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„Drivers and Barriers to the Adoption of Artificial Intelligence in Austrian Companies. An Empirical Analysis“

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Abstract (English)

Latest advancements in Artificial Intelligence (AI) leave little doubt about the enormous disruptive impact artificially intelligent systems will have on economy and society. The underlying technologies bear unimagined possibilities for companies to improve their business, whilst those who do not jump on the AI bandwagon risk to lose significant competitiveness in the medium- and long-run. Notwithstanding, adoption rates in Europe are still low, which leads to the question why this is the case. This study identifies and empirically tests both driving and impeding forces to AI adoption in companies focussing on Austria. The findings suggest that the forces identified represent significant drivers and barriers for managers to deploy AI, thereby yielding valuable insights on how AI implementation could be facilitated.

Abstract (Deutsch)

Jüngste Entwicklungen im Bereich der Künstlichen Intelligenz (KI, engl. AI) lassen wenige Zweifel an dem enormen, disruptiven Einfluss aufkommen, den künstlich intelligente Systeme auf die Wirtschaft und die Gesellschaft haben werden. Die zugrundeliegenden Technologien bergen ungeahnte Möglichkeiten für Unternehmen ihr Geschäft zu verbessern, wohingegen diejenigen, die sich nicht an dem KI-Trend beteiligen, das Risiko eingehen mittel- und langfristig Wettbewerbsfähigkeit zu verlieren. Dem zum Trotz sind die Implementierungsraten von KI in Europa immer noch sehr gering, was die Frage aufwirft, warum das der Fall ist. Diese Studie identifiziert treibende und erschwerende Kräfte für die Übernahme von KI durch Unternehmen mit einem Fokus auf Österreich und überprüft diese empirisch. Die Ergebnisse deuten darauf hin, dass die identifizierten Kräfte signifikante Treiber und Barrieren für Manager für die Annahme von KI-Technologien darstellen und lassen Rückschlüsse darauf zu, wie die Implementierung von KI für Unternehmen vereinfacht werden kann.

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Abbreviations

AI Artificial Intelligence

CEO Chief Executive Officer

DV Dependent Variable

GDP Gross Domestic Product

IBM International Business Machines Corporation

IoT Internet of Things

IV Independent Variable

NLP Natural Language Processing

NYU New York University

OECD Organisation for Economic Co-operation and Development

SME Small and Medium Enterprises

UK United Kingdom

USA United States of America

1 Introduction

1.1 Motivation and Background

"AI [Artificial Intelligence] is one of the most important things humanity is working on. It is more profound than, I don't know, electricity or fire," said *Google* CEO Sundar Pichai in 2018 (MSNBC, 2018). Although one might question this statement, there is little doubt about the exhaustive impact AI will have in particular on the economy, and subsequently on business. Scherk, Pöchhacker-Tröscher, and Wagner (2017) predict that the progress made in AI will leave no economic sector untouched (Scherk et al., 2017, p. 22). According to a research by *PricewaterhouseCoopers* (PwC) the adoption of AI-related technologies will increase global GDP by 14% in 2030 (Rao & Verweij, 2017, pp. 3–4). They argue that the tremendous increase in data generated by "digitalised" people and Internet of Things (IoT) represents the basis for the success of artificially intelligent technologies. The use of data has already led to standardisation, automation and personalisation of many products and services but exploiting data with AI allows for unsuspected "ways of doing things that we've not imagined before" (Rao & Verweij, 2017, p. 5). In concrete, they mention productivity gains through automated processes and rises in consumer demand due to higher quality and even more customised products (pp. 4–6). Similarly, Purdy and Daugherty (2016) assume that AI has the potential to double the economic growth rates of 12 industrialised countries (including Austria) by 2035. They consider AI a new factor of production in addition to labour and capital, which thus represents the key driver for future growth.

