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Machine Learning in SME: An Empirical Study on Enablers and Success Factors

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Completed Research

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Abstract

Machine learning (ML) techniques are rapidly evolving, both in academia and practice. However, enterprises show different maturity levels in successfully implementing ML techniques. Thus, we review the state of adoption of ML in enterprises. We find that ML technologies are being increasingly adopted in enterprises, but that small and medium-size enterprises (SME) are struggling with the introduction in comparison to larger enterprises. In order to identify enablers and success factors we conduct a qualitative empirical study with 18 companies in different industries. The results show that especially SME fail to apply ML technologies due to insufficient ML knowhow. However, partners and appropriate tools can compensate this lack of resources. We discuss approaches to bridge the gap for SME.

Keywords

machine learning, small and medium sized enterprises, success factors and enablers, demand forecasting

Introduction

Since the first appearance of Machine Learning (ML) in the 1950s, the field of ML has rapidly evolved: Numerous applications have been studied in research and practice, frameworks have been developed and implemented as well as fast hardware for computation is available and affordable (OECD 2015). Therefore, the adoption of ML applications in enterprises has significantly increased. Whereas in the year 2015, only 10% of companies reported the utilization of ML in every-day operations, recent studies find about one third of the companies relying on ML (Howard and Rowsell-Jones 2019).

However, studies also report a significant difference regarding the size of the companies. A study from 2019 indicates that companies with less than 500 employees are four times less likely to have ML applied than companies with more employees (Spiceworks 2020). This finding is in line with more general studies on the flexibility of SME to adopt new technologies compared to larger companies: Larger companies overall have a higher adoption rate of information and communication technologies (ICT) than SME (OECD 2004).

We want to find out where these differences derive from and pose the following research questions:

RQ1: What is the gap of the adoption of ML in small- and medium-sized enterprises (SME) compared to the state-of-the-art and best practice?

RQ2: What are challenges in the process of implementation of ML specific to SME and what success factors enable companies to mitigate these challenges? What conditions facilitate the utilization of ML in SME?

Our approach is a synthesis of a meta-analysis of literature and surveys in combination with a qualitative empirical approach, conducted in 2020 with a focus on businesses in the industries of manufacturing and production, retailing and logistics. We subsume all ML applications for internal processes and products.

Adoption of ML in Research and Enterprises

For this study, we follow the definition of Mitchell for ML: "A computer program is set to learn from an experience E with respect to some task T and some performance measure P if its performance on T as measured by P improves with experience E." (Mitchell 1997). We are aware that practitioners oftentimes also use the term artificial intelligence (AI) interchangeably, even though the terms are not identical.

Various studies on case specific applications of ML for business use cases have been published in academic literature. In this context we only provide an overview of sample applications to demonstrate the fact that the theoretical foundation for most ML applications in enterprises is available. For each application, we conducted a systematic literature review following Webster and Watson and Levy and Ellis and each chose one article with highest citation count (Levy and Ellis 2006; Webster and Watson 2002 – see Table 1).

We conclude that there is a high number of articles that provide both a theoretical foundation for ML technologies as well as application use cases as basic requirement of RQ1. Most relevant use cases for business applications are intensely studied and practical solutions were demonstrated by academia.

> **Finding I***: Research provides a strong foundation of ML basic techniques but also of ML applications for business applications. ML technologies are ripe for implementation in enterprises.*

<table>
<tr><th>Forecasting</th><th>Classification</th><th>Optimization</th><th>NLP & IR</th></tr>
<tr><td>6,500 papers*</td><td>8,200 papers*</td><td>7,500 papers*</td><td>7,700 papers*</td></tr>
<tr>
<td>• Supply Chain (Carbonneau et al. 2008)
• Fashion (Ren et al. 2017)
• Spare parts (Hua and Zhang 2006)
• Smart grids (Muralitharan et al. 2018)
• …</td>
<td>• Predictive maintenance (Susto et al. 2015)
• Credit risk assessment (Twala 2010)
• Intrusion detection (Tsai et al. 2009)
• Recommender systems (Zhang et al. 2019)
• …</td>
<td>• Robotics (Levine et al. 2016)
• Advertising (Jin et al. 2018)
• Plant control (Lazic et al. 2018)
• Job scheduling (Priore et al. 2006)
• Chemistry R&D (Zhou et al. 2019)
• …</td>
<td>• Chat bots (Xu et al. 2017)
• Warehouse inventory control (Xu et al. 2018)
• Legal document analysis (Ashley and Walker 2013)
• …</td>
</tr>
</table>

Table 1: Exemplary excerpts of research in ML applications for specific business use cases (Natural language processing: NLP, Image recognition: IR). The number of papers* is calculated by the number of peer-reviewed articles that apply to the query terms of the header, "ML"/"AI" and "enterprise application" in the semantic scholar database.

