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Is Automation the Future of Machine Learning?

A Qualitative Study Exploring the Influential Factors for Adoption of Automated Machine Learning in an Organizational Context

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Is Automation the Future of Machine Learning? - A Qualitative Study Exploring the Influential Factors for Adoption of Automated Machine Learning in an Organizational Context

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ABSTRACT (MAX. 200 WORDS):
Machine learning (ML) started as hype and an academic dream and throughout recent years has become reality for many organizations that are working towards becoming data-driven when making vital business decisions with the use of great amounts of data. Capitalizing on ML requires expertise which the job market is struggling to provide. This resulted in the introduction of the concept of automating the ML activities, namely AutoML. However, until today there is still little evidence of organizations adopting AutoML and a lack of understanding around the factors that influence the adoption of AutoML. Hence, this research aims to provide knowledge about what factors are critical to consider in the context of adopting the AutoML in an organizational context. This is done so by interviewing experts on the topic through the perspectives of a conceptual TOE-framework. These are technological, organizational and external environment. Seven factors were considered from the literature: technological readiness, benefits and barriers, size, management support, championship, competition and IS support. Additional two were proposed and motivated: Data availability

and Trust. The study found that all factors except championship and data availability were influential.

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1 Introduction

This chapter aims to briefly highlight the problem addressed in this research, its relevancy and significance to the academic and corporate worlds, followed by a formal description of the research questions, purpose and the delimitations imposed on the research scope.

1.1 Background

The field of Artificial intelligence (AI) had a profound impact on the way organizations are planning their strategies, conducting their operations, interacting with their customers and stakeholders across different industries such as higher education, logistics and healthcare to name a few (Stone, et al., 2016). It has been at the forefront of many critical breakthroughs on different problem areas including image recognition, logistics optimization, natural language processing and with ever more advancements and novel use cases being established regularly, the potential for AI seems endless (Russel & Norvig, 2020; Stone, et al., 2016) The rise of AI has been largely fuelled by advances in computational powers, the availability of huge amounts of data, and investments in research in the field (Jordan & Mitchell, 2015; Russel & Norvig, 2020).

Machine Learning (ML), a sub-area of AI, has gained prominence in recent years both in the industry and academia (Algorithmia Inc., 2020). Further, it can be observed that ML has an impact on society by affecting how people live their lives and how organizations run their operations (Vaccaro, et al., 2021). Popular services powered by ML help people pick which shows to watch on their leisure (Said, et al., 2011). ML has enabled a host of new augmented experiences that revolutionized how people interact with technology and is one of the fields that businesses utilize extensively to overcome their problems and deliver innovations to their customers (Russel & Norvig, 2020; Vaccaro, et al., 2021).

Algorithmia (2020) reports a 25% increase of IT spending in ML dedicated to deploying proven ML applications or identifying novel use cases. Furthermore, they report a significant uptick in ML adoption amongst organizations, especially the larger ones (Bauer, et al., 2020). Concerningly though, the development and deployment of advanced ML models are far from fully automated and usually requires heavy involvement by ML-specialists, who are high in demand, in a trial-and-error approach which is considered time- and resource-consuming even for large corporations (Algorithmia Inc., 2020; Yao, et al., 2018).

To address these challenges, scholars started developing techniques in a bid to reduce the human role out of the picture by automating their tasks with the end goal of automating the entire process pipeline for ML (He, et al., 2021). Once considered an academic dream (Mitchell, 1997), AutoML today is regarded as a novel sub-area in ML (Yao, et al., 2018). While considered important within the field of computer science, based on its potential, AutoML application efforts in industrial practices have been observed (Vaccaro, et al., 2021). However, the technical complexity of AutoML sets limitations to these efforts (Vaccaro, et al., 2021), hence making it a prerequisite for organizations to have access to experts that understand them (Crisan & Fiore-Gartland, 2021).

AutoML solutions aim to support feature engineering, hyper-parameter tuning, model selection and perchance data preparation, a more end-to-end approach (Crisan & Fiore-Gartland, 2021; Yao, et al., 2018). AutoML is mostly deployed in data science work by being developed in several commercial systems (Crisan & Fiore-Gartland, 2021). Crisan and Fiore-Gartland (2021) highlight the potential of AutoML to help alleviate the skill shortage issue by empowering domain experts to operate ML models without requiring deep technical expertise. Thereby democratizing ML and enabling more organizations to realize the benefits of ML for their business (Crisan & Fiore-Gartland, 2021).

As promising as AutoML can be when it comes to removing the human out of the pipeline to potentially reduce costs and shift the expertise focus of organizations towards more important questions, AutoML is yet to establish trust on a wide scale amongst practitioners (Drozdal, et al., 2020). Thus, the agency of experts is further required with the purpose of validating AutoML models (Crisan & Fiore-Gartland, 2021). Even though, some AutoML solutions proved to be successful in solving many problems (Yao, et al., 2018), however, research shows that the active adoption of such solutions is limited and observed mostly in the context of larger enterprises (Crisan & Fiore-Gartland, 2021). That begs to question what factors are necessary to consider when it comes to the adoption of AutoML in organizations.

1.2 Problem

In the modern era, harnessing the power of data analytics is not an optional matter but an essential ingredient for organizations that aspire for success Davenport (2006) argues. Studies have shown that data-driven organizations are more productive and profitable Miller and Hughes (2017). Companies such as Amazon and Netflix, who have become giants in their respective industries, are textbook examples of how powerful analytics can be when harnessed properly. Industry studies report a high interest and top priority of spending on analytics by organizations (Howard & Rowsell-Jones, 2019; Kappelman, et al., 2021).

Machine learning (ML), one of the powerful data analytics tools, enables organizations to achieve better decision making, better customer service, increased efficiency, revenues profits, lower costs amongst others (Tuggener, et al., 2019). ML has been applied to extract value and insights from data in many domains including healthcare (Callahan & Shah, 2017), banking (Viaene, et al., 2005), and predictive maintenance (Li, et al., 2014) to name a few.

Applying ML comes with its share of challenges (Elshawi, et al., 2019; Tuggener, et al., 2019). The shortage of data scientists is widely reported (Crisan & Fiore-Gartland, 2021; Tuggener, et al., 2019; Yao, et al., 2018). Moreover, building ML models is time-consuming which translates to significant productivity loss for data scientists (Tuggener, et al., 2019). Another issue is the under-utilization of data caused by data scientists' inability to keep up with the exponential growth in data volume (Elshawi, et al., 2019; Frankel, 2015).

The aforementioned challenges - shortage of data scientists coupled with the rapid growth of data and consequently underutilization of data - have motivated scholars and organizations to start striving towards automated ML solutions (Crisan & Fiore-Gartland, 2021). The goal is the democratization of data – namely making data available to non-experts including domain experts in organizations (e.g., physicians, accountants) and researchers – in order to empower them to independently conduct insightful analysis in addition to increasing the productivity of data scientists (Crisan & Fiore-Gartland, 2021; Elshawi, et al., 2019; Drozdal, et al., 2020).

However, AutoML brings challenges of its own on the way which scholars are working to address (Crisan & Fiore-Gartland, 2021; Drozdal, et al., 2020; Xin, et al., 2021). Some studies report that not all AutoML tools are accessible and user-friendly to be usable by domain experts (Elshawi, et al., 2019). Another challenge, which is a by-product of how some AutoML solutions operate as a black box, is the low level of explainability and interpretability for the models and results produced by AutoML which can be a significant concern in medical or law settings (Steinruecken, et al., 2019; Zöller & Huber, 2019).

Despite the benefits, AutoML adoption within organizations is limited and observed in large organizations (Crisan & Fiore-Gartland, 2021) but based on the authors' comprehensive literature review, most of the studies focus on the scientific and engineering side of AutoML, but there is a lack of academic studies exploring which factors are necessary for organizations when considering AutoML adoption, which indicates a novel research area and view to consider for AutoML.

1.3 Research Question

Based on the problem identified above, in order to provide an understanding of the factors that are deemed influential in the context of adopting AutoML in organizations, this study aims to answer the following research question:

> *RQ1: What factors influence the adoption of automated machine learning in an organizational context?*

1.4 Purpose

The purpose is to conduct a qualitative study that investigates what potential factors can influence AutoML adoption in an organizational context. The analysis will be based on the knowledge and experience of experts on the topic of AutoML. Hopefully, the findings of this study will generate a guideline for what factors to consider when it comes to the adoption of AutoML. Furthermore, the aim of the study is to encourage further research on the topic of Auto-ML adoption in enterprises based on the findings and conclusion provided.

1.5 Delimitation

The scope of this study is narrowed down to the factors that are deemed important to consider prior to implementing a novice technology solution such as AutoML. The factors are to be motivated based on already implemented initiatives. That, with the means to build a greater understanding of the factors that encourage such initiatives. Organizations that have implemented an AutoML or traditional ML will be considered in order to exploit their experience with the phenomenon and identify potential leads for AutoML. Organizations without experience within the field of ML are not included in the scope of this study. We further choose not to follow a specific domain based on insufficient knowledge regarding this phenomenon and in order to identify potential use-cases for future research. Additionally, the number of factors motivated by literature is limited due to time and framework constraints. We have chosen to guide the data collection and analysis of this study based on the Technology-Organization-Environment framework.

2 Review of related literature

In the following chapter, an overview of all relevant theories and definitions will be given based on findings from other academic scholars included in the literature review conducted in relation to this research.

2.1 Artificial Intelligence

The term Artificial Intelligence, or AI, was first mentioned in 1956 by John McCarthy in his intelligence studies and has later resolved in several AI waves that stretch until the present day (Russel & Norvig, 2020). The definition of AI and what it entails continuously evolved during these waves in correspondence to the advancements in the field and what was once a defining feature of AI is now considered an expected functionality of technology; therefore, AI has been described differently by scholars (Russel & Norvig, 2020). Most definitions of AI revolve around two aspects, namely thinking (reasoning), and acting (behavior) of AI systems relative to human performance (Russel & Norvig, 2020). Based on these aspects, the definitions of AI can broadly be grouped into four categories: thinking humanly, acting humanly, thinking rationally, and acting rationally (ibid). The groupings derive from the field of cognitive science in which theories of the human mind and intelligence are studied (ibid).

AI systems follow one of two paradigms to perform their assigned tasks: weak methods or strong methods (Russel & Norvig, 2020; Wang, et al., 2020). AI systems that adhere to *weak methods* are general-purpose systems that attempt to combine a series of reasoning steps to reach a solution and though they had an ambitious vision, they failed to scale to large problems (Russel & Norvig, 2020; Wang, et al., 2020). In contrast, s*trong methods* focused on narrower areas of expertise and incorporated domain knowledge to empower AI systems, known as expert systems, with higher reasoning capabilities and address scalability challenges (Russel & Norvig, 2020; Wang, et al., 2020). Machine learning systems, which are introduced in the next section, adhere to the strong methods (Russel & Norvig, 2020). Despite the numerous advancements, AI only started to gain prominence in the enterprise context in the 80s with expert systems (Russel & Norvig, 2020). Presently, computer vision, robotics, and machine learning are widely studied subfields of AI with numerous applications in the enterprise (Russel & Norvig, 2020).

2.2 Machine Learning (ML)

Machine Learning, first coined in 1959 by Arthur Samuel, is a subfield of AI (Russel & Norvig, 2020). Much like the larger field of AI, the increasing reliance on ML is driven by advancements in the techniques and algorithms that enable extracting knowledge from data, increasingly powerful tools and computing machines, and the availability of huge amounts of data (Wuest, et al., 2016). According to Gartner researchers, Howard and Rowsell-Jones

(2019), ML has been widely adopted in many organizations and as of 2019, one in three companies relied on ML with a steady rise expected in the future.

There are many definitions for ML, but for this study Mitchell's (1997) definition is adopted.

"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)

The definition above puts emphasis on the alignment between the variables experience and task that can be measured and thus validated with the help of a performance measure; thus, the main principle behind ML applications is that they can learn i.e. improve their performance from experience (Hua, et al., 2009; Mitchell, 1997).

Unlike traditional software systems which have to be fed rules for how to respond based on the users' input, ML applications are *trained to learn the desired behavior* by processing many examples of input data and the expected outcome (Chollet, 2020; Jordan & Mitchell, 2015). Figure 2.1 below illustrates the differences between the two systems design paradigms. In their studies, both Jordan and Mitchell (2015) and Wilka et al. (2018) highlight the advantage of ML over traditional software development in many practical applications like natural language processing or computer vision.

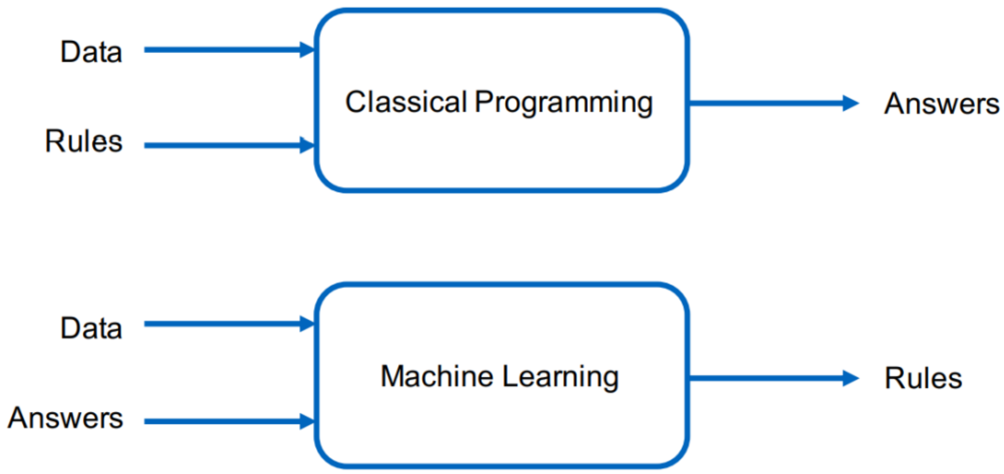

Figure 2.1: Classical programming vs Machine learning. Classical programming generates results from predefined rules whilst Machine learning derives the rules from the data and answers (Chollet, 2020, p. 3).

At the core of ML applications are advanced algorithms that are designed to handle different problems and data types which accomplish their tasks by searching through a space of available candidate programs to identify one that delivers the required performance by relying on the experience acquired during the training phase (Jordan & Mitchell, 2015). Two points differentiate ML algorithms from each other: firstly the way they represent potential programs e.g. decision trees or mathematical functions, and secondly the way they search through the space of programs to identify the optimal program e.g. some optimization algorithms adopt evolutionary search by evaluating successive generations of programs until the performance metrics are satisfied (Jordan & Mitchell, 2015).

Conceptually, ML algorithms fall into three categories, namely *Supervised Learning, Unsupervised Learning, and Reinforcement Learning* (Chollet, 2020; Jordan & Mitchell, 2015). Figure 2.2 below illustrates the differences between them visually.

2.2.1 Supervised Learning

The distinctive feature of supervised learning is that it operates on labeled data i.e. the data must be labeled before the learning can take place (Chollet, 2020; Escalante, 2020; Jordan & Mitchell, 2015). Supervised learning is studied extensively within ML and has many popular applications in areas such as image recognition, spam filtering, and recommendations (Chollet, 2020; Escalante, 2020; Jordan & Mitchell, 2015) and importantly for this study, most of the efforts concerned with automating machine learning processes are focused on supervised learning (Escalante, 2020).

2.2.2 Unsupervised learning

Unlike supervised learning, unsupervised learning algorithms operate without relying on model training or labeled data and instead solve problems by identifying patterns and common characteristics in the data (Chollet, 2020; Wilka, et al., 2018). It is used mainly for three types of tasks, clustering, association, and dimensionality reduction (Chollet, 2020; Delua, 2021). Common applications where unsupervised learning is used include computer vision, clustering, and segmentation (IBM Cloud Education, 2020; Jones, 2017).

2.2.3 Reinforcement learning

In this paradigm, a system agent interacts with its environment through actions that affect the state of the environment and receives a quantifiable reward or punishment as feedback thus teaching the agent how and which actions to choose to maximize the rewards by analyzing the results of taken actions over time (Chollet, 2020; Wilka, et al., 2018). Notable applications for this paradigm include the algorithms powering self-driving cars (Wilka, et al., 2018) and Google's DeepMind which was used to play Atari games, and the board game *Go* (Chollet, 2020). Chollet (2020) states that outside academia and games, not many real-world applications utilize algorithms falling under this paradigm.

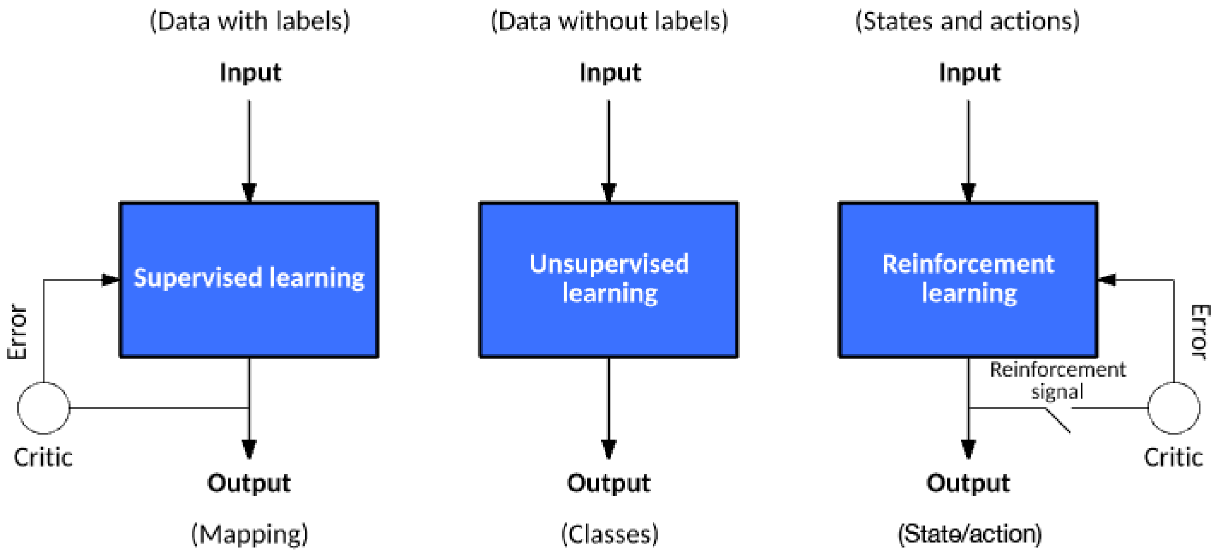

Figure 2.2: This figure illustrates the difference between the three models for machine learning (Jones, 2017).

2.2.4 ML pipeline

From a practical point of view, most ML projects broadly follow a similar lifecycle or workflow which consists of three phases: data preparation, model preparation, and model deployment (Polyzotis, et al., 2018; Wang, et al., 2019). Figure 2.3 below depicts the typical workflow for ML projects. A brief description of the steps involved is provided, but a detailed one is beyond the scope of this study.

As explained by Polyzotis et al. (2018) and Wang et al. (2010), the workflow starts with the preparation phase: firstly, the relevant data needed for building a ML model is collected, then the data is cleaned which usually refers to encoding categorical data and handling invalid and missing data after which the data is labeled or annotated if needed and lastly feature engineering takes place where the workers change the existing data or generate new data to fit into a format more meaningful or friendly to the ML models which includes applying data splitting, combining or transforming formulas.

In the modeling (model preparation) phase, the first step is selecting the model, e.g. random forest, that best fits the data and the nature of the problem e.g. regression or classification; next is hyperparameter optimization which is assigning the parameter values that bring out the optimal performance from the model (Polyzotis, et al., 2018; Wang, et al., 2019). To build a powerful model, *ensembling*, which refers to training multiple models with different combinations of models and parameters values and then combined and their results to inform a better model, is often applied (Polyzotis, et al., 2018; Wang, et al., 2019). Afterward, the model is validated against testing data to ensure it has not *under or over learned* and performs well when deployed in production (ibid). Once the model is ready, it is deployed into production and monitored for any observations to maintain and improve its performance (ibid).

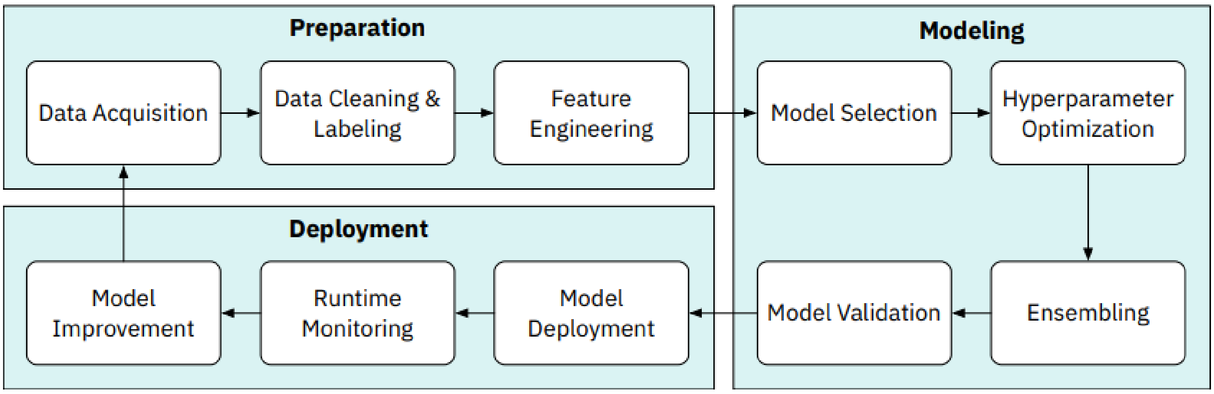

Figure 2.3: Typical ML workflow as described by Wang, et al., (2019).

2.2.5 ML challenges

For all its benefits, applying ML comes with many challenges (Elshawi, et al., 2019; Tuggener, et al., 2019). The huge shortage of data scientists who can turn data into actionable insights represents a major roadblock for organizations in their pursuit of transforming into data-driven entities (Crisan & Fiore-Gartland, 2021; Tuggener, et al., 2019; Yao, et al., 2018). The issue is further exacerbated considering that ML projects rely heavily on the active management and supervision of data scientists (Yao, et al., 2018). Furthermore, building ML models is a highly iterative, time-consuming, and error-prone endeavor which translates to a significant time loss; time that could have been used for identifying new business cases and delivering more value to their organization (Tuggener, et al., 2019). Another major challenge working against data scientists is the limited amount of ML models they can practically explore before settling on a model, thus potentially missing on better model and configuration choices (Elshawi, et al., 2019). Another related issue is the exponential growth of generated data; more data generally leads to better ML models but on the other hand, much of the data remain unutilized because human-powered data science cannot scale to keep up with the growth in data volume (Elshawi, et al., 2019; Frankel, 2015).

The aforementioned shortage of data scientists coupled with the rapid growth of data and consequently underutilization of data has motivated scholars and organizations to start striving towards automated ML solutions (Crisan & Fiore-Gartland, 2021).

2.3 Automated Machine Learning (AutoML)

Organizations need to manage large sets of both unstructured and structured data which can be costly (Rao, 2003). Consequences from such necessity have essentially led to the trend of automating ML pipelines among other things, for the sole purpose of generating value-creating insights (Crisan & Fiore-Gartland, 2021). As previously introduced, automated machine learning (AutoML) emerged as a popular sub-area of ML and can be described as an intersection between automation and ML and that has given birth to two definitions. The ML definition introduced in the previous section is given from a computer's point of view. The following definition bases on that from an automation's point of view.

"AutoML attempts to take the place of humans on identifying (all or a part of) configurations, which are proper to machine learning computer programs (specified by E, T and P in the ML definition), within limited computational budgets." (Yao, et al., 2018)

There are numerous definitions of the concept at hand (Crisan & Fiore-Gartland, 2021), but what Yao, Dai, and Lee (2018) and Escalante (2020) try to convey is that AutoML is a novel machine learning approach that involves a computer to achieve a high learning performance with less amount of human interference. He, et al. (2021), support their definition by also mentioning that the main idea with AutoML is to automate the entire ML pipeline and reduce the costs and time necessary in ML development. However, Zöller and Huber (2019) do not consider AutoML methods as novel as automatic hyper parameter optimization was offered in commercial solutions since the 1990s.

Some argue that an additional purpose with AutoML is to reduce the need for data scientists and provide the possibility to build ML-application in an automated way without any in-depth knowledge in statistics or ML (Zöller & Huber, 2019). Others see it as ML being combined with automation (He, et al., 2021), which He, et al. (2021) further explain as automating the construction of a ML pipeline on limited computational power. The same authors portray AutoML as an easy-to-use end-to-end ML system based on a dynamic variety of techniques that involve four main sections of the ML pipeline, namely data preparation, feature engineering, model generation, and model evaluation (see Figure 2.4) (He, et al., 2021).

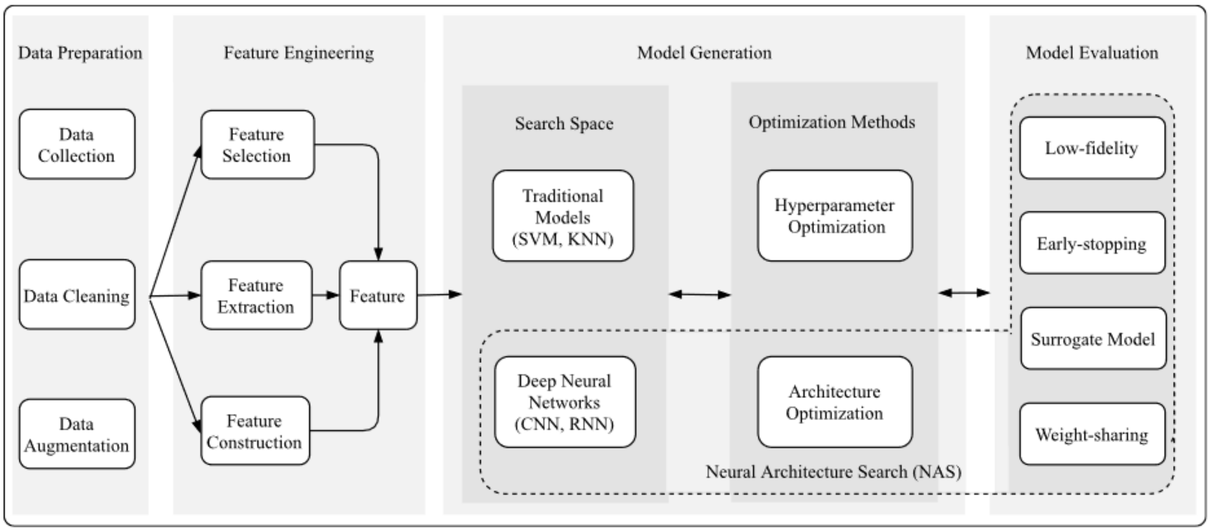

Figure 2.4: An overview of AutoML consisting of four sections – data preparation, feature engineering, model generation and model evaluation (He, et al., 2021).

Until recently AutoML has been confined to the academic contexts, however as of late, the novel concept has been utilized in several industries (Yao, et al., 2018). While some deem these as successful (Yao, et al., 2018), research has proven that the ideal easy-to-use end-to-end solution requires further development (He, et al., 2021). Henceforward a short review of the positive outcomes and challenges with AutoML will follow.

2.3.1 Applications and pros associated with AutoML

AutoML solutions have been developed to automate the computational work involved in building ML pipelines for data analysis purposes (Crisan & Fiore-Gartland, 2021). Consequently, making it easier for data scientists to (Zoph & Le, 2017) derive insights more efficiently (Crisan & Fiore-Gartland, 2021). There are already a number of that are being used in various organizations and industries (Crisan & Fiore-Gartland, 2021; Yao, et al., 2018). Some of these are Auto-sklearn, Google's Cloud AutoML, Feature Labs, AWS SageMaker AutoPilot, IBM's AutoAI and H20 Driverless AI (Amazon Inc., 2021; Crisan & Fiore-Gartland, 2021; Feurer, et al., 2015; H2O.ai, 2021; IBM Inc. , 2021; Kanter & Veermachaneni, 2015; Katz, et al., 2016; Kotthoff, et al., 2019; Liu, et al., 2018; Yao, et al., 2018). Some of the industries in which AutoML is being used are finance, healthcare, analytics, and telecommunications (Crisan & Fiore-Gartland, 2021)

Some of the existent AutoML tools and libraries help solve problems of matter for both researchers and organizations through supervised tasks e.g., maximizing predictive model performance, optimizing hyperparameter tuning, and feature engineering (Crisan & Fiore-Gartland, 2021; Yao, et al., 2018; Zöller & Huber, 2019). Research has shown that a library with automatic parameter tuning that reduces the knowledge requirements, such as the R package, is among the best performing libraries when it comes to solving classification problems (Fernández-Delgado, et al., 2014). According to Crisan and Fiore-Gartland (2021), the ongoing development of AutoML is focused on single components in the ML pipeline such as automating feature selection. On the other side AutoML development aims to include end-to-end solutions in the future, together with the data preparation within the scope (Crisan & Fiore-Gartland, 2021; Zöller & Huber, 2019). However, there is research arguing that the ideal AutoML end-to-end and easy-to-use solution will take more time and effort to develop (He, et al., 2021).

When it comes to usage scenarios in which AutoML can be applied, Crisan and Fiore-Gartland (2021) have identified three of them:

- Automating routine tasks
- Rapid exploration of potential solutions through low-effort prototyping
- Democratizing the ability to create ML solutions and empowering less-technical people

The first scenario results in reduced coding efforts and accelerated analysis processes (Crisan & Fiore-Gartland, 2021). The second scenario addresses individuals with varying levels of expertise and provides three opportunities for an organization (Crisan & Fiore-Gartland, 2021). First, it provides a quick foundation for data science experts which they can develop further into novel solutions (Crisan & Fiore-Gartland, 2021). Secondly, prototyping enables situations in which data can be communicated with customers and other stakeholders within the organization (ibid.). Thirdly, prototyping helps data scientists and other less- or non-technical people to identify errors and issues faster and consequently evaluating whether to invest in engineering efforts or not (ibid.). The last scenario, democratizing, enables non-technical users to create ML pipelines (ibid.). However, Crisan & Fiore-Gartland (2021) argue that these users will require heavy guidance and might be limited in their ability to identify errors within the AutoML solution and correct them.

2.3.2 Challenges associated with AutoML

As mentioned, AutoML aims to automate the entire ML pipeline and its creation to enable domain experts to use ML, however current solutions do not exist (Crisan & Fiore-Gartland, 2021). According to Zöller and Huber (2019), the ones that are in development are designed in the black box which leads to two downsides. One of them is the low level of interpretability, or explainability, which results in the domain user not being able to understand why a specific ML pipeline has been generated (Zöller & Huber, 2019). That view is also supported by Escalante (2020) with the argument that AutoML models ought to include an explainability mechanism in order to ease the accessibility for potential users and the understanding behind potential AutoML solutions.

Lee, et al. (2019) also addresses the importance of a thorough understanding of the artifacts, the behavior of existing models, and the relationships between artifacts in order to make sense of their setup and the possibility for correct adjustments. The other downside is the disregard of domain user's knowledge about the data set that will be used (Zöller & Huber, 2019). Taking that into consideration can reduce the search space for the AutoML system in terms of not having to search as much for a suiting solution (Zöller & Huber, 2019).

Data scientists usually spend 60-80% with data preparation and feature engineering and around 4 % with fine-tuning algorithms (Zöller & Huber, 2019). That shows the importance of the data sets as input for a ML pipeline. Furthermore, a challenge associated with data input when it comes to structured pipelines in AutoML, described by Zöller and Huber (2019) and highlighted by Crisan and Fiore-Gartland (2021). Structured pipelines are considered limited when it comes to applying different types of data that might require more flexibility in the structure of the pipeline (Zöller & Huber, 2019). In contrast to structured pipelines, variable structure pipelines have been developed (Zöller & Huber, 2019). What makes them different is that they learn a network of processes based on different datasets and user objectives (Crisan & Fiore-Gartland, 2021). However, AutoML based on variable structure pipelines is still basic in development (Zöller & Huber, 2019).

One of the goals with AutoML is to remove the human from the pipeline or the overall data science work (Crisan & Fiore-Gartland, 2021; Yao, et al., 2018). However, in order to accomplish that, building and using AutoML systems still requires human input and technical expertise (Crisan & Fiore-Gartland, 2021), which is already one of the challenges with traditional ML (Yao, et al., 2018). The need for high-level expertise is based on the complexity of the data science knowledge required and on the stiffness of the structured pipeline solutions (Zöller & Huber, 2019).

Another challenge associated with implementing AutoML according to Escalante (2020) is the capability of benchmarking and reproducibility in AutoML. The purpose of technology benchmarking can be explained as justifying investments in technology and guaranteeing that technology-related investments are aligned with technology trends (Doll, et al., 2003). Escalante (2020) argues that developing frameworks and platforms for evaluation of AutoML methodologies is an issue, due to that it cannot match the speed at which AutoML as an optimization process that uses data is growing.

An additional issue mentioned by Escalante (2020) is the concern with the scalability of AutoML. The author states that scale issues related to AutoML initiatives are still currently based on the low number of solutions that managed to perform search-intensive AutoML procedures (Escalante, 2020). It is motivated that, AutoML needs efficiency, especially in the context of deep learning models (Escalante, 2020).

Escalante (2020) emphasizes the need to address AutoML in feature engineering. That is motivated by data processing and preparation being a crucial part of the AutoML pipeline, specifically hyper-parameter tuning (Crisan & Fiore-Gartland, 2021; Escalante, 2020).

2.4 TOE Framework

Organizations adopt and apply innovations as part of their efforts to stay competitive. In their book undertaking the complexities involved in applying innovation at organizations, Tornatzky and Fleischer describe the technology–organization–environment (TOE) which is an organizational level theoretical artifact that focuses on how the state, context, and environment of an organization affect the decision-making process of whether to invest and apply a specific innovation which they surmised in three constructs or contexts: technological, organizational and environmental (Baker, 2012). Figure 2.5 below shows a depiction of the framework. Baker (2012), in their review of the TOE framework, mentions that it has since become one of the most used frameworks in the field of information systems due to its explanatory powers and applicability in a broad range of contexts including technological, industrial, and cultural contexts. The author mentions that it has been used to explain the adoption of many information systems including open systems, ERP systems, e-business across many industries such as retail, manufacturing, healthcare, fintech which were implemented in different cultural contexts including the Asian, the European, and American contexts (Baker, 2012). The framework has also been being tested in different economical contexts i.e., developed as well as developing economies (Baker, 2012). The framework explanatory powers and its proven record made it a suitable choice for this study. Table 2.1 lists some of the studies that used the TOE framework are listed in section 2.5 below:

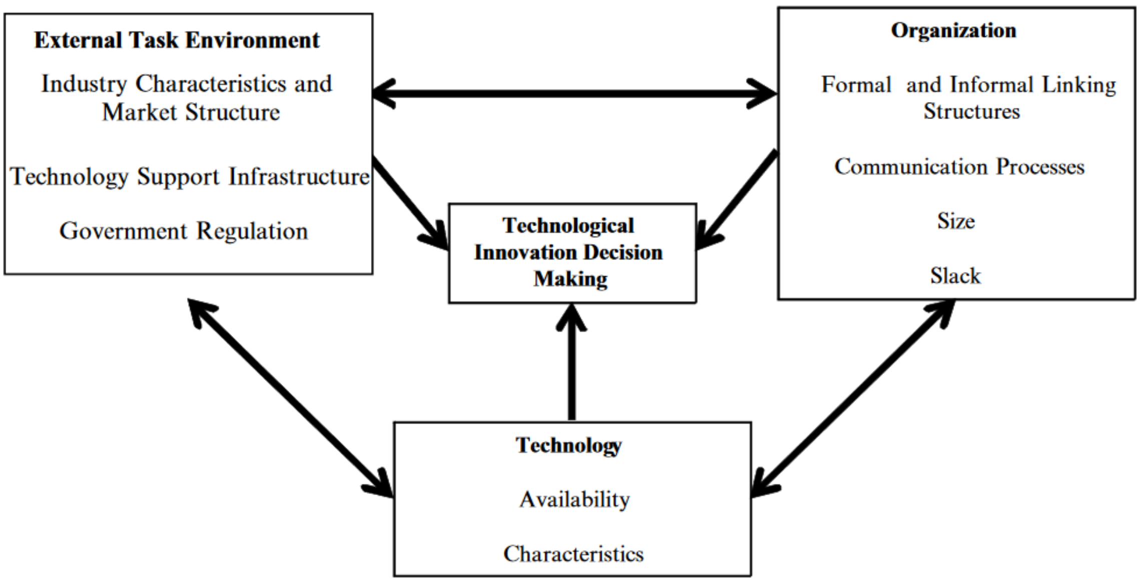

Figure 2.5: The technology–organization–environment framework from Baker (2012).

Below follows a brief explanation of the TOE framework constructs.

2.4.1 Technological Context

Baker (2012) describes it as the set of technologies accessible to an organization which can be the technologies already deployed by the organization internally or relevant external technologies that are not used but are available in the market and can be acquired. Baker (2012) states that external and internal technologies play a significant role because the former broadly highlight the upper limits of the currently available innovations and simultaneously provide a roadmap for organizations on how they can further evolve and adapt to cutting edge innovations; whereas the latter might set limits on what further technologies and innovations an organization can bring in due to compatibility issues.

External innovations in turn can be classified into three categories: incremental, moderate, or synthetic, and disruptive or discontinuous, as Baker (2012) mentions. The author describes incremental innovations as innovations that introduce minor changes or features over existing technologies such as a new release of CRM or ERP; disruptive innovations exist on the other end of the innovation's spectrum and they are characterized by significant leap from the current state or ways of operations such as the rise of Blockchain for book-keeping and cryptocurrencies in the world of fintech, and lastly, moderate innovations which lie in the middle between the previous two and are characterized by innovations that make novel use of existing technologies such as how Netflix changed the TV and Movie industry by streaming movies. Baker (2012) highlights the importance of this classification and states that whilst organizations need to pay attention to all innovations, incremental innovations usually do not threaten an organization's competitiveness and allow for steady adoption whereas moderate and disruptive innovations might threaten its competitiveness and survival and thus require swift decision to adopt and adapt to the changing dynamics of the organization's respective industry. Another classification is based on the effect the innovation has on the organizations' current competencies i.e., whether it enhances or diminishes them e.g., migrating to public cloud services comes with many proven benefits but renders any prior investments in internal data centers useless; thus, as seen from this example, it is imperative to consider the impacts of innovations from this angle as they might lead to potential organizational changes (Baker, 2012).

2.4.2 Organizational context

Refers to the effect of an organization's resources and characteristics on decision-making related to innovation adoption (Baker, 2012). Organizational size and slack are amongst the factors frequently discussed as being influential, yet questions persist over their impact (Baker, 2012). Rogers (1995) and Scherer (1971) argued they positively affect innovation adoption whilst some studies have indicated that slack is not necessary for innovation adoption (Tornatzky, et al., 1983) and others asserted that size is too broad a factor and potentially conceals more specific underlying factors (Kimberly, 1976); thus, whilst they are disputed factors (Baker, 2012) they remain highly relevant factors.

Top management support is also heavily cited amongst the factors promoting innovations (Baker, 2012). Acts of support from the top management such as defining the role of innovation to the overall objectives of the company or rewarding innovation cultivate an innovation-driven culture thus affecting innovation adoption (Tushman & Anderson, 1986).

Other critical factors for the adoption phase of innovation include organizational and communication structures (Baker, 2012). In their publications, authors Burns and Stalker (1963) and Daft and Becker (1979) claim that organic and decentralized organizational structures such as cross-functional teams, which are characterized by flexibility in employees' roles in addition to vertical and horizontal channels of communication, positively impact innovation adoption. Mechanisms that enable inter-organization and intra-organization communication such as gate keepers and cross-functional teams whether formally or informally promote innovation (Tushman & Anderson, 1986).

2.4.3 The Environmental Context

It refers to the surrounding contextual factors compelling an organization to adopt an innovation and the type of innovation it pursues. For example, Baker (2012) notes how in emerging markets organizations adopt innovations that enable them to expand quicker i.e. allow them to serve more customers whereas in saturated markets organizations tend to focus on innovations that optimize their costs. The author also mentions how markets characterized by fierce competition compel organizations to adopt innovations in their bids to outdo or keep up with competitors. Another factor mentioned by Baker (2012) is the maturity of the infrastructure supporting and supplying the innovation; the abundance and accessibility of expertise facilitate innovation adoption; but on the opposite side, organizations will consider adopting innovations that automate or minimize the need for skilled labor which is particularly relevant for our study related to AutoML but also for other similar innovations such as the Self-Service Business Intelligence (SSBI) (Alpar & Schulz, 2015).

Additionally, Baker (2012) elaborates on the role of government regulations by saying that regulations could positively impact innovations' adoption citing regulations examples related to users' privacy and environmental sustainability or negatively affect it if regulations mandate strict safety procedures. The controversy surrounding the development of Covid-19 and the calls by medicine companies to simplify the required approval processes whilst posing many ethical questions is a recent example of how regulations could affect the development and subsequent adoption of innovations (EMA, 2020; Megget, 2020). Similarly, influential groups of organizations can affect their partners and sometimes their competitors to adopt innovations (Baker, 2012) and Apple's impact on the Telecom, phone, and e-payments industries is a prime example (Bajarin, 2017; Black, 2017).

