RESEARCH IN PROGRESS

AUTOML AS FACILITATOR OF AI ADOPTION IN SMES: AN ANALYSIS OF AUTOML USE CASES

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While the uptake of AI and ML has been rising in recent years, SMEs still face various adoption challenges. In contrast to large enterprises, SMEs struggle to adopt AI as already the identification of suitable AI use cases requires substantial technical expertise. At the same time, productivity tools like AutoML promise easy access to AI capabilities to non-experts. This research-in-progress aims to investigate how AutoML tools can be utilised to facilitate the adoption of AI in SMEs. In a focus group with 11 representatives from SMEs, we identified and discussed potential AutoML use cases in detail. Results show that the identification of potential use cases rarely focused on existing and available data but rather repeated known use cases and success stories from large enterprises. We argue that a paradigm shift towards a data-centric approach would be beneficial to exhaust the capabilities of AutoML for SMEs.

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1 Introduction

Advancements in artificial intelligence (AI) such as large language models have recently gained attention and increased awareness among the broader public. However, the utilization of AI in organisations still faces various challenges, ranging from technological and organisational to social, legal, ethical, economical and data-related ones (Dwivedi et al., 2021). As such, many organisations still struggle to apply AI in their key operations and outside of proof of concept deployments (Dzhusupova et al., 2022). Especially small and medium-sized enterprises (SMEs) have a slow pace of adopting AI (Hansen & Bøgh, 2021). In contrast to large enterprises, SMEs lack the financial resources to invest in infrastructure, recruit AI talents in a competitive labour market or buy in external expertise (Bauer et al., 2020). The resulting lack of AI capabilities hinders the identification of potential AI use cases in SMEs (Bauer et al., 2020). Additionally, current approaches and tools that address challenges in AI adoption usually presume existing AI knowledge (Kirschbaum et al., 2022).

One approach that aims to provide easy access to AI based on machine learning (ML) to non-specialist users is AutoML (Zöller & Huber, 2021). Automated ML, short AutoML, subsumes the methods aiming to automate, at least to some extent, all stages of the design and development of ML-based systems (Hutter et al., 2019). AutoML simplifies the application of ML by reducing the number of steps of data preparation, model selection, model hyperparameters for the applicant and helps them with data visualisation, model comprehensibility and usage (Crisan & Fiore-Gartland, 2021). One of the main goals of AutoML is to democratise access to AI/ML Technology for people without in-depth knowledge of coding, statistics or ML (Zöller & Huber, 2021).

Already a myriad of AutoML frameworks and tools exist which enable users to build and explore AI. Depending on the level of expertise, users can utilise coding libraries such as auto-sklearn or autokeras that automate only specific parts in the ML development pipeline or commercial tools that can be utilised through graphical user interphases (GUI), e.g., Google AutoML or JadBio. While the development of AI systems by non-ML expert users through the use of AutoML is often seen as problematic (Crisan & Fiore-Gartland, 2021; Wang et al., 2019), AutoML does provide an opportunity for early exploration and easy trial runs by domain experts

(Xin et al., 2021). As such, AutoML provides professionals in different areas of expertise the opportunity to explore and identify possible AI use cases without the need for in-depth knowledge of AI/ML. However, research on the required knowledge of AutoML users or the appropriate integration of AutoML into the AI development process is very limited (Polzer & Thalmann, 2022).

As of now, little research has focused on how SMEs identify and select AI use cases. Additionally, there is little knowledge of how AutoML can be utilised by domain and business experts to recognise AI opportunities in different application fields. This study combines both research gaps and tries to answer the question *How can AutoML facilitate the adoption of AI in SMEs?* Thus, this research in progress (RiP) is a first explorative investigation on how AutoML can be introduced to SMEs to leverage their AI capabilities and how AutoML provides an easy-to-use exploration tool to identify possible AI use cases.

2 Methodology

A focus group with 11 representatives from 10 Austrian SMEs was held in February 2023. As seen in table 1, the participants came from different industry sectors and with different AI experience. The goal was to discuss SMEs' capabilities concerning AI and to discover potential AutoML use cases the SMEs representatives saw in their own organisations.