In a next step, we studied the current state of actual adoption of ML technologies in companies. For this purpose, we reviewed studies of the recent years that provide an overview of the implementation of ML technologies (opposed to Table 1, where we show the existence of a theoretical background). Our literature review shows that no considerable peer-review literature is available that answers the question to what extent these ML technologies are actually employed in companies. This emphasizes the need for further research in this field.

In order to also incorporate grey literature studies, we imposed the following restrictions on our search in order to filter considerable quality studies only: A. The study was conducted from 2018 to January 2020, B. The data foundation is documented: Number of respondents by company size, industry and ML implementation maturity level, C. The study is published by a renowned organization or company.

We will first summarize the findings of studies that incorporate both SMEs and larger companies (Set I). In the second part of this section, we narrow down the focus on studies that differentiate between companies of different sizes (Set II).

Set I comprises ten studies with an average number of respondents of 2,600 each (minimum 200; maximum 11,400) mostly from the Americas, Europe and Asia. The studies do not differentiate between company size.

About 20% of the companies interviewed in Set I confirm that they use an ML technology implementation in their planning, control or operational processes. The overall maturity level of ML technology implementations is low – about 25% are in early stages and are either gathering first experiences in ML technologies or are about to implement technologies. On average, the studies indicate that about 30% of the companies that have not yet implemented ML technologies are intending to do so soon. The remaining companies do not have specific plans yet to implement ML technologies or are investigating potential use cases. This intention is confirmed by the finding that about 30% of annual IT budgets were dedicated to the implementation of use cases where ML technologies were supposed to be deployed.

The studies of Set I also examine major challenges for companies when investigating potential use cases for machine learning and during implementation. The most frequent challenges are:

1. the lack of sufficient employees with ML/AI know how (by far most frequently),
2. limited budget and other (non-ML) projects competing for funds,
3. difficulties to identify positive business cases,
4. too little acceptance for ML on a managerial level.

(Algorithmia 2018; Chui and Malhotra 2018; Howard and Rowsell-Jones 2019; Lorica and Paco 2018, 2019; Loucks et al. 2018; Ransbotham et al. 2017; Ransbotham et al. 2018; Stancombe et al. 2017; Teradata 2017)

We conclude that the overall prevalence of ML technologies is still medium, however great interest in the technologies exists and applications are being evaluated by companies. Companies with a higher ML maturity level apply more advanced ML techniques than others – as assumed in RQ1.

> **Finding II**: *ML technologies are already established in business applications and interest in the technologies is high. Yet, the prevalence of the technologies is medium and the technologies applied are mostly of medium complexity also – however some companies already employ very advanced techniques.*

Set II, in contrast to Set I, comprises seven studies with an average number of respondents of 900 each (minimum 190; maximum 3,100), in part with a focus on North America and Europe. Using Set II, we highlight the differences of the studies' insights with respect to company size.

Compared to Set I, where about 20% of companies interviewed currently employ ML technologies and 25% are in the process of evaluation or implementation, Set II reveals a more differentiated picture. The studies in Set II confirm the data from Set I for companies with 500 or more employees. However, companies with 500 employees maximum exhibit significantly lower maturity: Only 8% of the companies have already deployed ML technologies and only 20% are evaluating ML technologies for business applications. However, other studies that also incorporate businesses that sell ML technologies as distinct products (ML consultancy, tools, …). Here, small companies and especially start-ups demonstrate their competencies and exhibit a ML maturity level equal to larger companies. Therefore, we consider companies that do not primarily apply ML to optimize internal processes or to enhance traditional products as a different company type of "tech start-ups".

The studies in Set II also report different challenges for companies concerning the implementation of ML technologies:

1. too little acceptance for ML amongst users and operatives,
2. data privacy concerns (e.g. violation of GDPR regulations),
3. the lack of sufficient employees with ML/AI know how,
4. too little acceptance for ML on a managerial level.