2.5 TOE in the literature

As mentioned earlier, TOE is frequently used to study and investigate technological innovation and has vast empirical support (Baker, 2012; Chong & Chan, 2012). The studies that relied on the TOE framework covered many different technological innovations including the cloud SaaS (software as a service) solutions (Martins, et al., 2016), RFID (Radio-frequency identification) (Lee & Shim, 2007), ERP (Enterprise resource planning) (Awa, et al., 2016) and each study investigated different factors which were tailored for the study (Baker, 2012). The studies adopted Tornatzky and Fleischer's (1990) view that the three contexts, technological, organizational, and environmental, influence technologies adoption but they asserted that each technology is affected by a unique set of factors, hence the tailored approach to factors (Baker, 2012). Table 2.1 provides a sample of the studies covering the TOE literature. The table highlights some of the common factors and some studies that cover them. Not all of them are introduced in the text, but the relevant ones are explained briefly in section 2.6.

Table 2.1: Some of the TOE factors in the literature.

Context	Factor	References
Technological	Perceived benefits and barriers	(Hasani, et al., 2017), (Ain, et al., 2019) (Pan & Jang, 2008) (Racherla, 2008) (Wang, et al., 2010)
	Technology readiness and competence	(Chong & Chan, 2012) (Martins, et al., 2016) (Oliveira, et al., 2014) (Wang, et al., 2010) (Zhu, et al., 2006)
	IT infrastructure	(Pan & Jang, 2008) (Zhu, et al., 2003)
	Complexity	(Li, et al., 2010) (Wang, et al., 2010)
	Vendor pressure	(Lee & Shim, 2007)
Organizational	Size	(Chong & Chan, 2012) (Chan & Chong, 2013) (Martins, et al., 2016) (Oliveira, et al., 2014) (ZHU, et al., 2004)
	Championship	(Lee & Shim, 2007)

		(Hsiao, et al., 2009) (Premkumar & Ramamurthy, 1995)
	Slack and Financial resources	(ZHU, et al., 2004) (Zhu, et al., 2006)
	Employees' IS knowledge	(Thong, 1999)
	Top management support	(Chan & Chong, 2013) (Chong & Chan, 2012) (Oliveira, et al., 2014) (Wang, et al., 2010)
	International scope	(Zhu, et al., 2006) (Xu, et al., 2004)
	Organizational readiness	(Ramdani, et al., 2009)
Environmental	Competition intensity	(Oliveira, et al., 2014) (Zhu, et al., 2006) (Chan & Chong, 2013) (Chong & Chan, 2012)
	Information intensity	(Wang, et al., 2010)
	Generic strategy	(Grover, 1993)
	External IS support	(Ramdani, et al., 2009) (Ramayah, et al., 2016)
	Performance gap	(Lee & Shim, 2007)
	Market uncertainty	(Lee & Shim, 2007)
	Regulatory environment	(Bose & Luo, 2011) (Zhu, et al., 2006) (Oliveira, et al., 2014)

2.6 Conceptual model for AutoML adoption

Based on a review of the factors emphasized, validated, and found to hold significance in the innovation literature in relation to the TOE framework, this study proposes *an initial* conceptual model as depicted in Figure 2.6. The literature indicates significant effects for the Perceived benefits and barriers, technological readiness within the technological context; organizational size, top management support and championship within the organizational context, and competition intensity and external information system (IS) support within the external environment context. Furthermore, data availability and trust in AutoML are two additional factors that were incorporated into the technological context to reflect the uniqueness of the automated machine learning context. Each of these factors is motivated in the following sections. This model is initial and exploratory and might be adjusted based on the evidence from the empirical findings collected through interviews.

2.6.1 Technological

Perceived benefits and barriers

This factor is concerned with the benefits that organizations expect to reap by investing in and implementing an innovation (Lee & Shim, 2007; Oliveira & Martins, 2010). The benefits can be savings of time or cost, but broadly the benefits refer to any features or characteristics that make a product better value for organizations compared to alternatives (Hasani, et al., 2017). Alternatively, organizations may adopt and implement innovations to provide better service to their clients or to gain a competitive advantage over their peers (Hasani, et al., 2017). Many studies in the literature claim perceived benefits as a critical motivation for organizations to pursue and adopt innovations and that better managerial understanding of the advantages provided by the innovation increases the likelihood of allocating the time and financial resources necessary to adopt the innovation (Hasani, et al., 2017; Iacovou, et al., 1995; Oliveira & Martins, 2010).

On the other side, studies indicate that organizations that perceive obstacles were less likely to adopt the technology and that adopters usually perceive barriers as manageable (Cho, 2006; Pan & Jang, 2008). Pan and Jang (2008) conclude a negative relationship between perceived barriers and adoption. The benefits achievable by adopting machine learning analytics depend on the context of the organization and its objectives but commonly cited benefits include better insights into customers' behavior, cost reductions due to optimized processes, higher revenue, etc. (Algorithmia Inc., 2020; Antonio, et al., 2017). AutoML adds to the benefits mentioned earlier cost reductions and or faster deployments achieved by empowering domain experts to work independently from IT and freeing up data scientists from repetitive tasks to focus on higher-value activities (Crisan & Fiore-Gartland, 2021). Based on the existing literature findings and the potential benefits, it can be argued that this factor has the potential to influences AutoML adoption and hence is included in this study to investigate its impact.

Technological readiness

Cruz-Jesus, et al. (2019), and Oliveira, et al.((2014) define readiness to be the technological capital available to organizations that enables them to adopt innovations and the scholars assert that it includes two aspects, IT infrastructure and human expertise. The infrastructure refers to installed technologies that the innovation can enhance or replace which can be applications, IS systems, or infrastructure (Oliveira, et al., 2014). Human expertise refers to the specialized people within the organization with the competency, capability, and knowledge to implement and use the innovation (Cruz-Jesus, et al., 2019). The literature claims this factor as an enabler for innovation adoption (Oliveira, et al., 2014; Crisan & Fiore-Gartland, 2021; ZHU, et al., 2004) and taking the steep requirements for operating any form of machine learning (including AutoML) into account (Sze, et al., 2017), it is possible that adopting AutoML requires organizations with equally steep readiness; thus, this factor is included in the study to investigate whether it influences AutoML adoption.

Data availability

In the authors' view, this is one of the most important factors to consider and it refers to organizations having data from which they aim to extract value. Many factors incentivize organizations to acquire data such as how success and competition are currently based on mastering data analytics (Davenport, 2006). Further incentives could be attributed to the benefits promised made by analytics technologies advocates for organizations that take their decisions based on data such as better decision making, increased automation, increased revenue, reduced costs, larger market share, happier clients, improved productivity, etc. (Sharma & Djiaw, 2011). The benefits extend to all fields; recent studies show how machine learning can transform healthcare by identifying a variety of health risks, predicting the onset of diseases, and even streamlining hospitals operations (Callahan & Shah, 2017). However, to implement any data analytics solution, it is essential not only to have data, but to have quality data to work with irrespective of where it resides, internally or externally, or how it was generated; having quality data is a prerequisite for implementing and running AutoML (Bauer, et al., 2020; Gudivada, et al., 2017). In fact, the lack of quality data is one of the main barriers hindering small and medium enterprises (SMEs) in adopting machine learning and having data, wanting to utilize it but failing to identify use cases for machine learning is one of the biggest issues facing SMEs (Bauer, et al., 2020). Considering the agreement in the machine learning and the broader analytics literature regarding the significance of having quality data for adopting and implementing analytics technologies, including ML, data availability is included to investigate its influence on adopting AutoML initiatives.

Trust in AutoML

In this study, trust refers to *"the extent to which a user is confident in and willing to act on the basis of, the recommendations, actions, and decisions of an artificially intelligent decision aid"* (Madsen & Gregor, 2000). The first element of trust has to do with the AutoML models' accuracy; accurate models are necessary but not sufficient to gain users' trust (Honeycutt, et al., 2020; Zhang, et al., 2020). Ongoing research and continuous advancements in AutoML reflect the interest in the technology and as AutoML matures he questions concerning user experience become ever more relevant but multiple studies highlight establishing users' trust as a major hurdle for widespread adoption of AutoML (Crisan & Fiore-Gartland, 2021; Drozdal, et al., 2020; Steinruecken, et al., 2019; Zöller & Huber, 2019). Steinruecken et al. (2019) and Zöller and Huber (2019) report that the black-box approaches used by many AutoML solutions make the suggested models difficult to understand, interpret and trust. This becomes especially relevant in sensitive settings such as medical, or law settings where explainability is mandatory (Steinruecken, et al., 2019). Zöller and Huber (2019) mention that many are struggling to understand how ML models work and in their pursuit for fully automated ML, black-boxed AutoML solutions add another layer of abstraction thus increasing the difficulty for users to reason how a model was selected. Crisan and Fiore-

Gartland (2021) cautioned against blind trust in AutoML and raised concerns that AutoML could potentially make it easier for users to automate bad decisions without them realizing it. Given the prominence of the issue in the literature and its significant impact it has, trust in AutoML is considered to study its influence on initiating or inhibiting AutoML initiatives.

2.6.2 Organizational factors

Organization Size

One of the relevant factors to be included in any innovation adoption study is organization size as it is shown to be a statistically significant factor in technological adoption (Baker, 2012) yet there are conflicting views in regard to the role an organization size plays in innovation adoption. Whilst there are different definitions for organizational size, most are based on two factors: the number of employees in an organization and/or the resources it has access to either directly or via partnerships, for example, medium-sized enterprises (SMEs) are those with less than 250 employees and income less than €50 m (European Commission, 2020).

In regard to size, large organizations tend to have more resources at their disposal in terms of technological competencies, skilled employees and financial resources (European Commission, 2020; Oliveira, et al., 2014) which scholars claim enables them to engage in pilot projects, take more risks and generally facilitate innovation adoption at a scale SMEs, which are presumed to suffer from smaller human and financial capital, cannot replicate i.e. large organizations are more likely to adopt innovations compared to SMEs (Chong & Chan, 2012; Oliveira, et al., 2014; Ramayah, et al., 2016; Zhu, et al., 2006). Other scholars counter by claiming that SMEs are more likely to adopt new IT technologies on the basis they are more flexible, have more agile decision-making processes, and have fewer legacy systems to overcome which translates to fewer issues with integrations and compatibilities amongst others in stark contrast to large organizations which not only, in general, have to contend with fragmented legacy systems, which is complex and costly, but usually require changes to its business processes and structures (Huang, et al., 2008; ZHU, et al., 2004).

Others claim that size does not affect organizational size (Dholakia & Kshetri, 2004; Ramayah, et al., 2016). A different view is taken by Zhu, et al., (2006) who suggested that organizational size effect on the innovation process is phase- dependant i.e. in the adoption phase larger organizations are more likely to adopt innovations thus indicating a positive correlation but when it comes to the routinization phase, the aforementioned compatibility and legacy system issues make implementing innovations much more difficult compared to SMEs thus indicating a negative correlation. Another view that was introduced earlier in section 2.4.2 above is that organizational size is too broad a factor to offer a useful understanding of innovation adoption and should be replaced by more specific factors (Kimberly, 1976).

In addition to the conflicting views about size influence above, the disparity of deployment of analytics technologies in general, including ML, between SMEs and large organizations is well documented in the literature despite the high interest in the value they bring to the business (Bauer, et al., 2020; Guarda, et al., 2013) make organizational size highly relevant factor to include in this study.

Top management support

Given that in any organization, the top management is responsible for decision-making and budget control, it is a matter of course that their involvement is essential for the success of any initiative. Top management support means that senior managers understand the benefits associated with the innovation and are willing to support it until it is implemented (Wang & Zander, 2018) which is crucial for innovation adoption, and "is one of the best predictors of IT adoption" (Chan & Chong, 2013). It has been found to be a statistically significant factor in enabling innovation adoption (Cruz-Jesus, et al., 2019). Support from top management can manifest in different ways such as instilling the importance of innovation in their strategies and vision or more concretely through direct support and intervention in the management process i.e. planning and following up on results, resolving management problems, or remotely by providing funding for acquiring and implementing technologies, employee training and providing a stable environment that promotes and supports innovation (Borgman, et al., 2013; Chong & Chan, 2012; Cruz-Jesus, et al., 2019). When it comes to ML specifically, Bauer, et al., (2020) findings were consistent with the information systems literature and concluded that management support was an essential factor for the success of ML initiatives. Considering the wide agreement in the literature regarding the significance of management support in adopting and implementing all innovative technologies, including ML, management support is included to study its influence on AutoML initiatives.

Championship

Champions play a significant role in the acceptance and adoption of innovation in its infancy (Hsiao, et al., 2009; Lee & Shim, 2007). They introduce the innovation to the organization, communicate its benefits the potentials enabled through it and outline the organization's need for it to their fellow employees and most importantly senior management (Premkumar & Ramamurthy, 1995). Lee and Shim (2007) limit the champion role to management-level figures who can lend their authority and support for the innovation adoption and implementation. The contributions of champions were shown to be positive and critical for the success of innovation adoption in many studies (Hsiao, et al., 2009; Premkumar & Ramamurthy, 1995); furthermore, they also reported to help mitigating and overcome any resistance issues. Given the novelty and unfamiliarity of AutoML for most non-technical people, hence the need to introduce it and communicate its value before they are convinced to adopt it, this factor is a suspect for being influential and thus is included in order to investigate its influence on AutoML adoption.

2.6.3 Environmental

Competition intensity

It is defined as the pressure an organization feels from its peers, partners, or competitors (Cruz-Jesus, et al., 2019). It is one of the important factors that compel organizations to adopt innovations in order to keep pace with peers, reduce costs, offer better service which ideally translates to a competitive advantage (Cruz-Jesus, et al., 2019). Several studies have shown that competition intensity is a critical factor that affects innovation adoption (Chong & Chan, 2012; Cruz-Jesus, et al., 2019; Zhu, et al., 2006). As previously mentioned in section 1.2, in a digital age characterized by interconnected products, huge volumes of data, and cloud computing where organizations in many industries increasingly offer similar services, compete with similar technologies, organizations that excel at data analytics, such as Amazon, dominate thus the benefits of implementing and mastering data analytics, of which ML in all its forms is part and parcel, cannot be overstated (Davenport, 2006).

Ransbotham, et al. (2017) assert that ML and AI when utilized and linked properly with organizational capabilities might change how the industry operates and the competitive landscape as a result. Given the advantages offered by AutoML, this factor is included in order to investigate its influence on AutoML adoption.

External IS support

This is an important factor given the rising popularity of outsourcing and reliance on third-party vendors' support for expertise not available internally for organizations (Ramdani, et al., 2009). External support corresponds to the support resources accessible to the organization adopting an innovation through entities such as independent experts/consultants, consulting firms, solution vendors (Ramdani, et al., 2009). Support provided can take many forms including assistance with implementation, employee training, and knowledge transfer, tools and solutions maintenance, and other forms of support (Ramayah, et al., 2016). Governments can also provide support through subsidies and other financial incentives (Ramayah, et al., 2016).

With regards to ML, the lack of internal expertise and difficulty identifying use cases were some of the major issues facing SMEs, issues which scholars had suggested can be addressed by partnering with consulting firms and adopting AutoML in order to boost ML adoption amongst enterprises especially SMEs (Bauer, et al., 2020), which is consistent with the studies in the literature which reports that the availably and accessibility of external support reduce the risks, accelerate and facilitate implementing innovation thus encouraging organizations to adopt innovations (Awa, et al., 2016; Ramayah, et al., 2016; Ramdani, et al., 2009).

Currently, there is a growing plethora of AutoML solutions and vendors that offer support at different levels for organizations looking to adopt AutoML, some open source such as AutoSklearn and others commercial including Google AutoML and Microsoft’s Automated ML (Crisan & Fiore-Gartland, 2021). Given the availability of external support for AutoML, it is worth investigating whether it has influence over organizations' decision to adopt AutoML thus it is included in the study.

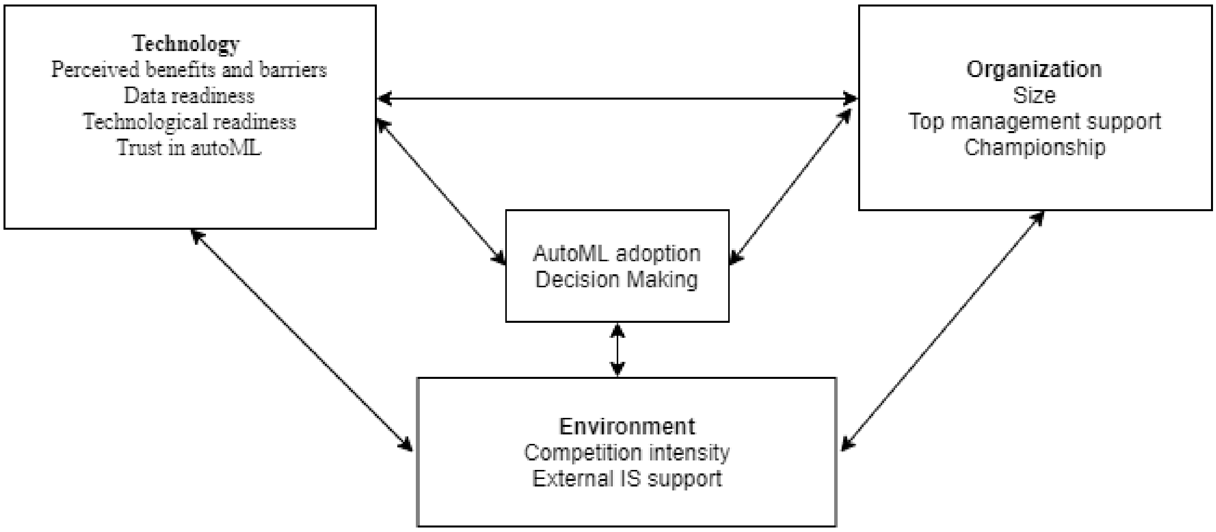

Figure 2.6: A Conceptual Model.

3 Research Methodology

This chapter outlines the chosen methodology approach for conducting this research. Within the scope of the chapter, the aspects of the research setting, method of data collection, method of analysis, ethical considerations, and the state of research quality will be discussed.

3.1 Research Strategy

Information systems research is considered a complex social science field in which a variety of research approaches can be undertaken (Recker, 2013), but specifically for the purpose of this study, the chosen method is qualitative. That, given that the aim of this study is to find an answer to the question:

"*What factors are important to consider for the adoption of automated machine learning in organizations?*".

The course of actions undertaken to achieve this aim is of both a descriptive and explorative character (Recker, 2013). By addressing the problem mentioned previously, we strive to generate new knowledge and in-depth understanding of a phenomenon in an organizational context, which is a social constraint, that we people interact and interpret in various means. Thus, making the qualitative approach the most appropriate choice for the circumstances of this study, which is also supported by Recker (2013) and Bhattacharjee (2012). However, the data collection process and analysis will be to a large extent guided based on previous literature, giving this study a somewhat descriptive character. Thus, becoming a semi-explorative study given that authors aim to answer a question that asks of "what" (Recker, 2013).

The decision for conducting semi-exploratory research is motivated due to the lack of empirical evidence on what factors influence the adoption of AutoML. Prior to addressing the problem (see subchapter 1.2), a thorough review of the theory about ML and AutoML was conducted which led to observing that automation holds great promise within the field of ML. Despite that, it was found that organizations did not only struggle with adopting it but as well understanding it and finding suitable use cases. Theory and evidence about what factors encourage organizations to adopt AutoML in ML initiatives are deemed little, meaning that the understanding of the phenomenon is not sufficient and requires further exploration.

Hence, it was decided to investigate further the so far perceived challenges, benefits of AutoML deployments in organizations based on academic evidence. These were then classified as potential factors that will be investigated in whether they affect organizational adoption of AutoML. The factors identified from previous research are grounded by the TOE framework by Tornatzky and Fleischer (1990) that was presented in the previous chapter (see subchapter 2.3). Having the TOE framework as a foundation for the presented conceptual framework (see subchapter 2.5) gives the research strategy a deductive character. According to Bhattacherjee (2012) deductive analysis is carried out for theory-testing purposes such as improving, refining, or in this case, extending a theory. Despite that a number of studies utilize similar variants of the TOE to analyze quantitative data and test already existing theory, it is determined to instead generate in-depth explanations of AutoML. Therefore, semi-structured interviews were conducted.

3.2 Literature review approach

The literature review approach is based on a three-folded approach (Bhattacherjee, 2012). It consists of three parts:

1. Surveying the current state of knowledge in the area of inquiry, which in this case is AutoML, ML and adoption.
2. Identifying key authors, articles, theories, and findings in the area.
3. Identifying gaps in knowledge in the research area (Bhattacherjee, 2012).

The first step was conducted to scan the topic of interest which was ML. After scanning several industrial reports and article papers, the interest narrowed down to AutoML and subsequently into the adoption of AutoML. Then the next phase was to identify key literature from which then the snowball approach was taken in order to get a better overview of all related research on the topic of adoption of AutoML in organizations. The last part consisted of identifying whether there are gaps or lack of research for the chosen topic which is the factors influencing AutoML adoption.

In order to find relevant literature for the literature review on which this study stands, the following inquiries were used on the web and in a variety of databases:

- (“machine learning” OR “ml”) AND “challenges” AND “adoption”
- “automated machine learning” OR “automl”
- (“automated machine learning” OR “automl”) AND “adoption” AND (“organizations” OR “organizations”)
- “automation” AND (“ai” OR “artificial intelligence”) AND (“ml” OR “machine learning”)
- “decision” AND (“organization” OR “organization”) AND “adoption” AND “new technology”
- “adoption” AND “new technology”

Based on the review of the above-mentioned search queries, which to a large extent regard AutoML, TOE, and theory of technology adoption in organizations, a conceptual framework was created. It can be observed further down in what manner the conceptual framework paves the way for data collection and analysis of the data collected.

3.3 Data collection technique

In order to align with the chosen research strategy and purpose, all empirical data was collected through semi-structured interviews in order to build an understanding and find an answer to “what” factors can influence organizations’ attitudes in regard to adopting AutoML as a phenomenon. Recker (2013) explains that among the various data collection techniques interviewing is considered most prominent for a qualitative study. Myers and Newman (2007) also suggest that interviews are an excellent means of gathering data. Furthermore, worth considering is that interviews can be descriptive, exploratory, or explanatory (Recker, 2013), however questions of exploratory nature are emphasized in the conducted interviews. That is motivated by the ambition of this study to build a deep understanding based on the experience and interpretations of experts related to the little-known phenomenon. Patton (2014) describes in-depth interviews as "walking a mile in someone's head", which is this study's attempt but at the same time due to their ranging, they might offer risks as well as benefits (Patton, 2014).

Interviews can be executed face-to-face, one-to-many, or via phone or conferencing (Recker, 2013). A handful of scholars put emphasis on several aspects of qualitative interviews and one worth considering is the stage, which can be one of many organizational settings and social situations at which interviews take place. Given the circumstances of the global pandemic, all interviews took place digitally with the help of Zoom Cloud Meetings (Zoom Video Communications, Inc., 2021). The location of each interviewee varied from one interview connection to another, making it possible to include target subjects from different countries and even continents. Some being in Sweden, others in other countries in Europe, third in North America. That, however, exposes us to some risks in terms of conducting a successful interview, compared to a traditional face-to-face situated session. Not being able to be present might make the process of gaining the interviewee's trust more difficult (Patton, 2014).

When discussing qualitative interviews as means of data collection, Patton (2014) states the following:

> *"... the quality of the information obtained during an interview is largely dependent on the interviewer."* (Patton, 2014, p. 630)

By that, it can be said that after deciding to conduct interviews as means to collect empirical evidence, proper planning and consideration ought to be made. The same author also mentions a list of principles and skills that interviewers ought to cultivate:

- Ask open-ended questions.
- Be clear.
- Listen.
- Probe as appropriate.
- Observe.
- Be both empathic and neutral.
- Make transitions.
- Distinguish types of questions.
- Be prepared for the unexpected.
- Be present throughout.

With the principles and skills mentioned above, it can be stated that all have been taken into consideration during the interview sessions. However, from a reader's point of view, this statement should not be taken for granted due to that all interviews are prompt to human errors (Recker, 2013 & Patton, 2015). Furthermore, the digital environment in which the interviews took place, compared to a traditional interaction in person compounded the difficulty of achieving the desired outcome when taking the principles and skills above into consideration. One of the points – being prepared for the unexpected – did exemplify itself more than others on several occasions, based on the technological dependency in the context in which the interviews took place. Lastly, worth mentioning is that too hard consideration of the principles and skills above can also lead to an overdoing which then can backfire. By not being a single researcher and interviewer did mitigate some of the risks and challenges through two sets of eyes and minds. According to Barry, et al. (1999), that approach can be beneficial to the research.

3.3.1 Interview Guide

To be able to follow the principles mentioned earlier, engage in an open knowledge-rich conversation, and have a proper focus on the predefined aspects of the topic in question during the interviews, an interview guide was created and used (Patton, 2014). Having that allows the outcome of the interviews to be suiting for building an understanding around a little-known phenomenon. As a motivation, Patton (2014) argues that the interview guide ensures that all-important topics are covered during an interview, which helps keep a structure in a sense, of the topics that are being discussed. Based on that, the interview guide used for this research was grounded on the literature that is mentioned in the second chapter, namely the adoption of AutoML, organizational decision making, and the TOE framework developed by Baker (2012).

The document itself begins with a short and brief introduction of the topic at hand and the study that is aimed to be produced. Following, questions 1-6 are of introductory character, with the purpose of building an image and a better understanding of the interviewee's background. One of the questions also checks any disclosure requirement related to anonymity. Questions 7-10 address the definition of AutoML with the purpose of extracting the interpretation of it by the interviewees and their experience with it. Questions 11-30 address the first perspective derived from the TOE framework, namely technology. Questions 31-42 address the organizational perspective whilst questions 43-48 are asked from an external environment perspective. The final questions 49-52 are closing questions that aim to validate if the interviewees might have considered that something is missing or that can be added.

3.3.2 Interviewees

As stated earlier, the data collection activity aims to gather valuable data for the purpose of this study. A sampling process motivated by Bhattacherjee (2012) was attempted in order to identify potential interviewees. At first, it was decided to approach candidates that are or have been involved in organizations that have adopted AutoML. Given the difficulty of identifying such organizations, it has been additionally decided to include experts that work with developing and providing AutoML solutions. In order to include high technical expertise, it was also agreed to include ML experts and developers from research organizations. The potential candidates were approached mainly through LinkedIn and personal contact. Unfortunately for this study, not many candidates responded to the interview invite which is due to the summer holidays.

The ones that did respond and showed interest in participating are showcased in the following table.

Table 3.1: Overview of all interviewees involved in the data collection process.

ID	Title	Organization	Date	Type
I1	Data Analytics Manager	Anonymous	08/08/2021	Zoom
I2	Research Engineer	AutoML.org Group	09/08/2021	Zoom
I3	Data Scientist	Anonymous	10/11/2021	Zoom
I4	Data Scientist	Anonymous	11/08/2021	Zoom
I5	PhD & Research Assistant	University of Iowa	11/08/2021	Zoom
I6	Chief Data Science Officer	Three UK	23/08/2021	Zoom

3.4 Data analysis

Conducting semi-structured interviews with emphasis on open-ended questions can generate a great amount of data of which some can be considered abundant (Recker, 2013). To minimize the effect of data abundance a coding process was undergone. Despite taking consideration to the literature review to generate contexts by which the data collection process was led, resulting in descriptive character, emphasis is put on a grounded theory approach. Thus, a mix of deductive and inductive approaches was considered while conducting the data analysis inspired by Bryman and Bell's (2018) explanation about qualitative analysis approaches. The authors explain that grounded theory, as an inductive technique helps to build an understanding of recorded data about a social phenomenon based on other's interpretations (Bell, et al., 2018), which is the aim of this study. However grounded theory tends to ignore any predefined contexts and meanings throughout data collection and coding (Bell, et al., 2018). To align with the purpose of this study it was necessary to consider the context of pre-adoption organizational decision making in order to conduct the semi-structured interviews. That can also be described as a hermeneutic approach (Bell, et al., 2018). Thus, engaging the analysis hermeneutically by considering a context and a set of categories, and then attempting to conduct an axial coding which gives the analysis a more interpretive character (Bell, et al., 2018).

As an outcome of the above mentioned, the coding process began with dividing all responses into four general categories or perspectives on the factors that are to follow, namely technological, organizational, external environment, and overall view on AutoML. Afterward, a secondary coding process was conducted, namely coding all responses additionally based on factors identified both prior to the data collection and post the data collection if not in alignment with the suspected factors.

3.5 Research Quality

Conducting research is a process that gives rise to several challenges, problems and pitfalls that are often identified throughout the process (Bhattacherjee, 2012). Discussing research quality tends to put emphasis on two important aspects with quality, namely reliability and validity (Bhattacherjee, 2012).

3.5.1 Reliability

Bhattacherjee (2012) is described as the degree to which a measure of a construct is consistent or dependable. Said differently would be to generate somewhat the same result by measuring the same construct multiple times, based on the assumption that the underlying phenomenon is unchanged (Bhattacherjee, 2012). The author further states that reliability is more about consistency rather than accuracy. When discussing unreliable types of measures, the authors mention that observations and interviews can be questioned and criticized based on the risk of subjectivity that they might involve. That, because an observation is not subjective but rather the subjective interoperation of a researcher in the context of academic research (Bhattacherjee, 2012). Further interviews bear the risk of asking imprecise or ambiguous questions (Bhattacherjee, 2012).

Thus, emphasis on including quantitative methods which are deemed as less bias-prompted, such as questionnaires is recommended. Despite this recommendation, interviews were deemed as a suitable approach for the research strategy of this study. To mitigate any risk of receiving divergent and unreliable answers, follow-up questions were asked in order to validate the responses of the interviewees. Further to strengthen the reliability of the data collected the questions were designed after a literature review was conducted. That in order to provide questions based on the knowledge gained from the literature review. Ideally, a good addition to the empirical data collected would be to conduct a questionnaire as a support to the data collected via interviews but the desired approach was not undertaken due to time and resource constraints.

3.5.2 Validity

Validity in research is viewed as the extent to which a measure adequately represents the underlying construct that it is measuring (Bhattacherjee, 2012; Recker, 2013). In other words, validity checks whether a measure is measuring what it is supposed to measure. In this particular case, validity refers to what extent the analysis of the collected data is done correctly. Furthermore, validity can be divided into internal and external (Bhattacherjee, 2012).

3.5.2.1 Internal Validity

Recker (2013) describes internal validity as the credibility of the findings in a study. That refers to whether the researchers have been able to provide sufficient substantiated evidence for the interpretations offered in qualitative data analysis (Recker, 2013). The internal validity has been approached through clear communication and documentation between the authors regarding any changes undertaken during the course of the study.

3.5.2.2 External Validity

Recker (2013) describes external validity as transferability, which addresses whether and how much the findings from a study can be generalized to other settings, domains, or cases. That requires a detailed and rich description of the context which the researchers have chosen to explore, so that extent to which the context characteristics match those of other fields of research (Recker, 2013). In this study, the context would be technological adoption in organizations. In order to achieve external validity with the findings of this study interviewees from different industries and domains were approached.

3.6 Ethics

Ethics can be described as conformance of conduct in a given profession or community or in other words, the principles of what actions are considered morally right and wrong (Bell, et al., 2018; Recker, 2013). Within scientific communities can be found expected principles of ethical behavior which researchers are expected to follow (Bell, et al., 2018). Thus, the authors of this study are also to abide by a set of principles of expected ethical behavior. In the context of this study, the first principle taken into account is voluntary participation and harmless (Bell, et al., 2018). Prior to the data collection process, all interviewees who participated were approached with an inquiry and invitation to an interview to which they could decline or withdraw at any point, prior to or during the conducted interviews. That without any following consequences. It was also ensured that none of the participants, the authors including were harmed in any physical or mental way through clear communication on LinkedIn.

Further, regarding the data collection process but as well the managing and analysis of the data ought to be done with consideration to anonymity and confidentiality. That, in order to protect the participating interviewee’s identity and career (Bell, et al., 2018). A possibility for anonymity was ensured through clear communication and confirmation with all participants. Furthermore, it was ensured that none of the statements or responses in the empirical data was associated with any of the interviewees and with anything that might give out their identities, thus providing certain confidentiality of the content of this study (Bell, et al., 2018). That was done by not sharing any of the collected data with external stakeholders outside the scope of this study. None of the gathered data is labeled or associated with any of the respondents in any way during both transcription, coding, and analysis.

As mentioned, through clear communication with all relevant stakeholders, full disclosure about the study, its context, and its authors was provided. That in order to comply with the first principle mentioned regarding participation and harmless (Bell, et al., 2018). However, all disclosure was performed with caution in order not to risk inflicting any bias on the respondents and their responses (ibid.). Hence the interview guide provided the necessary debriefing regarding the purpose and goal of this study. Finally, there is an obligation towards analysis and reporting (ibid.). It is ensured that any negative or unexpected findings are disclosed and that no new information was brought to the analysis process and further on in the study. Lastly, all challenges, limitations, and risks encountered throughout the course of conducting the study are disclosed. That in order to save future researchers from making similar mistakes (Bell, et al., 2018).

4 Results

The following section of the study outlines the findings gathered from the interviewees. To ease readability, the findings are organized around the conceptual model introduced in section 2.6. the views regarding AutoML are presented first, followed by their views about each factor within the technical, organizational, and environmental contexts.

4.1 AutoML

The interviews brought interesting results regarding the adoption and usage of AutoML technology. Since this study is focused on AutoML adoption, all interviewees worked for organizations that applied AutoML in some context whilst I2's organization is the creator of an open-source AutoML library. When it comes to open versus closed source AutoML solutions, the respondents were divided; the organizations of I1, I3, and I5 relied on commercial solutions (I1-56; I3-16; I5-30), the organizations of I2 and I4 used open-source libraries (I2-12; I4-58), whilst I6's organization relied on both (I6-138). which led to some notable differences which will be explored in the upcoming relevant sections.

When it comes to exploring the scope of AutoML application in automating the pipeline, all of the interviewees, except I2, mentioned that they were not using AutoML for data pre-processing (I1-28; I3-16; I4-16; I5-10; I6-12); their main reason being it was not yet up for the task, as I1 says:

> *"The ETL part is quite difficult, I would say because usually integrations are quite specific and it's not very easy to automate"* (I1-28).

I2, in contrast, mentioned that the library their organization was actively developing on Github can handle limited pre-processing for *structured data* (I2-16; I2-20). Further up the ML pipeline, in the model selection phase, all interviewees except I4(16) mentioned that their organizations relied on AutoML for model selection, whereas only I1's organization did not use AutoML for parameter tuning (I1-28) and instead relied on their data science team to do that (I1-28; I3-16; I4-16; I5-36; I6-29).

In terms of who used the AutoML I6(43), provided concrete examples of both domain experts whom he called "citizen data scientists" and data scientists utilizing AutoML in their organization with a major expansion on the domain expert planned in the upcoming September (I6-20). The others mentioned or indicated that it was only used by their internal data science team (I1-64; I3-22; I4-36; I5-95). When asked about the current and future prospects of AutoML, I6 asserted it is already accessible to domain experts, though some might require training, in addition to data scientists (I6-18; I6-43; I6-114). I4 (58), despite being optimistic for the future of AutoML, asserted that at the current stage, AutoML is still beyond most domain experts as at least some familiarity with coding is required.

"Yes, as I see it, it's mainly healthy to bridge the gap between machine learning/data science and software engineers. But with regard to domain experts, for the many different applications I don't see that they are helping to bridge that gap" (I4-58).

I1(162), I2(38), I3(90), I5(62) share the same view as they assert AutoML in its current form is still far from a technology that most corporate personnel can use.

In regard to the prospects of AutoML fully replacing data scientists, all respondents dismissed the idea and mentioned that they see AutoML as supporting not replacing data scientists (I1-162; I2-128; I3- I4-126; I6-148). I5 believes that in the near future, the entire pipeline can be automated (I5-20).

"Augment is the short answer. It's not replacing. You still need a data scientist or someone who understands data. But it just will help them in their job" (I6-148).

4.2 Technological Perspective

4.2.1 Perceived benefits and barriers

Except for I6's organization, all interviewees' organizations adopted AutoML within their technical teams only and mostly to aid with model selection and parameter tuning. The interviewees discussed and listed the benefits and challenges which were influential for adopting AutoML. The common benefits mentioned by the interviewees included time and cost savings which are the results of a reduced set of models and corresponding optimal parameter values to work with (I1-62; I2-100; I3-28; I4-86; I5-95; I6-122; I6-126).

"But I mean the benefit of like automating anything it's like then you don't have to do it anymore. And it saves you time and money" (I3-28).

I4 and I6 estimate the time savings to their workflows to be 10% (I4-88; I6-126). I1(62) estimate their time savings to be between 10% to 20% whilst I2 and I5 implied considerable time savings (I2-100; I5-18)

"…How much time does that save you? I mean, I would say orders of magnitude" (I2-100).

Time savings whilst "*incremental*" (I1-72), in the view of I1 and I4, are an important consideration in adopting AutoML.

I6 highlights the democratization of ML and empowerment of domain experts with ML as a major benefit (I6-69) and estimates the data utilization and subsequent value generated from the data to go up by 10% when they are empowered by AutoML (I6-71).

Additionally, the way the interviewees described the quality of the models generated AutoML was generally positive but with varying degrees; the organizations of I1 and I3 use the models recommended by AutoML but they apply changes to get the best model quality (I1-28; I3-20), whereas I4, I5, I6 thought the models generated or aided by AutoML were very good to be used as-is (I4-18; I5-28; I6-43). I6 cites 25% improvement brought by AutoML in some use-cases (I6-43). I2 claimed that in their estimates, between 90% to 95% of the time AutoML will produce better models than data scientists as they stated the following:

"But I would say 95% of the time you'll probably find a better and quicker model with auto-sklearn, or just in general with AutoML tools. They don't have human biases built into them, that's the main point" (I2-100).

I4 emphasizes the scalability of AutoML, the ability to configure large volumes of models in a short time, as a significant benefit for the maintenance industry (I4-56).

I4 also emphasized that the models generated by AutoML have a reduced bias, which is also mentioned by I2(100). I4 says that the reduced bias positively influenced their decision to adopt AutoML (I4-104). Concerning the concern about bias, I6 mentioned that he trusts AutoML (I6-53) but he does not trust the data to be prepared adequately which if true leads to the models generated by AutoML solutions being biased (I6-152).

When it comes to handling huge volumes of data, I5 noted the cloud advantage for AutoML solutions as:

*"I think the automated machine learning models might have a benefit on handling **big data** because the…cloud server… have more memory to handle those big data" (I5-44).*

I5 also highlighted their AutoML solution advantage in facilitating model deployment and sharing, which they deemed extremely important for their collaboration project with fellow researchers (I5-34).

On the barriers' side, all interviewees highlighted technical expertise at various levels as a requirement and often a barrier when it comes to implementing and using AutoML solutions (I1-46; I1-96; I2-38; I3-38; I4-10; I5-62). I6 asserts that AutoML is not accessible to all domain experts and mentions training as a mitigation to the issue (I6-88), a view which I1 shares (I1-46; I1-92; I1-94; I1-102). I6 warns of harmful models if AutoML is applied without due diligence in user training or data preparation (I6-31). Further I1 states that users and the business must be made aware of the power that AutoML solution possesses (I1-96; I1-106). Moreover, I2 mentions that users ought to consider the risk of the data in use being exploited when using an open-source solution (I2-136). I5 mentioned as well that there are privacy issues when it comes to managing e.g., patients' data within the medical sector and speculates that there could be moral issues with applying AutoML in terms of jurisdiction limitations which might decrease the demand for such an initiative (I5-112). In the case of AutoML solutions being applied in the processing industry, governments tend to regulate the industry resulting in difficult access to data (I4-32).

4.2.2 Technological readiness

Regarding the technical readiness, the interviewees offered varied insights. As aforementioned, two aspects are covered in this factor: IT infrastructure, and human expertise. When it comes to the infrastructure requirements required to operate AutoML, I4 asserted that it is computationally intensive to operate AutoML solutions (I4-60). I5 mentioned that good computing units with high GPU and memory specifications are required to run AutoML solutions internally (I5-62) whereas I2 said their AutoML framework can run well even on normal laptops.

"You can run auto SK learn on your own laptop. This guy here that I'm working on is very old but still runs fine and that's part of the goal with the research. Make it so you need as little hardware as possible" (I2-60).

I1, I3, and I6 mentioned that their organizations ran their operations over the cloud, I1 on Microsoft Azure and I3 on Amazon AWS whilst I6 did not specify (I1-144; I3-22; I6-79). In the view of I3, the AWS solution is affordable even for SMEs (I3-98). In I4's case, their organization used both their internal servers and external servers such as Azure based on their clients' situation (I4-58). In relation to using the cloud, I5 and I6 highlighted the necessity of having a good internet connection (I5-60; I6-77). When it comes to the software tools, as mentioned in section 4.1 above, the organizations of I1, I3, and I5 relied on commercial tools (I1-144; I3-22; I5-40), I4 uses an open-source framework (I4-62) whilst the organization of I6 used both (I6-138).

I1 described utilizing and integrating MS Azure AutoML software with their workflows as *"seamless"* (I1-80), I3 thinks AWS software is difficult to navigate (I3-34) despite its capabilities (I3-28). I4 mentioned that saving on costs (I4-62), active community support (I4-120), and being independent of solutions vendors were the main factors for choosing the open-source framework (I4-64). In terms of potential influence on decision-making I1, I4, and I6 believe that the infrastructure requirements did not play a major influence in their decision to adopt AutoML (I1-60; I5-74; I6-86), whereas I3 stated that their organization's acquisition of the hardware resources depended mostly on the benefits versus costs analysis (I3-96).

"It simply isn't the major drive for our work decisions. Hence there aren't any big hindrances." (I4-74).