After a short introduction to AI and its challenges, two demonstrators of exemplary use cases conducted with different AutoML tools were shown to foster the participants' creativity. The participants were grouped into two sub-groups in the second part of the workshop. In these focus groups, each participant was asked to think of possible AI use cases to be implemented using AutoML in their organisation. The participants were provided with template cards to elaborate on the identified use cases with additional information on what data would be needed, what type of analysis would be needed and what benefits and challenges they could encounter during the implementation of such an AI use case. The participants had 20 minutes to individually think of possible AI use cases and to fill the template. Afterwards, each participant presented their use case using the template, and the group discussed requirements, feasibility, and possible challenges in the implementation. Finally, we discussed and jointly reflected by the entire group. The focus groups were audio recorded and transcribed for analysis. The filled-in template cards were also analysed. Afterwards, all identified use cases of both focus groups were analysed and three distinct groups of AI use cases emerged.

Table 1: Participants

#	Industry sector[1]	Company Size[2]	AI/ML experience
1	Human health	Medium Sized	Novice
2	Professional, scientific & technical activities	Medium Sized	Some experience
3	Professional, scientific & technical activities	Medium Sized	Expert
4	Information & communication	Micro	Expert
5	Other service activities	Small	Some experience
6	Manufacturing	Small	Expert
7	Other service activities	not SME	Expert
8	Other service activities	Micro	Some experience
9	Transportation and storage	Small	Novice
10	Manufacturing	Small	Some experience
11	Information & communication	Micro	Expert

3 Results

In total, 15 distinct potential AutoML use cases were identified, discussed, and clustered into three groups depending on their purpose. As most use cases would influence either the primary value-adding activities (e.g., operations), or supporting activities (e.g. HR management) of a firm's value chain (Porter, 1998) value chain was used as the basis of the for the grouping of the use cases. As such, the first cluster focuses on improving the core activities of existing business models. The second cluster focuses on support activities, often managerial activities that are not specifically related to the value proposition of the business model. The third cluster

[1] Based on United Nations (2023): International Standard Industrial Classification, URL: https://unstats.un.org/unsd/publication/seriesM/seriesm_4rev4e.pdf [last retrieved March 31st]
[2] Based on Europan Commision SME Defintion (2003): https://single-market-economy.ec.europa.eu/smes/sme-definition_en [last retrived May 19th, 2023]

consists of the application of AI leading to extensions of the existing business model or business model innovations (see figure 1).

In the **primary activity cluster** seven AI use cases to be implemented with AutoML have been identified. A common theme across these use cases was quality management. Thus, the use cases focused on improving maintenance or quality testing activities. For this cluster, the participants had a clear idea of what input data might be needed and how implementing the use cases could influence their business as well as which challenges they might encounter. One exemplary use case was the prediction of the deterioration of plates used to punch out different components in a production process. The participant knew the data and analysis needed to implement the use case in their company. Clear benefits, such as better decision support for maintenance activities, were also recognised. The most important challenge for this use case was the availability of data, a common challenge across many identified use cases.

The use cases of the **support activity cluster** did not have a direct connection to any particular product or service offered by the SMEs. Instead, the five use cases were centred around supporting activities, such as improving project cost predictions or procurement needs. These use cases had a more general nature and were not focused on the core or value-adding processes of the SME. In contrast to the primary activity cluster, it seemed more challenging to estimate the business value and specially to make a proper cost–benefit analysis. For instance, one discussed use case suggested the segmentation of potential customers for acquisition purposes. The main advantage in this category of use cases was seen in freeing of resources, e.g., from routine and time-intensive tasks, which can then be better utilised in other activities.

The **business model innovation cluster** explored more innovative ways to use AI that were not variations of already broadly known use cases, like predictive maintenance. The use cases of this cluster had different purposes and application fields, such as decontamination acceleration through the support of AutoML models in healthcare facilities, emotion detectors for consumption predictions, or veracity evaluation of news. Participants had varying ideas about what input data was necessary for these use cases, and some were uncertain or had limited knowledge of what suitable input data would be necessary. However, with the novelty of the approaches also, the challenges and uncertainties concerning the implementation of such use cases increased. As such, aspects of privacy concerns in connection to GDPR were mentioned, but also the complexity and variety of data or the challenges in validation and ensuring compliance were mentioned.