(Abel-Koch et al. 2019; Algorithmia 2018, 2019; Böttcher et al. 2018; Reder 2018, 2019; Spiceworks 2020)

We conclude that, referring to RQ1, the prevalence of ML technology applications in SME is significantly lower than in the overall industry. Moreover, SME state elementary different challenges than larger companies: They struggle more with entry-barriers whereas larger companies typically rather have difficulties to scale their ambitions to apply ML-technologies to the resources available.

> **Finding III**: *Small and medium businesses are significantly less likely to have ML technologies deployed yet. Their present challenges differ from larger businesses and reflect their lower ML maturity: little acceptance for ML both amongst users and operatives as well as managers and limited ML know how.*

Survey Methodology and Insights

For our own survey, we interviewed 18 CXOs and Managing Directors of small, medium and large-sized companies. The interview involved (i) a self-assessment of the maturity level of the state of implementation of ML in the company (see Figure 1) and (ii) the respondents' assessment of challenges and success factors encountered in previous ML implementation projects and anticipated for future ML implementation projects (see Figure 2).

Figure 3 and Figure 4 give an overview of the interviewees of the survey. Interviewees are employed at companies of all sizes like tech-startups (less than 35 employees), small businesses (less than 500 employees), medium businesses (less than 1,000 employees) and large business (10,000 to 30,000 employees). The number of interviewees is relatively evenly distributed over all company sizes (see Figure 3). From the companies interviewed, 39% have reached a maturity level where ML is actually implemented in day-to-day operations or their products (levels 5 and 6). 39% of the companies do not use ML technologies yet but employ heuristics or statistical analysis to leverage internal processes or enhance their products (levels 3 and 4). The remaining 22% state that neither ML technologies nor heuristics or statistical analysis are employed at their company (levels 1 and 2). However, all companies report that they are actively evaluating use cases for ML applications at the moment of the survey (see Figure 4).

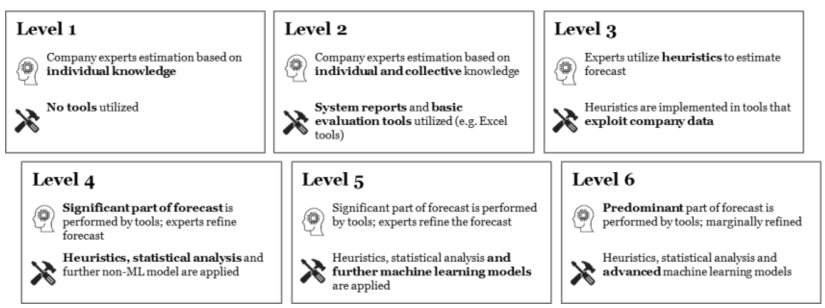

Figure 1: Six levels of ML implementation maturity for the respondents' self-assessment

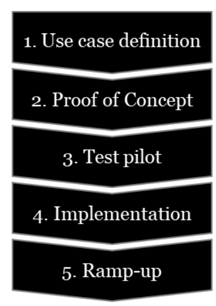

Figure 2: Five exemplary project phases during ML implementation

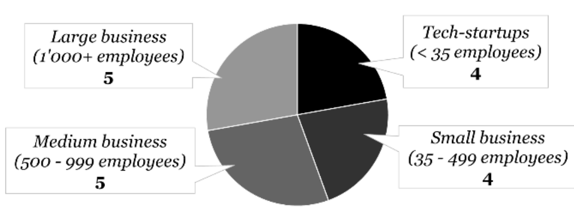

Figure 3: Respondents by company size

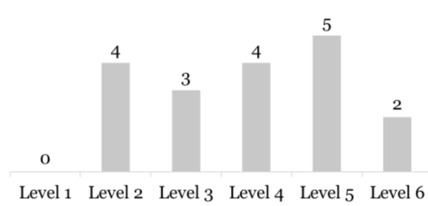

Figure 4: Respondents by ML-maturity level

Following the approach of Mayring, we conducted a qualitative analysis of the interviewees' replies to our survey. The answers were categorized and correlated to the company's characteristics: such as company size, ownership structure of the company and ML maturity level. In addition, we clustered the replies by their relationship to company size and maturity by qualitative assessment (Mayring 2000).