When it comes to the accumulated human expertise, there are two relevant groups, business users and technical users. From our interviewees, only I1 and I6 worked in organizations with business users, and they both believe that not all their employees possess the necessary skills to apply AutoML on their own and that they must be trained before their organization can consider adopting AutoML throughout the organization (I1-46; I6-88). As for technical users, all interviewees belonged to teams and organizations which had access to personnel with high technical skills (I1-30; I2-4; I3-10; I4-8; I5-10; I6-12). I3 describes his team as a cross-functional unit:

"We work in like kind of smaller teams…each team consists of a few programmers such as a back-end and front-end programmer, someone from the support team like customer support and then someone from the business side" (I3-12)

Furthermore, I1, I3, and I4 mention that their organizations have been using machine learning for at least a year (I1-20; I3-18; I4-66) whilst the organization of I6 has been using it for more than 10 years (I6-12).

Regarding the influence of the team expertise on adoption, I3 mentions that as their organization's chief data scientist, it was they who found out about AutoML, whilst exploring AWS offerings, and subsequently pushed for its adoption (I3-22). I5 states that his manager directed him to try AutoML whilst attending to the newest innovations trends in order to compare its results with theirs (I5-97). I1 and I4 indicate their reason for adopting AutoML was the potential productivity increase (I1-64; I4-110). In the case of I6, AutoML is already being utilized by some business and domain experts (I6-43), which I6 says encouraging an adoption on a wider scale (I6-69; I6-71).

4.2.3 Data availability

Each of the respondents' organizations had different use cases for their AutoML initiatives, but except for I2 they are all managing and attempting to extract value out of their data. Four out of six of the respondents claimed their organizations are data-driven i.e., rely on data to direct their operations (I1-14; I3-14; I4-14; I6-57), collect and manage data, and put emphasis on its quality as well as keeping the data up to date (I1-40; I1-42; I3-52; I4-50; I6-59; I6-65), and they all believe there is a room for improvements when it comes to the insights and value extracted from the data (I1-44; I3-56; I4-52; I6-67).

When it comes to their utilization of data, each case is different: I1's organization collects and manages data from internal and external sources (I1-40) for many purposes, but their team goal is to improve the internal business operations (I1-42), I3's organization uses its internally collected data to improve their organization product (I3-14), and I4's organization uses both internal and external data to predict machines malfunctioning (I4-6). I1 offers some examples of how their organization makes use of its data:

"We utilize data heavily in the organization, of course, for decisions regarding costing, projecting growth and so on, it's all dependent on the exact data. And yes, we are highly information-dependent" (I1-136).

As a researcher, I5 is involved in a *federated learning project,* which includes different universities such as Harvard and Yale and medical institutions (I5-26), that aims to use analytics to help doctors detect diseases at their early stages and improve patients' lives (I5-93). I5 is part of a team that develops and manages ML models which are trained on patients' CT records and images in a shared platform where other researchers are free to explore, train and test the model using their data (I5-24; I5-26). I5 states that they are collaborating with many institutes which provided their data to be included in the model training and subsequently utilized the model in their contexts (I5-62; I5-103).

I6's organization uses the data to model the customers' behavior and offer services accordingly (I6-12). They collect huge amounts of data, more than 22TB per day (I6-59), and they assert the difficulties in extracting value from this data is a major factor why they are recruiting citizen data scientists to help them (I6-71).

In relation to the types of data that are best suited for AutoML, I2 mentions that their framework is best suited for structured or tabular data which is common in organizations (I2-20;
I2-21; I2-72). I2 also mentions that their framework can automate many of the common tasks involved in data preprocessing when working on structured data (I2-16). If the data requires special transformations or is unstructured such as the different types of media, more direction and expertise is required from the user to encode the data in a sensible way (I2-14; I2-16). Furthermore, both I2, I3, I4 and I6 caution that data and AutoML are simply resources, and the users are still required to have a good understanding of their data and domain in order to

be able to ask questions that generate insights and extract value from their data (I2-126; I3-148, I4-126; I6-32).

4.2.4 Trust in AutoML

In relation to the matter of trust of AutoML solutions, below are the main points were highlighted by the respondents.

Firstly, the quality or performance of the models generated by AtrusiutoML. This was already addressed in section 4.2.1, but to summarize the respondents deemed the quality of the models generated by AutoML satisfactory.

Secondly, when it comes to how they validated the suitability of the models, I1, I4, I5, and I6 said they were evaluated using the same common metrics of quality for Machine learning models (I1-34; I4-38; I5-30; I6-35). I5 organization also tests AutoML results against their manually built models I5(30), whereas I3 mentioned that they are relying on the metrics provided by AWS to evaluate the model performance (I3-38) which can be monitored for deviations post-deployment in the user need to be alerted of any issues (I3-42).

Thirdly, explainability: I4 mentioned that explainability is a very critical factor for their clients in the machines-maintenance industry and cautioned that their clients were already having issues trusting ML and AutoML, which adds a layer of abstraction over ML, is further increasing their concerns and discourages the adoption of AutoML (I4-28; I4-30) a concern that I6 also raises in a similar analogy (I6-55). I2 also touches upon explainability and explains it is a popular research topic and that currently some solutions that emphasize the aspect of explainability exist, but their framework does not support it now (I2-46). I2 states that there is currently a tradeoff between explainability and performance of AutoML frameworks i.e., opting for explainable models limits the scope of the algorithms the AutoML can explore to identify the best model for solving the task (I2-46).

I4 says about the explainability issue:

“It's because the AI doesn't deliver. Another major requirement is explainability. You need to be able to understand what the feature is about. And then, in addition to the black box, that can be seen as ML, you have another black box, which can be featured in the engineering aspect. Rather than increasing trust in the entire system, you increase distrust” (I4-28).

The fourth aspect is the reduced bias in AutoML models, which was mentioned in section 4.2.1 earlier, but in short I2, I4 mention that AutoML models have reduced bias whilst I6 says the bias issue stems from the data issue, not the AutoML models.

The last insight is the trust exhibited by I3 and I5 in the commercial AutoML solutions provided by AWS and Nvidia respectively; they state that they trust AutoML and their results because they were made by these vendors (I3-72; I5-40), I3 says

“I have no problem especially AWS and they know what they're doing” (I3-72).

4.3 Organizational Perspective

4.3.1 Size

The organizations of which the interviewees are part of vary in size. Four out of six respondents describe their organizations as active in the practice of AutoML (I1, I2, I4, I6). The organization of I1, described as one of the top companies within the field of accounting and auditing on an international level and a large organization, is applying AutoML on ML solution in order to support internal processes (I1-6). I1 states as well that smaller enterprises that are willing to invest in ML will benefit from utilizing AutoML by reducing costs and boosting productivity (I1-88). Further when it comes to managing and implementation project I1 stated that it took management approximately 2-3 months to finalize the decision on implementing AutoML(I1-122). The motives behind engaging in an AutoML initiative were related to cuts of time and financial resources according to (I1-124).

Another organization that has adopted AutoML, which I3 is part of, is a market-leading organization operating within the domain of real estate marketplaces, working with end-to-end, e.g., from listing to contract-signing, and charging a recurring fee based on the rents that are transacted (I3-6; 145) with the focus of cross-teams collaboration and cross-discipline learning (I3-10; 14). The focus there is the customer experience based on the necessary interaction between the potential renters and the product website (I3-10). The organization consists of a development team, customer support that engages with potential renters and customers, a business team that works with management, and a single data analyst, embedded within all teams in order to provide data insights to all teams and nurture cross-discipline learning (I3-10; 13).

I3 considers commercial AutoML solutions such as AWS as a good and affordable alternative for small organizations that want to implement AutoML(I3-96). Commercial AutoML products are favored more than inhouse developed ones (I3-22). One important factor to consider when it comes to using AWS products is whether the return on investment is worth the initiative (I3-96). Commercial AutoML solutions can, even though considered affordable (I3-98), get expensive if the expected benefits are not assessed properly (I3-96). I3 mentions as well that if the benefits did not outweigh the costs, with a commercial AWS then that alternative would be disregarded, however, due to the small size of the organization the solution will remain used in the close future (I3-144).

The fourth interviewee (I4) is part of a three-year-old start-up consisting of 10 employees (I4-8) - a flat organization (I4-96) - that works with predictive maintenance of machines with the purpose of bridging the gap between engineers and data scientists when it comes to condition monitoring, reliability processes and maintenance (I4-8). I4(92) did not deem financial resources as necessary as time for implementing an open-source AutoML solution which was the case for their organization (I4-92). The same interviewee also argues that the size of their organization was a factor that made AutoML suitable (I4-96).

The last interviewee (I6) is part of a large international organization that is active within the telecommunication industry and has adopted AutoML through its current IT strategy and IT platforms with the reason to make better decisions (I6-75; 104). It is considered an add-value investment (I6-108). The investment in AutoML is not direct and it is not considered massive, but it is within the range of six digits (I6-83). I6 believes that open-source AutoML can be cheaper for smaller organizations (I6-110). Further I6 argues that size matters when it comes to the adoption of AutoML, bigger organizations require many data scientists (I6-112).

Furthermore, in terms of organizational size, I2(54; 56) possesses a strong belief that large organizations with full data science teams have their own internal automated machine learning libraries. I2 further motivates that belief by saying that large organizations can develop any kind of solutions and hire any kind of experts in order to do so (I2-54). I2 also puts emphasis on the definition of big organizations(I2-56) In addition to that the same interviewee also states that there is greater potential for AutoML initiatives within research and smaller organizations that have technical people (I2-54).

When addressing data expiration over time as an issue in ML overall, it is believed that in one of the interviews, larger organizations automate the process of retraining already established ML models in order to mitigate the risk of data expiring (I3-74). I2 argues that besides research groups, smaller organizations are potential candidates due to that the solution does not require deep technical knowledge (I2-84). I2 further states that data availability and accessibility and the size of organizations correlate positively:

“I’d say one of the benefits of being a smaller organization is you don’t have that much data. Maybe you do have a lot (of data) but there is only so much you can use. The larger your organization, the more data you get, the faster you get it.” (I2-88)

According to I2 that also generates the need for automation and the reliability of the output from ML pipelines in order to avoid the risk of the output not being trustworthy, which is something that smaller organizations will not have those big negative consequences from (I2-88). Further in their interview I2 also mention that their AutoML library reduces the number of expert users required to have a ML initiative, which is beneficial for smaller organizations(I2-106). However, I5 argues that to have a reliable AutoML solution, it is ideal to have a designated team that works with verifying the solution (I5-77).

In contrast to the statement of AutoML being affordable by I3(96), I5(79) argues that AutoML solutions can be costly, mainly at the beginning of the technical trend, and compares them to the product life cycle of new technologies – being expensive in the beginning and becoming more affordable as AutoML trend rises. I5 argues that the size of the organization as a factor has an influence on the organization’s decision for adopting AutoML and points out that the bigger an organization is, it is more likely to do so, with emphasis on the need for resources for verifying the outcome of an AutoML solution (I5-80).

4.3.2 Top management support

Regarding top management support, I4 and do not consider it important when it comes to AutoML adoption in business organizations (I4-98), and I1 agrees in the case where AutoML solutions are used for the sole purpose to support data scientists in their work (I1-104). However, in cases where power users are to be educated and given responsibility over a tool, I1 argues that it will require resources, thus the support from management (I1-104). In support of their statement of top management not being considered important, I4 adds that the founders that are part of the management in the organization trust the data science experts with choosing the best tools for a specific need (I4-98). However, I4 argues as well that a higher level of bureaucracy can limit the freedom of choice data scientists require when it comes to implementing new solutions and that it can result in time for decision-making being longer (I4-100).

I5 agrees on top management support not being important either, particularly for cases in which universities are utilizing AutoML for research purposes (I5-85). In cases where organizations are to decide on whether to adopt AutoML or not, I5 argues that top management is necessary for coordinating the necessary manpower to achieve a successful initiative(I5-85). I5 also emphasizes the need for communication between management and the technical experts in order for management to be aware of the potential benefits and downsides of a solution such as AutoML (I5-89). In addition, I5 asserted that management support in the context of university institutions is equivalent to the support from professors that tend to propose projects to science organizations from which funding is received (I5-91). What I2 had to say on the topic of top management support in AutoML initiatives is that management is not going to investigate such alternatives but will rather let someone else do that and convince them to proceed with it (I2-96).

From the response of I3, top management support is considered extremely important based on that ML projects do not get very far when operated in silos (I3-106). In addition to that I3 mentions that top management support is crucial for orchestrating the people that should be involved in the project (I3-106). Furthermore, I3 describes that product management, even though lacking technical expertise, is showing full support, including financial (I3-118), for ML initiatives, even AutoML ones included, as long they are deemed helpful in generating value to the business (I3-118), particularly for "*off the shelf solutions*" rather than inhouse ones, which I3 agrees with (I3-22). I3 also states that management in their organization does not apply micromanagement of new technology initiatives but instead puts perspective on the cost-benefit of investing time in a reasonable way (I3-116).

In the case of the organization that is represented by I6, the CEO is encouraging in terms of becoming data-driven (I6-57). The same interviewee further states that the amount of necessary support for adopting AutoML in their organization is employee training. That, to make sure that users have the necessary knowledge to use the cloud tools which include AutoML (I6-114). According to I6 the dependency of the adoption on the management support is obvious given that it implies future cost reductions (I6-122). It is stated in the last interview that management makes the decisions regarding technology adoption within the organization (I6-118). I6 further summarizes an example in which the new CEO brought influential actors such as the CTO upon initiation of their mandate. The encouragement from the CEO and the choice of IT strategy by the CTO has led to the organization adopting the current tools which include AutoML sub solutions (I6-118). However, if looking solely at ML-related activities, I6 is the one that manages and drives most changes related to work with ML with the current tools, which I6 further explains can be a consequence of AutoML not being that costly (I6-118).

4.3.3 Champions

Regarding the concept of champions or change initiators, according to I1, I3 and I4, AutoML or new implementation initiatives related to ML pipelines are driven internally within the team (I1-118; I3-30; I4-110, I6-118). I1 motivates that statement based on that such change is not considered organization-wide and that the technical team is the only one with the expertise and the idea of how to conduct the implementation (I1-118). On the other hand, I1 states that changes are initiated by business users (I1-120). I3 also mentions that in some cases the CTO or product manager can be the one managing the implementation or design of ML-related initiatives and that he/she is the one who initiated and motivated the AutoML initiative within I3's organization (I3-30). I4 mentions that the need of implementing AutoML was identified internally in conjunction with work related to tuning difficult parameters and particularly when that particular work started to take more time (I4-110).

I6 mentions that encouragement for the use of ML comes from the CEO, and the CTO is the one that makes the decisions about the IT strategy (I6-118). However, when it comes to making decisions regarding ML-related work, these are made mostly by I6 (I6-118). I6 also addresses the fact that the initial decisions regarding IT strategy were taken before I6 started their role in the organization(I6-124). Further, although there is an enthusiasm and alignment among employees and management about using more ML and AutoML, some of the data scientists are showing slight resistance towards AutoML (I6-126). I6 explains that there is a concern that the technology is threatening to replace and take over their responsibility (I6-126). Furthermore, that is rationalized by the lack of understanding that AutoML can augment the work of the data scientists, which I6 shares (I6-126). I6 also emphasizes the importance of successfully selling in a potential use-case if non-technical members of the organizations are to be convinced to use a new technology that is to be adopted (I6-126).

In the context of academia, described by I5, the initiation of new ideas tends to be based on conference attendance and research conducted by the professors within the university and furthermore, the respondent adds that the concept of AutoML can be explored further (I5-97).

4.4 External Environment Perspective

4.4.1 Competition intensity

Regarding whether AutoML initiatives have an underlying competitive reason, I1 argues that the organization aims to reduce time and costs which are indirectly affected by external competition and deemed as competitive advantages (1-128; 132). Due to that the AutoML initiative is being applied in conjunction with work related to internal business units of the organization and not any external stakeholders, there are no direct threats by external competition (I1-130). Based on that ML can be utilized for competitive advantage, I2 argues that the same can be done with AutoML (I2-114). However, it is dependent on what type of business will be using the solution and what type of data will be used and also in what means, e.g., logistics companies can have that as a motive in terms of saving time and resources (I2-114). I2 also mentions that what turns the solution into a profit is the data scientists figuring out how to manage that data that will be used in the solution (I2-124).

I3 does not view the use of AutoML motivated directly by competitive advantage with the motivation that having the people who ask smart questions and use the available data in a smart way is a bigger motive than beating the competition (I3-130). I3 further states that if an organization manages to use ML in a different way than the standard use, only then it can be considered as a competitive advantage, however, the respondent believes that the use of ML is at the state at which its use is standardized (I3-130). However, I3 confirms that making non-technical people aware of the benefits and possibilities of ML and AutoML and capable of exploiting these could contribute to competitive advantage (I3-132).

In the case of I4's organization, the use of AutoML is not either directly motivated by competitive advantage but rather by the need to scale up and monitor more customers and not having enough resources to do that (I4-112). However, in terms of being able to save time and focus elsewhere when utilizing AutoML can be deemed as an advantage (I4-113). I4 further motivates that statement with the fact that their organization does not pay for the software used:

"You need to consider that we are not paying for the software, so as of such it doesn't increase our cost. It might mainly increase our revenue." (I4-116)

I5 states that if an organization is using AutoML which will evaluate a large number of models meaning that a large amount of information processed and used, in comparison to peers that do not and that have a lesser information size in use, can be considered a competitive advantage (I5-110).

I6 has a general understanding that the use of technology and analytics specifically to process information is a competitive advantage and believes that the ones who have the answers quicker are the winners (I6-134). The goal of the organization which I6 represents is to become leading and stay on top, and any decision taken in regard to gain some advantage is towards that goal (I6-134). There is as well a desire to become more data-driven (I6-132). Even though high use of advanced technology I6 states that the organization is not considered fully data-driven and has more to do in order to achieve that (I6-57). In order to stay competitive I6 adds that the organization needs have an understanding of how well it and competition perform and without data that is not able to assess (I6-134). Further I6 emphasizes the importance of measuring performance with the help of data (I6-134).

4.4.2 External IS support

According to I1, the required software and hardware needed for implementing AutoML solutions can be found on demand. In the case of I1's organization utilizing AutoML, the tool being used is mainly Microsoft Stack (I1-56). The use of it is motivated by the fact that the tool is deemed straightforward and related documentation is readily available and accessible through the internet (I1-58), but utmost the organization's strategy is based on partnering with Microsoft's in-cloud solutions, which includes support (I1-144).

Regarding using AWS for AutoML, I3 states that the external support provided alongside it is good in terms of explaining what different metrics entail and how to manage them which helps in the selection of models when provided with e.g., 20 models after inserting the input data (I3-38). AWS allows as well to manage deviations in numbers with the help of manually set alarms and the tool is also considered good in showcasing reliability and accuracy of result sets (I3-42). However, I3 does emphasize the complexity of accessing and navigating within the AWS environment (I3-34). Despite AWS being an external solution, I3 managed to implement it on their own thanks to the available resources related to AWS (I3-138). That is partly based on how difficult it is to reach someone from AWS support (I3-142). Furthermore, even though the experience that I3 and their team have with AWS is positive, they will constantly aim towards minimizing the financial resources spent on ML and AutoML solutions, but in the current state, the benefits of AWS outweigh the requirements to leave them (I3-144).

In contrast to I3's use of external vendor solutions, I4's organization is mainly using opensource to develop their AutoML (I4-58). The main reason behind that choice is the flexibility of them being able to view what is happening in the software, do necessary adaptations on their own and not being reliable on a supplier when it comes to solving problems within the pipeline (I4-64). An additional pro with the open-source approach for I4's organization is the documentation and support tools that are available in conjunction with the libraries that are used (I4-120).

When deciding whether to use opensource or external vendor solutions, I5 puts emphasis on the deemed success, trust and reliability of the opensource provider and the alternative solution vendor and its support (I5-116), and as well on the financial resources available for use (I5-79). A successful commercial solution with good and available support that can aid in any issues that might arise can be worth the monthly payment according to I5(116).

When it comes to the case of I2, their organization provides an open-source AutoML library (auto sklearn) that can be utilized with available documentation on GitHub with a rating of around 5000 stars (I2-12; 32). Support in relation to the solution is provided via answers to code-related issue queries on the GitHub forum (I2-12; 116). The opensource solution stemmed initially from a research project and later as the demand for the library grew the solution became opensource and it was intended for research purposes mainly. However, it has the flexibility to be used for other means by individual users and organizations (I2-14, 36).

I6 mentioned using both open source and a commercial AutoML solution (I6-138). In terms of vendor support from the solutions being used, Valterix and Databricks are offering help and free training (I6-138). I6 deem the support and help materials from the vendors as beneficial (I6-140). I6 states as well that support is one of the factors important to consider when considering technology acquisition (I6-146). Lastly, I6 also indicates the importance of complying with regulations when data can be characterized as sensitive. That can limit the alternatives approaches that organizations have to choose between when considering the adoption of AutoML according to I6.

5 Discussion

This chapter compares the findings introduced in the previous chapter with the literature discussed in chapter 2 and at the end, the final conceptual model is presented. To make it easy to follow the discussion, this chapter adheres to the same structure as the previous one. AutoML is discussed first, followed by the technical, organizational, and environmental contexts.

5.1 AutoML

According to the literature, the goal behind AutoML is to ultimately automate the entire ML pipeline and reduce the dependency on data scientists (Escalante, 2020; Yao, et al., 2018). The findings from the results indicate this was only partially achieved. Apart from I2, all interviewees stated that they are not using AutoML during the data pre-processing phase because according to them, the technology is not capable enough to do so currently. For model selection and parameter tuning, the respondents mentioned that AutoML is helpful and they either use the models generated from it directly as in the case of I3 and I6 or work in collaboration with it as in the case of I1, and I4. I2 states that the AutoML framework their organization is developing can handle common ETL tasks but only with structured data and for simple transformations.

Another stated goal for AutoML is empowering domain experts to utilize ML without needing deep technical expertise (Zöller & Huber, 2019). The feedback from the respondents, except I6 however, is that presently the entry barrier is still high for most domain users as using AutoML requires familiarity with coding skills which they are unlikely to possess hence why AutoML is only used within their data science teams. I6 states, in contrast, that there are some domain experts in their organization who already are utilizing AutoML with a large scope initiative planned to be applied soon across their organization which was driven by their management and domain experts in a bid to be a more data-driven organization. Nonetheless, I6 mentions that not all users can use AutoML on their own, and adequate training is required, to which I1 agrees.

When it comes to the use case of AutoML for assisting data scientists, the findings from the results are aligned with the literature (He, et al., 2021); that utilizing AutoML leads to time and cost savings. All interviewees reported time savings of at least 10% in their workflow when using AutoML. I3 and I6 found the models generated good enough to be used as is whilst I1, I4 use it in conjunction with their manual tuning to get the best model possible. However, some of the responses argue that that the lack of specific use-cases for using AutoML is still an issue.

Regarding the potential for AutoML to fully replace data scientists (Zöller & Huber, 2019), the respondents disagreed by saying that it is unlikely to happen. Instead, they view AutoML as an incremental tool whose aim is to assist data scientists in building better models by considering a greater variety of models and doing so faster.

5.2 Technological

5.2.1 Perceived benefits and barriers

According to the literature, the value and benefits organizations attain from adopting innovation is a major factor affecting their decision (Lee & Shim, 2007; Oliveira & Martins, 2010). The findings from the interviews are in agreement with the literature. Increased productivity, time, and cost savings were the benefits all respondents reported. I1 reported their time savings ranged from 10% to 20% in relation to the typical ML workflow time. I2 states that in 90% of the cases, AutoML provides better models than data scientists. I4 cites the scalability of AutoML in configuring models as the main draw for their organization as they grow their business and get more customers. I6 reported that applying AutoML enabled a 25% improvement in some of their use-cases in comparison but for their organization, the optimism towards extracting more value from the data was the most significant benefit. Reduced bias is another benefit mentioned by I2 and I4 when using AutoML, but they did not state whether it was a major consideration in their decision. All the interviewees expressed that their main reason to adopt AutoML, more than anything, was a specific benefit thus in acknowledgment of the literature and the findings, it is concluded that this aspect, perceived benefits, plays a major role in adopting AutoML.

The literature implied a negative relationship between perceived barriers and adoption (Cho, 2006; Pan & Jang, 2008). Based on the findings of the results, a major issue that all respondents agreed on is that the skills required to use AutoML in its current states such as coding or statistics are seldom found in domain experts. Another issue according to I6 is that AutoML makes it easy to build useless or even harmful models when fed unprocessed data or used by untrained people. The perceived lack of skill in potential data science citizens is why the organizations of I1, I3, I4, and I5 limited their scope of AutoML adoption to their technical personnel. Thus, it is observed that the findings from the study support literature claims. Given the direct impact the perceived barriers had on the decision to adopt AutoML and the literature support, it is concluded that this aspect, perceived barriers also play a major role in adopting AutoML, and thus the overall factor to be significant in AutoML adoption.

5.2.2 Technological readiness

As mentioned earlier, this factor refers to the technical resources available for organizations that allow them to adopt innovations and it includes two aspects, IT infrastructure and human expertise. Oliveira et al., (2014) and Cruz-Jesus et al., (2019) claim this factor is an essential enabler for adopting innovations whereas Sze, et al., (2017) outlined the significant hardware requirements for operating machine learning solutions. However, the findings from the interviewees varied. When it comes to the hardware element part of the infrastructure, I5 agreed with Sze, et al., (2017) by stating that running AutoML on local hardware requires significant resources, but I2 argued the opposite and asserted that their AutoML library can run on normal laptops. I1, I3, and I6 who are utilizing cloud solutions are arguably not influenced by this element. I1, I4, and I6 explicitly state that hardware requirements were not an influence in their decision. It is also worth mentioning highlighting that I3 stated that AWS is affordable even for SMEs. By taking I1 and I4 direct feedback in addition to the claimed affordability of both the cloud solutions and the hardware required for running AutoML locally, it is argued that this element is not influential for adopting AutoML in contrast to Oliveira et al., (2014) and Cruz-Jesus et al., (2019) claims.

As for the human factor aspect, there are two groups, the domain experts, and the data scientist. For the domain experts, only the organization of I6 had empowered them with AutoML. The organization of I6 has ten years of experience with ML, the longest amongst all the respondents, and after observing successful results in some use-cases, they are pushing AutoML for their domain experts, thereby indicating a potential correlation between the level of experience and the maturity with the implementation. It is also relevant that in I6's case, the business users were actively pushing for AutoML adoption and I6 had confidence in their ability to handle AutoML with some training. I6 stated that the domain experts' understanding of business played an important role in their decision.

Regarding the data scientists, all the respondents were parts of organizations with highly skilled technical staff. Moreover, apart from I6, the scope of AutoML adoption was limited to the respondents' data science teams who decided to use it to achieve higher productivity as is the case with I1, I4, or because of their pursuit of the latest trends in the field in the case of I3 and I5. Thus, as observed from the empirical evidence in addition to the literature Oliveira et al., (2014) and Cruz-Jesus et al., (2019), it is concluded that human expertise and subsequently, technological readiness is an influential factor in adopting AutoML. However, considering that only human expertise was deemed to be influential for AutoML adoption, it can be argued that a more accurate factor, Staff technical skills, should be used.

5.2.3 Data availability

Driven by the promise of better decisions, higher revenues, profits, and lower costs, many organizations are collecting data and attempting to extract value out of it (Sharma & Djiaw, 2011). Apart from I2, the responses from the interviewees were in line with the Sharma and Djiaw (2011) findings. They stated that their organizations were managed based on insights derived from data analysis and they considered their organizations to be data driven. Despite operating in different domains and having different objectives for their data initiatives, these organizations all shared a common goal of trying to more insights and value from their data yet none of the interviewees highlighted this factor as a reason for adopting AutoML.

On the other hand, the availability of quality data is an essential enabler of machine learning initiatives (Bauer et al., 2020). Therefore, this factor as investigated within the scope of this study is considered a necessary factor or a prerequisite for AutoML adoption of AutoML however to specifically identify a factor related to data that is critical for the success of AutoML initiatives requires more in-depth research focusing solely on the circumstances of data availability based on all potential scenarios that might affect the decision for adopting AutoML. Thus, it is concluded that this is a factor that is not influential in the decision-making process for adopting AutoML.

5.2.4 Trust in AutoML

In relation to the issue of trust, an important condition for trust in AutoML is the accuracy of its models (Honeycutt, et al., 2020; Zhang, et al., 2020). Another aspect is the approach of AutoML; black-box AutoML solutions raise issues because their results are difficult to understand interpret and trust (Steinruecken, et al., 2019; Zöller & Huber, 2019). Furthermore, Crisan and Fiore-Gartland (2021) warned that blind trust in AutoML solutions without sufficient training to domain experts could lead to negative outcomes. The findings from the results closely echo these issues. When it comes to accuracy, the respondents had positive things to say about AutoML. The responses ranged from somewhat limited trust in AutoML accuracy by, I1 and I3 to high trust by I2 who asserts that in 90% of the cases AutoML can build better models than data scientists. These assessments were carried out based on the same metrics used to evaluate ML models. In the case of I6, the results were good enough that they are planning to implement a wide AutoML initiative in their organization.

The aspect of explainability was also highlighted. I4 and I6 stated that black box AutoML solutions results are difficult to trust for the users who view it as a black box (AutoML) containing a black box (ML). I4 highlights for some domains like machine maintenance explainability is a major concern and the lack of explainability discourages organizations in that domain from adopting AutoML. Moreover, I5 and I6 explained how the black-box nature of some AutoML solutions raises privacy and ethical issues in sensitive settings such as medical and law contexts and makes it difficult to comply with some regulations like GDPR thereby stopping organizations operating in these domains from adopting AutoML.

Given the continuous advancement in AutoML research, any concern regarding AutoML performance in terms of accuracy should decrease in the future. The explainability, privacy, and ethical concerns become more serious depending on the domain AutoML is used in. Based on the direct impact aspects of trust in AutoML had on the decision to adopt it in addition to the literature support, it is concluded that this factor is significant to AutoML adoption.

5.3 Organizational

5.3.1 Size

In accordance with the literature (Baker, 2012), the results imply that organizational size is a considerable factor with a noteworthy influence on deciding to adopt AutoML. However, there is a divided opinion among the respondents when it comes to arguing whether big or small organizations have more suitable circumstances for the adoption of AutoML. Hence, giving proof of conflicting views on the factor. There is an agreement with Kimberly (1976) that organizational size is somewhat a broad factor that involves many underlying sub-factors. That is being motivated due to the variety of statements in the results.

Part of the results is in accordance with that larger organizations have both the resources and the means to engage in pilot projects. However, the results also imply that smaller organizations are better fit to engage in attempts to adopt AutoML considering the potential risks if the attempt is to fail. According to one of the respondents, implementing a new technology such as AutoML that handles data could result in great risks for larger organizations. Further, ML requires expertise and data scientist expertise is considered costly and difficult to get, which makes AutoML somewhat a more lucrative alternative for smaller organizations. That can be considered a counterargument to what Rogers (1995) and Scherer (1971) think about how size affects new technology adoption, which is that size tends to have a positive correlation to technology adoption.

In addition, open-source solutions are free and do not require a great consideration whether to approach or not when it comes to revising financial resources. That, especially when considering the support available around some of the opensource solutions available, can be suited for a small or medium enterprise that does not have the slack to invest in a costly solution. However, choosing to approach open source will require the organization to have people with the necessary knowledge, which could lead to higher personnel expenses. Some of the results state that some of the commercial alternatives on the market are not expensive, but it is worth considering that these solutions might be more limited compared to others or to the open-source approach.

Worth considering is that setting the stage for the ML environment and its AutoML subparts will require data science expertise, but it can be argued that the need is solely for the installment of the AutoML solution, resulting in the need not being there after the solution is implemented. However, based on one of the responses, in order to be able to have users that can manage AutoML after an implementation some technical expertise will be needed from the domain users, which puts further requirements prior to decision-making. Results show that AutoML requires only basic computer science knowledge which is without a doubt less costly and more affordable for any organization.

5.3.2 Top management support

When it comes to top management support as a factor, according to literature management plays a vital role in innovation initiatives in organizations and it is deemed, according to Baker (2012), as a key factor to cultivating innovation adoption. According to Wang and Zander (2018), top management can be described as senior management encouraging innovation and being aware of its benefits. However, not all empirical evidence shows support to what literature has to say about it. I4 argues that top management support is not at all considered important. Especially in cases where the innovative technology is utilized for the purpose to support a technical team, thus not having an organizational-wide impact.

Moreover, one of the respondents in the results thinks that only in the case of an organization with a higher level of bureaucracy that is planning to acquire or develop AutoML, requires top management support. That is with the sole purpose to ensure an alignment between the implementation project that is to follow after deciding to adopt the technology and the business strategy. Furthermore, I5 is agreeing that top management support is necessary in terms of coordinating the manpower that will be involved in a case of adoption. However, I5 argues against top management support being necessary but in the context of AutoML being used for research endeavors.

5.3.3 Championship

Champions play a critical role in facilitating the adoption of an innovation in organizations in its early stages by communicating its value to the business and mitigating or overcoming resistance (Hsiao, et al., 2009; Lee & Shim, 2007) and according to the literature, this is one of the significant factors for most innovations (Hsiao, et al., 2009; Lee & Shim, 2007). Half the interviewees' responses conform with the literature. I3 mentions that they personally took charge and championed the adoption of AutoML within their organization whilst I5 stated that it was their manager who championed the adoption of AutoML. I1 and I4 indicated that it was the decision of the team collectively to adopt AutoML.

Taking into consideration that the organizations included in this study only applied AutoML within their data science teams, it is not easy to judge whether the presence of champions played a significant role for two reasons. The shared background of the team and the relatively small number of people involved might make the decision to adopt much easier than in larger contexts. This factor whilst supported in the literature is not sufficiently supported by the collected empirical evidence, therefore it is undecided whether it is influential or not and a more in-depth study is required to ascertain that.

5.4 Environmental

5.4.1 Competition intensity

The pressure from competitors and peer organizations often drives organizations to adopt innovations either to create a sustainable advantage over competitors or to keep up with them (Chan & Chong, 2013; Cruz-Jesus, et al., 2019; Zhu, et al., 2006). Based on the feedback from this study respondents, they are divided over AutoML and whether it is enough to create a competitive advantage. I1, I2 mention that AutoML benefits in saving time and resources can be considered a competitive advantage indirectly. I3 mentions that using AutoML leads to cost and time savings but in agreement with I4, they do not believe that AutoML is sufficient to create a competitive advantage on its own rather it is up to the users to be creative in how they use it to generate any form of advantage.

According to literature, competitive intensity and advantages are what compels organizations to adopt innovations (Cruz-Jesus, et al., 2019). Two of the respondents, I5 and I6, who deem competitive intensity as influential, put emphasis specifically on the ability, efficiency, and the need to use data and derive insights in order to be competitively strong if not a leading actor on the market. That supports the theoretically proven need of using ML effectively (Ransbotham, et al., 2017). The organization which I6 is part of have changed their strategy in order to align it with the goal of becoming data-driven and the best on the market. That organizational behavior can be explained partly with a statement that when ML is utilized properly, it can change competitive landscapes and the way industries operate (Ransbotham, et al., 2017).

5.4.2 External IS support

When it comes to external IS support, the empirical evidence deems that factor as important to consider when deciding whether to adopt AutoML or not, and how. The responses from the interviews regarding the factor indicate additional factors to consider when it comes to deciding whether to outsource the entire or parts of the work related to the adoption process or to have it in-house.

One of the evident factors to consider based on the findings is whether the AutoML solution will be commercial or based on open source. According to the respondents, it is important to evaluate the alternatives based on trust, success, availability, and accessibility. Some of the commercial solutions are deemed as quite straightforward at explaining different measures and aspects included in the solutions, which minimizes the knowledge requirement of the user. Only the ability to access and navigate in the environment for some commercial solutions, e.g., AWS, is deemed slightly too complex to be viewed as user-friendly which can imply difficulties in finding answers in situations where the user is trying to solve a problem regarding the related AutoML solution.

Even though some of the open-source alternatives are deemed good enough to use, they are still criticized when it comes to the need for personal support with problems that might arise. That can undoubtedly be explained by the fact that open source is non-financed development. Although the lack of support, open-source solutions tend to be applied in-house which according to the respondents gives the flexibility of adjusting the solution and having a better understanding of what is happening behind the scenes.

6 Conclusion

The purpose of the study was to investigate what factor could potentially be deemed as influential to AutoML adoption in organizations and to hopefully guide practitioners towards more informed adoption initiatives. By doing so the following research question had to be answered:

> *RQ1: What factors influence the adoption of automated machine learning in an organizational context?*

This study investigated nine factors with the help of the TOE-framework and the perception of AutoML adoption as a phenomenon. Seven of the factors were perceived as influential. Thus, two of the factors are not perceived as such. When it comes to the overall perception of AutoML of the respondents, the view on AutoML was somewhat divided where some view AutoML as automating the entire pipeline while others see it as a partial implementation of a ML pipeline. The responses show evidence of four organizations that have adopted AutoML to various extents. The responses also indicate and support the view of literature that AutoML is far from automating the entire ML pipeline due to the complexity of data preparation or ETL and due to the lack of ML maturity and expert knowledge within organizations.

Furthermore, the idea with AutoML empowering domain experts and achieving democratization of ML is viewed as considerably challenging and requires effort to ensure that the domain experts have the necessary technical knowledge and accessible technology in order to make these ideas into a reality. Lastly on the view of AutoML, all respondents view AutoML as means to augment data scientists and their work within an organization.

From the technical point of view, three out of the four factors addressed were deemed important. First are the *benefits* and *barriers*. Two of these received the attention of all respondents. As a technical benefit, the *increased productivity* was most common, while considering barriers, *employee training* was deemed the most common challenge in all the interviews.

Additionally, *technological readiness was* also considered as important in the majority of the interviews. The responses about readiness circled mostly around the element of human knowledge and expertise regarding ML, domain experts, and data scientists. There is no questioning that ML requires a great amount of storage and computation power in addition to an advanced solution, yet it seems the relevancy of infrastructure concerns is no longer a major concern for organizations thanks to the power of cloud computing. Thus, the authors propose shifting the focus on the skillset of the staff.

Lastly from the technological factors that were perceived as important is *trust.* Half of the respondents emphasized the importance of trust in an AutoML solution. That is further motivated by the attention showed to the degree of explainability that follows with an AutoML solution. The respondents that emphasized trust highlighted the need to explain and understand a AutoML solution and its results. That in order for the implemented solution to generate any value for the organization adopting it and for it to be evaluated post-adoption. Furthermore, the importance of trust and explainability according to some respondents is extra crucial in sensitive industries such as health care or telecommunication due to the sensitive data that is being collected and used or regulations.

The factor that is not perceived as important to consider is *data availability*. The motivation to that conclusion is that data availability is the first keystone necessary to even think of approaching ML in the first place. A majority of the respondents mention that their organizations have an abundance of data that is not fully utilized, which results in data availability not being an influential factor but rather a given prerequisite.

When it comes to the organizational perspective, two out of three factors are considered important. Firstly, *organizational size*. Even though organizational size was deemed influential, the respondents had somewhat conflicting views on whether an organization of bigger size is more considerable for the adoption of AutoML or a smaller one. Some respondents viewed AutoML a fitting technology solution for small organizations by motivating that smaller organizations have limited resources and less complexity in the data that will be processed. In contrast to that, others viewed larger organizations as more suitable environment for AutoML to be adopted in, based on the large amounts of data that needs to be processed and the large amount of computational power necessary to handle it.

Furthermore, *top management support* is deemed influential by the majority of the respondents. However, one respondent highlighted that the chosen use-case and the scope in which the desired AutoML will be used determines how important top management support is and if it is at all necessary. The respondent motivated that in order for top management to be relevant, the use of AutoML needs to have an organization-wide impact. Another respondent did not either deem top management support important if AutoML is being implemented in the scopes of a technical team with aim to simply support their own work. Consequently, not having any impact on other parts of the organization more than providing a more efficient internal support.

Lastly for the organizational context, when it comes to *organizational champions,* there was a low agreement amongst the respondents on its importance. Most of the respondents did not view it as important and instead motivated that business users or top management are the ones who drive technological changes in organizations. Particularly in the case of I6, in which the CEO and CTO were the initiators of the current business and IT strategy of the organization.

From the perspective of the *external environment*, both *competition intensity* and *external IS support* are considered important based on the findings from the interviews. Regarding competition, some of the respondents agree that saving time and resources can be considered a competitive advantage. While others highlight the importance of being able to utilize available data efficiently in order to generate strong and competitive insights. Regarding the external IS support, the respondents agree on it being important. The results further emphasize the different aspects with commercial and open-source solutions imply. Worth mentioning is that the varying characteristics of each technology open flexibility of approaches to consider in terms of IT strategy.

Lastly and conclusively the factors that were alleged important to consider when adopting AutoML based on the responses collected are *the technical benefits and barriers, staff technical skills (technical readiness), trust, organizational size, top management support, competitive intensity and external IS support.*

6.1 Further research

Conducting this research has resulted in new and confirming knowledge about AutoML and its adoption in organizations and new reflections and potential ideas for further research.

We managed to identify use cases of AutoML and domains in which AutoML is applied. Without a doubt conducting research with a focus on a single domain or set of use-cases would have been more ideal. Based on the findings of this study that indicate some domain dependency, we would like to encourage future research to further investigate the factors of this study related to AutoML in a specific domain, supposedly one the identified ones like telecommunication, health care, or predictive maintenance.

Due to that this study is delimited to the TOE-framework, we would like to encourage similar future studies to be conducted through the lens of other technology adoption frameworks such as the theory of diffusion of innovation and the technology acceptance model 1, 2 or 3.

We would also like to encourage explorative research on the concept of ML as a service (MLaaS).

Furthermore, in order to give some significant relevance to the findings of this study, we would as well encourage future research of the same factors through a quantitative or mixed methodology approach in order to check the reliability of the current findings. The potential outcomes will hopefully generalize our findings.

Reflecting on the process of conducting this study, ideally would have been to use both quantitively and qualitative approach but due to time constraints and other limitations, the opportunities of doing so were not big.

