strategy	Executive team, team leaders	Align AI/ML initiatives with business objectives
Design	Data scientists, IT personnel, domain experts, legal advisors	Ensure relevant data collection and privacy compliance
Train	Data scientists, machine learning engineers, subject matter experts	Build and evaluate AI/ML models
Deploy	Data scientists, IT teams, system administrators, cloud service providers	Integrate models and establish monitoring
Optimize	Executive leadership, project managers, team leaders	Measure impact and support collaboration

To better implement the AutoML Solution Process Framework, we identified several best practices and guidelines for SMEs to ensure responsible integration of collaborative AutoML tools:

1. Align AI/ML initiatives with business goals: Ensure projects are directly tied to specific objectives to maximize impact.
2. Start small and scale gradually: Begin with pilot projects to demonstrate value before scaling based on initial successes.
3. Focus on data quality: Prioritize high-quality, relevant data to improve model accuracy and reliability.
4. Incorporate industry-specific use cases: Tailor the framework with relevant examples to enhance practicality.
5. Address ethical and environmental implications: Provide guidelines for responsible AI usage, including considerations for bias and transparency.
6. Emphasize change management and training: Develop programs to build AI/ML literacy among employees.
7. Leverage existing infrastructure: Utilize current resources to reduce costs and ensure smoother integration.
8. Foster collaboration: Encourage cross-functional teamwork to leverage diverse perspectives in AI/ML projects.
9. Continuous monitoring and evaluation: Regularly update the framework based on feedback and emerging trends.
10. Engage with external experts: Maintain a network of industry experts and consultants for ongoing support.

By adhering to these best practices, SMEs can effectively integrate collaborative AutoML tools, enhancing their data-driven decision-making capabilities and supporting their growth in an increasingly competitive landscape.

4.3. Evaluation

Following the development of the AutoML framework, we undertook an evaluation stage, employing Design Science Research (DSR) strategies and evaluation methods, including feedback collection from subject matter experts (SMEs) as outlined by Peffers et al. (2007). The primary aim of this stage was to evaluate the proposed process framework, gather critical comments, and identify potential improvements.

Experts from both industry and academia were selected for their diverse perspectives. Interviews were conducted through online meetings, structured as follows:

1. **Presentation**: A brief overview of the AutoML framework, its background, objectives, and key components was provided to contextualize the discussion.
2. **Interview Phase**: Predefined questions focused on assessing the framework's relevance, practicality, and effectiveness in addressing SMEs' challenges in adopting AI/ML.

Table 2.
Interviewed experts.

Expert	Professional role	Area of expertise
Chief operations officer	Operations	Hospitality
Account manager	Sales	Retail
Data scientist	Business strategy	Green energy

By engaging experts from various industries, we gathered valuable insights and feedback on the AutoML framework.

- The Chief Operating Officer from the hospitality sector highlighted the framework's focus on identifying and prioritizing use cases aligned with business objectives. They emphasized its potential to optimize operations and enhance customer experiences.
- An Account Executive from retail praised the framework's emphasis on model optimization and scaling successful AI/ML applications. They recommended including sections on change management and employee training to foster a data-driven culture.
- A Data Scientist from the green energy sector appreciated the framework's data management practices and suggested adding a focus on the ethical and environmental implications of AI/ML technologies.

The expert feedback indicates that our proposed AutoML framework is well-received and provides a solid foundation for SMEs to adopt AI/ML technologies effectively. While suggestions for improvement have emerged, such as incorporating industry-specific examples and addressing ethical considerations, these can be viewed as enhancements rather than fundamental changes to the framework.

Considering this feedback, we recognize the importance of balancing the core structure and simplicity of the framework while integrating new insights. Regular evaluation and adaptation of the AutoML framework will be essential to ensure its effectiveness in guiding SMEs through the adoption process.

5. Discussion

The development and validation of the AutoML framework provides a substantial contribution to the understanding of how small and medium-sized enterprises (SMEs) can effectively adopt AI/ML technologies. Our findings, validated through expert interviews, highlight the framework's alignment with SMEs' needs while addressing their unique challenges. Experts emphasized the importance of prioritizing use cases that align with business objectives, reinforcing the framework's practical relevance. The positive reception from industry professionals, particularly the Chief Operating Officer in the hospitality sector and the Account Executive in retail, underscores the framework's utility in optimizing operations and enhancing decision-making processes.