From the analysis, we summarize the following main statements:

A. There is a clear dependency between the ML maturity level and the company size. SME are much less matured than large business. The only exception to this finding are the tech start-ups that are extremely small but see ML technologies as their main product – they are the most ML mature companies of the survey.
B. Small businesses (SB) are currently still struggling to identify use cases for ML applications (process stage 1)
    - *ML know how*: SB possess too little knowledge and experience to assess ML suitable use cases.
    - *Personnel capacities*: Too few personnel capacities to systematically advance use cases from the use case identification to a first proof of concept. SB strongly rely on the personal initiative of single employees to investigate ML use cases.
    - *Data availability*: SB report to lack the quantity of records required to train ML algorithms.
    - *Acceptance of ML technologies*: Limited knowledge of ML results in concerns about ML technologies amongst operatives and management. However, SB can benefit from flat hierarchy and from a determined management that encourages employees to advance in ML technologies.
    - *Interdisciplinarity*: ML initiatives lay in the hands of individual persons in the company which combine data science, domain and IT expertise in one person with no interfaces.
    - *External partners*: Dissent amongst SB whether to consult external partners to advance in ML applications. However, those open to external partners, all prefer software providers that specialized in domain specific solutions.
C. Medium businesses (MB) have typically passed the use case definition phase.
    - *ML know how*: MB asses their ML know how to be sufficient for the definition of ML use cases. However, MB are not able to independently implement the technology with internal knowledge.
    - *Personnel capacities*: Rely on personal initiative of employees to advance ML use cases. Regard use cases as pilots to prove the worthiness of technology and are hesitant to dedicate resources to it.
    - *Data availability*: Have accrued sufficient data records but typically not in a standardized form – they are not used to data driven approaches in their usual operations.
    - *Acceptance of ML technologies*: Successful, where ML strategy is installed by their management. The management identifies ML as an important impact to their business. The concerns towards ML are more distinguished than in small businesses: Lacking "explainability" and transparency of ML algorithms as well as the thread of the substitution of labor by algorithms are the main concerns of operatives. However, there is also a positive perspective that ML can help to focus on more valuable work by having simple and repetitive tasks executed by ML algorithms.
    - *Interdisciplinarity*: MB face the problem of interdisciplinarity more than SB. Data science, domain knowledge and IT are represented by separate persons and departments. However, in contrast to LB, interdisciplinary collaboration is less supported by frameworks and standardized processes and rely more on the individual experience and ability for collaboration.
    - *External partners*: Open to external cooperation. Research projects with universities and business schools preferred as aim to build up ML know how in the course of the cooperation.
D. Large businesses (LB) have experience in the field of ML applications and implemented use cases.
    - *ML know how*: LB have specialized data science departments that are able to implement ML technologies fully internally.
    - *Personnel capacities*: Due to the AI strategies employed, resources are actively dedicated to the identification and implementation of ML technologies. However, LB find it challenging to employ enough data science experts to realize the identified use cases. They exhibit that the demand for data science experts exceeds the market supply of free experts at this point of time.
    - *Data availability*: LB systematically gather and record business data and have identified data as important advantage.
    - *Acceptance of ML technologies*: LB consistently state that they consider ML applications as a vital part of their business strategy. ML is widely accepted due to positive experience in practice.
    - *Interdisciplinarity*: Strong division of labor and specialization complicates the interdisciplinary cooperation within LB. LB face the challenge that the specialists "do not speak the same language". However, LB also report that the outcome of ML implementation projects heavily depends on a successful exchange between data science, process owners and IT department.

- *External partners*: External partners do not play a significant role to LB as they already possess the necessary ML know how. Moreover, third party tools are often restricted by governance policies and difficult to integrate into existing systems.

E. Tech start-ups (TS) exhibit the highest maturity levels of all companies of the survey and a high specialization on distinct industries.
   - *ML know how*: TS excel in ML technologies and apply advanced techniques.
   - *Personnel capacities*: TS consider ML know how as a primary asset. Therefore, they concentrate to establish attractive work environment for ML experts.
   - *Data availability*: With specialization, TS develop interfaces optimized for their customers industry and requirements, such that the available data can be efficiently used.
   - *Acceptance of ML technologies*: TS mainly generate acceptance by show casing successful implementations from previous projects.
   - *Interdisciplinarity*: Experts in small teams combine ML, domain and IT know how.
   - *External partners*: External partners do not play a relevant role.