Appendix 1: Interview Guide

Background

Automated machine learning (AutoML) is considered a novel technology solution and a trendy research topic for data scientists and organizations. This research aims to explore it from an information systems' angle, specifically, expectantly to uncover the most relevant factors that affect organizations' decision-making process in terms of its adoption and surrounding circumstances. To conduct this semi-exploratory research, the Technology–Organization–Environment (TOE) framework has been chosen in order to construct the interview guide. Like other new technologies it is believed that AutoML is affected by factors that are included in the TOE framework. More information regarding the framework can be found here. The creators of the TOE-framework claim that the factors influencing the decision to adopt innovations usually fall into one of three groups:

- Technological: refers to technologies accessible to an organization be it already employed or accessible through the market.
- Organizational: Such as management support or available resources.
- Environmental: Such as industrial or governmental regulations, accessibility of vendors or pressure to catch up/get ahead of the competition.

We hope you share our excitement for this topic, and we are looking forward to discussing your experiences and observations regarding AutoML.

Research inquiry: What factors affect organizations' decision to adopt AutoML?

Interview

Introduction:

1. Do you wish to remain anonymous?
2. What is your background and education?
3. Can you describe your organization? Domain? Industry position?
4. What are the different roles and responsibilities in the organization?
5. What is your role and what are your responsibilities?
6. What is the size of your team?

Auto Machine Learning utilization:

7. Does your organization in any capacity utilize AutoML or ML? For how long and to what extent? If not fully, then in what stages of the ML workflow?
8. If no, do you have any upcoming AutoML initiatives planned?

9. In what way are you utilizing /planning on applying AutoML? Applications & benefits examples.
10. How are AutoML initiatives/solutions being managed? By whom? Role/Responsibility?

TOE contexts:

Technological Context:
Trust in AutoML

11. How would you verify the reliability & accuracy of results produced by AutoML?
    a. What measures were applied (if any) and how did AutoML perform?
12. Could you describe the perceived challenges associated with trust in AutoML?
13. How are the results from your AutoML system interpreted by people in the organization?
14. How did that affect the process of adoption?

Data

15. Do you consider your organization data-driven?
16. How much data does your organization collect/manage? Is it all internally acquired or accessed from external sources?
17. How important is the data collection in your organization?
18. To what extent is the data utilized?
19. What impact does AutoML have on the value generated from the data that is being used?
20. To what extent did that affect the decision to adopt AutoML?

IT infrastructure

21. What is required in terms of IT infrastructure to implement AutoML?
22. To what extent did that affect the decision to adopt AutoML?

Employee knowledge and expertise

23. What is the required level of employee expertise and readiness necessary for adoption of AutoML?
24. How ready was the organization for AutoML when it decided to adopt it? In terms of familiarity & maturity of existing data analytics implementations and the availability of skilled personnel and domain experts?
25. How were any challenges addressed?
26. To what extent did that affect the decision to adopt AutoML?

Perceived benefits

27. Which benefits of AutoML were used to justify the decision to apply it? How were they measured/projected? How much was realized?

28. Was AutoML seen as an incremental or disruptive addition? Elaborate.
29. What were the unexpected benefits (if any)?
30. To what extent did that affect the decision to adopt AutoML?

Organizational Context:

Organizational size

31. What is the headcount of the organisation?
32. How was the budget for AutoML initiatives allocated?
33. Was it considered a necessary or luxury investment?
34. What impact did the organization size and resources have on the decision of adopting AutoML?

Top management support

35. What forms of support are necessary for adopting AutoML?
36. In your case, to what extent is the top management support evident?
37. Are such initiatives followed up by top management or are they solely entrusted to a specific team?
38. How important is top management support in facilitating AutoML adoption?
39. To what extent did that affect the decision to adopt AutoML?

Championship

40. Who made the case for adopting AutoML and how?
41. Were there any challenges or resistance for AutoML? How were they resolved?
42. How did the presence of initiator(s) affect the adoption and implementation of AutoML?

External Environment context:

Competition

43. To what extent does the organisation's line of business emphasize the use of analytics?
44. What impact did the organizational strategy have on the decision to adopt AutoML?
45. What impact did the competition (if any) have?

Factor: External support

46. How did you implement or plan to implement AutoML? Open source vs commercial? With a vendor help or by relying on inhouse development? Elaborate.
47. How do you rate the support from the solution provider and their chain of partners? How accessible is it?
48. How did that influence the decision to implement AutoML?

Closing questions:

49. In the long run, how do you view the impact of AutoML on data analytics works/teams? Augment vs replace.
50. Would you like to add anything?
51. Do you feel there was anything we missed?
52. Do you have any questions for us?

Appendix 2: Coding Guide

Full form	Code	Meaning
Automated Machine Learning	AUTOML	Covers how respondents view AutoML presently and in the future
Data Availability	TDA	A factor
Trust in AutoML	TTR	A factor
Technology Readiness	TTR	Both codes cover the technological readiness factor.
IT Infrastructure	TINF	
Perceived benefits and barriers	TPBB	A factor
Organizational size	OS	A factor
Top management support	OTM	A factor
Championship	OC	A factor
Competition intensity	EC	A factor
External IS support	EIS	A factor
MISCEALENOUS	MISC	Refers to general interesting points of discussion that is not covered within the suggested factors.

Appendix 3: Interview Transcript – I1

Company: Anonymous

Interviewee: interviewee 1 (I1).

Title: Data Analytics Manager

Date: 08/08/2021

Row	Transcription	Factor
I1-1	Would you like to remain anonymous and keep the company name confidential?	
I1-2	Myself – no, the company should be confidential.	
I1-3	What is your background and current career title?	
I1-4	My background is from electrical engineering and software engineering, but I would say mostly software engineering since this is what I mostly worked with and in my company. Currently I am an AI and cloud architect, so I work with designing AI and cloud solutions and so on, with some development work as well.	
I1-5	Can you describe the business strategy of the organization for the domain or the business strategy in which you are involved?	
I1-6	Yes. “Company” is a British company working in several fields. It's mainly accounting and auditing, but there is some work in strategy consulting for cybersecurity and digital transformation, and so on. So I would say the organization is multi linked in a few domains. It's considered an industry leader especially in the accounting field, along with other three competitors. To be honest, I don't have exact figures for the organization revenues, but I think if you Google it, they’re around 40 billion per year, plus or minus.	OS
I1-7	But when it comes to your work as an AI and cloud architect, which domain are you mainly active?	
I1-8	We are mostly active in the local solutions for the organisations, so I am within a department called internal firm services. Within “Company” itself we have internal systems and internal things that needs some sort of AI and the data and analytics and I'm working in that area.	MISC
I1-9	What are the different roles and responsibilities in the organization? This is more or less answered by mentioning the domains, but maybe	

	you can add something on what your role and what your responsibilities are?	
I1-10	My responsibilities are more on the side of preparing the solutions to analyse the data, provisioning the required infrastructure and servers, helping with the choice of some machine learning algorithms and so on and running a couple of experiments. That's on the data science side, and there are other things on the cloud side. But I don't think that will fall within the interview scope.	
I1-11	What is the size of your team in which you're working?	
I1-12	Ah, good question. There has been lots of movement, but I would say we are 6 to 9.	OS, TTR
I1-13	Do you consider “Company” as data driven?	
I1-14	That's a good question. It's quite difficult to answer on behalf of the whole “Company” around the world because it's a big company. But in Sweden I would say to some extent.	TDA
I1-15	If you were to say a percentage of the company being data driven, what would it be?	
I1-16	65-70%?	TDA
I1-17	Does your organization in any capacity utilize machine learning or auto-machine learning?	
I1-18	Yes, we utilize it, but the AutoML is not used for production solutions as far as I know, it's still under prototyping and experimentation. The data scientists are mostly using the normal machine learning. And there are still some doubts about the abilities of the AutoML.	AUTOM L
I1-19	For how long and to what extent are you using machine learning today?	
I1-20	Since I joined the organization there were some machine learning initiatives, so I would say at least more than 2 years.	TTR
I1-21	You mentioned that there are some prototypes in conjunction with automated machine learning. Does that mean that you have any upcoming initiatives that are planned?	
I1-22	Nothing concrete yet for the auto-ML, but we have some ongoing projects for the machine learning. Some of them are customer cases and some are proprietary work for internal systems, and so on.	AUTOM L

I1-23	In what way are you utilizing automated machine learning?	
I1-24	Mostly we use it for the regression solutions. There isn't much classification and clustering as far as I see.	
I1-25	Could we get some specifics about the applications?	
I1-26	I'm not quite sure I can go into the details due to confidentiality constraints, but I would say projecting figures, expecting certain sales and the like (*analytics purposes*).	
I1-27	How far have these auto machine learning prototypes managed to progress? Are they used for model selection, hyper-optimization or are they also able to automate the ETL as well?	
I1-28	The ETL part is quite difficult, I would say, because usually integrations are quite specific and it's not very easy to automate. It's mostly the model selection part that the auto machine learning helps us with. And I would say it helps to direct us towards which model to use, afterwards you need to start doing some manual manipulation of the model in order to fine tune it and get better results so it helps us by guiding our model selection	AUTOML, TPBB
I1-29	If there were to be any automated machine learning initiatives or solutions, by whom would they be managed?	
I1-30	I would say they will be managed internally within our team because it is easy for us to implement it given our technical expertise. Usually we make it in a collective responsibility way, so you can think about it in a scrum model way. And then we have a product owner who acts as a point of contact with the business.	OC
I1-31	One of the promises of the automated machine learning process is that it will empower domain expert or power users to be able to do machine learning work on their own. From what you are saying, in the short term that is not in your plans. Is it specifically because you prefer to work in a particular way?	
I1-32	I think it's more about our case and the type of data we are working with, but I would guess there are other scenarios, if you have simpler data, that can work for power users directly with auto-ML.	AUTOML
I1-33	You are making prototypes using automated machine learning. So how would you verify the reliability and accuracy of the results produced by the prototypes?	
I1-34	Similarly to normal ML. Whenever you configure an auto algorithm or experiment, you can specify which algorithms you want to test and then you choose a collection of them. You assign what we call a	TTE

	training budget: we set a specific time limit for the algorithm or the auto-ML to train say 1-2 hours. Then a combination of algorithms are tested and each of them gets measured through the regular measures depending on the type. Say, if you are having a regression then we use things like the R-squared. If you are using classification, we use the confusion matrix and so on.	
I1-35	How would you rate the improvements added later on by fine tuning? Is it a small percentage or is it a big difference in terms of the base model and final model?	
I1-36	Sometimes it's big, Sometimes it's small, depending on the type of improvements you made and on the training data.	TTE
I1-37	You did mention that you have your regular routines for validating the outputs of a machine learning solution, which will some to some extent, require you to be manually active with it. But could that be automated?	
I1-38	I would say no because that's more art than science. Sometimes you see that you have a highly fitting data set, which means your data set is working quite well on the training data but not on the testing data. Hence you need to do more work on your training data. Sometimes you need to enable extra standardization on your data. So that requires you (the data-scientist) to apply some judgment. Maybe in the future the technology is able to make this, but not as I see it now.	MISC
I1-39	How much data does your organization collect and how does it manage it? Do you use external sources or just internal?	
I1-40	We are a big organization so we have many different data sources. Either internal systems that we use to manage the organization, or external providers that we utilize for certain services and certain integrations. Data collection and management is quite important for us, especially the part of data quality, ensuring data being up-to-date and so on.	TDA
I1-41	How important is data collection and management to your organization?	
I1-42	It's very important, so we try to collect as much data and keep things organized and well managed (to directly enhance the business operations).	TDA
I1-43	Do you consider your data as fully-utilised or do you feel like there's a bit more that you could do with some more resources?	
I1-44	I think we can do much more.	TDA

I1-45	And is it in any way possible that you relegate some of the simpler tasks that can be handled by automated machine learning to power users or domain experts, thus utilising the capabilities of the data science or analytics teams in more valuable or important activities?	
I1-46	I would say maybe some of the tasks because there are couple of things in the way. #1. We need to educate those power users in order to be able to do that themselves. #2. We need to get them to sit with business board in order to find out what questions need to be answered by machine learning. #3. There should be some intervention by more techie people to help with preparing the required data and all of that requires resource utilization and prioritization within the organization plans.	TPBB
I1-47	Is it possible for power users to try and prepare data for simple scenarios? Or usually you would put it beyond their expertise?	
I1-48	I would put that beyond their expertise because there are so many challenges that are of a more technical nature. I mean they wouldn't be able to fully utilize the existing data unless they have a very simple data set in Excel file or something like this, but the more complicated datasets in databases, APIs and.	AUTOM L
I1-49	How much time do you spend with model selection and optimization versus how much time do you take doing the ETL, from the upstream system all the way up to training data and testing it?	
I1-50	The most consuming part is the ETL, so I would say that can easily take up to 70% of the time.	
I1-51	Why do you think there's more you can get from your data?	
I1-52	I would say based on intuition and common sense: there is a lot of data, but not that many insights generated from it.	TDA
I1-53	Did this organization possess or had access to the hardware and the software needed to for automated machine learning?	
I1-54	I mean right now everything is in cloud, so all these resources can be just requested and released on demand.	TINF
I1-55	What tools are you using?	
I1-56	We are relying mostly on Microsoft Stack, so that's possible within something called the Microsoft Machine Learning studio.	TINF, EIS
I1-57	Since these are cloud based tools, I'm guessing it is relatively easy to acquire or get access to them, right?	

I1-58	Yes, it's straightforward and the documentation is readily available in the Internet and it's just a matter of reading and learning.	EIS
I1-59	Did the availability aspect of IT resources in any way affect the utilisation of automated machine learning?	
I1-60	I would say it's not about the availability but it's more about the prioritisation. The prototyping of the AutoML is not highly prioritized. And I would say yes, because the resources are being directed to somewhere else.	TTR,TINF
I1-61	Right now as you apply automated machine learning, does it enhance your productivity?	
I1-62	It's tough to get a figure for model selection, especially since I'm not implementing all of those things, but I would say it can help to go from 30% to 20% of total time spent on model selection during a machine learning routine.	TPBB
I1-63	The motivation for using auto-machine learning was to seek productivity, so would we be able to say that the lack of human resources in any way lead you to utilize AutoML? Do you feel your team members are a bit overwhelmed with their tasks? What would motivate you to actually implement or apply automated machine learning?	
I1-64	As Yahia mentioned, it will be mostly the productivity. So if we are able to make things much faster for the data scientist, help them to limit the research on which algorithms to be used and to be optimized, that would be quite good factor, because injecting AutoML to our existing pipelines and replacing the normal way, it's not that difficult. So I would say that's one factor. Another factor is just raising the awareness about this AutoML and making sure that the data scientists include it within their plan to implement it. why it wasn’t used till now intensively because up to now it’s considered something extra that we are looking at, but we need to strategize that more and provide these prototypes in a more concrete business case to include it within the formal working processes.	TPBB
I1-65	What level of readiness do you think is necessary for organizations that want to adopt auto-machine learning? How would you describe your team’s level of competence?	
I1-66	It's more about the organization understanding and having a clear expectation about what the AutoML cannot do. So firstly, having clear understanding mostly helps in the model selection. Secondly, understanding that it would require a good amount of resources because you need to test so many models and compare the results of	TTR

	those models. Also having the required infrastructure to implement those things, either if its cloud based or maybe on premise based. #4. Having the capacity and resources to include that within their prototypes for experimentation, as they can get a good decision on whether they want to proceed with it. In my organization I think we need to work more in that area. We have the case of AutoML, when to use it and when not to use it under clear budget and performance improvement expectations.	
I1-67	Could you give an example of the type of resources that are required, but that you have not obtained yet or do not have the capacity for?	
I1-68	In this context, resources means computing power, needed to run experiments and so on.	
I1-69	But let's also take a bit of time with the other term in the equation - human factors. Basically, the experts and consultants available. In your organization, I think previously you mentioned being involved in consultancy, so I'm wondering if it is because your team members are all very highly trained and skilled that you deem this part to not be a problem for your case? If it were to be applied in the original thought way to empower the staff, what kind of skills and what kind of readiness would they require before they are able to try machine learning?	
I1-70	Actually, yes, it's easy because of the skill set of the team we have in “Company”, but, from a power user point of view, it can be made easy if the required prerequisites are met. So the platform to perform is being provisioned and created by the IT team. The permissions are being managed, the required datasets are connected to the platform and it's purely a matter of just selecting the required features from the data set and choosing the machine learning algorithms and performing the training. Uh, the tricky part for power users is to learn which machine learning algorithms to use and to understand how they can perform the comparison between the results, at least in the platform we are using, because it's not abstracting that away from the user it: expects you to understand what machine learning algorithms are being used and how to compare the resulting metrics. I know that there are some other platforms like Atrix? and so on. They have gone further steps and they even abstracted that part away from the end user. So the algorithm will automatically test, compare the data and so on.	TTR, AUTOML
I1-71	Would you describe automated machine learning as incremental addition to your function, or does it feel like something disruptive?	
I1-72	I would say it's incremental, it's not that big a disruptive change.	TPBB

I1-73	What made you to decide to incorporate machine learning into your workflow?	
I1-74	The perceived performance improvement. Possibilities when selecting the models and limiting the search of the possible algorithm. So if you've been working with 50 algorithms, maybe with auto-ML we can limit that down to 10.	TPBB
I1-75	Say, when the decision was made, how did you measure "What kind of benefits are we getting?" Did you quantify them in any specific way and how would you describe your return of investment?	
I1-76	Uh, that's a good question. We haven't measured actually exactly how much time we would have spent manually if we didn't implement auto-ML versus implementing it, but I'm quite sure there is an improvement.	TPBB
I1-77	Did you in any way find any unexpected benefits or anything of that sort?	
I1-78	I would say the benefits were pretty much what we expected in our case, since we've been mainly looking into what could be the good algorithms to further optimize, and that's what we achieved.	
I1-79	Did you find or encounter any obstacles or barriers to use it or utilize it?	
I1-80	The integration of it into our workflow was seamless, actually, in our case. Maybe it's because of the platform we are using because it's quite powerful in that area.	
I1-81	With the benefits that you discussed, are they from machine learning initiatives or are they from the AutoML prototypes?	
I1-82	It's been discussed purely from the auto-ML prototypes perspective.	
I1-83	OK, then we can proceed to the next context. Here we are focusing on the organizational aspects of the decisions. So first, how many employees do you have in your organization?	
I1-84	I think it's more than 300K across the globe.	OS
I1-85	Do you believe that the size of your organization encourages or discourages any decision for adopting the use of auto-ML?	
I1-86	I would say no. In our case it's most. It's mostly like a local team decision.	OS

I1-87	So you think even a small organization could have applied, or could in theory apply and use auto-machine learning?	
I1-88	Yes, of course. They may be incentivized to do to do that because it helps them to increase their productivity to some extent. And if it's a small company then most likely they have a limited budget and resources and that can help them reduce the budget spent on machine learning. But of course, here comes another question. If they are using a commercial platform, how expensive is it for them? And so on.	OS, TPBB
I1-89	Yes, then do you think that open-source software would be the more preferred one when it comes to younger organizations?	
I1-90	It might not be, but I don't have experience with open-source options. But if it provides a good enough automation and main functionality without much money or work it may be worth it, otherwise they may need to spend more time customizing those open-source solutions - time which could be better spent on the commercial one.	MISC
I1-91	According to you, what are the prerequisites for adopting auto-ML in terms of organizational (not only IT) infrastructure?	
I1-92	The most important thing, if you are speaking from power users' perspective, is #1 educating the users about what auto-ML is, when to use it, what type of business problems it can answer and #2 identifying the business problem is to be answered.	TPBB, TTR
I1-93	Then would you say that "Company" possesses these prerequisites?	
I1-94	It's quite difficult to judge since we are quite a big organization, but at least based, on the Swedish context, I would say that we need to do more work in that area: to educate, explain the possible benefits and possible scenarios to use it also.	
I1-95	And maybe it's been a bit of repetitive, but which aspects from the infrastructure that you mentioned are the most important to prioritize?	
I1-96	I would say the education and awareness part. Like you don't know what you don't know, so we need to first make the users or the business aware of this power actually existing and that they should start considering that.	
I1-97	So if we were to describe this in even more abstract terms, could we say you need to set up some sort of advocates or communication channels?	
I1-98	Yeah, how to do, that's a very good question. It could be running the proof of concepts across the business, it could be presentations and it	MISC

	could be stations for the business teams. There are so many ways how that can be done.	
I1-99	And one more follow-up question here, how is this team set up in “Company”? Is your internal team of data scientists only working on its own, or are you working as cross-functionally?	
I1-100	We work as cross-functional teams so we support a couple of other internal business units.	
I1-101	Then, how possible is it for you to educate other teams to use machine learning, because you have the interaction and communication link available?	
I1-102	Yes, it's possible to do that as long as we get the prioritization and the resources to do it.	
I1-103	And do you consider top management support as important when it comes to adopting new technology or new solution (such as auto-machine learning)?	
I1-104	It depends on the scenario. If it's like ours, where we use auto-ML just as a way to improve the work of data scientists, I would say top management support is not important. we just inject a new solution to our daily routine. But if you are speaking about widespread auto-ML for power users, then you need the session, you need the education and so on. Then you need the support of top management since you need more resources and time to do that.	OT
I1-105	Are the top management aware of this technology and its implications in the long run?	
I1-106	I wouldn’t say yes, that’s too detailed for them. But I would say for the power users, they would definitely know about it and understand it.	OT
I1-107	Are certain initiatives followed up by management? Throughout the whole process of implementation.	
I1-108	Yes, of course. Like any other initiative, because those folks are usually supported by some business cases and those business cases are linked and so on, so they are definitely followed up. We follow up everything that we spend money on.	OT
I1-109	Would you say that it's also followed up after the application is deemed successful?	

I1-110	I would say yes, we will provide a report with the success story, discuss the benefits and the possible implementation plan in other areas.	
I1-111	What is the general purpose of your plan for auto-machine learning initiatives?	
I1-112	Improving the productivity in our case.	
I1-113	Maybe it would that would be deeper if you told us what drove the necessity of auto-ML within your team.	
I1-114	There’s been a discussion on how we can improve our way of working and making things faster. Auto-ML was one of the suggestions that we can test in that area and see if it can reduce the time in model selection and so on.	
I1-115	Would you then consider that trying auto-ML is less of an effort and less costly than improving the current ML? Or is auto-ML complementary?	
I1-116	That's what we are exactly trying to figure out at the moment. We want to compare if we start with auto-ML, limit our algorithms and then research with those algorithms instead of developing our own ML.	
I1-117	And does that kind of initiative require a change champion? Or did this suggestion come from higher up even though you mentioned that it's within the team?	
I1-118	I would say it's within the team. Also, because it's not a organization wide change, it was quite easy and smooth to implement, since everyone pretty much had an idea on how that would help.	OC
I1-119	But if there was to be a change champion present, who tries to push through that idea, would that typically be a power user or a business user?	
I1-120	Most likely I would say it would be a business user.	OC
I1-121	How much budget was allocated for your auto machine learning prototypes?	
I1-122	I'm afraid I cannot answer that question since I'm not working with the project management so I don't have any visibility into budget. But I would say it was some time frame I think, two or three months.	OS
I1-123	And do you consider that this type of initiative was planned and executed because of slack of financial resources? Or were there any resources left on top for the initiative?	

I1-124	no Actually we did it because we wanted to reduce time, which translates to reducing the financial resources.	OS
I1-125	So it was mainly prioritized, rather than just seeing it as an opportunity. “OK, we have a little bit of extra, but it we can use it to try to improve anything.”	
I1-126	Yes.	
I1-127	The last section of questions is related to external environment, context and aspects and how they influence the organization decision. Was this auto-machine learning initiative in any way driven by competitive reasons?	
I1-128	As an organization we want to reduce our time to market and want to reduce our costs, which of course is a factor that's affected by the external competition. So you can say yes, the external competition plays a role, albeit indirectly, towards this type of initiatives.	EC
I1-129	Was there a factor that for specific projects people worked on something, and your team, for example, to quickly deliver something? Maybe that forced you to try auto-machine learning. Or was it just in terms of increasing productivity?	
I1-130	Since our team is working like the internal business unit of the organisation, we don't face that external competition. Maybe other business areas within “Company” that work with external clients would feel that much more than we do.	EC
I1-131	Do you consider automatic machine learning to generate any sort of competitive advantage to our company?	
I1-132	It's mostly faster delivery time and the reduced costs.	EC
I1-133	Do you think your competitors would also be using machine learning to enhance their operations and optimize it?	
I1-134	I think they will use it definitely. I mean it’s a well-known technology. And in my scenario - are we threatened or not? I don't think we feel that much since we don't work directly with the external clients, but maybe other business units start working with that. They can feel the direct competition threat more than we do.	EC
I1-135	To what extent do you emphasize these analytics to run your operations? And do you consider your organization as information dependent?	

I1-136	We utilize data heavily in the organization, of course, for decisions regarding costing, projecting growth and so on, it's all dependent on the exact data. And yes, we are highly information-dependent.	TDA
I1-137	And to what extent is there a delivery of information intensity, strategy and for current, upcoming or potential machine learning initiatives?	
I1-138	I would say it has a high effect because the more as an organization we are aware that we have more valuable datasets and data points, the stronger the business case. We have to implement new machine learning initiatives.	TDA
I1-139	And have there been any projects that were initiated in such a way?	
I1-140	Yes, definitely, for machine learning, yes.	
I1-141	So maybe automated machine learning?	
I1-142	I would say why not?	
I1-143	Was the choice of solution based in any way on generic strategy?	
I1-144	It's a combination of combinations, of course, so we have some strategy in the organization to work with them. Like Microsoft Technology. But within Microsoft Technology itself we pick and choose the useful technology. In our specific scenario it was Azure machine learning.	
I1-145	Does organisation consider the strategy in terms of competing in the market? For example, competing based on analytics, and try to deliver the cheapest or optimized values of products. Something to that extent.	
I1-146	I would say that would apply for more external facing business units. But in our case the more strategic goal is time improvement.	EC
I1-147	So you would say that the choice for utilising auto-ML was be based on a high-level strategy: to improve internal processes rather than work externally towards the clients?	
I1-148	Yes, that's in our case, but I totally understand it's possible to have other strategic reasons.	AUTOM L
I1-149	Do you consider it as a higher priority to apply AutoML internally before externally, or it doesn't matter?	
I1-150	In my case, I would say it doesn't matter. Actually if I had the decision I would apply it externally as well. Both ways, simultaneously.	AUTOM L

I1-151	Was there any strategic purpose for your automated machine learning initiatives? And in the long run do you see yourself utilizing it more than just for better productivity?	
I1-152	not at the moment but empowering experts to work independently and delivering more valuable solutions to the end client would be the goal. I would say there are just some discussions and hype around the long-term, but nothing concrete yet.	AUTOML
I1-153	Do you consider that auto-ML initiatives could generate a strategic purpose to open up time and resources for actual data scientists like you to work with something else, or just to shift the priorities in your work?	
I1-154	Yeah, definitely. Since that will save up sometimes for the technical people working with those solutions, which at that time can be utilized somewhere else.	TPBB
I1-155	Do you have a vision of what you could focus more on in the future, which you are not doing currently?	
I1-156	Maybe running more experiments implementing more machine learning projects, so it's increasing the team capacity.	
I1-157	You mentioned earlier that you are using Microsoft Solution, which is a commercial solution, right? Why did you choose this option? Did you in any way need support from the vendor, or you were just supervising your own internal team's skills?	
I1-158	I would say for all the reasons, so number one, as an organisation we had the strategy to partner with Microsoft's in-cloud solutions, so that's something from top to bottom. Then we had to use one of those solutions from Microsoft to implement machine learning, and that was among one of the available options. And of course you get support and help from Microsoft on top of that.	EIS
I1-159	Did you need the help of implementation firms?	
I1-160	Uh, no, it's us doing that.	EIS
I1-161	in the long run how do you feel the impact of automated machine learning on data analytics? For example, do you think they might replace data scientists eventually? Or do you see them as enhancing their workflow?	
I1-162	No, it's it will be mostly enhancing the way of working and providing more space in terms of time, but in terms of full replacement, that's not possible. It's similar to the drag and drop UI applications when we think they can replace the developers, right? There are some tools that	AUTOML

	can help you with simple code, but if we are speaking about them replacing developers, that's a joke. The same thing goes with auto-ML now. There is a lot of judgment and intuition that needs to be applied with machine learning that auto-ML is not able to provide.	

Appendix 4: Interview Transcript – I2

Company: AutoML.org group

Interviewee: Interviewee 2 (I2)

Title: Research Engineer

Date: 09/08/2021

Row	Transcript	Code
I2-1	Is it OK that we use your name or the name of the organization that you are part of?	
I2-2	I would figure they are OK, but can I get back to you later on? That answer? My own personal name is fine.But yes, the organization name I can ask in a chat and then yeah.	
I2-3	Could you just tell us a little bit about your background?	
I2-4	So I started a PhD back in Ireland where I originally come from that was in automated algorithm selection. Then I moved to Germany to kind of pursue this PhD. Further, my supervisor moved over but yeah, after a while I realized it wasn't really for me. I'd much prefer software development. I'm still interested in the research, but not as like a huge you know not as an academic career. And then yeah, when I quit PhD, I managed to get a group with as I get a job as a research engineer with my current group, which is the AutoML.org group which consists of the University of Freiburg and the University of Hannover, and their focus is on automated machine learning. So yeah, my current title, I guess, is research engineer.	
I2-5	How long have you been doing this?	
I2-6	About a month so far. But they are very much- I'm sorry I don't know how much to derail from the actual question - but the AutoML org are very much involved with kind of organizing conferences and things, so I've been kind of part of those conferences I'm well aware of what they've been doing beforehand.	
I2-7	Is your organization involved in implementation products within organizations? For example when a company migrates from a	

	database to a cloud or to a data hub that requires the expertise of the application. Has your organization or any of you been working with similar projects regarding AutoML?	
I2-8	No, we don't directly work with companies. I think there's some correspondence here and there just to kind of see what they use machine learning and automated machine learning for. But no, we don't directly interact with companies. Now there is funding for the university from certain groups, but again, that's more research focused rather than, you know, doing the day-to-day operations of the companies.	
I2-9	Do you in any way interact and monitor some projects and their results? Have you been involved in anything like that?	
I2-10	In terms of organizations doing so, not directly. Of course we monitor our own performance of the software we develop to make sure that it doesn't degrade if we change something. But with an organization itself no, we don't have any kind of end users that we cooperate with to track that kind of thing.	MISC
I2-11	As an organization, do you provide your solution as an open source or do you sell it?	
I2-12	So it's open source on GitHub and it has about 5000 stars. So for an automated machine learning library it's up there. There's H2O as well, which is quite popular and then a teapot, and then there's another one I'm forgetting. Those would be kind of the main ones, so we'd be considered one of the more popular and used ones. Again, it's very hard to tell how many people actually use this production versus how many students use this in their own side projects or whatever. So in terms of how many people use it, we're not directly sure. But definitely people do use it. There are issues and queries that come up. One of the biggest ways of finding bugs and how to improve it is people using it and finding problems with it.	EIS, AUTOML, MISC
I2-13	The solution or the library which you have developed or that your organization has developed: Is it purposely made for a specific kind of organization, for example big enterprises, small medium enterprises or only small ones.	

I2-14	So it wasn't really made for organizations in the first place, so the project itself stemmed from kind of the research background. How can we find algorithms that can be used in the least amount of time with the least amount of prior knowledge. But from there it developed into an application people can kind of use, so we focused mainly on tabular data, which you know CSV files, a lot of companies have tons of that. But you know, that does limit the usability in some contexts. You know audio data, for example, can't be used - not easily anyway. That requires your own expertise, and then you could feed it into the systems we have. Generally speaking, we would want to obviously make it more broad and more accessible, but there are prior things that we should really focus on first. Yes, but to answer your question specifically, no, we don't have a direct organization that we kind of focus on.	MISC, TPBB, TTR, TDA
I2-15	If an organization wants to inject their machine learning pipeline with AutoML, is there a set of particular requirements that are usually not needed with traditional ML but that are evident with AutoML?	
I2-16	Yeah, I mean so this is kind of a more general question. I can answer, which I think will answer this question more specifically. I mean the goal with automated machine learning is to take away as much expertise - that's not the right way to put it. Basically, at the moment the amount of activities required to implement machine learning pipeline from data to something you can act on, requires - I mean it's simple to just code (and I mean I say simple, but you know, relatively speaking) - but do you have just so many options and choices. And so the goal of automated in machine learning in my eyes and from an organization's point of view is. You want to basically just say, “hey, I don't know about machine learning or models. I just know that I can give this input and this is the outputs that I kind of want” and that's what we focus on with the software. It should just be click a button and it works. In terms of injecting it into a pipeline, our software is meant to almost replace. I think where it fits into the whole pipeline is, you know they can do the data gathering and any preprocessing that they want to do beforehand. We do machine learning and then they get the outputs and they do whatever business decisions they want to do with that. Or, you know, just have to be business, but whatever their application may be. And so that's kind of where we slot our software in. It does do a lot of the data preprocessing, kind of the basic stuff that you'd have to do often. But you know, if you have very specific data that needs to be transformed in some way, then you know we don't know what you have and how you want it to be transformed.	MISC, TTR, AUTOML, TDA, TPBB

	And we can't make those assumptions, because as soon as you start making those assumptions, what you get out may not be what you actually want. So whatever assumptions we can do safely, we try to automate that. But of course there are some we can't.	
I2-17	So you are saying even to some extent you are able to automate ETL?	
I2-18	Yes, so you know again just to speak about like the whole choosing the model. That's the part that requires hiring someone who has a PhD or has studied a lot of statistics. You need an expert to decide *this* is the model that will suit our task best, but that's expensive for small organisations. So to reduce that barrier to entry, you just need to get rid of that expertise requirement and so that's where we're focusing on how do you automatically select an algorithm for the problem that will do the best given whatever performance metric you want to monitor.	TDA, TTR, TPBB,
I2-19	What happens when it comes to the automation of the ETL phase? Like the abstract transformer is that also in some way or? Is that also automated? Like do I just inject the sources or the data and simple manipulations able to do that, or is it required to at least have some insights into how you can maybe provide algorithms and some others like this is processed in some ways for a level to operate?	
I2-20	Yeah, we operate on CSV essentially. It can be in other specific coded formats, but let's just say CSV tabular data. Yeah, if your data is already in the CSV, you can just feed it in. You don't have to say, oh maybe this column is not relevant. Of course you can do that, there's nothing stopping you. We can’t decide what you do before that, but if you put it in, the models, for example, should pick out which one are relevant or not. There are certain encodings we do too. That's another big part of the data pipeline. Like if you have five different categories, they need to be encoded in a certain way. So we try to automate that as well, but again, anytime you have to extract data from like a certain source and you have to do it in a certain way that requires some domain knowledge, we can't assume anything about that, so we can't really touch that part of the pipeline.	MISC, TDA
I2-21	Is the input data expected to be structured?	
I2-22	Yes, we required some structure on the input data. Again, there's just so many ways data could look that it's really impossible to automate	TDA, TPBB

	it. Maybe it's not impossible, but it's just, you know, one step at a time.	
I2-23	Have you tried to approach unstructured data within a specific domain?	
I2-24	I mean there are ones for text data that's structured in certain ways. We can't operate on text data at the moment. Sure, it could be possible in the future and that would be a nice goal. But yes, you'd have to do the encoding from text to some kind of tabular or numeric format, and then you can feed it in and we can take over from there.	TPBB, TDA, MISC
I2-25	How far have you come with automating the delimitor function, turn text to table?	
I2-26	So there's so many decisions in what you can do there. So if you have, let's say reviews, and you have a lot of paragraphs and you want to say is this restaurant good or bad based on the reviews. Do you look at the keywords? Do you look at every single word in the paragraph? And then what's your..? You know, I made an assumption there immediately. Are you trying to see if this restaurant is good or bad? Maybe you wanted to predict. Are the reviewers male or female? I guess you could come up with a metric about that, but again, that's we would have to make a lot of assumptions on how to preprocess your text to make it efficient in the first place. Of course, that could be a goal in the future. I don't actually know if there are tools that can automate that, but at that point you do need an expert to decide. This is how we should encode our data to best fit the kind of prediction we want.	MISC, TDA, TTR
I2-27	Can all the applications that are normally done with machine learning can be done with this tool as well?	
I2-28	Yes, I mean, you’ve probably heard recently of alpha fold. That's a very specific application to do with protein folding. There's no way we can automate that in advance. This, like very specific kinds of data, the only automation we can kind of do in terms of preprocessing and general workflows is just if you have tabular CSV data with, let's say, general kinds of data formats so you know dates, addresses, numerical columns, maybe some small text strings. Yes, we can work with them, but you will probably get more performance if you can actually encode that in a way that you think makes sense, because anything we do is an assumption.	MISC, TPBB

I2-29	Assuming we have done the purpose impact right after it is able to perform the same kind of functions that the sentence would perform, right?	
I2-30	Yes, yes.	
I2-31	So if I'm talking about application, we can think of all the normal scenarios for machine learning predictions to whatever?	
I2-32	It should be. We focus mainly on the sklearn library. So that's a common library for machine learning models. It’s this auto sklearn and it fills around that on the selection, so anything you could do in sklearn is possible with auto sklearn. So in general that's predicted. Anytime you need to predict a number, that's fine. If you need to predict a text output, sklearn doesn't do that, so we cannot do that, for example.	MISC
I2-33	Would you say that your current software or the current auto ML library that is in GitHub is most suitable for data analytics?	
I2-34	Sure, the whole point of it is to reduce the amount of expertise required to actually select a model. So if you're already using SK learn for your data science tool, this should just improve your performance straight up. I have more I could say, but I don't know if it comes up in future questions. But anyway, let's just go and if it does, we can, I guess skip it.	TPBB
I2-35	In your opinion, is your tool ready right now to be used by let's say domain experts? Like, not the scientists, but people who are aware of their domain but not really skilled with ...	
I2-36	Yeah, I mean, I would feel like anyone who's a domain expert and wants to apply machine learning needs some knowledge of let's say how to program in the first place. If you go to the documentation of Auto SK learn, the first thing you see there is like machine learning in four lines of code and that's kind of the goal of it. You just import it. You say fit data and then it gives you a model and tells you about it and gives you the performance and some metrics that you need. But then again, it really depends on what your domain is. If your domain just gives you tabular data back, yeah, you can just feed that in and it works. If your domain is molecule modeling. I don't know what that data looks like. You know we can't operate on that. Just always comes back to something.	TTR,

I2-37	If I were to think about the audience for this library specifically, I would say you are referring to maybe software engineers, or at least said they are ready to get their hands dirty with this code, so to speak, but for like corporate employees or similar, it's still a bit far. The barrier is a bit high for them. Correct me if I am wrong?	
I2-38	Yeah, so we don't have a graphical GUI or anything that you can use. You need to interact with this library with code. And now maybe in the future, yes, we'd like to have a GUI, but there's a lot of other things that need to be ironed out first. At the moment, I'd say this tool is most applicable to researchers. You know, it's a very common thing now that researchers need to know a little bit of programming. Especially if you want to use machine learning, you need to know a little bit because you need to process the data you have and you need to get an output. I have a few friends doing PHDs in other topics and they all know the basics of coding, not enough to make big software, but just to get the results they need. And so this library is perfect for them. With bigger industries who have software engineers or the capabilities to hire at least one software engineer, or even like a college student, they could get it to work and it should work fine. But if you're, you know, a small shop and I don't know why you are applying machine learning to your small shop, but let's say you are, and you don't really have technical expertise. This tool wouldn't be usable. It's not just a Windows executable, you click and it opens and you say import this file. We don't do that at the moment.	MISC, TTR, TPBB
I2-39	Would you say that there are similar software to your software? For example Knime - it could be used for ETL, the IT also includes machine learning nodes for some specific models.	
I2-40	Yeah, I mean so from the brief look at like what they advertise in their front, they look like they handle a lot of that kind of graphical interface, part of like you know, you just import your data and you get some analytics out. Our software again comes into… So the thing about this data knime thing is like how do they choose the model? Do you choose it yourself? Do they just try a bunch? And this is going into something I wanted to mention a bit later in the “did we miss anything”, but one of the big problems is, you know, if you want to take away that expertise knowledge, in a sense	

	you do have to try all the models and find the most performant ones. Now there's a lot of theoretical ways of doing this without wasting so much compute time. Anyone can just try them. Try all the different configurations, turn all the dials and knobs. But you know, there's millions of configurations you could come up with, infinite, you could spend eternity trying to look for the best one. So how do you do that efficiently? And that's where we try to come in. So you know. It's how our software, for example, within 10 minutes you can find a very high performing model depending on the task, whereas if you are trying manually you could spend hours trying to train one that just will never work. Or you could spend hours just trying lots of different models and tuning it and trying to make it as good as possible. You get to 80% and you say OK, this is the best we can do where if you just tried another model it would have got 90 in like 2 minutes. And so, yes, that's kind of where we slot in - less so putting data in and getting the nice visualizations out, but more on finding the model efficiently and quickly.	
I2-41	That was an interesting reflection. How much configuration power do you have if a user is going to use your solution?	
I2-42	So that's kind of the goal: as little as possible. So there is some configuration of course you can do. You can tune, you can say “OK, don't look at these models” if you want, you know we may as well look at them, like, we quickly discard them if they are not usable. But the goal is to make it as frictionless as possible, and you know the more configuration you add, the more the user needs to know about the software and what they're actually configuring. But if you just say, hey put your data in and you will get predictions out. That's what most people want, you don't want to spend ages configuring. And if you are more technically able, you can go in, you can start configuring it. But the goal is to basically just have no configuration required.	
I2-43	So even though you try to avoid as much configuration as possible, there is still the liberty of actually checking the code?	
I2-44	Oh yeah, yeah. So that's part of where Ics is coming in now, like the software as it is. You know it works and you can again have this minimal configuration. You get an output, but most of the issues I see on GitHub are like “hey, but I want to do this kind of configuration, how do I do it?” And as well you need to understand	

	the source code where you need to go in and change things. But that should be made easier, and that's kind of what my main goal is at the moment. Of course, improve performance and other things, but making it so those expertise users who actually do want to take this further, make it something that they can use.	
I2-45	When it comes to trusting the solution, how do you verify the output? Or how do you promote the reliability and accuracy of it?	
I2-46	So that's a big research question at the moment. If you have a domain expert and they have all this expertise and they pick a model, they know about this model and they can interpret the results. But at the moment we provide a black box solution, you put data in and you get your predictions out. So what model did they choose? You know we can show you the model and we can show you the hyperparameters, but it still doesn't answer the question of why they chose that one. Why are the hyperparameters like that? You know, if I tell you the learning rate was configured to be 0.01. That means nothing to an end user, especially if you have no expertise. You just look at that number and it means nothing. So the group itself, automML.org, does have a kind of branch on focusing on explainability of AI systems. It's not incorporated into our actual code base at the moment. Now you can use other libraries and analyze the models we produce. But that requires domain experts, and as far as I'm aware, I'm not entirely sure it's a solved problem. I imagine some software claims that you can interpret all the results you get, but at the end of the day, it's a machine learning model. There are some that kind of have explainability built in, but then you're limited to using that one model where that does work. The performance may not be so good, but at least you have some explainability. So I guess it would be good in the future if you have a configurability option: you only want to look at explainable models, then we only search for explainable models. And then for the reliability of the results, that’s another big machine learning problem. You can train it to great accuracy, but then you put it into	TTE

	production and then what you get out? Is it any good? How do you know? Will it stay good? We don't handle that at the end of the day. That's really kind of more part of the machine learning pipeline, that, I'm assuming there's a lot of paid software for that kind of thing. We can't do that at the moment. It's very much an open research question: How do you train something but make sure it's still actually reliable and accurate once you get to real life scenarios?	
I2-47	If I recall from an AI course, they mentioned that for each algorithm for each month and trend, there's usually some sort of measures for the performance of the models. Is there something similar with your solution?	
I2-48	Yes, normally you train on a certain set and you have a validation set. So generally you train it and you say OK, this one looks good. But then on your validation set it performs terribly, then you know: OK, this model is overfitted, it's not so good. And then there's a thing called cross validation, which essentially is that you segment the data and you train it multiple times, but always leave a different segment out and then see how it performs. There's lots of different ways of doing that, and auto SK learn uses these things. It's kind of a staple of any automated machine learning library that you do these things, at least with research papers and things. If you don't have a validation set, your paper gets rejected immediately, it's just considered like a vital flaw. So we do use everything we can at the moment, but there's still very much open research in how we can make it better.	AUTOM LSC,
I2-49	I had in mind metrics such as R-square as one of many. Are there such metrics for model evaluation applied within the library? How easy are they for interpreting for scientists, power users or domain users?	