In comparing our results with existing literature, it is evident that our framework aligns with broader trends in AI/ML adoption among SMEs. Previous studies have indicated that SMEs face significant barriers, such as limited access to data science expertise, resource constraints, and data privacy concerns. Our framework directly addresses these issues by providing a structured approach that democratizes access to AI/ML capabilities, enabling non-technical users to engage in the model development process. The focus on collaboration among stakeholders, including executives, data scientists, and domain experts, reflects best practices identified in the literature, emphasizing the need for a multi-disciplinary approach to AI/ML integration.

Furthermore, the iterative process of framework validation through expert feedback demonstrates a commitment to grounding theoretical constructs in practical realities. While our framework provides a robust foundation for AI/ML adoption, the feedback highlighted opportunities for improvement, such as the inclusion of industry-specific examples and ethical considerations. These suggestions are critical for enhancing the framework's applicability across diverse sectors, ensuring that it not only remains relevant but also addresses the specific nuances of each industry.

As we consider the implications of our findings, it becomes apparent that the successful integration of AutoML technologies within SMEs can catalyze innovation, improve efficiency, and foster a data-driven culture. However, the path to adoption is not without challenges. Continued collaboration between researchers and industry practitioners will be essential to refine the framework and adapt it to the evolving AI/ML landscape. Engaging with a broader array of stakeholders will also facilitate a more comprehensive understanding of the framework's impact across different contexts.

5.1. Conclusions and Future Work

This research culminated in the development and validation of the AutoML framework, designed as a practical guide for SMEs seeking to adopt AI/ML technologies. Our structured approach began with identifying the specific challenges SMEs encounter in this domain, followed by a comprehensive literature review that provided a solid theoretical foundation. The resulting framework focuses on aligning AI/ML initiatives with business objectives, managing data effectively, and facilitating model development and deployment.

The iterative validation process through expert interviews enriched the framework, ensuring its continued relevance and effectiveness for SMEs. The feedback collected highlights areas for improvement, such as the need for industry-specific examples and ethical guidelines, which will enhance the framework's applicability across various sectors. Our research contributes to the growing body of knowledge on AI/ML adoption by offering a tailored solution that meets the unique needs of SMEs.

5.2. Research Limitations

While our study provides valuable insights, it is not without limitations. The validation of the AutoML framework relied on interviews with a limited sample of three industry experts. Although their feedback was instrumental, a larger sample size would yield a more comprehensive view of the framework's effectiveness across different industries and contexts. Additionally, while the framework aims to be universally applicable, it may not fully account for the specific challenges and opportunities faced by certain sectors, such as healthcare or finance. Future research should explore industry-tailored versions of the framework to enhance its applicability.

Moreover, while expert interviews facilitated theoretical validation, practical implementation and testing in real-life situations remain essential for assessing the framework's effectiveness. Time constraints also limited our ability to conduct further communication stages, which could gather additional feedback from a broader range of stakeholders. Addressing these limitations in future research will enhance the framework and contribute to understanding AI/ML adoption in SMEs.

5.3. Future Work

Future studies can further refine the AutoML framework by exploring emerging trends, challenges, and innovations within the AI/ML landscape. Key areas for future research include:

- Investigating strategies for reducing costs and mitigating potential risks associated with AI/ML adoption in SMEs.
- Examining the role of policymakers and regulatory authorities in promoting responsible AI/ML adoption among SMEs.
- Evaluating how AI/ML technologies can foster sustainability and address environmental challenges across various industries.
- Developing industry-specific versions of the AutoML framework to cater to the distinct needs and constraints of different sectors.

As the AI/ML domain continues to evolve, ongoing research and refinement of the AutoML framework will be critical in supporting SMEs throughout the adoption process. By addressing emerging challenges and fostering collaboration among researchers, industry experts, and policymakers, we can empower small and medium-sized enterprises to leverage the full potential of AI/ML technologies, driving growth, innovation, and resilience in an increasingly competitive landscape.

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