In general, the survey results are in line with the findings from the previous section: First, ML is already established in enterprises, however only to a medium degree of prevalence and maturity (see Finding II). Second, SME lag behind larger enterprises with respect of prevalence and maturity of the application of ML and exhibit challenges that are specific to SME (see Finding III).

In addition, we summarize the following main challenges and success factors as addressed in RQ2 for small and medium businesses:

> **Finding IV**: *Company size and ML maturity are strongly dependent: Larger businesses are more mature than smaller businesses.*

> **Finding V**: *Primary challenges to small businesses are basic understanding of ML capabilities for use case definition and the availability of data. Primary success factors are flat hierarchies and a determined management which supports and encourages committed employees as well as external partners with the appropriate domain knowledge.*

> **Finding VI**: *Primary challenges to medium businesses are ML implementation know how and the increasing issues of interdisciplinary collaboration. Primary success factors are an external research cooperation and a pronounced ML strategy by the management that provides the necessary support for committed and volunteering employees.*

Finding IV raises the question whether the relationship between maturity and company size is causally determined – which we address in the following section.

Size and Maturity Related Challenges and Success Factors

In the previous section, we observed the correlation between company size and ML maturity (see Finding IV). One could therefore conclude that there is one path of development that all companies follow – and larger companies might have just already progressed further than smaller companies. However, this would be a misconception, as we will show based on the survey. According to the respondents' replies, challenges are allocated to their relationship to company size and maturity (see Table 2).

Table 2 shows several relevant challenges that are mainly correlated to company size and cannot or only marginally be compensated by increasing ML experience from ML maturity. Especially determining is the issue of sufficiently trained personnel: SB typically do not have the economies of scale to afford to employ data scientists dedicated to the implementation of ML technologies. Therefore, they cannot go beyond the first stages of the process of ML implementation (cf. Finding V and Finding VI) accounting to RQ2.

> **Finding VII**: *Challenges can be company size related and not or only marginally influenced by ML maturity. Such challenges prevent companies of different size from undergoing the same maturity development process. Therefore, SME should use different approaches in ML projects.*

	Maturity related	Size related
Challenges	• Data availability and quality (-) • Lack of ML know how (-) • Insufficient ML results (-) • Governance policies (+) • Acceptance of ML (-)	• Lack of personnel capacities (-) • Dedicated ML experts (-) • Insufficient input data (-) • Division of labor and specialization (+) • Computation power in-house (-)
Success factors	• Existing ML know how (+) • Standardized data interfaces (+) • External partners (-) • Small steps and early success stories (-)	• Existing business intelligence / data science team (+) • Commitment of individual employees (-) • Good interdisciplinary collaboration (+) • Fast decision-making (+)

Table 2: Overview of maturity and size related challenges and success factors. (+/-) denotes a positive or negative correlation: Importance increases / decreases with increasing maturity or size respectively.

Approaches to Close the Gap for SME

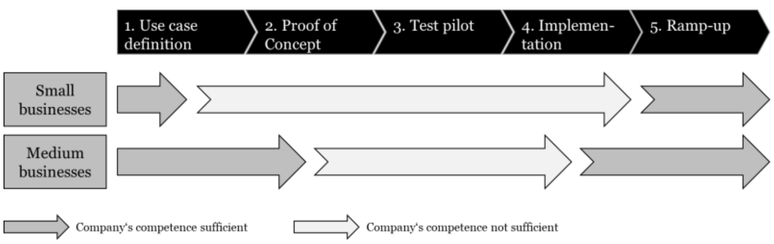

Figure 5: Company size related challenges lead to differences in ML implementation competences.

From Finding VII we conclude that SME can benefit from specific approaches in ML projects. As shown before, challenges for SB start already during the use case definition phase and maintain during all phases that require deeper ML know how. MB typically have more ML know how, but still face challenges during proof of concept, testing and implementation (see Finding VI). In the following, we use the previous findings to briefly discuss general measures that facilitate the access of SME to ML technologies. We then discuss a particular framework for demand forecasting in SME.