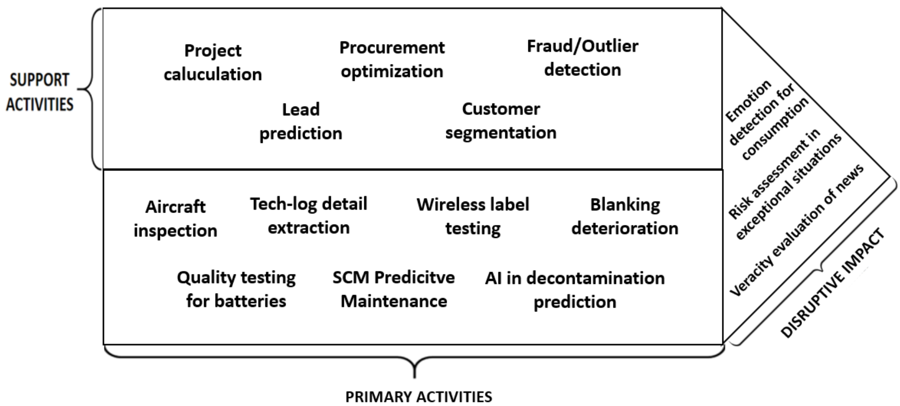

Figure 1: Identified use cases

4 Discussion and Outlook

Overall, our 11 participants acknowledged the capabilities of AutoML to start thinking about AI use cases in their SMEs. As the ideation and identification of AI use cases can either be purpose-driven or data-driven (Strum et al., 2021), AutoML, especially regarding data-driven identification, can provide beneficial support, as it provides easy to use access for exploring existing data sets (Wang et al., 2019). Therefore, we provided first evidence that AutoML can support the identification of AI use cases.

The analysis of the focus groups showcased that the identification of the use cases was based on already known success stories that can be observed in literature and are present in the public discourse, such as predictive maintenance or customer segmentation (Thalmann et al., 2018). In this regard, mostly a purpose-driven approach to finding AI use cases was utilised, which aimed at improving process steps, tasks, or decisions through AI. However, especially a data-driven explorative approach of use case identification can lead to new ideas and approaches on how to use AI.

In this regard, participants who already have good knowledge or experience with AI, proposed novel and disruptive AI use cases. The use cases of the business model innovation cluster were proposed by participants who at least had some experience in the field of AI/ML. As such, a minimum of training regarding AI applications upfront is required, which also influences the necessary level of knowledge required to utilise AutoML effectively (Polzer & Thalmann, 2022). Thus, the identification and further the implementation of AI use cases (especially with disruptive impact) still requires conscious effort in the development of organizational AI capabilities (Sjödin et al., 2021).

The black-box character of AI was discussed as a potential barrier, especially regarding its adoption in sensitive use cases. Participants demanded explainability features (see (Gashi et al., 2022) for an overview) and many times envisioned causal discovery (see (Vuković & Thalmann, 2022) for an overview). Similarly, also the feasibility of the proposed use cases in relation to ethical and privacy issues was discussed. Thus, especially in use cases relying on personal data, like in the emotion detection use case, considerable challenges concerning legal but also ethical perspectives were highlighted. Therefore, there is a need for providing user guidance on AutoML tools to ensure the development of fair, accountable, and transparent AI systems (Polzer & Thalmann, 2022).

This RiP paper has many limitations and serves as starting point for future research. First, we used AutoML demos to spark discussions among SME representatives and to identify use cases. So far, we do not have evidence that such use cases can be implemented in SMEs. For this purpose, we plan implementation case studies with SMEs organised as think-aloud studies. Second, the AutoML knowledge of some participants was limited, and our data suggest that more knowledge could facilitate the capabilities to "think out of the box". Also, in our case studies, we will investigate which knowledge is needed to use AutoML in a responsible way and how more knowledge affects the capability to identify new use cases. Third, so far, our sample relies on a small sample of SMEs just from Austria. For this purpose, we plan additional workshops in Austria, Germany, Portugal, and Spain to broaden our focus. This future work will especially focus on the limitations and challenges in implementing AutoML into SMEs.

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