I2-50	Yeah, we apply these metrics. That's part of how you search for a good model: you need a metric to basically say is it good or bad? So when we're doing this big search through all models, we need to measure their performance in some way. We currently choose default metrics depending on what the kind of task is. So we've taken the data and we try to identify if it is a regression problem, or is it a classification problem? Is it Multilabel classification? There's different kinds so the user can specify exactly what it is or we try to automatically guess and then we apply the default metric. But the user comes into the configuration part, if they want to use this specific metric like the area under the curve, R-squared accuracy or whatever it is, they can provide that but we provide a sensible default metric. But again, once the model is trained, you can see the performance of the final model you get out, but you can also see the performance of the models that were not considered or you know were tried but then discarded.	TTE
I2-51	All right then. And you are saying you provide the metrics for each model described. And one more question, you provided earlier the comparison between how long AutoML takes vs traditional ML - trying to figure out manually a decent model for the problem at hand. So you are saying it's usually just a matter of minutes for it to perform, right? So, could we maybe consider the time it takes to complete the task as some sort of measure for the performance of auto machine learning? I'm just hypothetically imagining a company or any other person using the model, how would they evaluate this with AutoML versus traditional ML?	
I2-52	Yeah, when you're comparing different automated machine learning libraries, one of the things they always compare about is the time to reach... you know. There's two ways you can compare automated machine learning libraries, and then this carries over to model	TTE, TPBB

	evaluations as well. You can say: OK, they both have 10 minutes to train as much as they can. Bots or automated machine learning libraries. What's the best model they can find and what's the best performance they can get in 10 minutes? Or you could go the other way around and you could say: OK, how long does it take each automated machine learning library to reach 90% accuracy on this task or whatever metric? So there are time limits, you can set the time limit. That's one of the things that must be configured by the user. You know, we can't assume that you want to run for 10 minutes or 10 days. You know if you give it 10 days, we'll keep searching and then we'll do the best we can. But if you only give it 10 minutes, it will do the best it can in 10 minutes. More in research, you'll find the comparison between the different libraries, how good of a model you can find in 10 minutes. But with automated machine learning, it's more like you give it as much time as you can afford, and then it will do the best it can in that time. Well, I suppose you could provide the option to just stop once you reach 80% accuracy, we actually don't have that in, but I feel like that could actually be a good feature. You know, sometimes people don't know, don't really care how long it runs, they just want to reach a certain level of performance. I'll add that on the feature list to do.	
I2-53	So based on what you have described, how would you rate the potentials and the actual performance shown so far for machine learning solutions versus normal service corporate models?	
I2-54	I think the most applicable place is people who don't use machine learning at the moment and want to try it, because 5-6 years ago if you were a researcher, for example, or even a small organization, you say “oh, machine learning is good, other people are using it, they seem to get benefit.” And then you dip your toes and you google machine learning and you're just like “OK, what the hell am I looking at?” And you know, it's kind of impossible to sift through all the information, make an informed choice. So for those people, you go from manual predictions. People usually square whatever methods they are already using just to be able to reach state of the art kind of	MISC, OS

	research on their problem in as few lines of code as possible. So there's definitely huge potential there. With larger organizations who already have these full data scientist teams. I'm sure they already have their own internal automated machine learning libraries. I don't think our software is specifically... Well, I hope it would be better than theirs. I don't know, I don't talk to them. It's not an organization we're aiming towards. Basically they can afford to develop whatever solutions they want and hire whoever they want. I think the main potential is in research and small organizations who maybe have one technical person, or maybe want to dip their toes in.	
I2-55	How often is the case of big organizations that actually have automated machine learning solutions?	
I2-56	I mean, it depends what your definition of big is. In conferences and different talks there's this whole thing about help set up machine learning pipelines, reevaluating models. I'm sure they've automated that as much as possible because they don't want to manually do that each time. I figure a lot of big organizations have their own automated machine learning kind of setup. Then that depends also on what you mean by automated machine learning. You know, automating the data collection and preprocessing, automating the reevaluation of models is one thing. Our automated machine learning that we specifically do is finding models as quickly as possible and as efficiently as possible, and then taking as much of the user configuration out as possible, or required user configuration, to be precise. Yeah, larger corporations, I would assume definitely have some kind of automated machine learning systems.	OS, AUTOML

I2-57	Compared to traditional machine learning, do you think that auto machine learning gives the flexibility to try out different datasets from the ones that are usually used in the pipeline?	
I2-58	Yeah, that's part of the flexibility of not having to do it yourself. We do most of the basic preprocessing that we can assume and a lot of the data sets that are available online are already kind of ready to be put into machine learning pipeline. And if you're collecting your own data yourself, you're always going to have to do some preprocessing. Maybe some of them are empty again, we can kind of work around that, but we can only do so much. I'm actually going to plug open end ML, I don't know if you've heard about it. It's basically a large collection of publicly available data sets, and you can see other machine learning. You can basically see machine learning performances, albeit for different models and for different auto machine learning libraries. They have an easy kind of download of the data set so you don't have to manually, they give it in multiple formats. It's actually what we use for benchmarking, a lot of automated machine learning libraries use this or are moving towards using this for some kind of benchmarking. Also, you're probably familiar with Kaggle. Most of the data on there is kind of tabular and that's something that our library can very much work with. So if you're a new user and you want to just try out new data sets, not just the typical IRIS, there's the MNIST data set, you can probably just get these and then play with it in auto SK learn and it should work fine. And again it depends on the data set, but if it's very particular, there's only so much we can do.	AUTOML, TDA
I2-59	When it comes to trying to utilize auto machine learning, do you think that there's also a set of requirements in terms of hardware and software, or like an IT infrastructure?	
I2-60	Google is a good example. They have a huge amount of compute and so they were one of the very first ones to do this kind of automated machine learning libraries and I'm sure they have efficient	TINF

	ways of doing it. Don't get me wrong, but their research is targeted for their kind of infrastructure. The research we're doing is very much about "OK, can you even do it on your own laptop?" And yes, you can run auto SK learn on your own laptop. This guy here that I'm working on is very old but still runs fine and that's part of the goal with the research. Make it so you need as little hardware as possible. And of course we do have more hardware for actual testing. It's lots of different data sets to make sure it actually runs fine, but if you're just using it yourself now, you can do it on your own laptop and it should be fine. And software tools: yes, you need some programming experience to implement it. Not much but you need a little bit.	
I2-61	And can your solution usually be combined with other commercial software or is it easiest through just open source manually or program solutions or adjustments?	
I2-62	The inputs you get and the outputs you get, at the moment we need to use code to integrate in with our open source library. Now I don't know if people have built commercial products around it but you definitely could, but that would require some programming interaction to get from one place to another. You can export the predictions as a CSV and then use whatever other application you are using to read in that CSV. No, I think if you want to export it as a CSV, you need to know how to do that at the moment, but that would be another nice feature to just "When it's done, just export the predictions here."	MISC
I2-63	How would you compare your tool versus other commercial and other open source? Which ones usually tend to perform better and also in terms of cost?	
I2-64	We compare against other open source tools that we can. I think there's auto SKlearn 2 which is still kind of experimental, but at least in the benchmarks we run, it seems to perform the best. Other papers may say differently, it depends how you benchmark it up. But yes, we do compare to other open source tools in terms of what features they provide, how they provide it. The benefit of being open source is that we can actually look at their implementation. It's almost like friendly competition, except you get inspired by the other libraries and things. But yeah, we compare performance because we do the actual finding of the algorithms and models in a different theoretical	MISC, TPBB

	way, and it's always interesting to compare how that works, specially when you start introducing new models.	
I2-65	And what about commercial tools, like the ones provided by Microsoft or Google, or another person as well?	
I2-66	We don't do any comparison with the cost.	
I2-67	Generally speaking, how is the open source versus the commercial ones? Is there a noticeable difference in performance?	
I2-68	I don't actually know if there's an analysis between them, that would be interesting to see. The main thing that comes in there is cost. If you're a small organization and you want to use auto ML you don't want to start setting up a Google Cloud account and start paying however much - it depends on your problem of course. I don't exactly know the pricing at the moment. It used to be kind of expensive, but I'm sure they brought that down. It would be interesting to see, but I don't know at the moment how they compare.	MISC
I2-69	What level of expertise or readiness does one need to use your tool?	
I2-70	I don't know if you have the term Kiwi wherever you're from, but basically a student worker who is doing a bachelors in computer science or maybe an engineering student who's done some programming, they should be able to use it fine. Now you get predictions out and you do what you want with those predictions. You need to have enough domain expertise in that sense. If you tell us to predict something, we'll do the best predictions we can. But at the end of the day, we can't tell you “OK, based on these predictions now you should invest in whatever” - that's domain expertise. You need to know that machine learning will give you an output and you need to know how to translate that output into something you can actually work with and do.	TTR

	So I guess you would need that expertise, but the main requirement as I said is just a very small level of expertise with programming. I wouldn't even call it expertise, more like fimilarity.	
I2-71	Generally speaking the tools that are applied for automatic machine learning are not very good at handling the ETL. Are there any plans or ongoing research on how to empower domain experts to be able to use automation in order to handle that part of the pipeline?	
I2-72	Yes, that would definitely help and something we'd be interested in doing is actually talking to the people who use the software and see what kind of data they actually have. Tabular data is the most generic one, so it's the easiest one to work with. Again, just to specify, if you have some missing values, that’s fine, we can do that. If you have some addresses and things we can convert them to whatever needs to be done so it actually can fit into the models that will use it. But I don't know why I keep going back to the molecule modeling kind of example, but there's other kinds of data domains and we can only understand so much. The best way to do so would actually be to talk to the people who do these things, but first of all they need to reach out to us in some sense, we can't find them. So that's something that we want to address at some point. If you know any people who have specific kinds of data we would love it, tell them to get in touch.	MISC, TDA
I2-73	Beside the gap or challenges regarding ETL when it comes to automating ML pipelines, are there any others that need to be addressed?	
I2-74	One we touched on earlier is explainability. I wouldn't really call it a gap about introducing auto ML into your pipeline. It certainly introduces a black box that you just can't really peek into. And even if you do, you don't actually know what's going on in there. That's an ongoing part of research. You can come up with all these theoretical ways to produce a number which has some explainability, but at the	TTE

	end of the day the user needs to read something that makes sense to them and tells them what they need to know. What are the things they need to know, is another problem. I think there should be possibly more research into what kind of things do people actually want to know with an automated machine learning system. People say they want to know what model it shows. OK, but then the next question is what does this model value? How do you express how much they value something? There's lots of different things that people want to know about a black box. So that's one of the gaps where there is some research, but I think honestly there may need to be more surveys and just general information from users, not just researchers who are developing new methods of doing things. I don't think it requires new research to explain all that explainability particularly, there's plenty of it, but it's getting from that research to the end user where there's another gap at the moment. I'm not sure actually how other AutoML systems do this, but another gap in auto ML could be that data expires. Your data from last year is not relevant this year, generally speaking, and so you need to retrain models. You need to store them, you need to analyze all of this, and as far as I'm aware that's not fully automated. Maybe the big corporations have ways of automating this, but the open source tools files will just get you the model with the data you have now, and auto ML tools at the moment won't deal with this, but it would be a great thing to deal with.	
I2-75	To reflect on that, that has been discussed recently, especially when it comes to the pandemic situation. E.g. Logistic companies have had to update their models retrained due to that the data available changed drastically based on the new routines that COVID caused. Suddenly people were more inhouse, life style changed and that affected e.g. delivery businesses which in term of using ML affected the model maintenance and relevance. It is good to know that this	

	area is also considered within AutoML due to that it can be an evident issue.	
I2-76	Just to elaborate, I think that's outside of our scope of what we do, and that maybe there are some commercial tools that do that. But the main thing is how do you identify when there is a drastic change in your kind of data? What do you do? Say you retrain a model, but you don't know what the future data is going to look like so retrain it on what? COVID hits, there's going to be a huge change in how orders are done, and you want a new model. Well, you have to wait a month till you know what this new data looks like and then you can actually use that model. So can you progressively learn and slowly adapt and change, but this has its own problems. It would be a great feature to have an AutoML. It's kind of the monitoring part of the pipeline which comes at the end and it's continuous. But again, it's not part of the pipeline that we deal with at the moment. If we could, we would, but then it needs to be constantly active. It needs software that's constantly running and our software is more of like, you run it, you get your model and you can do with that what you like.	MISC
I2-77	You mentioned that the models do not have a developed explainability within the solution. And in that case, would you then say that that gap is about converting already existing research, rather than doing new research and can you elaborate?	
I2-78	So I'll give you an example of where explainability needs more research. Neural networks for example, which I'm sure you're probably familiar with. It's just a very complicated function that gets learned, and the only thing you get out of this thing at the end is a bunch of weights and biases which are just numbers. There are ways where you can try and track the flow through the neural network to try and understand what inputs and values win, but that requires some kind of good research and then again depends on the domain. Numbers in numbers out, but what do those numbers mean? There needs to be some kind of explainability before that, so then you can translate it all the way through. But as an easier example of something that can be explained. Random forests, just like a tree based model. They basically start at	

	the top. You have your data in and it just filters down based on if this value is greater or less than three, and then you can look at that internally and you can say oh the interest rate was above 0.3 and that's why it fell towards some certain category. This person was classified as reliable at paying back their loan or something. So you can directly see that the interest rate was above 3 and the model thinks this is someone we should probably give a loan to. So it's kind of built into how the actual model works, but if you're considering 20 different models, they all work in different ways and they all need to be explained in different ways. But at the end of the day the user probably just wants a textual description that says "hey, because of this and this and this and this, this is why we gave out the prediction." For the models we have, for example, this random forest, that would be a great feature, just a textual output giving the main summary why this decision was made. But at the moment it's explainable in the sense that you need to look at the random forests and analyze the values that come out. With some expertise you can actually understand that and explain it. But again, with a small organization or someone who's new to it, this textual output is a lot easier. It's something that can be done now and doesn't need more research, but it's just not really done as far as I'm aware. Again, maybe large organizations. We don't know what goes on behind closed doors.	
I2-79	That was a valuable input, thank you. I think it would definitely be classed as one of the factors that might affect the decision of actually trying to adopt a machine learning solution or not.	
I2-80	Oh, for sure.	
I2-81	Did you or your team find any unexpected benefits with this solution while developing it?	
I2-82	I'm not sure how much it applies. I mean, the goal was to find the best algorithm in the shortest amount of time. I mean, one of the unexpected benefits of the game was that it was for a competition but it kind of developed into an open source software which people can use. Maybe that was the goal originally, I don't exactly know but, I mean one of the benefits is people actually use it now. And the more people use it, the more we can work on it and actually know what people need from it. Again, winning a Kaggle competition is very different from an actual business application. So the more people use it, the more we understand what it actually gets used for.	MISC, TPBB

	But yes, maybe a bit different from the other answers from organizations.	
I2-83	You mentioned earlier that mostly larger organizations supposedly have alternative solutions already implemented, and they might also have some level of explainability for their outputs, or they should be having it and be using it. For what type of organisations in terms of size do you think that your solution is mostly suited?	
I2-84	I would say it’s mostly suited towards researchers at the moment because you need that little bit of technical expertise. But that could easily be extended to a small organization if they can hire a bachelor student who doesn’t need to know the internets of data science, they just need to be able to implement the actual software for it. Yeah, I mean it’s mainly targeted towards students as well. Actually, they use it, researchers and then small organizations - again, we don’t really know, that’s kind of one of the problems. We get very little feedback on who uses it because it’s open source.	TTR, OS, MISC
I2-85	And do you think that, even though the solution is mostly focused towards research, if organizations that haven't used machine learning and want to try it out by using your software: do you think that the size of the organization would have an impact on the attitude towards using it? Would it encourage or discourage the management to approach it?	
I2-86	Oh so you mean like, does the size of the business impact their willingness to adopt the software?	
I2-87	Yeah, let’s say a distribution company that grew exponentially for the last two years, that needs to look into their data in order to maintain that growth, compared to a smaller company that works with perhaps online selling and doesn’t have that many employees but still has a lot of operations that need managing…	
I2-88	That’s where you start to need setting up this automatic pipeline of retraining models and monitoring. I think smaller organisations would definitely benefit more from this. I think the more data you have, the less likely you are to be able to use these just out of the box because we don't solve those whole pipeline monitoring problems. And the larger the organization the more reliable the actual outputs have to be. I'm not saying we’re not reliable but again, explainability comes into this thing, you need to be able to trust it. Yeah, I think smaller organizations can take that risk. They can try it out and if it doesn't work it's not going to sink the company.	OS, TTDA, TPBB
I2-89	By what you said I assume that small organizations with less data perhaps have more freedom to try to utilize it more. That might also mean that larger organizations are limited to having just one type of	

	data and standardized data formats, while smaller organizations might have the freedom to use a bigger variety of datasets and formats.	
I2-90	Yeah, my opinion on it - and once again, it’s just an opinion - is that larger organizations, or let’s say a very fast growth company: at the end of the day, AutoML is fairly new. Do you trust your rapidly expanding company which has maybe got a bunch of investments, do you bet it all on this new technology? Or do you go with the traditional, what’s been established and has worked for other companies? So that's why I think smaller organizations can just try it out, take on the risk and if it doesn’t work out that’s fine. They haven't wasted too much on it. But again, we’d love to know more from organizations about it but we don’t.	OS, TTE, MISC
I2-91	We touched upon the prerequisites for actually using auto machine learning. Could you summarize it quickly?	
I2-92	Yeah, so in terms of the prerequisites from a hardware point of view you can run it on a laptop, this one doesn't even have a good graphics card like, you know the fancy ones, and it’s just a CPU with two cores or something. And just like 8 gigabytes of RAM, it’s a fairly standard laptop and it works fine. And it scales up if you want to send if you want to send more compute at it, it works. That’s fine and it’s something we kind of had put in fairly recently, like a few months ago, that like it should scale better. And then, in terms of the prerequisites of knowledge and like, what you need to know to do it, again just to summarize, you need a little bit of coding expertise to basically feed your data in. Hopefully it's already in a CSV file and you can just say “use this”. But if you're a domain expert and you have very complicated data, you need to know how to convert that. And again, we don't know how to do that because we're not in that domain. And then the final thing is the output you actually get. You need to be able to know what that means. It's easy if it's a classification problem and you're saying “hey, this person is likely to pay back their loan and this person isn't”. But you know, if it's a lot more complicated in terms of the outputs you want, you need to know how to interpret those outputs. But again, that's not something we can solve with AutoML, that's just domain expertise.	TTR, TTR, TTE
I2-93	Can you think of any other organizational prerequisites or necessary parts of the organizational infrastructure as such?	
I2-94	It depends on your application. I guess if you go back to your example of the logistics company and the coronavirus example earlier, you know they changed how the data looks. You need an organizational unit, then engineers to monitor it, be able to redeploy it and hook it up to their other systems so it can make decisions about where to order new goods, whatever that is. That’s just	MISC

	something that any organization who wants to apply it on that scale will need those requirements - we can't automate that from our end. We can't say "yes, based on your data, you need to order more. We will order more things for you." We can't do that. So yeah, the main requirement of an organization is that you actually have to be able to use the output, you know. We can't do anything about that.	
I2-95	Maybe you don't have much to say about top management support within organizations? Maybe it's rational that the idea is necessary in order to make a decision that will make a change?	
I2-96	Yeah, the only thought I have on it is that top management isn't going to spend the time to investigate it themselves, but if they're willing enough to let someone experiment with their data with AutoML, that's kind of the best you can hope for. Then whoever is doing it has to convince top management, but there needs to be initial support.	OTM
I2-97	Would you say that the current state of the machine learning tools bring sufficient benefits and at least cost savings, to convince top management to support such endeavors in this test?	
I2-98	It depends on what they have beforehand. In terms of cost benefits, it really depends on the application and what they're using it for at the moment. If you're going from not using machine learning at all to using automated machine learning, I would assume there's some benefits in the 1st place if you're considering it, and you know, we can do the best we can and actually just making those predictions and getting from data to an output that you require and learn that mapping between them. But whether that's actually useful for a company? I mean, that's based on the company. If you can sink 30,000 into hiring someone to implement a machine learning pipeline, but your business is, I don't know, making candles by hand, I don't know what kind of benefits you're going to get out of that.	TTR, TPBB, TTE
I2-99	How much time would you estimate that people spend on the machine learning pipeline and how much time do they spend on training the model, such as selecting the right model and optimizing it afterwards?	
I2-100	Let's take this from two perspectives. If you say there's no time limit and you're asked to use either just normal machine learning to find a model or use automated machine learning, you will get a drastic improvement for using automated machine learning. You don't have to manually trial the models, do all the tuning. Again, how much time does that save you? I mean, I would say orders of magnitude. Especially depends on your prior knowledge - if you know that a particular model is going to be good beforehand for your data. you can try it out, and then we could do the tuning faster. But I would	AUTOML, TPBB, TTR

	say 95% of the time you'll probably find a better and quicker model with auto-sklearn, or just in general with AutoML tools. They don't have human biases built into them, that's the main point. They just find the best way they can as quickly as they can and do it in a theoretically good way rather than the human way which is "Yeah it doesn't work, or kind of works - I'll try the next one, then." The next benefit in that sense is, let's say you are looking for a model by hand and you get 85% on your data, and you keep tuning and tuning it and maybe get up to 86% and you're like "ok, 86% is as good as we can do." But you may have missed out on another easier solution that you just never would have tried. With automated machine learning, maybe they could have gotten to 95% in like 20 minutes or something, and you would just never know if you're doing that manually. It's not to say that manual finding can't find better algorithms, like if you have very particular kinds of data and you have a very difficult data set then sure, you can probably find a better one. But I'd say for like 95 - I don't want to give a figure, especially if this is going to be quoted in any way but I think 90 to 95% is a good figure of the amount of cases where you will get better performance with automated machine learning. And if not, at least it can quickly evaluate which models you should not consider if you want to do the thing by hand and you want to have that input. This is maybe a good way to quickly survey the landscape of all the different models and say "hey, this one just really didn't work" or "these ones were very promising". Maybe you can look at those promising ones and then do your own fine tuning. I don't know how much time that saves you but I would figure a lot.	
I2-101	How much time would you say it usually takes to do the data preparation and processing? How much time would it take you to do the model selection?	
I2-102	Again, it depends on the expertise. If you've been doing it for years, data preprocessing doesn't take you that long. If you're in college and you have an assignment, that could take you ages, or if you're in a company and it's a new kind of data and you've never seen it before, maybe it could take you a while. The bits we can do, well it's automated, so if it takes you X minutes we can automate it down to five, four seconds, however long to process it. It's done automatically, there's no manual thinking, googling how to do it. And then with the model selection: if you have ten hours to find a model and, I don't know, let's say you get 80% accuracy after ten hours, how long will it take the automated machine learning tool to find something that gets equally as good of a result? It really depends on the data set. You know it's impossible to give a general answer for this. It's really hard to give an answer. It depends on the difficulty, on the expertise as well. I'd say an order of magnitude of	TTR, TDA

	time saved, maybe two. It really depends on the person's prior expertise.	
I2-103	All right, maybe I will add a bit from the literature. We have Council so far. They usually report data centers when they are surveyed on websites like Kaggle. They say they usually spend 75-80% of the time on data processing fields, and only 20% on the model selection optimization. Would you agree that the model selection optimization takes the least amount of time?	
I2-104	Depends on the data. I mean, so Kaggle has a lot of already preprocessed data sets, so I'm surprised it takes them 80% of their time. Then again, Kaggle also has a lot of new people who don't do this as their daily job for example so there's a lot of new things processing, but I'm making assumptions here, I don’t know. In that case about the 20% with model selection: I know XG boost is a very popular model on Kaggle, so that's something people reach for first and then they get 80% through like “cool I'm done”. Was that the best model? Maybe try other ones. You know they say spend 20% of the time on it, but would they get a better result with spending 50% of the time on it? Maybe they just get a result and think it's good enough.	TDA, TTR,
I2-105	*(And from what you have said, if we would just have developers, they are usually able to use it on their own even without expertise. So if we add how this shortage of data scientists is reported in the literature as well, one of the reasons why people invested in creating multi machine learning tools in the first place.)* Do you consider your tool to be able to enhance productivity on outputs from existing or current employees, like software engineers, enough that they might not require to hire data scientists in the companies? Is this something top management would consider and support initiative for such components, like with the service in their components?	
I2-106	It's an interesting question. I mean, I would always advocate you should have a data scientist. You know. Software engineer and this doesn't necessarily work with data a lot. You know they could be building software which doesn't require the exact same kind of data. I know that nowadays it’s more of it blending together. A lot of software engineers do need to understand that, and data scientists need to understand software engineers so making that distinction is getting harder and harder. You have data engineers, so let's blend the two terms together. I think it could reduce requirements in terms of how many you need, especially for smaller organizations. It was big	TTR, OS, TPBB

	data for a while, it was data mining, these different terms that always come up. Then whenever these new terms come up there's kind of a huge hype, at least from what I see on Reddit, like new people trying to get into it like "How can I learn this? It pays well, I want to do this" and then after a while, they're like "Oh, we actually didn't need 10 data scientists, we just needed like two good data scientists". So I think it could definitely help us small data scientists or like a single data scientist in a smaller organization, or maybe a small team, to - at least with our tool - quickly evaluate a bunch of models and then do whatever they need to do on top of that. But it wouldn't be replacing people's jobs if that's the kind of point you were getting at, at least not now. Maybe in 10 years, but not at the moment.	
I2-107	Maybe it cannot replace them, but if it just reduces the requirements. Let's say you'll hire a data scientist who is really good, but you surround him with a team of engineers, he could maybe guide them to do some of the simpler tasks while he works on the advanced stuff. So in a way that would also make them able to harness the power of machine learning in their organization while still keeping it at a reasonable rate for their scenarios.	
I2-108	I'd agree with you on that completely. It depends, you know, if you have five data scientists, what are they all doing in an organization, it would be interesting to know. I think in your scenario where you have one data scientist, this would help them to quickly manually find models, find different models, do some of the data preprocessing and other things. If he can quickly get a landscape of all these different models and he wants to implement them, he can just assign each one to a different engineer, for example. So instead of him manually waiting and trying to find something, let's 10 engineers all need to implement some model for something. If you can quickly evaluate models and quickly dispatch a task to each engineer, that's great. And that's what at least our tool auto sklearn would help them do. Automated machine learning is a very broad term, so maybe other tools could let them change how that works. But I would see it more as empowering a small team of data scientists to quickly come up with models, so that they can then do whatever they need to do. Like evaluate how good it is and how it can be used, rather than waiting five hours and spending 10 days looking for a good enough model to then start implementing whatever they need.	TPBB, MISC, AUTOM L
I2-109	How expensive is using such software for an organization?	
I2-110	Not any more expensive than whatever they're already doing if they are using machine learning. I can go back to say it can run on your laptop, but if you have terabytes of data you need a better computer. The software itself doesn't cost anything, it's open source. That's the best part of open source I guess. The actual hardware costs really	MISC,

	scale to whatever your problem is in the first place and automated machine learning isn't going to solve that.	
I2-111	I'm assuming how much you need to integrate depending on if you're gonna build some explanatory outputs in terms of the actual output of the models, which might get from the software.	
I2-112	Mhm.	
I2-113	Even though you mentioned that the solution is mostly used for research, do you think that it could be utilized for competitive advantage?	
I2-114	I mean, let's start with the simple question. Can machine learning be used for competitive advantage? Sure, depends on what your business is. Your fear logistics company for sure. And using the same example, can automated machine learning make logistics companies be competitive with the others? Yes, for sure. Depends how you use your data. All we can do is generate predictions or outputs from whatever inputs there are and learn a connection between them. How you use that is up to you. If you can use it for a competitive advantage, for sure. I mean yes, it can give you a competitive advantage over a company that doesn't use them. Saving time, resources. Maybe you hire one less data scientist than you otherwise would have.	EC, AUTOML, TDA, TPBB
I2-115	For the solution that you have provided, do you also provide any sort of support?	
I2-116	Not in the sense of like a commercial product. I answer GitHub issues which are sometimes questions on how to use it, you know the users who want to do something a little different. They have questions about that, and that's not something we explained clearly, so to make sure if that's something that we need to document or change to make it more accessible. But they're generally related to code. If someone says “hey, I have a business and I need help writing the code to make it work for my infrastructure”, now we don't do that kind of support. It's more kind of code specific questions.	EIS
I2-117	Do you know if there is any organization or a group that actually does that?	EIS
I2-118	Google, I guess Microsoft with their cloud services Amazon. Those are the commercial ones that I would know of now. But yeah, other than that I don't really know. I think H2O also provide a commercial service or another automated machine learning.	

I2-119	Do you think that an organization could provide service or support for an open source solution?	
I2-120	Not really, there's no financial gain in open source. If you have 100 companies all using your open source tool, and they all have very business related questions that aren't related to the code but more about machine learning and how to apply it to their business: I'm sorry, we just can't do anything in that aspect.	EC
I2-121	One of the most cited issues with SMEs and analytics tools, generally speaking only about machine learning or auto machine learning, is that they do not have clear cases for it. They do not know where and when or how to utilize it. Could you reflect upon this a bit?	
I2-122	So just to see if I understand you correctly, people don't know how to actually apply machine learning to whatever benefit they would want to get?	
I2-123	That using this will give them an advantage somehow, but they don't know how and what sort of data they should use to maybe get some benefit from it.	
I2-124	Yeah, I mean that's what I would consider the role of a data scientist to primarily be. How can you convert data into financial benefit? And as you know from an AutoML perspective tool all you can do is inform the data scientist, or whoever is in charge of converting data into profit or you know competitive advantage. It's kind of the role of the data scientist, or you know someone who is, let's say, data literate in that sense. To be able to see data, know what they need to get some advantage. In the end, you can also work backwards and say hey if we knew this, we could get some advantage. OK, what kind of data would help inform this? Or, what data do we have and then just can we make a relationship between them? Yeah, that's that's kind of my only thoughts on that I guess.	TTR, MISC
I2-125	So we could basically say that while auto machine learning will help you get the job done, maybe faster or at better results, it still requires you to know how to use it in the first place and know what you want to do with it in advance.	
I2-126	Yeah, I mean at the end of the day we don't know what data you're collecting. We don't even really know what is in the first place, at the end of the day what goes into the machine learning model is numbers. What those numbers actually mean, and from a business sense where they come from, we don't know. How often are they collected? We don't know. The numbers coming out, how are you using them? So machine learning model learns to predict zero or one. That could mean you know this person has cancer or doesn't.	TDA, TTR, TTE

	You still need a data scientist to interpret the inputs and outputs of a machine learning model, and that requires knowing about your domain and that requires knowing a bit about data as well, and I don't think automated machine learning can really fix that. Unless you have a specific tool made for your business in the first place.	
I2-127	Do you think that we can just give a summarized answer to the closing questions?	
I2-128	Augment is the short answer. It's not replacing. You still need a data scientist or someone who understands data. But it just will help them in their job.	
I2-129	Would you like to add anything that you thought that we should have asked about, and that you also wonder or think that we should look into with organizations?	
I2-130	I have an interesting anecdote. Before I got the job here I was applying at another company who used machine learning for highly regulated industries. And so, during the first interview, we were just talking about things and one thing they brought up, which I don't know if you're aware of, but people try to exploit machine learning and if someone has a machine learning pipeline. There's a thing called adversarial attacks. If it's an image classification thing and it learns to predict pictures of cats or dogs, maybe it's clearly a picture of a dog to us, but you just change a few key pixels and then suddenly the machine learning pipeline thinks it's a cat. But to the human eye it looks like a dog and you can tell it's a dog, but the machine learning model, it looks at the pixels as numbers and you just change the few right ones. So they were very concerned about that as an organization. That these machine learning models can get high accuracy on the data you give them, but if someone actually tries to target them and make them work, not as not as intended, that's actually very easy to do. Not easy, but let's just say it's a big problem at the moment, especially with neural networks and certain kinds of machine learning models. It's just that they can very easily be exploited to mess up the results. I just thought it's interesting, something you should know about.	MISC
I2-131	Who would do that and why?	
I2-132	I guess it really depends. I mean, you'd have to know about what the business is using machine learning for. I guess we need some little insider knowledge as to how they're actually implementing the machine learning pipeline. There's some interesting work on treating it as a black box. You can give an input and you get an output out, and you assume it's a machine learning model of some kind. You know you give it a bunch of pictures again of cats and dogs and you can say “OK, this clearly gives a one for a cat and a zero for a dog.”	TTE, MISC

	How can we get a picture of a dog and make it output the wrong number? Now this is not a very good example of an attack you would do, but the same kind of principles apply. Let's just say you know the company uses the output, but you have some way of seeing it. Then maybe you can start giving it some bad data that makes the company make decisions that they really shouldn't be making. I don't know, maybe it's a bad example, but let's say you know Amazon uses machine learning for deciding when to preemptively buy a bunch of stock for a warehouse. And then somehow you're aware of the outputs of the Amazon machine learning model, and you'd say OK if we order 30 of this item, 30 water bottles, Amazon will order 500 to their warehouse there because they think there's going to be a large increase in water bottles, but that was just an attack you made and Amazon have wasted a lot of money in production on getting 500 water bottles to somewhere where it didn't need to go. And as you can probably guess, in highly regulated legal industries or just highly regulated industries that's a huge problem. You can't have someone exploiting the systems in ways that you don't expect. So they actually had researchers specifically focusing on how to make defensive machine learning. Interesting topic. I don't know a huge amount about it, but I know it exists.	
I2-133	And this is a very big issue right now, or still something very new that people are researching and trying to find ways to counter?	
I2-134	So here's actually a much better example that I think illustrates the point a lot more and why it's relevant. Not that it's exactly new but self-driving cars. They take in a lot of images and they do a lot of image processing. If you hold up a fake cardboard sign of a person on the street, maybe you could cause the cars to turn and crash. Actually, I don't know why you do that. Hopefully no one is that crazy, but you know you were exploiting a machine learning system with fake data. A fake cardboard cutout of a person. And so the problem isn't exactly new, as soon as there's machine learning, this problem exists. But there's a lot of research into that at the moment, both on the attacking side and defensive side, of how do you defend against these things and how do you exploit these things? The exploiting nature is not of course to actually exploit anyone that does this like a research thing. It's like, you have white hat hackers and I don't remember the other side. But people who hack for good and people who hack defensively.	

I2-135	Earlier you said right now there's still maybe a bit of a high barrier to be able to use machine learning, that they need to be able to code, or at least have some coding skills. But on top of that, now they will also have to know if something has been tampered with. Even if somehow all the problems of explainability for models have been addressed, there's also this matter of how to make sure that our model is safe.	
I2-136	Yeah, for sure. I mean it depends on your industry. I don't know how to really describe it. Yes, if you were giving a lot of the inputs and outputs of your machine learning model and making it public in some way or in some way that people can figure it out. Then yes, it can be exploited. That's why I guess for the highly regulated industry. It's very important. If it's not critical to you, if someone tries to exploit it a little bit, then you can kind of afford that happens a little bit, then you see it happen, then you address the situation. But I don't think this problem is specific to machine learning, there are hackers in general. You have software. You can be hacked. That’s it. Does every company need to know how to prevent hacking? Not necessarily. Hopefully it gets built into tools they use, but yeah, at the moment it's still an active area of research. How to hack and defend from it. Just to be clear, it's not exactly an automated machine learning problem, it's just a machine learning problem in general.	MISC
I2-137	Do commercial tools in any way have maybe counter measures to mitigate this problem? Or there is no way right now to address this problem on set?	
I2-138	I mean they are. They can do the best they can, I guess. I don't think it really affects for example our tool or other tools in the sense that the data that you give it will work. The security comes before the tool, the data that actually gets into the model in the first place.	
I2-139	That's why they emphasize the quality of the data models, right?	
I2-140	Yeah, the best way to defend against these exploitative attacks is to have a varied enough data so that the machine learning has seen it before. Basically it's seen it before, your data covers that kind of thing. So the best way of preventing those attacks is just having better data. And again my very naive view, maybe there's better things, it's an ongoing research and I'm not involved in that area. I'm just aware of it. But yes, that could be a concern, but that's not really a tool thing you can solve with that tool necessarily. You can't. You can do data augmentation but then it's making some assumptions on the data, ultimately. I guess it could be possible, but I don't think that's the first kind of thing that needs to be focused on. In the highly regulated industries the lack of explainability is already reason enough maybe not to use it. The security aspect is just one other	MISC, TTE

	thing that in general needs to be addressed in the machine learning community and will probably be an ongoing problem as hacking always is.	
I2-141	And I think in terms of mitigating, such risks come from not only the solution provider, but also from the ones that are using the commercial solution for their product.	
I2-142	I would hope so. But I mean, I think there's probably a rush at the moment to get out as many tools as you can and sell them as quickly as possible, and then the ones that survive will probably be the ones that have some good countermeasures. But those are the, I guess, more commercial tools that implement the whole pipeline step.	EC
I2-143	Is there anything else that we might have missed that you might want to mention as well?	
I2-144	I have one last thing that I'd at least like you to know. Siince we're not a commercial company as with Auto sklearn and smaller open source tool, it would be great to reach out to more people who actually use the tool, so we actually know what they're using it for, but we just don't have that capability and we don't get that kind of feedback. So from AutoML developer tool, you obviously are interested in how companies use the tool, but we developers would also like to know how the companies use the tool so we can actually make a better tool. Yeah, I guess that's it, we'll end it there I guess.	MISC
I2-145	End of Interview.	