General measures to facilitate ML in SME

In the following, we will address facilitating conditions as mentioned in RQ2. According to Finding V and Finding VI, especially SB but also MB face their initial challenge during the use case definition phase: Assessment of the applicability of ML in particular use cases. Interviewees report three ways to pass this hurdle: The exchange with other companies that already passed this step, support by consultancies or software service providers as well as research cooperations. The interviewees agree that a crucial factor is the domain or industry specific knowledge combined with ML experience. We conclude that SB can benefit most if suitable products are available that match their use case requirements. In this case, the product can fulfill their needs without the need to deeply understand ML technologies. MB can benefit most if they cooperate in a research project with an external partner with the appropriate ML know how. This way, the partner can elaborate a use case specific solution and the company can build up ML know how internally during the project. Both approaches also mitigate the challenge of interdisciplinary collaboration between data science, which arises already in MB.

> **Finding VIII**: *Small and medium businesses can mitigate the lack of ML know how in ML use case definition and implementation through external partners. The survey results suggest software providers with market-ready products for small and research cooperations for medium businesses.*

Based on this finding, we encourage universities and research faculties to enter cooperation with MB to develop further ML applications together. We also suggest that politics and governments should support the funding of such research cooperations.

In Finding V and Finding VI we also showed that success in ML implementation projects strongly depends on the personal initiative and interest of employees as well as short decision-making processes. We propose that the companies' management should actively encourage employees by creating favorable conditions: Allow for advanced training of employees, establishment of ML labs with the necessary hardware equipment and interdisciplinary workshops for interested employees for use case definition.

> **Finding IX**: *Personal initiative of employees is found to be crucial for the success of ML projects in SME and should be fostered by the management of companies by favorable conditions. Trainings, equipment, interdisciplinary work and short decision-making processes are proposed.*

A suitable framework as entry point to ML applications

The measures described above address the challenges of SME on an entrepreneur and governmental level. In addition to this, we also consider the contribution of research and the IS community to the issue. The survey shows that SME require ML technologies of a confined complexity that can be implemented with the limited experience and knowledge of SMEs. ML frameworks with auto-hyperparameter tuning (AutoML) exist from various research projects (e.g. Auto-WEKA, Thornton et al. 2013; Auto-sklearn, Feurer et al. 2019; TPOT, Olson and Moore 2019; Auto-keras, Jin et al. 2019) and vendors (e.g. AzureML, Uber Ludwig; Google Cloud AutoML). The specific advantages and disadvantages have been investigated in several studies and competitions, showing that AutoML frameworks can achieve good results compared to instance specific implementations and are significantly easier to manage (Guyon et al. 2019; He et al. 2019; Truong et al. 2019).

> **Finding X**: *AutoML frameworks encapsulate and automate major parts of the ML implementation and optimization process. Companies can use these frameworks to speed up ML projects, if they possess limited ML implementation know how and if their problem instance can be solved using generic optimization strategies.*

Apart from these general auto-tuning frameworks, our literature research shows that no relevant studies exist that systematically address the issues and requirements of SME in the application of ML technologies. In this context, the survey shows two areas where SME could benefit most from research: Comprehendible use cases and suitable ML applications and SME specific frameworks that can be applied with limited ML know how.

Conclusion and Outlook

In this work, we raised two questions: 1. What is the gap of SME in ML adoption compared to the state of the art and 2. what challenges and success factors are typical for SME in the ML adoption process. We find that research provides a strong theoretical foundation, but practice is yet in the process of the adoption of ML technologies and that SME significantly stay behind larger companies. We observe that larger companies are generally more mature in the adoption of ML, and that size-specific factors prevent SME from taking the same path of ML knowledge development as larger businesses.

We also identified the major challenges of SME in the adoption of ML: Insufficient ML know how in SME for the identification of use cases and implementations, poor data quality in small businesses and obstacles in interdisciplinary work in medium businesses. We find that external cooperations were observed as major success factors to overcome the challenges, as well as personal initiative of employees. We propose three concrete measures to facilitate ML in SME.

This study reflects the current situation of companies interviewed in our survey. The situation may change in the next years. However, while large businesses are systematically progressing in ML applications, SME risk to fall behind. Research can contribute to further facilitate the access of SME to ML technologies by appropriate frameworks that reduce the need for technical knowledge and that are adopted to the requirements of SME. As shown in this study, the prevalence of such frameworks is too low, yet.

Also, we are aware that the survey was conducted over a relatively small set of companies. Therefore, we can only deduct qualitative statements. However, the findings are in line with surveys that involve a higher number of respondents and logically sound. A larger survey could show the statistical significance of the statements.

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