Appendix 5: Interview Transcript – I3

Company: Anonymous

Interviewee: Interviewee 3 (I3)

Title: Data scientist

Date: 10/08/2021

Row	Transcription	Factor
I3-1	Would you like to remain anonymous and keep the company name confidential?	
I3-2	Myself – no, the company should be confidential.	
I3-3	What is your background and current career title?	
I3-4	I've been in academic engineering from 2007 until 2019. Basically I did bachelors, masters, PhD and then a postdoc all in Environmental engineering mostly like biochemistry kinds of stuff. A lot of like lab experimentations. And then I switched to data scientist because a lot of academics people handle large amounts of data and drawing conclusions based on statistics and modelling. So it was kind of a natural transition.	
I3-5	Can you describe the business strategy of the organization for the domain or the business strategy in which you are involved?	
I3-6	We do real estate marketplaces, end-to-end (ie from listing to contract signing), and that charge a recurring fee based on the rents we transact. We’re the market leader in Sweden and Finland	
I3-7	But when it comes to your work as a data scientist, which domain are you mainly active?	
I3-8	(Interviewee declined to answer)	
I3-9	What are the different roles and responsibilities in the organization? maybe you can add something on what your role and what your responsibilities are?	
I3-10	(Interviewee answered Question 6 before this question) We have a handful of back-end developers to work on the core product for the website and then we have a support team which interacts with the customers, gets their feedback and then we have	TTR

	the business team, which is in charge of making business decisions and generating revenue. The UX UI designer is the kind of moving around in the same way that I do where we help the engineers and business team as a support team to utilise the tools that we have. So I (and the UX/UI designer) will be embedded within these teams and give our opinions on how they could use the data we have to solve their particular problem and the UX/UI designer will be embedded in these teams too, and talk about how you can make the nicest product: the product that is nice to interact with for the users, something that's intuitive. So it's a very cross collaborative environment within the teams and everyone brings their own perspectives. This method works quite well.	
I3-11	What is the size of your team in which you're working?	
I3-12	Yeah, so generally we work in like kind of smaller teams like these like groups. And we work within several weeks to track and tackle a particular task. So, each team consists of a few programmers such as a back-end and front-end programmer, someone from the support team like customer support and then someone from the business side. So we're trying to like simulate a start-up vibe in each of these teams and everyone feels like they have ownership and accountability on the projects. And each of those teams are generally supported by some supplementary roles like a UX UI designer or <u>a data scientist like myself</u> or product manager.	TTR
I3-13	Do you consider “Company” as data driven?	
I3-14	yes I do. We use data to inform internal end user facing decisions. So like if I don't know if we want to decide something within the business, (not something that is demanded by the users), then we use data. We use data to make our product better. We encourage like cross discipline learning to help everyone in the company get insights from data. For example, people from support team can have ask questions of the data or if we find something interesting, we'll share it across the whole company. Because our team is small, so we have the flexibility to do that. As I said before, like the data team that I'm in, we regularly consult with all aspects of the company such as business support team or finance team for data, insights or analysis, or even predictive models depending on a business question that they might have. We find that the more we collaborate, the better model we can build. And we found that the more we interact between the different fields, like with support or business team, the more we get back	TDA, MISC, TCC

	from these colleagues. So like if we just show them the capabilities that we have with statistics or machine learning models, then they will help us with some sparked ideas for them. And these colleagues also feedback us with some valuable questions. This kind of process is like data driven feedback loop for the whole company.	
I3-15	Does your organization in any capacity utilize machine learning or auto-machine learning?	
I3-16	Yes, we use both. I would consider our way is that we used auto ML in the way that we built the automation process. So, we built the pipeline, firstly we collect data, we transform it, we pick which samples we want. Then, we train a model on it. The model gets deployed into the site and then we monitor how the model performs and then as we get more data, it just continuously updates and so on. So now it's fully automated. Of course, we still monitor it for weaknesses. We've also experimented with like AWS, which is a purely auto ML service, where you don't really need to do anything except for sending your data in and you can get response. But even the auto ML tools that I've seen on AWS, you still need to make sure that your data is what you think it is. Data input is 90% of the work.	AUTOM L
I3-17	For how long and to what extent are you using machine learning today?	
I3-18	So we have been using ML and auto ML maybe about a year until now. Before that, we had a more traditional types of models for certain products, but now we're employing ML.	TTR
I3-19	When you mentioned the automated entire pipeline, I should assume that the model selection is also made automated?	
I3-20	No, that's not. I mean now it is like we experiment with different models and chose one. This only one will go in our pipeline now and that is the one that is automated. For example, we input the data to AWS and it provided us maybe 20 different models. And I will decide which one is the best model to use.	AUTOM L

I3-21	Your colleagues may have less of experience when it comes to academic engineering or perhaps even data analytics and data science. Have they heard of it or had any curiosity? Or were you the one that drove the motivation?	
I3-22	It was only me. But our data team, if you even want to call that, is about 2.5 (two and a half) people. Therefore, it's pretty much I'm the only one that's fully dedicated to the data science role. I work a lot with like back-end developers who helped me with like data shuffling around and with our product manager. But when it comes to actual machine learning and model building, it's mostly me and maybe someone else. About Auto ML, nobody in the company is anti-AML. I personally found the Auto ML from just poking around on AWS. I don't know if you guys have any experience with AWS universe and it's like being lost in the jungle. They have massive amount of products, and AWS is incredible and I find a new one every day. Our product manager is also very much pushing machine learning. He is like very involved in these sorts of initiatives. Maybe not on like the technical level like using auto ML, but he's very much encouraging of using tools that can help. The process of ML and Auto ML for example. He's very much in favour of, you know, using off the shelf solutions rather than trying to build something yourself. And I generally agree with that too.	OS, OT, TTR, MISC
I3-23	To what extent has your organization applied AutoML?	
I3-24	It depends on the problem that we're trying to solve. We have one problem where it's estimating how much home is valued at? That pipeline is fully automated now. But we have other purposes as well. The fully automated process is like data collection to data monitoring. Like every step, we don't have to touch it anymore. Of course, we do monitor it because it's very important that it's accurate and representative. But then we have other purposes of where we use a machine learning model where it's not so sensitive that it's like it's not in production, so it's not as dependent on being up to date all the time, it's something that we can run kind of like in a one off, maybe once a month. We need some insights on something and in case it is not so important to automate it and it is time-consuming, then we won't. It is like, if it's something that needs to be accurate and updated daily, we will automate that. It's not worth the time to automate then we won't. It ultimately depends on the task that we're trying to solve.	AUTOML, O

I3-25	So you've automated almost an entire pipeline, and also maybe some parts of other pipelines depending on the set task?	
I3-26	Yep, and we automate it. We use our own back-end tools that we've built and tools within AWS. AWS provides you with some tools that can help you to move data from here to there or transform it or something, but it's not part of their auto ML. A framework is just part of their broader tool set that they provide.	
I3-27	What benefits do you see with the automated solutions that you have?	
I3-28	If we're talking about like these AWS type of auto amount pipelines, the benefits are, I mean, time. you can just put in your data and go walk away and have a coffee or something. The benefits of the Auto ML that we've built in house is also time. Once you have it built, of course it takes some time and effort to build it, which can be quite a lot. But you also get an idea of how sensitive the model is, if it is something you built by yourself. But I mean the benefit of like automating anything it's like then you don't have to do it anymore. And it saves you time and money. That's ultimately the benefit of automating any task. Whether it's like an auto reply to an email or machine learning model.	TPBB
I3-29	Who is managing the entire auto ML in your organization?	
I3-30	The ideas for any sort of machine learning approach to a problem are gathered from all over the company. And they're generally managed by me and our product manager and some supporting developers. But, like I said, each team is generally responsible for the product that they work on. But the implementation of auto ML or ML pipeline is mostly by myself and maybe another person for support. If it's just a ML experiment, then it's usually just one person, me or my colleague. If it's something that we're going to implement into the product itself, then it's still usually managed by me, but the implementation of it might be managed by the product manager. In addition, a UX/UI designer (may also involve) who wants to make sure that this number or response that the model spits out actually has some utility to the end user. And that's a very important. There's a hugely important part that I didn't realize until recently is to get a designer involved early. Because it's easy for me to be directly like this is a question and here's the answer to your to your question. But it's not valuable unless it encourages some sort	OC

	of actions. For example, this is the price that your house is, but how will end-user interact with that? I'm getting off the question here, but, it's usually managed by myself or product manager and we have a UX/UI designer also involved in the design of it in the in the end.	
I3-31	When it comes to solutions that have been already deployed into production, are you still the one who keeps monitoring and contacting some other responsible for, for example your shadow colleagues, to maybe keep the thing running and to some extent be able to?	
I3-32	Yeah, pretty much everyone in the company has access to monitor. We have created these dashboards that everyone can see and interact with including for our models, so it's publicly available. but I take it on as my responsibility to make sure that they're behaving as they as they should, but sometimes you know we might get a message from support saying “This customer said this number is really weird. Can you look at it and maybe the model is kind of out of whack?”. Generally it is my responsibility, but it's everyone in the company is able to see the responses of the model.	MISC
I3-33	One of the promises of the automated machine learning process is that it will empower domain expert or power users to be able to do machine learning work on their own. From what you are saying, is there possible to include AWS and get some sort of results, so I was like if not now maybe is there any plans for that?	
I3-34	Right now, I think that would be very difficult because even navigating within AWS is very difficult. Like even for me, who works daily in it, it could still be overwhelming. But in the future, yeah, I do. I mean the tool will be become much more intuitive and people can use it in the same way that, like I don't know, like most people can use excel these days. Of course, some people are better at Excel and in some cases you need to know what you're actually doing, but I just view it as a tool that will only get more and more convenient for everyday users to use.	TPBB

I3-35	That second follow-up question would be when it comes to machine learning capabilities on news cases like you are the expert, of course, and how things can be done. But are the people in your company aware of like the kind of problems that can be solved or aided by machine learning like they are able to come up with ideas?	
I3-36	Yeah, we make that to be a point to share between my colleagues. We weekly have data discussions or we'll present the capabilities of a machine learning model or a new task that we're working on so that people in support team might get an idea; or people that don't really understand and aren't aware of the type of answers to the questions that you can answer with machine learning from like image recognition to text response or regression or classification models. We're very proactive in sharing the capabilities. That's one of our data team’s cornerstones as to spread the ideas and capabilities of machine learning so that people get more creative in the way they think about problem solving.	TCC
I3-37	How do you verify the results from AML?	
I3-38	The one time that I've used AWS is that they'll provide you with a metric. Of course, you need to know like what these metrics means like if it's a regression problem or classification problem. But I think they do a pretty good job of explaining like what a root mean squared error is, and that you want to minimize that for a better performance. I meant If you put in a bunch of data and it gives you back 20 different models and all of their metrics, you can just say this is the lowest one. That's the best one. And something I realized when I was using auto ML is that, it's especially important that the datasets are what you think they are. Because I mean, if the majority of your training set, for example contains images of cats and dogs with only a very few goats in it, then the classification model will mislabel goats a lot because it just hasn't seen that many. And then you would want to make sure you have an equal balance of goats, cats, and dogs, for example. And if you just have a crappy data set, you'll still find the best model based on the 20 metrics that they spit out and it depends on your question. Because like it depends on the question you're trying to answer, then certain metrics you need to know. Certain metrics balance minority reporting of underrepresented cases. For in the goat example I gave, there are certain metrics that you want to use. If you don't care about goats and you just want to focus on cats and dogs, you still need some like domain knowledge on what metric you're using. But the AML does a pretty good job of or from what I've seen like providing the metrics as long as you	TTE,

	know what you're looking for and as long as you know what's going in to the old AML pipeline and where we're beginning to use. Uhm, like data set documentation to explain what the recommend uses for this data set would be, what the motivation is, the composition, how the data was collected. And this ultimately helps with transparency and accountability because the data set is everything.	
I3-39	So you are saying that you need to know what you are doing, even if you are using Amazon automated machine learning like in the language, that wouldn't be able to tell or like interpret, so to speak the results and the metrics they get from this models?	EIS,
I3-40	I don't think you really necessarily need to know what you're doing to use it. I mean, like a programmer, a developer will be able to use it much easier than a non-developer. It's just like data manipulation or data inputs and outputs. But if you want to optimize the question you're asking or like what the actual question is, in my experience using auto ML, it helps to know what metrics you're looking at and what the shape and like quality of the data going in.	TPBB
I3-41	You mentioned that you had automated some sort of workflows and pipelines on your own to make it for your customers and support team members, you also made some dashboards based on visual cues, so these dashboards are able to tell if there's something wrong with it, and also help for your own monitoring. So do you think or have you seen Amazon any sort of similar tools before or they just provide metrics that are maybe a bit hard to interpret?	
I3-42	Yeah, I think they're pretty good at that. I don't think I'm making better metrics on my auto ML pipeline dashboards than Amazon. So I don't think it's necessarily harder to see, but it is harder to access because going into AWS and navigating within the universe is not accessible right now for non-technical people. AML from AWS also allow you to setup alarm if your numbers are off by a certain amount or so, they do a pretty good job for the reliability and the accuracy of the result sets.	AUTOM L
I3-43	You are kind of experimenting with automated ML to some extent, so did that encourage you in any way to apply AML to future projects?	
I3-44	Yeah, yeah, I'm going to. I'm going to continue to.	TTE,

I3-45	In terms of saving time or maybe producing reasonable models, is this AML promising enough for you?	TPBB
I3-46	Yeah, it wasn't time saving the first time. I did it because it's a whole learning process. Once I'm comfortable with how it operates then it would save time. So I'm encouraged by it and I'll definitely continue to use it and even try to get non ML people like just other back-end developers to use it too like because I know it's just a tool that I think anyone will be able to use.	
I3-47	What amounts of data does your organization collect and manage? Uh, and you kind of answered to that before, but is it mainly done internally? Or is it also they also manage external sources data? Like maybe from your partners if you are operating contractors or some supply chain vendors, something like that.	OC
I3-48	What I personally work with is all internal. There are probably some untapped resources in both internally and externally. But yeah, just so far it's just internal.	
I3-49	I just provide a specific example. Like if you're selling products to a customer or client which is a store somewhere in the country. And in order to track how their products are actually being sold and managed, will that client provides data on their operations?	TPBB, OC
I3-50	The way our product is set up it's pretty much all data is internal from the client. But they may not provide it fully. Like payments are handled by like Stripe for example, which is a third party. But we hadn’t used that external data in any ML processes. Maybe in the future, but we haven't done that yet.	
I3-51	How important are data collection and management to your organisation?	TDA
I3-52	Uh, important. But I don't know.	
I3-53	Then there's the intensity of the data that you're collecting and managing, uh, does it have any impact on what decisions are made in conjunction with implementing machine learning and also machine learning?	TDA
I3-54	With machine learning, you're always limited by the amount of data you have. Then definitely yes.	
I3-55	Do you consider your data as fully utilised?	TDA

I3-56	Uhm, there is room for improvement. we're still a pretty young data team. Like I said, we've only kind of been messing with this for a year, so we still not fully utilized the data.	
I3-57	And do you have an idea of how you can reach to that point?	TDA
I3-58	I think we're on the right track. I mean just be driven by asking creative questions from the data, such as what data you have? and what you wish the data could tell and then try to collect data to answer that question. If we discuss about fully utilized data, I feel like that's like an asymptote that you'll just never reach. It's kind of a hard thing to answer. If we continue to grow and work on this. We'll get closer to fully utilized but I don't really know what that even would look like. It just means like every question around the business is answered with a model. It seems like you like utopian sort of thinking.	
I3-59	You do not filter out a lot of data when you put it in there? Some tables might bring some unnecessary details that you might just have to get rid of.	TDA
I3-60	Yeah, that's probably true. I mean sometimes you don't really know what's valuable or what's not when you're collecting it until years later, you wish you did something differently. It's always an evolving field of data management and collection.	
I3-61	And you did mention that you've started using machine learning since last year and you're currently having prototypes with or you have implemented all to machine learning?	TDA
I3-62	But only in the ones that we've build the automation process, but we've like prototyped some of the services, like AWS.	
I3-63	And you have some prototypes for AWS as well?	TDA, MISC
I3-64	Yeah, we've used that.	
I3-65	The AWS solution which does the model selection for you, and perhaps also the training. Do you think that they will improve or even more utilization of data? Will it have any other impact according to you?	TTR
I3-66	Oh yeah. I think it could make work more efficient like you could utilize the data quicker if you use auto ML. Because you don't have to worry about building these pipelines every time. So yeah, I think it definitely help us utilize data quicker. I don't know the best model or something. Maybe it would be better than anything I could ever	

	come up with on my own. Probably I mean AWS has a lot more knowledge than I do so.	
I3-67	How do you approach the explainability of the outputs from both your machine learning solution but also from the prototypes that you have?	
I3-68	We're trying to start to use these things called. I can send you a link. I forget what they're called. Something that Google made up model cards. I mean, you don't need to look at that now, but it's just like a way to help people understand models. It's kind of just like a protocol to follow that they suggest helping anyone understand like what's going into a model, what's coming out of it, how confident it might be in that particular answer. Because that's definitely. I mean, I don't think people need to necessarily need to know the math behind a model, but it's important to know its potential weaknesses and strengths, I would say. So we're looking into using these model cards specifically for model explanation ability.	
I3-69	Is your organization rather skeptical to the alternative solutions that are being prototyped and also the one that you have developed and how much emphasis is put on the actual?	TPBB, AUTOML
I3-70	There's no skepticism I've experienced. If there is any, it's from my own ego like “no, you can’t do this”. So there is no skepticism in the organisation. And then the fact that it's a black box, I mean such as how are neural networks like? Even if you build them yourself? You still need to reflect on what you're getting and see which parameters influence the decision you're getting out. At least for our application, this was something like a war weapon or like crime law enforcement or something with serious repercussions. Like a home price estimation, it was a little bit of black box but I don't really see it is a problem. For me, I don't feel it is a black box because I know how these models work, but it might be the case for non-technical person.	
I3-71	How is the trust within AML solutions?	TTE
I3-72	I don't really feel it that there's a trust issue. I think that maybe someone who hasn't built models themselves would be less trusting, but for myself I trust them because they show me what model they use and what the parameters are and the hyperparameters and the metrics. I have no problem especially AWS and they know what they're doing.	
I3-73	Did your organization possess the necessary infrastructure in the beginning in order to implement automated machine learning or machine learning solutions with your product?	TTE

I3-74	Yeah, pretty much we have. I mean by the time I got there, it had been set up and I'd known that interviewers had AML at the time, but each case is different. In some cases, we do have to build software or data collection. In other cases, you can just use off the shelf AML.	
I3-75	Have decisions about advancing AML affected or led to a change in the IT infrastructure?	TTE
I3-76	Well it's not. It is not really auto related, but sometimes, for example, we want to monitor the response of a model and we then need to change a database where we actually store that. So it is like minimal change but for most of them, we didn't really have to do big structural changes.	
I3-77	What do you consider the necessary level of readiness prior to deciding for adopting AML?	TINF
I3-78	(It is all about) Data, I would say. You need enough data and high quality data and clean data. And you need to have it stored so I think data is the number one bottleneck. And then of course you need to balance the time it takes to learn the auto ML versus the value it brings to your customers. Like will it actually make the product better? So let's say it is the data and like business questions.	
I3-79	And how ready do you consider yourselves when you started using AML?	TINF
I3-80	I thought we were ready but we did get some help from our parent company who since we're a very small team. But we're fortunate so AWS has really great resources, but we're also able to talk to some like senior data scientists who have been through here before. But another thing is that our data team is very interested in learning and improving. So, even though there's a learning curve, we were set up to do OK with it, because we enjoyed that part of it. So that might be another thing that's necessary level of readiness like willingness and excitement to learn and try something new.	
I3-81	Have there been any gaps in the work towards implementing AML?	TDA
I3-82	No, I don't remember if there was any gap. It's just a matter of familiarizing yourself with the tool which is hard to do because it's not that straightforward, yet it's still a very new tool, the Auto ML. But no, I didn't really experience any. I mean other than just learning and the learning process in general, just like learning any new piece of software.	
I3-83	Was AML seen as an incremental or disruptive addition?	TDA, EIS

I3-84	It felt incremental. It's like it was but you also don't feel like it. You don't know if it is disruptive until maybe you look back and you're like wow, a lot was done, just doesn't feel like it when you're working through it at the time.	
I3-85	Would you consider AML as a sort of injection within your machine learning pipeline?	TPBB
I3-86	I feel like it would replace it. Except for maybe the pre-processing step. Then you could add it like a monitoring step. Yeah, maybe it could be in injected. Actually, I haven't really tried that, but I will try it actually.	
I3-87	which benefits on the AML are used to justify your decision to even try it, and also implement it?	AUTOM L
I3-88	Development time.	
I3-89	Have any other factors?	AUTOM L
I3-90	It's potential to be used by other people that aren't data scientists. We haven't gotten there yet, but I see that as a definite potential use because they might skip the model selecting for example and they don't need to worry about it because the automated pipeline will take care of that. I think it's something that we're going to try to get other developers on board to see how they like it.	
I3-91	Were there any unexpected benefits?	
I3-92	Realizing how easy it is. Anyone can do this, not only me. It is very accessible.	
I3-93	What do you think is the minimum requirement for someone in order to succeed with AML?	TPBB, AUTOM L
I3-94	I think you need to have some programming or developer experience. Like my mom couldn't do it. But I don't think I could have done it probably a couple years ago. And I had been working with computers but not like to that level. Again, this is just my experience with AWS. But like you need some comfort in navigating around their world and patience.	
I3-95	Do you think AWS is affordable or do you think it is kind of a big investment?	AUTOM L
I3-96	So anytime we come to a question of can we buy this resource from AWS or something, it's always a matter of what will we get in	

	return? It's not like anything over 100,000 SEK and it's like, is it worth it? So each resource is assessed on its potential benefit. I would say it is very good at getting money from you. They know how to charge up so it can. It can get quite expensive.	
I3-97	Do you think if small medium enterprises, they would be able to afford it?	TPBB
I3-98	I don't remember especially about the AML, because like it depends on what tier you have with AWS. But they're pretty good at having different options depending on your company size, so I would say it's probably it should be affordable for small enterprises.	
I3-99	Do you think in companies that have their budgets like a lot for innovation projects, they would invest a lot in terms of experimenting with automated machine learning or just like what you are just trying on the side when you are driven by its benefits?	OS
I3-100	I do. I think so.	
I3-101	Does the size of your team encourage or discourage the decision of adopting/using AML?	OS
I3-102	Yeah, we work in those small like cross functional teams where we have front-end back-end business support data, UX/UI product manager. So, like I said, one of our data team's core tasks is to share knowledges and receive comments to increase data thinking. And I see it in certain people that are not in the technical side of the company, get really excited by it and want to learn more. And I think one of the tools to bridge this gap would be something like auto ML. The knowledge sharing encourages me or gives me hope that auto amount will be more used in the future.	
I3-103	If you can advocate the AML to your colleagues, like giving them 30 minutes orientation, will you do that?	OS
I3-104	Yeah, I will. But it is like the AWS universe, you still need some programming knowledge. But I think it will become easier and easier and also I think people will also get more and more computer savvy over time as well. I mean it's going to have to go both ways. In short, you need Computer literacy but I'm encouraged by it.	
I3-105	Do you consider top management support as important factor when it comes to adopting AML?	OT ,OC, MISC
I3-106	I think that's extremely important to get encouragement from top management. Because in my experience, like ML projects don't get very far if they operate just like alone in a silo, just in my own head or on my own computer, they're not going to get anywhere. You	

	need to work with people from different backgrounds, like I said before, like UX/UI designer, I didn't realize how important that was to my job until we got one and it's like OK, now I can actually discuss ideas and not just sit in my own head. So I think having top level management support is really crucial in orchestrating all the different people to get involved in setting up a good product that's built behind machine learning. And aside from that, if auto ML means that my work will be more efficient then management will always be supportive of that.	
I3-107	Does the management right now know about automatic machine learning existence?	OC
I3-108	Yeah, they know it exists. We've talked about it.	
I3-109	Do the management know the benefits of AutoML?	OT
I3-110	I don't think it's actually that they know all the sides of AutoML, maybe the small data team like us can know better at that.	
I3-111	From what you mentioned your view that automated machine learning is a tool for making our work more productive. Some sort of getting domain experts participating on this, or it's like some sort of strategic or kind of a broad plan.	OT
I3-112	Yeah, I that's accurate on how I view it. I mean, what's more important than asking smart questions and having the data to answer it? And if a model is better or worse, that's something you can deal with using a tool or experimenting yourself. But I think there's more important things.	
I3-113	How do you feel about the support from the company for implementing AML?	OT
I3-114	Our company is very supportive and encouraging of Machine learning and my work so I feel very lucky that there's never any roadblocks. They're always encouraging. If I want to just try to learn something new, even though it might not Turn into anything productive, they still support me.	
I3-115	So they are providing a good environment, but in terms of timetable, do they maybe give some 2-3 hours for you to experiment?	

I3-116	It's not very micromanaged because they trust me. There's a time when I've been talking about the same problem for maybe a month and they're like should we maybe try to move on? They put perspective on the cost benefit of putting time into it, but I would say in a very reasonable way. It's always an open discussion, very not like a top-down decision. It's always a two way to a conversation about that. But yeah, we won't waste months trying to do something that isn't going to have a big improvement on the product itself.	
I3-117	what about any sort of financial support for those that need to be, for example, acquired or purchased or whatever are they supportive of such experiments?	OT
I3-118	It always depends on the potential benefit. It's not like there's a magic number. It is just will it make a huge impact? Then we'll make the investment. If it's the potential gain is tiny, then it's probably not worth spending that much money on.	
I3-119	If you want to invest heavily, would the management support you on that?	OT
I3-120	Yeah, I think if I can present a strong case as to why I think there's a benefit, I feel like they would definitely listen and support if it makes sense but it is usually difficult.	
I3-121	when you are experimenting with machine learning, do you like to discuss this with your management and give them your views about its benefits?	OT
I3-122	Yeah, We work very closely, me and the product manager/CTO and CEO. We're every other day we're giving updates on things about it.	
I3-123	Do they actively follow up with that?	OT
I3-124	Yes.	
I3-125	Did the AML initiative require a change champion like you?	OT, OC
I3-126	No, it's not up to me, I would say our CTO/product manager is very much a champion of this type of stuff, so it's not. It's not just me, it comes from different people.	

I3-127	For your AML initiative, is it also driven by, for example, external competition?	OT
I3-128	No. It is in a way that all about having the best products and when machine learning or auto ML would result in a better product or user experience, then we'll explore it but I would say ML is standard practice now. So I don't know, I guess it's like any business: you want it, you want it to be the best. Maybe it is a driver for any business decision is to beat the competitors, but I don't really view it as a necessary way.	
I3-129	Do you think AML generating competitive advantages?	OC
I3-130	Like I said, I think almost every tech company now is using it. So, AML itself it's not necessarily an advantage. I think what's way more important is having smart, creative people who can ask smart questions. And you utilize the data in a very creative way and having like the right data that you need. So, it's a combination of the data and like intelligent questions to ask of the data. In order to use ML in a competitive way, because if you're doing the same thing that everyone else is with ML, then that's not going to give you competitive advantages. So, in our domain I don't see it necessarily as a competitive edge, but it's more of like a tool.	
I3-131	You mentioned that according to you, it is not really going to make any difference which is true, but you have already kind of background work for machine learning and automated machine learning. But it will be helpful by training more other colleagues in the company about the benefits and how or what kind of applications in machine learning could be utilized, or how ML and AML can lead to better decision which could translate or should translate to sort of advantage. At least that's what's being argued in the literature.	EC
I3-132	You're right actually when you put it that way, I think there's there is potential for it. So I guess we're not there yet, because it's not being used, but I understand what you're saying and I guess it would be a competitive advantage to have everyone thinking and taking advantage of ML opportunities.	
I3-133	So it's good to know that it's not the strongest reason when you started to implement ML.	EC
I3-134	I should clarify just because I don't feel that, doesn't mean that's not the case. Because we're being, you know, like our CTO may have this vision and AML can provide competitive advantage and that we can have all this data and make intelligent systems out of it. But I mean, that's not necessarily part of it.	

I3-135	Are you threatened by other competitors using ML and AML? What raises the concern?	EC
I3-136	Yeah. I think is my answer is going to be similar to before like we always want to have the best product and user experience and right now I think we are. A part of that is thanks to ML, but it's much more than that. And I know that most of our competitors is will also use machine learning applications and it makes sense. Yeah, it's becoming like standard practice so I would not say that just because a competitor uses ML makes them more or less threatening.	
I3-137	Does your organization rely on in-house skills on its ML and AML implementation or need other vendors in order to apply them?	EC
I3-138	It's a mix. Some in-house, some resources that we get from our parent company and like online resources. It's such an incredible community, like the amount of open source projects that are going and knowledge sharing. I'm shocked that people give out the amount of code and knowledge when they can charge money for that. I love it, but it's just surprising that it's there's that many resources out there. So it's a blend, but mostly in house or like online resources.	
I3-139	And how helpful do you deem them?	EC
I3-140	In some cases, they're essential like the services that AWS provides when we have our whole business depend on their cloud platform service. So yeah, in some cases helpful and essential.	
I3-141	How did you view their support in terms of maybe training materials documentation?	EIS
I3-142	AWS is difficult to like actually just talk to someone. I don't even know how to do that, but their resources like video tutorials and examples are pretty comprehensive. So, it's good and bad. I wish sometimes I wish I could just call someone and ask how the hell do I do this? And maybe there is a way I don't know. I haven't seen that, but they're pretty good at just giving you the tutorial when you when you need it.	
I3-143	Do you have any plans on being vendor-independent or do you want AWS to continue being your vendor?	EIS
I3-144	We're pretty happy with AWS, but like we're always looking for ways to save us a lot of money if we could. If we could ditch them. But right now the benefits of working with vendors outweighs the	

	requirements to leave them. But like technology moves very quick so and so does our development team, so there's definitely a future in which all of our solutions could be vendor independent but right now with we're still pretty small size, it's probably to be like that for a little bit.	
I3-145	How did the availability and accessibility of vendor support influence the AML adoption in your side?	EIS
I3-146	I think it would need to be much better so it can be more widely adapted. Or at least more accessible like maybe you do need to chat with someone like how do I do this? Like here's my screen, what am I doing wrong? Because sometimes the tutorials just off a little bit, or like you just run into a weird circumstance where it doesn't line up perfectly with the tutorial. And if it was a non-technical person trying to do that, it would be the end. It would just be a dead end. So I think the support, or at least like the user experience would have to be improved a bit to be widely adopted.	
I3-147	In the long run, how do you view the impact of AML on your data analysis work?	EIS, MISC OS
I3-148	I view ML and auto ML as just a tool to help people work more efficiently. And sometimes when somethings become more efficient, certain things or tools or people become obsolete. So, I guess that some data teams or some members of data analytics teams will become less necessary. I don't really know what those positions would be but I would assume auto ML would replace some roles in the future, or at least take some of the burden off of some people in the future. I do think it will be like an essential tool for data teams going forward and it will eventually become as common as Excel in today. Maybe that's not true, but I think it'll be much more common like you still don't need to be an expert to work in Excel, but some people are better at it than others. I mean, the auto field is so young, so there's a lot of room for improvement and I imagine that the more improvement, the less important certain roles within a data team. The data team might shift more towards people who can think of creative ways to ask questions of the data and not necessarily rely on PhD's who are good at matrix math, like maybe that's you don't need to have that much representation in the data team, but I don't know. Maybe they're the same people as those that are really good at matrix math are the best ones that are asking questions of the data.	
I3-149	Would you like to add anything in terms of factors that might affect the decision for adopting AML within an organization?	EIS, AUTOML

I3-150	I think we covered it all. Just make sure AML is well-defined. Because I wasn't aware of the name when I was doing this. I wasn't really sure until Yahia said the name.	
I3-151	In which areas of an organization, should AML be most applied? Or which areas are easiest to apply?	AUTOM L
I3-152	I don't know of any. I haven't like met anyone that uses it. I have no idea where it's being used. But I don't think it's being used. I've only seen it is used for regression problems, like if you wanted numbers based on a bunch of parameters or like classification problems like is it a fraudulent user or something like that. It's probably going to help in those very clear-cut questions. I don't really know if they have AML for like video recognition or text generation or these other type of deep learning tasks. I don't know if AML got there yet, maybe it has. I know AWS has image detection which doesn't require any training on your part. You showed an image, and it says yes or no.	
I3-153	So I would assume that you believe it's only tabular data that is relevant to AML?	
I3-154	That I've seen, but I wouldn't be surprised if they have something for images and videos too. Like I said that AWS universe is massive, I haven't really seen it all. But based on just what I've seen, the AML type I'm used for.	
I3-155	End of interview	AUTOM L

Appendix 6: Interview Transcript – I4

Company: Anonymous

Interviewee: interviewee.

Title: Data Scientist

Date: 11/08/2021

Row	Transcription	Factor
I4-1	Would you like to remain anonymous and keep the company name confidential?	
I4-2	Yes.	
I4-3	What is your background and current career title?	
I4-4	I'm originally from Mexico where I studied mechatronics engineering. After that I worked as a design engineer for three years. After I moved to Europe where I studied for my Masters, then I continued with a PhD in machine learning in New York University of Technology. After the PhD I continued with a postdoc, again - machine learning, but for industrial processes. In particular, diagnostics of wind turbines. February last year I joined a startup here in Gothenburg. At the company I am a data scientist.	
I4-5	Can you describe the business strategy of the organization for the domain or the business strategy in which you are involved?	
I4-6	Our company is mainly focusing towards predictive maintenance. Mainly we want to bridge the gap between the data scientists in condition monitoring, reliability process engineers and maintenance experts. The idea is to be able to scale up analysis capabilities across a number of machines, to be able to detect whenever there is an issue in machines such as motors, pumps, heat exchangers or bulbs. Mainly machines that are used in the processing industry, refineries, manufacturing etc.	
I4-7	Could you describe your specific role in the company?	
I4-8	Our company isn't large, just a startup, we are around only 10 employees. So my role, percentage wise, is large. I am a data scientist/subject domain expert. I personally have some experience dealing with condition monitoring and maintenance in those kinds of	OS, TTR,

	issues. Most of my colleagues are either software engineers or data scientists, focusing only on the machine learning side. In my case, I also have the knowledge within the domains that we are working with. Hence, mainly I help with translating the information from the machine learning data science analytics processes into how they are useful within the particular (industrial) domain we are working in.	
I4-9	Does the role require some sort of computing knowledge? Such as basic programming or databases?	TTE
I4-10	Certainly. As a data scientist, I work on algorithm development, mainly using Python. that's part of the work that I do here, but I also require certain knowledge on actual machines the customers are talking about. Mainly: vibration analysis, understanding how pumps, motors and similar machines work.	
I4-11	But the end user does not need to program because you mentioned that it's supposed to be understandable for both non-data scientists and data scientists.	
I4-12	Most of our users aren’t programmers, no. Our end product is not specifically geared towards data scientists, rather - process engineers, condition monitoring experts. So, no, having those sort of programming capabilities is not a requirement for the end user.	
I4-13	Do you consider your company as data-driven?	
I4-14	Yes, certainly it is a rapid data-driven organization. We mainly need to order different data before we are able to produce something. But most of our approaches are completely unsupervised or semi-unsupervised. We are aware that most of our information comes without labelling. That’s one of the challenges we face in these industries.	
I4-15	Does your organization in any capacity utilize machine learning or auto-machine learning?	TDA
I4-16	Yes, we use it, but not very significantly, mainly for very specific algorithms, like hyper-parameter tuning of different models. We have seen that given different machines with different processes means they are not the same, so each one of them needs to be tuned to different conditions. That's the only part in which we are using it right now.	
I4-17	For how long have you been using auto-ML? What are the perceived benefits?	AUTOML, TPBB

I4-18	These specific tools have been in use for around six months. The benefit is that we don't need to focus on patrolling through all the different parameters for all the different machines/assets to find the specific best values.	
I4-19	What disadvantages with machine learning solutions do you have?	TTR,TPBB
I4-20	Well, the main disadvantage is it takes way more time to solve everything. Many of these algorithms keep searching through the feature space of the same most-fitable values, without optimizing the remaining features. Thus it takes way more time as opposed to one using custom made or selected algorithms. We can expedite the entire process mainly because we build a stone-solid model for each particular machine/independent process. On the other hand, using ML certainly takes way more time when you're trying to rethink the model quite often.	
I4-21	What kind of model are you building?	TPBB
I4-22	We tend to build models for each type of machine, doing a different kind of process, so it's not that we use the same model. This (model construction) can take plenty of time too, especially when you have to expand to accommodate for many other machines.	
I4-23	You are willing that ML takes a really long time, so you'd instead focus on something that might be of greater importance. For example, building the different models?	
I4-24	The thing is one needs to have this kind of trade-off between how often you want to retrain the model and how often and how much time it will take to retrain the model each time. Possibly, at this large scale, we don't have the time to retrain. Our product generates reports to the user who sees them when he/she is unaware of the time taken. But we would rather incorporate our strategies to develop these models to evaluate everything in real-time instead of the end user relying on our reports. The former, integrated with other user systems, has a response much faster than anything AutoML can provide.	
I4-25	Do you plan on dissolving the AutoML solution that you have currently? Or do you plan on uploading it?	
I4-26	There are no plans about that. I guess all auto-ML requires a is a certain level of better evaluation when it is actually needed, rather than just running it all the time when you try to build the models. Just enabling or disabling the auto-ML depending on certain circumstances.	

I4-27	What kind of challenges are you aware of when it comes to the adoption of auto-ML?	
I4-28	Right now I'm talking about it just as we use it in our case, mainly for parameter tuning. Something we have seen auto-ML explore, but we don't use it, is the automatic feature generation stage, mainly because we work a lot with time series analysis. It can provide some good results. The issue is that, at least in the industry that we work with - maintenance, condition monitoring etc., there's already a great hesitance about using machine learning in AI. Not only because the resulting samples are already being born with scarring, which looks promising. It's because the AI doesn't deliver. Another major requirement is explainability. You need to be able to understand what the feature is about. And then, in addition to the black box, that can be seen as ML, you have another black box, which can be featured in the engineering aspect. Rather than increasing trust in the entire system, you increase distrust. And that's something difficult to overcome with many final customers.	
I4-29	This is kind of depicted in the IT bubble, but instead it's like a machine learning or technology bubble.	AUTOML, TPBB
I4-30	Exactly. So there is the ML bubble, but then there is another bubble inside the first bubble. A double layer of trust needs to be built. For a lot of these companies or processes we deal with ourselves, the former are too traditional. It's not that easy at all. That's the reason why many industries, like processing, have been slow to incorporate benefits of machine learning or AI. This is one of the several other issues.	
I4-31	Have you experienced or how has your organization experienced any government or regulations as a hindrance? When it comes to using automated machine learning?	TPBB
I4-32	The processing industry tends to be highly regulated by the government. Simple access to data isn't available. As another example, say you are working with the energy industry. There is no possibility to create a direct connection to wherever the data is stored, mainly because of government regulations. Hence, the industries that we deal with are highly regulated. So, at this level, any challenges auto-ML might have due to the former are shared with machine learning in general.	
I4-33	Are there any evident enablers for auto-ML in your case?	
I4-34	Certainly, it is. In the way which we use it, it is useful in the sense that we can save time when trying to do parameter tuning. Just trying to identify the most suitable values is rather useful. However, with many of the closest systems like Azure AWS, many of the processes	

	can be rather fast, so auto-ML fails to take advantage of computational power. At the end of the day, it is just a tool. You must have a strategy of what you want to do.	
I4-35	In relation to the trust and reliability of results that come from auto-ML, you mentioned that you use machine learning to find optimal values for parameters. So how would you verify and trust these values that come out of a ML process?	TPBB
I4-36	I will say we have very complex scrolling because at the start we don't have labelled data. In our industry we have problems in which the data is highly, highly imbalanced, meaning there are lots of anomalies quite close to one another in terms of the large amount of data that we have. Our solutions are developed internally. The validation stage with many of our customers' data is quite lengthy. The language we speak to our auto-ML is a certain initial assessment of our data. That's where, perhaps, my domain knowledge comes in handy. Do the results that we are getting make sense in terms of what we're expecting? If auto-ML makes something that sounds too great, but doesn't make any sense, we narrow down the search space for deeper parameter tuning or constrain it in certain ways. If the result continues not to be positive we proceed to a more manual tuning. But all these points go hand in hand with the overall verification validation process of our solution. And afterwards we have certain metrics to ensure that wherever we are getting is consistent overtime. Having in mind the main problems we deal with as a company in general, the validation of data only makes things more difficult.	
I4-37	If you were to operate manually versus using automated machine learning, would there be any difference in how you evaluate the resulting model and its accuracy?	TTE
I4-38	So far we have not changed the way in which we are evaluating it. We are evaluating mostly in a similar way.	
I4-39	Could you give us examples of measures that you were using to evaluate how much ML was helping?	TTE
I4-40	The process of validation is something that goes hand in hand with our end customers. Naturally, this is the staging of collaboration with our customers, us generating an engagement out of them. Also ensuring that the results kind of made sense to them or were presented in the right way.	
I4-41	So it is dependent on the context of the company and the problem they have?	TTE
I4-42	Exactly.	

I4-43	When you applied auto-ML, how did it perform? Did it give you reasonable values? Was the performance fast?	
I4-44	Generally they're reasonable values, and most of the times we'll be satisfied, and other times, when we have not reached that, perhaps we won't. Sometimes when you put auto-ML's focus too much on specific areas it goes to some sort of local minimum and halts. Perhaps it makes sense algorithmically, but during a process, that we are dealing with the particular circumstances, we don't always need to analyse in such detail. Mainly because the small area is just part of a larger issue. So we need to find this kind of balance between what to and not to focus on the algorithmic level: what is the overall process that we are dealing with?	
I4-45	If you were to assume there was someone responsible in your company to do the hyperparameter optimization and that person was "automated machine learning", would you trust it to be able to do the job on its own?	TTE
I4-46	At the end of the day, whenever you start working as part of a team, you need to be able to trust what your colleagues are doing. At the same time, certainly there needs to be a level of discussion of whatever the results of the project are. It needs a level of transparency or what has been used to generate those results, but I do not believe that micromanaging your colleagues is a good way to work. (I.e., he doesn't trust auto-ML to be his colleague, for example, in feature evaluation. Maybe he trusts auto-ML enough to optimize his parameters) You don't think of your computer as a colleague. You think of the computer as a tool for your work.	
I4-47	How much data does your organization collect and how does it manage it? As you said, you use external and internal sources. Could you elaborate on that?	TTE
I4-48	The kind of data that we mainly deal with is called vibration data and it varies from organization to organization, from process to process. In some applications, they shared vibration waveforms with us once or twice a day, or once every hour or so. It varies. In some cases we do part of the data storage. In other cases they do storage themselves, providing us access.	
I4-49	And when it comes to the large amounts of data, is auto-ML able to handle all kinds of models and data? Are there any challenges it faces based on the size of the data?	TDA, TINF
I4-50	Like I said, we build models for processing machines. So certainly there's a large amount of data there and there's a large effort that goes into data pre-processing before it can be used. In fact, this part is not done by auto-ML. We have automated our other processes in regard	

	to how to extract the most useful information. We only use auto-ML for hyperparameter tuning based on pre-processed data.	
I4-51	Do you consider your data as fully utilised (most insights have been gained, you’ve delivered all the value to the organizations etc.) or do you feel like there's a bit more that you could do with some more resources?	TDA,
I4-52	I do believe that we make really good use of the data, but certainly there's always room for improvement and I see that as a never ending job. Mainly because we want to get the data in such a way that is interpretable to our customers, so we are able to translate it. I will also say the part of looking into what's happening with the data during extraction of the most useful parts. But that should be a constantly ongoing process. You can never say with certainty “it’s not doing the best”, because you never know how the data is always changing. We are not using the auto-ML in the early stage, say, for down sampling, feature selection and engineering… For all those steps don't use auto-ML, we only use it for the hyperparameter tuning, which is considered to be what it’s best at. (It's mainly used for the process of the pipeline and not applied to actual data)	AUTOM L
I4-53	Would you try to use auto-ML for feature selection or previous stages in the pipeline? Or maybe ETL in the future?	
I4-54	We have tried a little bit of initial work in that regard. But it will require a higher level of trust for us to be able to say “it is good enough”, because a lot of times it's not clear what has been selected and what it actually means. These are the issues that we want to deal with. We work in an area of business in which the explainability is hugely important. And a lot of times having auto-ML do early processing doesn’t increase explainability - it reduces it. So it might be able to do greater results, but you're not able to explain why, where is it happening? What do the results actually mean on a physical level? Like translation from a machine. It becomes way more difficult to to propel use out of it.	TDA, AUTOM L
I4-55	But do you feel auto-ML has the potential to give you more out of your models and give you better utilization in data science, maybe in the near future?	
I4-56	Certainly it helps to narrow down certain areas. Say, in a sort of exploration, mainly when building some models. In that regard it’s helpful.	TPBB

I4-57	When it comes to hardware requirements and tools that you use for auto-ML, how did you acquire them? Was it easy? How expensive was it?	
I4-58	for software: Mainly we are using open source libraries. (For hardware): Depending on the problem, we had either our own servers or we used external servers to search, such as Azure. But the choice isn't influenced by auto-ML, more so by the situation with the customer.	TPBB
I4-59	Alright, how would you describe the hardware resources required for running automated machine learning? Do they need to be extensive or are limited resources enough for computations?	
I4-60	It can be rather computationally expensive. It's another one of the challenges. So that translates to needing more computational power, which extends the problem in many other ways.	TINF
I4-61	why do you prefer to use open source versus commercial solutions?	
I4-62	Certainly because of the cost.	TINF
I4-63	How about the flexibility factor?	
I4-64	Absolutely, that also plays an important factor, #1 because at the end of the day you are able to see what is happening in your software and you are not dependent on a supplier to be able to deal with problems. #2 Also, you are able to do your own adaptations based on needs for certain circumstances. #2 Usually there's a fast iteration of fixing whenever there is a problem, so it's easier to see what is happening.	TINF
I4-65	A recall question: how long has your startup been active?	
I4-66	The startup is around three years old. Certainly with the kind of problems we were dealing with, we have been dealing with them for a year and a half. But the business strategy at the beginning was completely different. Before we launched our latest broader product, it was leaning towards the side of data scientists rather than internal experts. But we realized that that can be way more difficult, not on the technical side, but on the business side. That's the reason we started to rely more on condition monitoring and maintenance companies as customers, rather than original equipment manufacturers. As such, we developed a new product, and as we were starting to develop it (since late last year), that's when we decided to use auto-ML.	EIS

I4-67	You said the previous business strategy was data science. Wouldn't it be possible to apply auto-ML there as well? Or would it be much more advanced compared to the current solution?	
I4-68	The reason for change had nothing to do with the technical side. It was mainly from the business side of the company.	OS, TTR, MISC
I4-69	Could you elaborate on the business reason why you chose to change the idea up?	
I4-70	The thing is, in this business you need to deal with the original equipment manufacturers, the ones who produce the parts and all these components. The number of these client companies is limited and the engagement that is required is long, lasting years and certain evaluations. Many of these companies had way more resources, financial resources, and often treated us as a consultancy - which we are not! We want to develop our own product! So, it becomes rather complicated. Meanwhile, when dealing with maintenance companies, which tend to be rather small, we have a product that we made and they can just buy it. Think about it, say, you make pastries. And you started producing cakes. To whom is it easier to sell: to Walmart? ICA? Coop? Or to restaurants? Or to people directly? OK, perhaps selling it to Coop or ICA may bring you a large check at some point, but before you can enter their market you need to be able to have an investment for a long period of time, go through many evaluation processes and everything before they decide. Only then will they start buying cakes from you, while all this time you have been selling directly to customers or two good restaurants. This way the business cycle is faster.	
I4-71	**	
I4-72	**	
I4-73	Would you say the availability of hardware and software resources make it easy for you to adopt machine learning?	
I4-74	Right now I don't see any major factor on our decision whether to use auto-ML or not. It simply isn’t the major drive for our work decisions. Hence there aren’t any big hindrances.	
I4-75	On to the next factor, which is related to the readiness and the skill set is required to utilize automatic machine learning. You mentioned that you use open source libraries. So what is the minimal barrier for the user to be able to use them, would everyone be able to use it? Maybe even business users?	
I4-76	Well, there certainly needs to be familiarity with coding. The libraries need to be properly maintained, since they are used frequently. Either	TINF

	that, or we usually pick libraries that are already properly maintained by someone else.	
I4-77	One of the goals behind automatic machine learning was that it is supposed to empower domain users who are not very technical people. They might be familiar with large domains, but not necessarily with data science and all the complexities that come with it. So do you think they would be able to use this? Perhaps with comercial libraries?	
I4-78	At least in the industry I work with, they will not be able to use it, mainly because they don't even have coding skills. Most of the time I feel comfortable with them using excel, but nothing beyond that.	TTR, TPBB
I4-79	So the minimum barrier for someone to be able to use these libraries is to be able to code. So maybe a developer, even if they are not an expert with machine learning, can use it?	
I4-80	Certainly, for developers it might be possible. They might not understand what is happening all the time, but they certainly can use it.	TPBB, AUTOML
I4-81	So supposedly the dream that any developer can use data science is still far from being a reality right now.	
I4-82	Yes, as I see it, it's mainly healthy to bridge the gap between machine learning/data science and software engineers. But with regard to domain experts, for the many different applications I don't see that they are helping to bridge that gap.	AUTOML
I4-83	When you decided to adopt and incorporate auto-ML into your workflows, how would you describe your readiness at that time? Did it require any sort of training? Was it just easy to incorporate and use it within your organization?	
I4-84	We certainly had to do a few modifications, but it was relatively straightforward.	AUTOML
I4-85	How would you describe the benefits in terms of saving resources or time? Or anything else?	
I4-86	It saves time in the fact that we don't have to invest so much time in identifying the most suitable hyperparameters for our algorithms. Earlier we had certain algorithms that we had developed ourselves from our work, and those are really fine tuned and fast. It's our own intellectual property. The moment when I try to incorporate hyperparameters into those algorithms without auto-ML, that’s when it slows down and everything takes more time.	EIS

I4-87	In some studies they say that 70% of the time in ML is just spent on data processing, while model and parameter selection take only 20 to 30%. So out of that, how much time would you say you are saving because of the auto-ML part as opposed to not having it?	
I4-88	To be honest, I will say not that much, 10% perhaps in the parameter selection.	TPBB
I4-89	Was there anything that you didn't expect to get out of auto-ML level before you started using it?	
I4-90	None that can come to mind.	TPBB
I4-91	Then we'll dive into some organizational questions. You did mention that you're using an open source solution. Did it require a lot of budget in order to implement auto-ML?	
I4-92	No, it wasn't much. The internal team decided that it might be worth exploring. So it was just mainly the time allocated for the exploration of his use, but I would say it was not too significant.	
I4-93	Do you think that the size of the organization encourages or discourages the use of automated machine learning?	
I4-94	It was more suitable given that we are a small company, not that we needed to go through a large group reactive process. Before we did this, we made a decision on what can be or cannot be used.	OS
I4-95	You said that your organization has less than 10 employees. Does that mean you all work together and it's quite a flat organization?	
I4-96	It's a rather flat organization. We had perhaps two teams, mainly focussing on two products. But we are pretty much merged in our day to day activities.	OS
I4-97	Do you consider top management support important when it comes to adopting auto-machine learning?	
I4-98	No, we have the trust from the founders in our top management and they trust us. We are choosing the best tools ourselves, for what is needed.	OS
I4-99	Perhaps that could be due to the fact that you run such a close and familiar organization. Do you think the case would be different if the organization was significantly larger?	
I4-100	It could be: if there was more bureaucracy surrounding what you can or cannot use, the time for decision making would be longer.	OT

I4-101	The general purpose of using the auto-ML so that you could focus on something else in the actual pipeline. If it's not the case, could you just fill out any missing points to that I said? Or do you think that the purpose of using auto-ML will also change with time?	
I4-102	It’s not only that it lets you focus on somewhere else. Also, if trying to get less variance of your results at the end of the day, when you use the auto-MLl, it investigates the entire feature space of options that you give and it gives you the most of what we consider the solution. In our work you do manual insertion, but it requires more time. And perhaps you might not need to explore to a certain level, so there's that benefit. Auto-ML gives you the opportunity to cross check all the possible situations but it comes with the cost that it takes more time to explore all these different. options. That’s where one needs to put some sort of balance.	OT
I4-103	Do you think that there is less bias by using auto-ML?	
I4-104	Yes and no. There is the opportunity to decrease bias. But at the same time, while introducing a certain bias, it reduces the mono-bias in regions you give the option for a space of possibilities. But if that space is not, uh, equal uh, selected correctly adequately, certainly the overall bias of the model will be far larger.	TPBB
I4-105	in order to avoid bias in any sort of machine learning work such as classification or prediction, perhaps the concept of having an outside ML expert could be a thing? Similar to when you do accounting: an outside objective accountant or bookkeeper looks at your finances so that they are not biased when you report them.	
I4-106	No, that's the role of the person to be able to monitor and see what is happening around. An outsider could not explain what is in the actual output.	MISC, TPBB
I4-107	Do you think that the purpose of what you have currently will change throughout time? For the auto-ML solution?	
I4-108	Certainly, we have started exploring auto-ML being used in other areas, but we are still in the exploration stage and so we will see what happens in the future and how it could improve in that regard.	
I4-109	You did mention that it was a consensus in the team or the organization to start using auto-ML. But what drove the necessity of using auto-ML?	
I4-110	Mainly we were spending time on the tuning of difficult parameters. As we started to get more customers, for most of our models the	AUTOM L

	overall time spent on tuning started to increase, so that's when we came to the decision: "OK, perhaps we should use it (auto-ML) too."	
I4-111	The use of auto-ML, could it be motivated with a competitive advantage purpose?	
I4-112	Not necessarily because of our competitors. The main drive was the need to scale up as we started to want to monitor more customers and the resources that we had available were limited.	OC
I4-113	Is this not also some sort of advantage? If you are able to keep the cost as minimum as possible?..	
I4-114	It helps in that regard. It enables the scale up. And given that we may need to reduce a little bit of time individually and to do this exploration or tuning of the hyperparameters, it allows us to focus elsewhere.	EC
I4-115	I was going to say if you can do that then maybe that would keep the costs low, which in a way will help you to have lower bids, when competing with other projects.	
I4-116	You need to consider that we are not paying for the software, so as of such it doesn't increase our cost. It might mainly increase our revenue.	EC
I4-117	The auto-ML solution itself is mainly internal and open source. Will it continue to be that or are you potentially thinking that an external solution might be more beneficial?	
I4-118	Right now we have not given any thoughts on that. So far we are satisfied with what we have been getting. That's the reason we are keeping it that way.	EC
I4-119	A follow up question: when it comes to tools and framework. Is proper documentation, support and tools offered and is it easy for you to use?	
I4-120	Yeah, that's the point. The library, the frameworks that we use certainly need to be absolutely supported and in continuous use, not something obscure not used by anybody. So, yes.	EIS
I4-121	In the long run, how do you view the impact of all the automated machine learning on data analytics or on the data analytics work within your organization?	

I4-122	Within our organization I think we are happy right now with what we have. Certainly we will continue to explore some other uses, but incorporating more of it will be a gradual process.	EIS
I4-123	And the impact: do you deem it positive?	
I4-124	Yes, so far the impact has been beneficial, certainly.	AUTOML
I4-125	Would you like to add anything before we finish?	
I4-126	Maybe to sum-up the main things I have said. The tools of auto-ML can be rather useful. But at the end of the day, there's already quite a large level of distrust with machine learning in general, in that it promises a lot, but has not been able to deliver what has been promised. And when you add procedures trying to automate that, which is not even delivering, certainly adoption of auto-ML will become even more challenging. As it's portrayed now, auto-ML tries to bridge the gap with domain experts - those people who might not know a lot about data science or machine learning. But at the end of the day, without interpretability it will still be really, really difficult. In a lot of times these tools do not help with interpretability or explainability. So, it's a tool, and it needs to be used as a tool. If there is no strategy, look at what happens: a lot of companies have a lot of data. And they don't even know what to do with it. That's the reason they want to use machine learning. But it's already difficult for these organizations to trust in whatever is useful in machine learning, because they don't even know what to do. They are only collecting data. That's the new oil, and they just want to get out of the hat solutions. They assume that auto-ML will do everything automatically. Certainly, the expectations grow bigger. But it will not deliver anything because auto-ML will not generate anything by itself, without any clear strategy. It's not artificial intelligence.	AUTOML

Appendix 7: Interview Transcript – I5

Orgnization: University of Iowa

Interviewee: Yauhoa or Interviewee 5 (I5).

Title: PhD student & Research assistant

Date: 11/08/2021

Row	Transcription	Factor
I5-1	Can we use the name of your organization and your name in our thesis Or do you wish that both or one of them remain anonymous?	
I5-2	yes	
I5-3	Could you just describe your background and your current work?	
I5-4	Yeah, so currently I am working in the University of Iowa as a PhD student and also research assistant. My background is on the electrical engineering side that mainly focus on the machine learning and like deep learning and Currently what I'm working on is applying novel deep learning model on some medical domain.	
I5-5	could you also describe the project of auto machine learning that you were involved in?	
I5-6	Yeah, so this project is one of the federated learning things like project, which means we basically are building a like part of the automated machine learning system where we collect the data from our end and building and training the model the machine, the neural network model or machine learning model ourselves. And once we train the models we send the model to other organizations which they can then use. They can train, they can test the model with their data to compare results. At the end of day what we hope we can achieve is that the model we build is just universal enough so that you know other organizations can just test the data on this model and get good results. So this particular project is actually there and it's necessary to be there since some hospitals might have patient privacy they cannot share the patient images or on some cancer or something, right? So this is why this system is necessary to be there. So companies or hospitals don't need to share their private stuff, they can Just test on their own and then get back results better results. This is like how this project is the motivation of this project.	MISC

I5-7	How big is the team that you're working within in order to develop this these models?	
I5-8	That team is pretty big and this is also across university project on our and I belong to a team of five, but we are one of the team of this big project. I think there are four to five teams so I think overall there is about like 20 to 30 People involving this project.	OS
I5-9	Which part of the entire automation solution did your team develop?	
I5-10	Yeah so we are basically developing the model. The data collected needs to be fit into a model and then so we train the model so then once the model is trained, it can be sent somewhere else and then another one can use this model to test their data right? So what we are working on is to collect the raw data and then to do some data transformations. So then the transformed data can be fit to the to the machine learning model and then the model can start training, right? So we're basically just doing the sort of intermediate processing between the raw data and at the model and this is my particular job and the other people in the team is have different roles so yeah, one of the members in the team, his main job is building the model like connecting different layers of networks together and then make this model robust enough or can make this model have good accuracy about those images or data he is being fitting, so yeah.	AUTOML
I5-11	You mentioned that the university that you are employed at is at some extent using automated machine learning, to what extent is that particularly?	
I5-12	Yeah, so you know, since it's about that project we just talked about. Since we were building part of the automated machine learning systems so at some point we might encounter some difficulties, and maybe some part of this automated machine learning system is not working very well, right? So then we need to find a backup, right? We need to find an alternate alternative system and that's where we start looking at some existing automated machine learning product on the market And we ended up picking The media, a product related to the Federated learning. Uh, and we also so at some point we just use a media product. I think it's called the clearer imaging or something. Then that product too. We pretend you know this is like our systems to get some results because the results is necessary to put on a paper or some conference report right? So then people will know, oh. Uh, you know, you built a system. But against but it also has pretty good results rather than you just build a system, but you don't have any results.	AUTOML
I5-13	Yeah, and for what are you particularly using the automated machine learning? For which part of the machine learning pipeline?	

I5-14	So that product is basically for building the model themselves. So we basically end up using the lydius networks. So yeah, I think that clearer things is related to the transfer learning part. So this is more like, after we build the models right, we need to distribute the model to different organizations and in that part we encounter some challenges and then we end up using Nvidia's network to send it. So basically, it's like a server. So we basically save our trained model to their server and then using their network to connect all the organizations who wants to use the model, so that's the part of the automated machine learning solution, yeah	AUTOML , TTR
I5-15	Do you plan on automating other parts of the actual machine learning pipeline?	
I5-16	Yeah, I mean eventually the ultimate goal is to just develop a fully automated machine learning system which, specifically is federated learning, or like a transferable learning platform so at the end of the day companies can just use that network to easily get some results from their data, so yeah.	TPBB
I5-17	When you, automated machine learning, what do you think of precisely? How would you define it?	
I5-18	Uhm, ok so yeah, when I think of automated machine learning it is just rather than, what I'm currently doing is like collecting data, building a, building the model, training the model test model manually by myself which might take you know weeks or months to get some results back, with mature automated machine learning systems, somebody has already combined all of these pipelining together, and ultimately what user does is just feeding the data to this system and then maybe just like wait with a cup of tea or something. You can get some results back, right? but that's given the fact that the automated to machine learning systems is working very good and there are no errors or like an incomplete part in the completed part in between right so that like a good automated machine, learning systems can definitely speed up the process of You know research or the process of product decisions? so yeah if this technology is getting matured, yeah, it definitely will be a game changing thing in organizations or the industry, yeah.	AUTOML , TPBB
I5-19	Do you think about automated machine learning as an automation of the entire pipeline? Or do you just see it as suitable for just specific parts of the pipeline? Can you see a pipeline fully automated?	
I5-20	Yeah definitely, I think currently it's already like semi-automated, I mean there are already see some products that you know cover some part of the machine learning pipeline and I think in the near future it will just be a fully automated machine learning platform. It will be	AUTOML

	there, there definitely will be a platform, but how good is that platform is the next question.	
I5-21	Regarding using auto machine learning initiatives. Who are they being managed by? You can also mention who the developers of it were with in terms of background and experience, but also what people are utilizing it after you send further the solutions to organizations?	
I5-22	Yeah, so on our project, particularly there is a leading professor who is doing all of these management. Well, yeah, because this is as a like across university project, but you know, we actually have some issues about some things. Each university has a leading professor, right? So some universities are really behind the schedule in their stages, so and their leading professor just want to have more time so that that's how these projects end up being not very productive. But well, each university have a people like the person to manage that, but yeah when it comes to more, it's just come along	OC, TTR
I5-23	What kind of organizations have you sent the solution to?	
I5-24	Yeah, so that's basically other universities which have some hospitals resources right? So they have their patient records or patient images and they're going to test our model on their patient images. So basically, it's like a institution, sort of we're sending it to.	MISC
I5-25	So there are universities that are more connected to a specific domain when it comes to the type of project that you are involved in, like a Medical University for example?	
I5-26	Yeah, it is. I think he involves Yale University and Harvard University. Like both of them have some good and big hospital in the local area and then maybe even their University Medical department or you know. Yeah, so yeah, they basically have those data.	MISC
I5-27	Can you elaborate on the reliability and accuracy of the results that the automated machine learning is providing, how are you verifying it as well?	
I5-28	Yeah so the automated machine learning Product we used definitely give us some results, but that results I think it's definitely acceptable, but about the reliability That's a part we are not very sure about because we only used one automated machining product and at that time our own manually built models so that's the only two results that we have. So due to the lack of samples or the lack of results. So we're not sure if you know that, uh, automated machine learning product is reliable, but the accuracy is good.	TTE

	And for how do we measure it, we just compare the automated product in the market with our own results which is manually done.	
I5-29	You said the results were pretty good. So how would you compare them with your manual models? And regarding the metrics measuring accuracy and rapidity, are they the same for manual and automated machine learning models?	
I5-30	yeah, so what we are doing is we ask the automated machine learning product to give us the same results based on the same metric. So for example, the accuracy right? So the we want the automated machine learning model on the market to give us some accuracy results. And then we'll compare that accuracy with our own manually built models accuracy. And the thing is for example that automated machine learning models results is, as far as I remember, actually have a big difference. Yeah, they actually have a big difference between the automated machine learning model and our manually built machine learning models so then we're confused. You know, in this way since we didn't find another solution. It's not because it that there is no third automated machine learning models existing on the market. It's also because trying to learn that alternative automated machine learning product, take time, right? So we didn't find a third one on the market, so there's only two results, and they're different you know, in in some degree, and it's actually pretty big, so then we get confused so we don't know which one Should we trust So yeah.	TTE, TPBB, MISC
I5-31	Your manually built model, does it include automated machine learning?	
I5-32	Yeah, it's more like a semi-automated machine learning model. Some parts are already automated, but some parts may need to do the transformations and stuff, yeah.	
I5-33	From the entire pipeline, which parts are being emphasised with automation? ETL, model selection, hyperparameter selection or other parts?	
I5-34	Yeah let me see. Uh, so we automated everything up to when the model is built and after that when we need to deploy the models to others, that's where we met some challenges so that's why we used the product on market. So in terms of processing, it's the model deployment stage that we need some help from the market.	TPBB, MISC
I5-35	What were the perceived benefits with the automated solution that you tried using?	

I5-36	Yeah, so the benefits of our model is that since it's just manually built we can see the skeletons in between the stages and also the network and each slices of this process. So I think the benefits include getting more information about the systems, but with the automated it's fully automated learning product on the market. We just give it the data and then they give us the results but we sort of have no idea what's happening between, so that's one of the things I think the manually built systems has as a benefit but I think if later on, the automated machine learning systems on the market can give the user some degree of freedom to look into the middle of the network that will be a better approach, yeah	TTE, MISC
I5-37	So between your solution and the commercial ones is there a tradeoff between the flexibility in terms of what you can do, and the explainability of the results versus convenience of just giving the input and getting the results back?	
I5-38	To me I think getting results is not like very difficult things to reach right, but it depends on if the result is a is a thoroughly good results or this is just a, you know some results from some Easy work, right? So I think we need to provide a results that is robust that and thoroughly tested so that that's what I think we should give priority.	MIS
I5-39	The results from the commercial automated machine learning system, when compared to your system, do you think they are promising enough to be tried not only in academic context but in industrial contexts, like your health industry? Is it good enough?	
I5-40	To be honest, I would like to trust it right but I mean the automated machine learning model we use from the media is being tested by tons of new media engineers and related people, so yeah, I would like to trust the idea, but it's like this: the results for that automated machine learning model If that results is close to your manually built results Then it will be a very good more like improvements or like it will. It will encourage you, right? Because you think “oh so. Our result is very close to the alternative learning result” but you know if the results are different, then we might think that as a disruptor or something so. We might question our approach right because if we trust media a lot, that must means our own models have some something wrong, right? But that also means we might need to pivot a lot of our previous work so in this case it's a little bit hard to choose. I mean, we would like to trust the automated learning machine learning product especially since it's by NVIDIA, right? It's also a very promising company. But it it's just like we also don't want to, you know, admit that our work like Has some fundamental failure or something. So yeah, it's hard to say, yeah.	TTE, TPBB

I5-41	From your experience, Can results and potential shown by the by an ultimate machine learning solution influence adoption in organizations? In your case was it good enough that you considered to actively use automated machine learning?	
I5-42	What we are doing is we're sort of propose some innovative, like new models that we're using in our model, whilst automated machine learning is limited to preprogrammed models so there might be some differences on the results, but overall I think yeah, the automated machine learning models will give us good results and it can be used In the in the decisions or you know the commercial yeah.	TTE
I5-43	Compared to traditional machine learning, how much data can an ultimate machine learning solution handle?	
I5-44	Oh OK, that's based on the data preprocessing stage of the automated machine learning model. I think the automated machine learning models might have a benefit on handling big data because the automated machine learning systems if it's, you know provided by a company or something the data can be in the company's cloud server where for example, if you have millions of rows of data or something it might get very big in terms of the size, right? So the cloud server can actually handle that and then they also can use the cloud computing using for example, the GPU from server farm, right? So they can have more memory to handle those big data versus if it's just like a manually built data model running in our local network, which has less capacity for handling big data. So yeah, in in that case I think the automated machine learning models can handle big data better than our manually built models.	
I5-45	The data that you've been using in machine learning projects, have you utilized the data fully? Or do you? Or was it just a limited utilization based on the limited development?	
I5-46	Uh, yeah, the data. I think we didn't use all of the data well. There are like two things in common, so fully. It can be. For example, did we use all of the patients right? In that case, yes, we use all of the patients, but did we use all of the patients details, right? So for example, each patient might have different columns of data, right? So in that case we didn't use all of the columns of the data, we just use some of them and that might be the limitation. It's mainly because some columns are letters or words, not numbers, so it's hard to convert that into numbers which can be feed into the machine learning systems, but ultimately what we can do is we can do some word coding maybe change the word numbers and then send them to the machine learning models, and that's what we're trying to do in next step.	MIS

I5-47	So the solutions that you've been working on are mostly focused on numerical data.	
I5-48	Yes, or we change some word. For example cancer stages, right? 1234 we change that to numerical data and then feed it through the Machine learning systems.	
I5-49	Can you elaborate on the factor of explainability of the results of the automated machine learning. Do you, do you deem it as a challenge or have you managed to tackle that issue well?	
I5-50	The automated machine learning systems we use will just give us some results like accuracy or like the mean square error, right? But it didn't give us anything related to the insight Like some of the insights or the factors that leads to solutions. So in that case I think this is one thing that automated learning systems can try to improve and I think in the near future will have these features. For example, they will have a grid which can show some insights or they can do some like principal component analysis to basically Shrink down the dimensions of the data to give us some representative factors that affect the patients or the things right so?	TTE
I5-51	Do you think that automated machine learning can be used in order to bring out a more of the data potential within organizations? Do you think that they will yield from it?	
I5-52	Well, I think if the automated machine learning technology is getting matured then you know any company that can pay the money will probably lean to use it right because right now, machine learning is a useful tool that can be applying to almost all kinds of aspects, right? we've seen that being used on like Mechanical Engineers and my area which is the medical area. So you know, as long as this technology is getting is getting robust enough and also the price is affordable then companies might rather than asking people and employee to do some investigations on the market, they just collect the data from the user and then throw that data to the automated machine learning models and they can get results back. So and it's quick Right, maybe it will just take one afternoon or a few days. They can use their results and this is a very game changing stuff.	TTE
I5-53	And is there like a significant factor that affects the decision of organizations to adopt machine learning. You mentioned finances is one of them.	
I5-54	Yeah, I think the big factor is how reliable or maybe one thing one solutions to this is. They can compare the results between different automated machine learning systems to conquer that.	TTE

I5-55	when you talk about adopting automated machine learning by organizations you seem to be focused on that, auto machine learning is going to be a commercial product, that organizations are going to purchase mostly and not develop by themselves.	
I5-56	yeah, I think, in the future, that will more becoming like a commercial product since well, it's easy to use. Basically, you don't need to, for example, have a machine learning degree to actually use it, so you can just click on some buttons. It's a little bit like, you know, paid websites builders. Later on, I think automated machine learning system might just become another website builder or something so yeah.	
I5-57	Do you see any challenges with coming to that stage?	
I5-58	Yeah so I mean the main challenge is just like you know the dream is sweet but to achieve that sweet dream we need do a lot of work in the background. So it's like because it's like user friendly, right? So we need to sort of set up the user interface part with the users right and that actually my have my generates a lot of bugs that need to be taken care of and also in terms of training the models right? We how do we make sure the automated machining system is doing the correct job and that also needs to be verified and the process also needs to be verified so that's like the main challenges. And yeah I think that's the two things, Yep.	MIS
I5-59	If an organization is to acquire or adopt the automated machine learning solution, what do they require in terms of software and hardware or IT infrastructure?	
I5-60	like I said earlier if the automated machine learning systems is running in the cloud, the company trying to adopt it does not need to have a lot of GPUs or a lot of you know computers to do the trainings or to use that system. They just need a good connection I guess so they can just send their data to the Alex server and then the cloud computing can just take care of everything.	TINF
I5-61	That is a commercial part, would there be differences for in House solutions?	
I5-62	Yeah then, based on how big your data is, you might encounter some difficulties right? Because for example hardware you need enough memory to keep your data's so that the machine learning model can train right? So and for example, the image we are talking about earlier, for just one patient image might just be several megabytes, right? So in our case we're dealing with, for example 1000 patients and it's already getting like 60 or 70 gigabytes, right? So with like 1000 patients you already need that big space to just save that images. So yeah, you need large hard drive. And also when	TINF, TDA, TPBB, TTR

	you are trying to feed the data into the machine learning models, we usually require a good GPU to process the data and train the models and it can actually cost a tons of money to get a very big GPU memory to do the training, but usually it's just like 8 gigabytes or something, so you need to do like, pipelining, right? So you feed 8 Gigabytes 1st and then another 8 gigabytes and so on. So that's also another limitation and software wise you need to get familiar with programming languages like Python which is usually the most popular one or R for statistical people. You also need to <u>have some background of the software</u> to do the automated machine learning.	
I5-63	So, if the resources are not available or accessible for an organization it might lean towards adopting a more commercial solution rather than an inhouse one?	
I5-64	yeah.	
I5-65	Are there any other differences between the commercial one and the in-house one that you would like to bring out?	
I5-66	Yeah, so the in-house one might also have a little bit downside of sharing the results, because with commercial, there's a platform, right? So once you get the results, you can just notify everybody else and then everybody else can just build in from where you are. When you're in house, although there are tools that help you to share the results to others it might <u>take like several more steps</u> to achieve that for the in-house solutions, yeah?	TPBB
I5-67	What is the necessary level of readiness prior to deciding even to adopt an automated machine Learning for an organization?	
I5-68	Yeah, so you need to have some idea about what the machine learning is doing. You don't want to just apply automated machine learning models on something where you don't know what is in that black box, right so? because for example the outcome model might just give you accuracy, but some other machine learning models might give you the outcome as error, so if you don't know anything about it you might just have some results but you don't know what to do with the results, but if you have some basic idea about what this automated machine learning is doing and you know what is going in and what is going out, it <u>should be easy to just start using this automated machine learning models.</u>	TTR
I5-69	As someone who is involved in machine learning research how do you think the ongoing research is working to bridge the gap between	

	how easy it is to use AutoML tools right now versus how they should be used?	
I5-70	It is going in the right directions and it's moving pretty fast. When I did the search on automated machine learning for this interview, I found some platforms that can do automated machine learning but I don't know how robust they are but that means some companies already used this as a commercial product to attract different organizations to use their product. So I think later on the trend will just be how well or robust this automated machine learning model is being built and how that's being verified. That's the next important stage.	AUTOML
I5-71	Do you consider automated machine learning as an incremental or a disruptive addition?	
I5-72	Yeah I think depends on the context. In our in our project it looks like to be a little bit disruptive because the results are different by some degree. So and it actually turns us back to scan our work to see if there's anything that is wrong But overall I think the addition will be incremental.	AUTOML
I5-73	Were there any unexpected benefits or challenges with developing and using the automated machine learning?	
I5-74	Not that I can remember	
I5-75	OK then we are jumping into the organizational context.	
I5-76	From an organizational perspective, what kind of resources are required? Maybe some expertise or maybe a specific structure, or in terms of strategy.	
I5-77	Yeah, I think an important infrastructure is having a verifying department. Although I said earlier automated machine learning model is incremental we still need to question its reliability. So organizations can have like a verifying team to do some verifications on the results and also there should be like a management department to basically utilize all of the different results that is coming from different automated machine learning models, because at the end of the day we need to pick one model or we what we can do is hybrid. You know to combine two or three results of the automated machine learning and that depends on how the management is going to take care of this.	OS, TTR
I5-78	Do you deem an automated machine learning initiative as costly? Does it require a lot of financial risk?	

I5-79	Yeah, based on how well mature that product is. So it's just like you know when the cell phone comes to the market at the at the early stage, right? It's pretty expensive, but when the technology is getting better and better or the cost goes down dramatically, right? So right now you can just buy a cell phone cheaply unlike early times. Also there are competitors right in the market, right? So if this is a monopoly situation, then yeah you might need to a lot of financial assistance to acquire the product, but as I said earlier this is a fast moving stage, so everybody wants to jump into this market and then share the cake right? So yeah, I guess there are more companies joining this. Thus prices will go down. It's basically just writing some code to some stages, at the back end, right? so once you get that stage, you bundle this code and then send it to everywhere. So then it's not that cost.	OS, OSL
I5-80	Do you think that size of organizations encourages or discourage the decision of adopting automated machine learning?	
I5-81	Yeah, I think in some degree it does because if you have a big size of the organizations right, you might have more manpower to like to verify or manage the results of the ultimate machine learning models. You might even have the manpower to do the manual Machine learning decisions right? So you will have a lot of information to learn from compared to if you just had a little science organizations like just two or three people in the extreme way. For example, I think the only choice you can do is just grab a cheap alternative machine learning model online, use it and then take the results. You cannot do anything else so because it will be time and money consuming So in this case you need to try to find some objective ways to. Verify your verified results, so yeah.	OS
I5-82	Could you describe an ideal team for adopting automated machine learning in an organization? For example cross functional teams	
I5-83	Yeah, I think so like I mentioned earlier, it's a good to have two or three teams just trying different automated machine learning models and then they can compare the results later. For this current stage, because the automated machine learning model is still not that mature enough so it's good to have another team to do the traditional approach and maybe another team to verify the results of the automated division models and another team to manage all of these results so then you can have the best solutions when at the at the very final stage.	OS
I5-84	Do you consider management support a vital factor when it comes to adopting or implementing automated machine learning?	

I5-85	Yeah, so from my own perspective, since I just report to my professor and she is basically The top boss, right? So this is a single stage management and you know if we think about this whole university they have a very slack and loose top management structure right? Because the Dean of the college Engineering just give the money to the chair of our department and the Chair of the Department and professors actually also try to find their own fundings by writing the proposals to different organizations like science, science organizations in The US, so since universities emphasize on the diversity we might have different kinds of projects, so I think this is so. So then for the university it doesn't require really good strict Top management support But if it's a company you have ultimate goal and the top management support is important because You need a someone at the top to make the directions right to where we lead the company and in that sense a top management support can basically just combine the different manpower, Different teams like I mentioned in the companies to all go to the same directions, which can speed up the process and can make the company successful.	OT, OSL, OS
I5-86	What is the general purpose with developing automated machine learning initiatives? Is it to provide Findings and results to academia? Or do you want to provide solutions that might be implemented later in industries or different domains?	
I5-87	The ultimate goal is to help the patients to Have a better quality of life. So what we're trying to do is just using the machine learnings technologies to help the doctors To digest and detect some situations at the early stage rather than find that in later stages.	MIS
I5-88	When it comes to automated machine learning, would you say the executives and top management, in your industry and generally speaking, are aware of its benefits and potential? Are they communicated properly?	
I5-89	The top people might not realize this. They might not have this recognition, but I think they must have some technical guys, that trying to explain to them what's going on, right? So I guess that can help them to realize what's happening in the in the automated machine learning part.	TO
I5-90	When it comes to simple flat organization, would you say that your top management is supporting you directly and how would you describe that support? Whether there's a financial or other kind of support.	
I5-91	From my own perspective it's a bit different. It's more like the professor proposes some projects and will just send this proposal to science organisations, for example the National Science Foundations	TO, OSL

	in the US or the national execution of house Something like that, and they just give you the money for three or five years and then you don't need to worry about the finance part you. You just use that funding to your work.	
I5-92	Was she was encouraging you to try an experiment with the technology and see what you get out of that? Was she following up?	
I5-93	Yeah, this is another thing that is unlike the companies, right? So we need to take a think about different kinds of factors like limiting factors. So in the university we're encouraged to try as much I we can with automated machine systems to try different models but the ultimate goal is to find a good way to Get some good results so that we can help the patients to have the better lives.	TO
I5-94	What motivated you to experiment and use automated machine learning?	
I5-95	Yeah, so one of the motivations Of that is just we can use it to compare its results with ours to see if the results are close and if so then we can just use the automatic learning machine learning systems to speed up our process like comparing different models or achieve some faster results and It will speed up the process of their research.	MIS, TPBB
I5-96	Who brought the idea of using automated machine learning? your manager?	
I5-97	Well, it is mainly the management (professor) that comes with the idea and it's because. I Am doing what the professors ask me to do but the professor is basically reading different papers and attending different conferences she might know what's the trend right now And automated machine learning is definitely one thing we can try in the research.	OC
I5-98	When your professor asked you to use AutoML, was there some sort of discussion about it?	
I5-99	Yeah, we discuss and list different kinds of possible approaches and based on what state we're on and select the most related approach with the tools.	OT
I5-100	In the projects you're doing and with automated machine learning, do you have full freedom to do as you deem like most efficient and they will give better best results? Or are you managed by a contact person from the organization which you have a collaboration with?	
I5-101	There's a contact person which like the leaders of the teams which is a professor for example, and we have a weekly meeting in which he	OT

	gives us the directions of the what we're going to do for this week and in terms of how we are doing, it's our freedom to pick so we just try different solutions to solve this problem.	
I5-102	You Mention that your professor is the one that gives the suggestions for projects, but does it happen in the opposite direction? Do organizations contact you like “we want to do this. Can you help us”?	
I5-103	Yeah, that's the case, so some other universities actually are willing to train their data on our semi automated machine Models and then we also collaborated one of the universities in South Korea who use their patients records on our models to see how the results is. So and we always say in the machine learning area the more the data, the better the results so that that means if there are more organisations or companies join into this platform the model will just become better and better. For example, one thing we found is earlier is that our models is doing very well in like Americans But when it comes to South Korea, who are Asian they have slightly differences In in the patients organs or something so and their images are slightly different. So our model at first was not doing very good on their data, but then we did some improvements and now the difference is getting closer.	MIS
I5-104	You're mainly working with visual data?	
I5-105	Yes, it's basically just some CT images for the patients lung cancer or something so.	
I5-106	Have you tried to develop an automated pipeline for another type of data?	
I5-107	The other project I'm working on. So in that one we're doing some time series data from the patients rather than images where everything is like in pixels. The other project I'm working on is time series data, where it's like at this beginning of the treatment at one week of the treatment at the second week of the treatment, the patients will self reported their feelings on some side effects Like you know, pain or vomiting or like diarrhea or something like that from a scale from zero to 10 to see like in the The process of the treatment and after the treatments, how their feelings is changing right so that data is actually a time series data and Currently I'm working on that project, so yeah, it's Different from the images.	
I5-108	OK, we can then go further to the external environment context.	

I5-109	Would you say utilizing automated machine learning would provide some sort of competitive advantage to organization in comparison to their peers?	
I5-110	If we assume this automated machine learning model is a good one Definitely it will. It will create a competitive advantage and mainly because You can think of that as somebody already tested or trained a lot of models or train a lot of data on some model So you have already grabbed the resources from so many people right? So you already have a very big sample space, So in in that sense, that's a big advantage against your competitors who might only their local sample size right? So in terms of the sample size or in terms of the information size, you have a big advantage versus your competitors. If it is an automated machine learning.	EC
I5-111	Do you think that there might be any governmental regulations that might prohibit a smooth implementation from an organization?	
I5-112	Yeah, one of the big challenge is the privacy right? Because we're talking about patients information. The reason we're building this federated learning systems is to try to avoid privacy issues, but privacy will Limit us from collecting user information and even also sharing information with others so and that might be Where the regulations comes from. For example, some automated machine learning models might accidentally use some users data that is not allowed to share right? And training without all users' data, well that that's going to be time consuming and another thing I could think of is that like to what degree do you want to use this automated machine learning models, right? For example, if you're a lawyer, right? You're in a court, How can you just say this criminal has committed a crime Based on some automated machine learning systems based on some big data, right? The computer is telling you have a crime, right? But it's the judge who is going to tell you, you have a crime! so they do have some moral issues in there and that might lead to regulations for implementing the automated machine learning systems, yeah.	TPBB, ER
I5-113	Would you say there are different considerations, regulations between regular and auto machine learning?	
I5-114	So, like I said earlier, the regular machine learning approach will give you more flexibility, freedoms on how you approach this question. So for example You can manually just throw out some images or some data that is user sensitive, right? Versus the automated machine Learning which might just grab everything. Well, you can definitely write some code to reject some right, but so there might accidentally be some data that is being processed in because it's automated assistance without a very good verification mechanisms it may just accidentally bringing something that you	TPBB

	don't want versus the regular ones, you're doing everything by yourself and it's easy to just going back and throw something else, right so You will have more control of the systems, right so In the current stage where we just see some companies publish their automated machine learning systems, I think this is something we definitely need to worry about or that's the main differences. But when the time goes on, when the automated machine learning system is developed better and better At some point This differences can be eliminated because it's already good enough it can reject Everything we want. It can be verified very well and up to that stage. You know there's like this is the pivot points, right? We can just start to trust the computers, but not like fully trust it.	
I5-115	For organizations adopting automated machine learning should they rely on commercial or focus on developing in-house solutions?	
I5-116	So that’s based on the vendor if it’s just some company that can be trusted, right? Yeah, they can rely on the commercial one, and also it's based on if the company is has a very good financial ability or not, right? So if they have financial ability, they can have their own research team to do some in-house automated machine learnings and then they can compare the results. Or but if they don’t and actually this is mostly the cases right? So if it turns out that if the commercial one is really successful enough and is really developed good enough. Then everybody might just pay some monthly payment right and then to just ask the commercial service to basically service them, yeah. Because we see for example The cloud service, for example, right now it's just the Google Cloud services Google Drive, right? Amazon and Microsoft. It's just like the three of them, right? So most for most of the company they just use like the Amazon Cloud services or the Google Cloud services to be the company servers.	EIS
I5-117	What impact will support from commercial solutions vendors have on the utilization of automated machine learning in organizations?	
I5-118	Yeah, I mean, this support is definitely a must. It is very important because without the vendor support the Client might don't know what they're doing when they encounter some difficulties, so they might just seek for Technical Support To solve their problems. So in that case the vendor support is very important. The vendor support team needs to have a good background for sure and also need to know what the client area is so they then they can sort of connect the client to this existing automated machine learning systems which can lower you know the entry bar of the clients which can allow the automated machine learning system to be used more broadly than just to some in some specific background stuff. if the automated machine learning systems is already to a very mature stage, then it	EIS

	doesn't require the user to have a lot of backgrounds on machine learning or even on computers.	
I5-119	Do you believe that a vendor dependent future for automated machine learning is better suited for the technology development and organizations so that they can adapt?	
I5-120	I think so, yeah.	
I5-121	From your point of view, could you summarize the benefits, challenges and enablers for automated machine learning?	
I5-122	The advantage is definitely you saves time, automated machine learning will speed up the process of whatever decisions you want to make. The challenges include whether the models are Trustable enough. The enablers could be a good environment for this innovation. It's I mean it has a very good demand, which I think it does, right? Also it depends on if the companies who are developing this automated or machine learning models. If they have in talented employees or engineers to build all of these things and also it needs to have a good community or society to maybe report back the bugs and I mean the community is the core you know to make the company improve, right so It's like it should have a good like discussion mechanism between the company who developed these models and the society or the community who uses automated machine learning. Also the environment of the law should be open and pretty flexible to this to development. they shouldn't have, you know, tons of regulations on not using AutoML on some levels because it will decrease the demands right? And it will make it difficult for companies achieve what they're trying to do so and also an open and cooperative atmosphere. These will be the enablers, yeah?	TPBB, MIS
I5-123	Would you like to add anything? Or do you think that we missed anything that we should have mentioned in terms of automated machine learning and factors that affect the adoption?	
I5-124	This interview pretty much covered every aspect of the opinion on this topic.	
I5-125	Thank you very much. We reached the end of the interview.	

Appendix 8: Interview Transcript – I6

Orgnization: Three UK

Interviewee: Georgios Yorg or Interviewee 6 (I6).

Title: Chief Data Science Officer

Row	Transcript	Codes
I6-1	Do you wish to remain anonymous?	
I6-2	No, that's fine.	
I6-3	What is your background and education?	
I6-4	So I'm a computer scientist. I guess that's what you would call me. I studied computer science at Brunel University in the UK lots of years ago. I after I finished with my academic career, I started working in computer games. And one of my first job was in computer games and particularly board computer games like chess and backgammon and go those sorts of stuff. So, I was into neural networks and artificial intelligence from almost my first job. I spent the next 25 years working with artificial intelligence and machine learning, so I'm a very early adopter of data science. Let's call it machine learning. I've been in three UK, my title there is a chief data science officer. I have been with them for the last year. Before that I've held roles with the Ambassador Theatre group, Teradata, British Cars. So mainly companies that have to do a lot of servicing, you know for services to customers and so on and. Most of the applications of my machine learning are related to customers.	
I6-5	Can you describe your organization?	
I6-6	As you probably know from 3 UK is a telecommunications provider. But we can cover that later I think.	
I6-7	Can you describe the different roles and responsibilities within your organization?	
I6-8	So in three UK, like I said, I joined as chief Data Science officer. So my role is to make sure that the business gets the most value out of its data by using machine learning and data science in general and artificial intelligence subsequently. Before myself, the application of machine learning was the typical stuff you would expect from a service organization like building propensity models, that sort of stuff, but with me coming in we're looking into applying machine learning and artificial intelligence in almost every decisioning aspect of the business. So that's the vision. My role is to organize all this is to set up the infrastructure, hire the	TTR

	team, upskill existing personnel, make sure that everything happens basically.	
I6-9	What is the size of your team?	
I6-10	And for the size of my team, to cheat on the next question is currently 8 people, but I also have several people within the business which we call champion on data scientists who are also have dotted lines to into me.	TTR
I6-11	Does your organization in any capacity use AutoML or machine learning? and for how long and to what extent? and if not, fully they need at what stages is the machine workflow automated?	
I6-12	We are using machine learning for sure and I'll answer this first and then we can go back to the AutoML. We've been using machine learning, for a while, even before I joined, they were using some aspects of machine learning as I mentioned and I believe it goes back to almost 10 years. That they started deploying these kind of models and we're talking about basic statistical models that model a behavior of a customer and then based on the model scores that we get from the customer, they apply different outcomes and different treatments to these customers. We have moved quite a bit since I joined in. Like I said, trying to utilize machine learning almost everywhere that will make the biggest value and where we can. In terms of AutoML you may need to be more specific. There are multiple different ways you can say what is AutoML. So we have algorithms that do build models themselves. So rather than somebody building the model every day or whatever, we have algorithms that build models and deploy them and score some data and we get back the scores and so on. We don't utilize heavily. There are some is in aspects of AutoML with teams using things like grid search in SAS because SAS is the main machine learning tool that the business had been using before I joined. We are now moving to Python, so there are some elements, but we we're not using it heavily. We are using it and yeah, we're we are planning to use a lot.	AUTOML, TTR
I6-13	You kind of answered it, but do you plan on using more AutoML as well?	
I6-14	We are deploying a tool called Alteryx Designer in the business and it has it has some elements of AutoML that comes with it, but again, it's quite basic, so given some data it will build some models and it will give you some score and we do have access actually to things like data bricks.	TTR
I6-15	In what way are you using the current amount of AutoML that you are using?	
I6-16	So AutoML we would probably use for citizen data scientists. I don't know if you're familiar with this term, Citizen data scientist is a data scientist who works within the business. Their main role is not a data scientist, but it's for example a finance controller or it may be like a	AUTOML, TPBB

	fraud analyst or something like that, but they occasionally need to build models to help them with their job themselves. So rather than coming to a centralized team and asking them to build models they may want to have a tool that would help them create some machine learning algorithm to learn from something. and I view it being used there or being used as a, let's call it a quick and dirty approach currently, because the issue that I see personally with AutoML is that it depends a lot on the data you feed to it, and you're if you're not careful, it tends to basically focus on what we call self-fulfilling variables. Variables that basically are not realistic when you deploy the model, and I think we can talk about it a bit later so that I don't take too much time on this question. But mainly I would see AutoML being used by citizen data scientists or full-time data scientists when they try to do something quick and then tune it up. So, use AutoML to come to a quick approach and then you know, take this approach and tune it further.	
I6-17	Do you have any plans to have citizen data scientists in your organization?	
I6-18	We already have some. We have a couple, yeah.	AUTOM L
I6-19	And are they able to use it successfully?	
I6-20	They don't have the tool yet. we're rolling out Alteryx. Once we roll out Alteryx which actually should be soon, at the end of October, the people should be able to use AutoML.	AUTOM L
I6-21	How will AutoML solutions be managed? By whom?	
I6-22	So Alteryx comes with a server solution, so if you want to publish your ML and make it run in a schedule, it has to go through that server and it has to be approved by us, so people will be able to promote things to production and then we'll be able to review them and say, yeah, this is good for consumption, check it and then it comes into production like that. So it is like you know, whenever somebody puts something in production, it needs to be peer reviewed. So yeah, it's it would be managed like any other ML.	MSC
I6-23	From what you are saying, it is going to be jointly managed by your team and the citizen data scientist?	
I6-24	Yes. (Referring to the citizens and the DS team)	
I6-25	So AutoML is not used only by the DS team, but other teams within the organization?	
I6-26	We have people use them in the past as well. I would think and a lot of them basically are very interested in this in this feature, yeah? Like I said, there is a some AutoML functionality in SAS which is called grid search, but it's really the earliest form of AutoML and some of the data scientists have used it. But in the end, what they do is they use the AutoML, then they will see what model it creates, what performs best almost use it as a proof of concept to choose the	AUTOM L,TPBB

	solution. Now usually a good data scientists would know this stuff beforehand, but it's easier to do it this way and then take the model and work further on it.	
I6-27	Are you familiar with hyperparameter tuning?	
I6-28	Ah yes, as a concept.	
I6-29	Yeah so AutoML will let you pick between models model types right? then once you even focus on specific model there again so many different combinations to try to see what's best but I guess some AutoML functions already do that these days so yes.	AUTOML, TPBB
I6-30	Could you also phrase it as democratizing the data science responsibility?	
I6-31	Yeah, exactly and the thing about it though is it needs to be coming with proper data preparation because the dangerous thing about AutoML is it may produce if your data is dodgy, it will produce dodgy models and I have seen people being burned by dodgy models in the past. You know, implementing something that is really nothing basically, and sometimes even negative	TPBB
I6-32	How would you verify the reliability and accuracy of results that are produced by AutoML?	
I6-33	Uh, out of sample testing always. So basically always save data that the model hasn't seen during its training, preferably non contemporary data either. So train the model in a different area of time and then score it, test it on a sample in a different time period that it corresponds to if time is involved into the thing. Or save copies of production data just for testing so that you can test the models on this production data only, just to make sure that when you were training the model you didn't have these elements of self fulfilled variables and so on.	TTE
I6-34	What kind of measures can be applied?	
I6-35	The same as all models you know, it depends on the model, right? I mean if you're doing a regression or you're doing classification it depends on what the model you're using e.g. how many true positives you have versus false positives? What percentage of the correct answers there are? There are many different ways, but I would use exactly the same measures that they use in others but compare the results that I got into the test on onto the actual out of sample group.	TTE
I6-36	When it comes to these measures which you are applying out, are they very technical? Can normal citizen data scientist understand them?	
I6-37	The truth matrix for binary models and classification models is quite simple to understand because if you have a binary model you have, for example of the correct answers, we have a percentage so you can say 70% of the answers were correct, which anyone can understand, right? Right answers 70% of the times, but then it's actually quite important to understand how it was wrong. Was it wrong when it was predicting yes, or was it wrong in predicting no? So it's a truth matrix. It's a very	TPBB

	simple way of showing off classification things, which is the majority of the models that we're building. In terms of forecasting models, models that predict the number, again, we provide a narrow margin and we say your the forecast is 96% for example accurate or it's only it has an error margin of that. It's typical statistical stuff so. It is quite important for models to be easily explained and seeing how accurate they are.	
I6-38	So it is possible for simple cases, but would that be applicable to like the other scenarios as well?	
I6-39	It depends on you know what the use case I guess but for the AutoML use cases, which is usually classification and regression, I would think the measures are usually easy to apply. I'm pretty sure there's standard measures that people use these days. You know the truth matrix and RMS error for example.	TPBB, TTE
I6-40	Are you saying that for the scenarios where AutoML is currently being utilized, the measures are very simple to interpret?	
I6-41	Yes	TTE
I6-42	When it comes to AutoML performance, does it offer reasonable performance? How was it like?	
I6-43	The performance. Well I cannot say yet. We haven't had a solid use case where we said that… There is one use case actually from a guy in finance, but I'm not sure whether he used AutoML or not. so I think he's also using RMS because it was a forecasting thing.. Uh.. the performance was OK. I think he got better performance than not having a model, but that's the thing that, if you don't have a model in place versus having a model place, you'll always get a better performance, right? But this always depends on the use case. There's some areas that you can apply machine learning and get nothing. You don't really know what you know what the value is going to be, and it is the data that has the value rather than the algorithm itself. So in in a lot of cases you know it will help people understand the data better without them because they can think do things like segmentations for example. They can do things like you know the basic stuff .. They can segment their customer base to understand different behaviors which they cannot do without AutoML. You know it requires a lot more segmentation is a lot more integrated …Uhm, they can forecast the stuff if they want to estimate things that you know that they have, you know for the deliveries done….and again, this is much better than doing some kind of average. Or they can you know they can They can figure out the specific behaviors who is likely to perform something, which again they don't have anything, any information, they just go randomly really. So AutoML will always be an improvement over do nothing. Now I don't have exact numbers though, because like I said, there's one guy that already deployed it and the other stuff was processed after	TPBB

	AutoML was picked and I don't really remember. You know, I don't know off the top of my head how much better it was. I don't know off the top of my head how much better it was but I can give you an indication. We have a use case where we use a kind of AutoML. Let's say we use a process that builds models. It builds about 15,000 models a day and it uses them to predict something. And in this use case, originally we had naive modeling, so the forecast was based on a moving average of the value that we were trying to forecast, so that's a NAIVE modeling. You say “I expect next week to have the same sales as I had my moving average over the last three months”. And we compared the auto AML versus the naïve forecasts and it reduced even on the most basic stuff because we're still developing this thing. For example within feed seasonality variables we got a 25% improvement in accuracy versus the thing. And it's actually quite important, because this algorithm is used in order to understand whether there are anomalies on the way we charge or being charged by third parties. So in order to understand the anomalies, you understand what's normal, so we're using these models to understand what is normal and when there is a deviation from the actual to the normal we flag it to the business to investigate. So we used AutoML with that and we managed to reduce the number of times that there were false positives 25% which is a big number and it will improve things better if we give it more data, that's the thing. So yeah, does this answer the question?	
I6-44	The AutoML solution that you just mentioned, is it mainly about model creation or model selection?	
I6-45	Both, the model selection and method selection. But the method selection is quite limited. It's choosing between Elastic Net, cross validated Elastic Net, Poisson regression, linear regression and MLPs (multilayer perceptrons) as well, so it is only this fact because it's 15,000 models guys! It takes a while so it chooses between one of these five techniques and deploys the one that has the least error, the smallest error. But the data is very well controlled there, so it's not like the aspect of oh, I have some data I'm gonna throw some AutoML with it. It's just that there is an algorithm that chooses which model you know build through the models, choose which one is best, apply some hyperparameter tuning anyway while it's building the models and then automatically deploys the model.	AUTOML, TDA
I6-46	OK, I was actually going to ask about the about the data processing and before but you just answered that it is quite structured	
I6-47	Yeah, the data is quite structured in this case.	TDA
I6-48	How are the results from your AutoML system interpreted by the people in the organization?	
I6-49	Like any model, I guess. There are lots of different ways that people can interpret them, but we use visualization, obviously. In that project I just mentioned it automatically flags things up. So, they don't even	TTE

	know that it's there, it's just that they do get the score and they say, for example, that we expect it to have that but we're having that now and that would mean that we're losing that much money, so it's a yeah, uhm, it's a difficult question to answer. There are so many different results.	
I6-50	The results that you generate from your AutoML solution, do they affect the process of adoption of AutoML?	
I6-51	I think it will. It hasn't yet, but it will once we have more seats in data scientists and they can use more AutoML or even normal ML, it will affect the adoption a lot. People do get jealous about this finance guy then I do have people that come in and say “OK how come finance have this have capability and we don't?” so we're working it has affected yeah.	TTE, MIS
I6-52	How do the citizens DS feel about AutoML in terms of its results when they are creating on their own? Do they trust it?	
I6-53	Yeah, I trust the AutoML, we don't trust the data. So that's The thing is you almost always need someone to validate it. So we trust the process of building it, but we usually need an analyst to validate.	TTE
I6-54	How are the results from your AutoML system interpreted by people in the organization?	
I6-55	And a lot of times we have the business asking that the models need to built to make sense. And I guess that's part of question 13 (the question above) that you have there, so a lot of times the business may say alright, so how did the model decide that you know the number is 14, for example and you have to explain this. Sometimes you get away by not having to explain but a lot of times you have to explain. and that's a typical problem we have with neural networks in that, it's very difficult to explain. You know how a decision is made through the neural network. I mean, how do you tell people that you have like 4 nodes for example, and then the goes through sigmoid functions and you have all these weights? you can visualize it somehow, and you can tell them what's important or not, but it's difficult to explain, so there is a bit of mistrust in ML in general, not AutoML I would say. People who don't understand ML see it as magic. It's even trickier when AutoML is involved, because you know, you cannot explain how he did it, so you get less trust if that makes sense. While when you build your model manually, there is more trust, because you can usually explain it. But the good data scientist shouldn't have trouble explaining the outcome of an AutoML model.	TTE
I6-56	So do you consider your organization data driven?	
I6-57	It should be. It's not yet, but we're getting there. It's not data driven yet. There are lots of decisions that are being made based on gut instinct or very simple analysis. So we're not there yet, but it should be, and it wants to be. We have sponsorship from the CEO to become data driven. And we're going to get there because we do have the data as	TDA, OT

	well. It's that the irony is we have so much data; Telecoms organizations have more data on Google, apparently. So yeah, it's getting there, but it's not yet.	
I6-58	How much data does your organization collects or manage approximately?	
I6-59	Oh, I can give you a figure, 22 terabytes per day, so in a year we are talking about Petabyte. It's a lot of data and we could collect more, that's the thing.	TDA
I6-60	Should people be concerned about their privacy with organizations collecting so much data?	
I6-61	They should not worry that much because it's so much data, It's hard for us to do anything with it. Data ocean we're calling it, but yeah, the way we collect data anyway. We anonymize it so when we get data from our network back end, anything that can identify you gets obfuscated. If you think about it, a telecom company, we look at all the traffic from your mobile phone and by law we are expected to store this information for policing or whatever for some time. It's more than Google because Google will only see what you said, we have not only what you said but also what you browsed and everything.	TDA, ER
I6-62	Is the data collected internally? You mentioned having a back end network, is that an internal network?	
I6-63	Our cloud we're storing it to the cloud. So it is only accessible by us, obviously, but it's we're using cloud storage.	TINF
I6-64	How important is the data collection in your organization?	
I6-65	Very important, for multiple reasons. Like I said, it's we are contractually obligated by law to collect the data first. But also it's huge value for us because you know data is money these days. It is the new oil, isn't it? So yeah.	ER, TDA
I6-66	So to what extent is the data utilized? You mentioned that you have too much data.	
I6-67	So we have a lot of data and we are not utilizing it to its maximum extent. I would say we are only exploiting like maybe 10% of the value of our data, and that's probably a made-up number as well you know, because you don't know until you build the use case. But we do have, for example, a data monetization team that is looking at our data and creates data products and these data products are for example things like advertisers would come to us and say which area of the UK has the most traffic of affluent customers, and we can tell them because we aggregate stuff at high level and with mobile phones now you can see where people are going with their mobile and whether they have their mobile phone or not. So it's almost like Google and you know by customers subscribing to those services we can get this data aggregated up and sell it to third parties. Or we can use that data like I said to make decisions about organization.	TDA

	How do we roll out for us? Data and the network itself is the number one priority and you will see. I think there's a question later about the business priorities that we can go over later but it's underutilized and we're running a transformation project currently that will help us utilize it more by moving to the cloud like I said, you know because actually, this data was all in like third party and very difficult to access. So now we're getting more control of it.	
I6-68	What impact does AutoML have on the value generated from the data that is being used?	
I6-69	I won't say too much at the moment, but like I said the value of the data can be massive, because it's you know, it's much data in so many use cases. We have upwards of 40 use case candidates that we want to work in the next six months or so. AutoML is not part of those, so we haven't measured yet, but I expect it will be very valuable, because we cannot really think of everything. And when you have your citizen data scientists, they know the business better than the data scientist and they know the problems better than the data scientist and they have time sometimes because our data scientists don't have that much time you know, there's like them fully allocated to projects. So with AutoML, we expect our citizen data scientists to come up, create proof of concept using AutoML and then we can either keep them as AutoML or maybe deploy them even and develop them even further. But we don't have any solid the impact at the moment, but I definitely expect it to make more impact. You could consider the revenue assurance use cases, in which case it does have impact already.	TPBB
I6-70	Going by your current utilization estimates of 10%, and assuming successful AutoML utilization, how much improvement do you expect?	
I6-71	Like I said, 10% is very low. We want to go up to 50% or even more within the next year. AutoML I see it contributing an extra 5 or an extra another maybe 10% depending on how many users, but again it's a very wild guess. We do have some capable people in across the business that could be using ML and providing them with something like AutoML I think would definitely help them.	TPBB, TDA
I6-72	To what extent did that affect the decision to adopt AutoML? Was the potential for more utilization a major factor for why you decided to utilize?	
I6-73	Value is always a factor, right? I mean if there was no value we wouldn't be utilizing it. So I would say yes, but we don’t have solid evidence yet. We have anecdotal evidence, but we need more solid and within the next couple of months we should get the evidence that we need.	TDA
I6-74	You have an ocean of data, so was just the data volume a factor as well?	
I6-75	No, unfortunately it's not that. I think the volume of data probably goes against AutoML because to apply models to such a massive volume of	TDA, TTR

	data for example, our OSS data, which is our network sensors data, is so massive and it's quite narrow you cannot really just keep playing with it. You know you have to you have to go at it with something that almost you know that it's gonna work because, you know, it costs a lot to train models. All those things. So, it's more have to do the amount of users that we have in the business, we have 5000 employees and finance alone has like 100 analysts. I'm pretty sure these guys can make better decisions by using machine learning. So I think that's the main reason we want to use it.	
I6-76	What is required in terms of IT infrastructure to implement AutoML?	
I6-77	Uh, data connectivity is the number one requirement being able to connect the data to the compute. I know it sounds funny we have this 22 terabytes a day but we cannot access it most of the time because it's either behind the firewall for example, or because we run out of compute or because the compute itself doesn't connect to it, so you know to be able to deploy it you need first and foremost to be able to connect to the data that you're using and also I don't know how much auto data preparation… because a lot of times you need to prepare the data for the model, right? And, I know that a lot of some of the algorithms have some ways of preparing data, but you still need a person to prepare the data. To retrieve the data already prepared is considered as IT infrastructure. Then, uh, yeah But the main thing that the IT is needed is compute and connectivity of that compute to the data.	TINF
I6-78	So the data and the AutoML solution, will all be deployed in the cloud or there will be some servers that will have to be purchased?	
I6-79	So there is a Alteryx will be deployed on the cloud. Alteryx server would be on the cloud as well. Databricks, which is our preferred machine learning solution, is also in the cloud. But we do have data on Prem as well and we are talking about Solutions that help people push data from on Prem to the cloud so that it can be used for all sorts of stuff, not just the AutoML. Well, we're talking about BI in general but currently everything is planned to be on the cloud.	TINF
I6-80	So in terms of data and other kind of requirement, AutoML doesn't require anything new besides just renting new servers on the cloud that will run the automated solutions?	
I6-81	Yeah, I think we don't. We didn't really know need anything, you know?	TINF
I6-82	And in terms of cost requirements, would this be a significant?	
I6-83	So Alteryx it is quite a significant investment. Well, I don't know what you call significant. Do you want actual figures or whether we consider it significant or not? So let's, let's say let's say the Alteryx solution is We're not investing massive in terms of our revenue, right? So it's fraction of a percent of our revenue, so it's in the six digits. The Alteryx investment and Databricks are similar, so we're spending almost 7 digits on this capability, the compute capability. It's not just	OS

	AutoML though. It will give us a lot more capability. Just part of this capability is also AutoML. Six almost seven figures. There you go. Yeah, but it's not massive.	
I6-84		
I6-85	Did the IT infrastructure requirements affect the decision to adopt AutoML?	
I6-86	No, those are generic data requirements, so we have the same issues with BI and reporting for example.	TINF
I6-87	What is the required level of employee expertise and readiness necessary for adoption of AutoML?	
I6-88	They need to have some analytics background and some training to understand it since it’s a cloud product. It costs money to run a model, so they need to understand statistics, have an understanding of standard deviation and average, for example. They also need to understand their business. The big thing with AutoML is that it allows people that know the business but don’t necessarily have a machine learning background to create models, get quick indications of trends and so on. And of course, they need to have a budget as well.	TTR
I6-89	How prepared was your organization to adopt AutoML?	
I6-90	I don’t think it was prepared, mainly because of the infrastructure problems we had when moving to the cloud to make ourselves ready for AutoML. Before that we had lot of dispersed systems that were very difficult to connect. There was lots of data preparation needed to build any model. The models are very easy to do with autoM, but it’s not as easy to do the data prep with AutoML. You need people to join the data from multiple resources aggregated in a way that can be reused, and eventually also to deploy the AutoML because you need the format of data to be in a certain way. So, it’s not just about building models and interpreting the results. In order to keep using it going forward, you need to have machine learning engineers – AutoML engineers – who deploy it somewhere. We still have issues with connectivity to data and data preparation. *I think that’s 25 as well.* We address the issue by normalizing our data now, we’re creating something that’s called an event fabric, or data fabric, that presents the data in a way that’s suitable for AutoML. For example, we build AutoML models for a lot of customers. We prepare our data in a massive table that says, “this is our customer, and these are all the variables available for this customer.” We also keep a snapshot of it across time, showing what our customer looked like a year ago, six months ago and so on. That’s a lot of data stored because	TINF, TDA

	it’s so flat. Then we also have all these different events of when the customer needed support or made a complaint. This is perfect for AutoML because all you have to do is to tell it to find the customers who did what I want to predict and to find the customers who didn’t do that. Then we can see what the data looked like right before those events and build models. Once we have this in place it allows us to use AutoML reliably, because people don’t have to prepare data, it’s already in that flat file format. Or if they want to use recurrent neural networks then they can go and use the events themselves and all the events are in one place. We create APIs that present data to the users, so that when they want to apply AutoML or ML, they have a standardized, normalized data set. And when they come to deploy it, the same data will be calculated again, every day. This flat file exists for each customer every day. So that’s how we’re addressing the challenge of connectivity, bringing all the data from multiple sources into this big flat format – a virtual table that shows each customer, like an Excel spreadsheet with thousands of columns. It has unstructured data as well, some of the columns may be JSON datasets or could even have pictures. You can think of it as a feature space. When you build the model you have your feature space, which is all the candidate variables that your model can use. We prepare something that looks like a massive Excel spreadsheet. The data is stored in multiple places, but there is a mechanism that can find specific information from the table. Your model can scan through all these features and say which ones are important.	
I6-91	How prepared were the employees to adopt AutoML?	
I6-92	Finance has about 100 analysts now. We don’t expect all of them to it but you never know, maybe all of them will and that case it will be a bit of a headache. But the more decisions that can be based on statistical models the better. As they say: “In God we trust, everyone else bring data.”	TTR
I6-93	To what extent will employee knowledge affect the decision of adopting AutoML?	
I6-94	Obviously, the fact that anyone with very little knowledge of machine learning can start utilizing it is a big reason to adopt it.	TTR
I6-95	What benefits of AutoML were used to motivate the decision to apply it and how are they measured or projected?	

I6-96	It’s difficult to measure it. First of all, if we didn’t use AutoML we’d have to hire data scientists to do the task. There are two elements of value: you either hire data scientists and you send them across the business, or you have citizen data scientists, in which case you don’t have to hire data scientists. We try to use the best of both worlds, so we have some data scientists that are the experts, supporting the people that create the AutoML models. Then we have business users that know the problems, but it’s impossible for me to interview everyone in the business and solve their problems. So, the idea is that you give the people a tool to solve the problems. The value may be massive, or it may be nothing as well, as with anything with ML. We haven’t finished calculating the benefits yet but I’m pretty confident that there will be benefits.	TPBB
I6-97	Was AutoML seen as an incremental or disruptive decision?	
I6-98	Incremental. We are using ML now and I’ve had no problems with it in data science. I have been leading teams for over 10 years now and I always encourage the business to think about how the models work and to build models with the business. A lot of times we’re using things like the triads. Back in the day, a data scientist would be doing the business analysis, do the data preparation and build the models as well. That was split eventually, and we started having people focusing on only the BA aspect of data science, the business experts and then you had your data engineers. Then you had machine learning engineers who AutoML would be replacing. But AutoML only replaces 1/3 of the data science, so I see it as incremental because it lets the people who know the other two to do the thing that they would do with a third person. There are teams that have full stack data scientists that can deliver end to end anyway, so that’s why I say incremental.	TPBB
I6-99	Were there any unexpected benefits?	
I6-100	I have one example but it is not AutoML related but rather data citizen related. It can show you how AutoML can facilitate more. We trained a team recently on revenue assurance how to do segmentations and clustering on data in order to understand outliers. But, they only know how to use came-ins, they haven't used AutoML. But even with just knowing came-ins, they discovered a system issue that we had that is costing us 40 thousand GBP a day. So look at that, an unexpected benefit. In a sense, AutoML would allow us to do that to more people. These people could really use SaS, so that they could do came-ins. They could use just a simple algorithm that we taught them how to use. And immediately they used and they found 40 thousand GBP a day. It is a lot of money. You could class that as a benefit that could come from AutoML.	TPBB

I6-101	You describe AutoML as incremental, to what extent do you think that particular characteristic would affect the decision to adopt AutoML?	
I6-102	I think that even if it was disruptive we would still use it. Because, the benefit that you can get from it, which is allowing people to solve a problem and every model you build needs a problem. Without the problem you cannot build ML, most of the times you need the problem to apply ML and it is the business that knows that. So AutoML allows us to go to the business and lets you experiment as much as you want as long as you do not burn all the credits on the cloud.	TPBB
I6-103	What is the headcount in your organization?	
I6-104	Around 5 000 in the UK, and globally around hundreds of thousands , but in the UK it is around 5 000.	OS
I6-105	How is the budget allocated for AutoML initiatives?	
I6-106	It is part of our data strategy. I do not think that there is a specific budget that we are allocated. It comes as part of the cost for our ML tools that we have. These tools allow you to do a lot more than just AutoML. Tricky to say.	
I6-107	Was it considered as a necessary or a luxury investment when you decided to use AutoML?	
I6-108	I would say neither. I would not say necessary nor luxury, I would say it is something in between. It is a value-add investment. It did not cost us that much, it came as part of the platforms used. It is like a no-brainer.	OS
I6-109	Regarding your commercial solution, which you are using, and also if you are to reflect generally speaking on open source solutions, when it comes to the cost of adopting AutoML solutions, do you think it will be affordable even for smaller organizations, small to medium sized?	
I6-110	Yeah, I mean there is open source stuff, great stuff that you can use. I do not think that they are less affordable but maybe cheaper for small organizations. They may not be able to afford data scientists. We are struggling to find and keep data scientists. Commercial solutions may allow small organizations to utilize their own personnel to come up to speed with data science and ML sooner. Even if it comes with a small cost over the long term it will be probably beneficial to them.	OS, TPBB, MISC

I6-111	What impact did organization size and resources have on deciding on adopting AutoML?	
I6-112	I would say big. A big organization would need many data scientists.	OS
I6-113	What forms of support are necessary in order to adopt AutoML?	
I6-114	A little bit of training, not much. The infrastructure that we mentioned, but again this infrastructure is not specifically for AutoML but ML/AutoML. We see it the same. To be honest, no more support than ML itself apart from this extra training for the users to make sure, well they are not safeguards, but to make sure how to use the cloud. I do not think we need any support to implement AutoML in the organization. Like I said, it is included in the tools that we have. It is already part of them.	OT
I6-115	You mentioned that you need to train the employees, hold training sessions, to have a budget allocated for that you would need some sort of support? Or was this also included in the budget for data initiatives?	
I6-116	It was part of the budget, as part of the self-serve, so one of the major selling points of our transformation project was that we learned to facilitate self-serve to the business and self-serve had to do three things, reporting, BI which is basically the same thing if you ask me, and ML… AI. It was part of it.	
I6-117	Is the digital transformation work in your organization dependent on top management or is the management dependent on the digital transformation work and the technical teams?	
I6-118	I would say the first one. Top management makes the choices. We had an interesting takeover. Three Irland is doing very well. I think they are number one in Ireland. Before I joined the organization the CEO of Three Ireland became the CEO of Three UK. He brought in a lot of people from Three Irland to Three UK. So the CTO used to be the Three Irland CTO. He is implementing basically the stuff that he did there. It is not a lot in the ML space but it is mostly CRM solutions used and the cloud providers. A lot of driven by the top management. ML is mostly driven by myself.	
I6-119	To what extent is the top management support evident around AutoML?	

I6-120	It is not a massive bet due to that the cost for AutoML is low. It is a no-brainer bet to enable people to use AutoML, and ML with some support from a centralized team. AutoML initiatives are entrusted to our team. However, I need to add that AutoML and ML, it is both of them. The business is adopting ML in general. AutoML is part of it.	TO
I6-121	What extent did top management influence the decision taken for adopting AutoML?	
I6-122	They have a big effect on it obviously, AutoML is associated with costs. Top management loves cost reduction. If they don't have to hire data scientists it is a cost saving.	TO, TPBB
I6-123	Who made the case of adopting AutoML in the beginning?	
I6-124	It was made before me, by the architects that chose the infrastructure and the tools. When they decided to work with databricks, Azure and alderix, part of it was enabling AutoML. It was a selling point for the current infrastructure. It was made by the designers and architects of the solution before me.	OC
I6-125	Were there any challenges and resistance and how were they resolved?	
I6-126	Funny, there is some resistance from the data scientists. Because they see it (AutoML) as a threat sometimes. I do not have such thinking but the business do want to use it more. And how was it resolved? I basically told them to get used to it. They need to understand that it is something that will help them do things faster. A good data scientists doesn't need AutoML. But once the data scientists start using it it will start making their lives easier. Data scientists spend most of their time on data wrangling. Even using AutoML will save 10% of their time maybe.	TPBB, OC
I6-127	How does the presence of an initiator affect the implementation of AutoML/ML?	
I6-128	We have the example of the finance guy who uses AutoML to do stuff. It is kind of word of mouth. If you have a successful usecase and you show that it works then it is easier to adopt it. Like i said, for us it is a no-brainer. There is no one who really says let's not adopt AutoML. Everyone is enthusiastic.	OC
I6-129	To what extent does the line of business of the organization emphasize the use of analytics?	
I6-130	Big extent. We are investing up to 30 million GBP in the next couple of years, to improve the data quality and democratize the data and part of that is AutoML. We invest big in data infrastructure to make analytics more effective.	EC

I6-131	What impact did the organizational strategy have on the decision to adopt AutoML?	
I6-132	Big impact, because we want to be more data driven and it comes from the top.	EC
I6-133	What impact did competition have on that decision ?	
I6-134	We are trying to stay on top. We are a disruptor in the UK. We are changing strategy now and we want to be the best and have the best network, have the best customer experience and we have to have the best propositions for our customers. To do all that, first we need to understand what is best and without data that cannot be achieved, nor understand what is better. You need to be able to measure yourself. Competition is already doing it and we know that we are behind. It is a big impact on what competitors can do with data that we are not doing. People who have the answers quicker are the ones that are going to win eventually.	EC
I6-135	Are you thinking of using AutoML as a way to enhance your competitive position, so to speak?	
I6-136	Yes, we will have better and quicker decisions made. If Vodafone does not have AutoML and we have it, we will have an advantage and we know that. But it is in general all analytics, not only AutoML.	EC
I6-137	How did you implement or plan to implement AutoML? Was it an open source or a commercial solution? Did you as well receive any vendor help or are you relying on inhouse development and management?	
I6-138	Both, opensource and commercial. We are using Apache, Apache Spark. Databrics is Spark basically. It comes with its own proprietary library but we have also access to the whole spectrum of apache and all python and spark. We have Valterix which is commercial and we have Azzure ML which is also commercial. In terms of vendor help, Valterix and Databrics are offering help and free training currently.	EIS
I6-139	How would you rate the support that you are receiving?	
I6-140	Good. It is very easy, as long as you have an email address you can go on the self-paced courses. Once many have passed the self paced courses we organize instructor-led courses for them.	EIS
I6-141	Do they offer any other kind of support? e.g. with bugs, missing documentation?	
I6-142	Yes, everything is included.	EIS

I6-143	How did the previously mentioned influence the decision to implement AutoML?	
I6-144	It came with the tools and the tools were not just for ML or AutoML. We use databricks for data pipelines to move across and save our data and we use Alterix in conjunction with data discovery - taking data from 3D, from excel sheets and getting it together, to the cloud and creating reports.	EIS
I6-145	Looking from a more holistic point of view, when considering acquisition options or technology stack, was the support from the vendors something you considered as important before you decided to conduct the adoption?	
I6-146	Yeah, I was not part of the decision, it came before me but I am pretty sure that focus was put on making sure of having support and making it easy to implement. I remember seeing one of the old presentations and it was included in there.	EIS
I6-147	In the long run, how do you view the impact of AutoML on data analytics, its work and the teams?	
I6-148	I would say augment rather than replace.	AUTOML
I6-149	Do all your teams think the same, because you mentioned that there was some resistance, some of them maybe see it in a different way?	
I6-150	I do not know, maybe. Like I said, in the future I think AutoML is still in an early stage. It can do the auto-data preparation - prepare the data automatically. You need a person to do that and you need one person to sanity check the model. And that is the tricky bit, how could we make AutoML sanity check itself? I can not really think of this, there will always be someone needed with some kind of knowledge to almost sanity check. It may replace some data scientists, and some numbers but it would not completely replace them I believe. But who knows, you never know. You could possibly have a use case of using ML and AutoML itself to make a decision on what model to use. If you think about it, a data scientists, if somebody comes to me and says, I need to figure out how many power stations I need to build in the next three years. As a data scientists I would be like, you need a regression model and you need the data for that stuff. In my mind already I have something that says ok here it is. But with AutoML, what is that person going to do? They need to feed some data to this model and they need to figure out, what data is going to be relevant for this model? And also then AutoML will pick what relevant model to use. A classification or regression or whatever. You almost thinking that the perfect AutoML would be, something that reads text, picks the data that is needed, picks the model that will be needed, tests it and deploys it. Once we get to	AUTOML

	that stage, or we do have some solutions like chat bots, google has a bot that you talk to and you think it is a real person, but still once we do that, people might be replaced, yes. But we still have not replaced call center agents. How are we going to replace data scientists? I think they are going to augment data scientists and help them work faster, as well help people who do not have data science experience to have the power of ML in their decisions. There will always be some need for data scientists to keep the controls.	
I6-151	The issue of biases - what of the benefits that have been doubted by scholars advocating for AutoML is that it will reduce bias in how models are developed and which ones to use. Data scientists are still human and they might have some say and biases when they are designing, even though they might not be aware of it, would that be a relevant factor?	
I6-152	Yes, potentially. Scientists probably can do as much, the other problem with AutoML is that it can create biases. Now we are talking about ethical AI right? When you trust everything in an algorithm, you are risking things. We know for sure that data itself can be biased. AutoML would look at the data and make the decision and that is it and you might not even be able to explain it. A human, yes, they can make a mistake. The value of their AutoML may be ok. To be honest, most of the mistakes happen with the data preparation rather than the modeling bit. I have hardly seen any problems with somebody building a logistic instead of a linear model. For me it would not be a massive value. It is almost like retracting in that you have a machine launching the data and it might result in some difficulties.	MISC
I6-153	Another question regarding regulation. You did mention that there are some regressions specifically related to the telecommunication industry, but would this apply or in any way influence AutoML?	
I6-154	Yes, there are some areas. You will have to restrict the algorithms from which AutoML can pick from. You need to make sure e.g., you cannot use boosted or sample algorithms because they are very difficult to explain. Sometimes you need to be able to explain your decisions. E.g., for credit risk, if you come to me and say that you want a phone. Part of that will mean me giving you a contract with credit control included. With GDPR we need to be able to explain why we said no to you. With AutoML, that is part of the ethical thing again, if we let it loose completely and let it use all the parameters that are there and build a model or a neural network, and you also have AutoML that does ensampling, you build multiple models and they all vote, how are you going to explain that to someone? And there is a risk that people might think they are excluded in a racist manner. And they might be right, because models can be racist. They can be racist. You need to be careful when you build a model. That is why I see AutoML more like a discovery tool rather than a production tool. I see it as a proof of	ER

	concept thing that helps create proof of concept and potentially use it for automated reasons too, use cases with no issues for bias. You need to be careful where you apply it.	
I6-155	If we are to look at industries with heavy regulations, generally speaking, would you think that because of the issue of explainability, that AutoML would have a difficulty of being applied there?	
I6-156	I would apply it but I would still need a person to look at the outcome and then process it further. As mentioned, you can use it to see whether the data can give you something first of all. You give your data, it builds a model quickly, and okay so, AutoML is telling me that my data can provide an answer to these questions. ML is a simple concept. Usually in a program you have the data and you have logic. And you apply the logic to the data and you get an answer. Right? That is how you do typical programs. In ML it is the opposite. You have the data and you have the answers but you do not have the logic. You train something that is similar to a particular logic, you get that logic and apply it to other data and get answers. You can do it and then you can see whether you can use that logic or not. Most of the time for areas that are gray, you can see that the logic exists based on your data, meaning that there is some logic that I can essentially do with my data. Now I have to do the proper work and find it, what are the things in the data that require fixing for lawyers, medical experts etc.	ER
I6-157	Would you like to add on anything that you might think that we have missed?	
I6-158	No, like I mentioned there are three aspects with AutoML. AutoML does the data science, it is maybe worth noting that is not the only aspect, you need the business understanding as well. The problem, it is a very big part of data science. Describing the problem. Saying what data you need to answer this problem, what data you have and preparing this data so that it can be used for AutoML. Only 32% of the problem is being solved. If we manage to solve all three areas, then we have a proper AutoML. The process is including all of it, not just the modeling part. That is my comment.	AUTOM L
I6-159	The three parts of AutoML, one of which AutoML is covering is around 33%, could you elaborate more on that?	
I6-160	Business, data preparation and machine learning. In order to do machine learning, you need the other two as well. They are not in isolation. If you do not have the business then okay you may get some idea of the data but most of the application of ML, you have a problem, and what explains the problem is the business aspect, you have data prepared in a way that can be used by your model, and then you have your ML algorithm which is roughly around 33 %.	

I6-161	Do you have any questions for us?	
I6-162	No, thank you guys!	

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