There seems to be no denying that AI is on the rise and "is set to be the key source of transformation, disruption and competitive advantage in today's fast changing economy" (Rao & Verweij, 2017, p. 10). Having recognised the fundamental impact for the future of business, it is not surprising that China and the USA heavily invest in research and development of AI. Between 2007 and 2017, 3054 AI-related patents were filed worldwide, with the USA (1030) and China (674) accounting for the bulk of applications (Sloan & He, 2017). In 2019, both in the academic and in the business sector Chinese institutions are leading. For instance, out of the world's top 500 patent applicants of public research organisations such as universities, China accounts for 100, followed by the US and the Republic of Korea with 20 applicants each (World Intellectual Property Organization, 2019, pp. 59–62). Beijing is strongly pushing AI implementation in its public and private organisations (Fischer, 2018) and although the United States are still considered leaders in AI innovation, China is catching up fast. In fact, the latter is predicted to benefit most from AI adoption, increasing its GDP by more than 26% by 2030, compared to 14.5% in North America and almost 11% in Europe (Rao & Verweij, 2017, pp. 6–8).

Leaving the global race for being a leading nation in Artificial Intelligence to the USA, China and other countries would naturally diminish Europe's, and subsequently Austria's global competitiveness. The authors of a *The Washington Pos*t article allege that in the face of *Google*, *Facebook* and *Twitter* "Europe has become a colony in the American tech empire" (Berggruen & Gardels, 2018). Nonetheless, the authors continue, there is still the chance for Europe to not be left behind. What is needed is a unified strategy and concrete measures jointly taken by Europe's leaders to boost innovation, research and investment in AI.

On a national level, the German Government, for example, released a comprehensive strategy paper on Artificial Intelligence in November 2018 (Bundesregierung Deutschland, 2018), thereby responding to signals from economy, science and politics urging to finally recognise AI as the future technology and to assume an active role in its development. Investment in AI totals three billion euros for Germany until 2025 (p. 6), which encompasses this notion. However, comparison to, for instance, the fifteen billion US dollars invested in AI research by Tianjin, a city in China (Tagesschau, 2018), reveals the relatively small dimension of Germany's expenditures on AI.

Also, Austria has made endeavours to tackle the need for an AI strategy. In the course of the Austrian Digital Agenda, the *Ministry for Transport, Innovation and Technology* and the *Ministry for Digital and Economic Affairs* developed the "Artificial Intelligence Mission Austria 2030" framing political, scientific, economic, societal, and ethical aspects of AI (Wiesmüller et al., 2018). It further states that the Austrian government had funded AI research in Austria between 2012 and 2017, however with a total sum of 0.35 billion euros (p. 8), which, as the German-Chinese comparison shows, cannot be considered a lot, and future investments are not mentioned at this point. According to the *Government AI Readiness Index* of *Oxford Insights*, which takes into account several factors decisive for the captivation and exploitation of AI, Austria is only ranked number 16 out of 35 of the OECD[1] countries (Oxford Insights, 2017).

The Austrian federal state *Oberösterreich* (Upper Austria) already went one step further by financing the foundation of the *Artificial Intelligence Lab* where extensive research and educational programmes of AI are realised (Johannes Kepler Universität, 2018). The project, amongst others, aims at reducing the shortage of AI experts and developers in Austria (Innerhofer, 2018).

According to the capital's mayor, Vienna is supposed to become the "capital of artificial intelligence" (Mey, 2018). Indeed, several projects including self-driving buses, intelligent chat-bots and smart cities are being tested by the city administration, yet, it is still far from being the most important city of Artificial Intelligence.

[1] Organisation for Economic Co-operation and Development; the ranking only takes into account the 35 member countries of 2017, in 2019 the number has risen to 37 member states.

Concluding, it can be remarked that action is taken in Europe and Austria, however, there is a lot more to be done to catch up with China and the USA. Clearly, competitive advantage through AI on the macro-level can only be achieved if the basis for it is set on the meso-level. In other words, organisations and companies must invest in and embrace AI, so that additional value, new insights, and know-how can be created. Findings in literature prove how beneficial implementation of AI technologies in basically any domain can be as will be further outlined in chapter 2.4 (Thomas Davenport & Ronanki, 2018; Makridakis, 2017; Wirth, 2018; World Intellectual Property Organization, 2019).

1.2 Problem Definition and Research Gap

According to a global study on AI ambitions and efforts, 75% of companies' executives believe that AI will help them create new businesses and 85% think that it will build competitive advantage (Ransbotham, Kiron, Gerbert, & Reeves, 2017, p. 1). Notwithstanding this conviction, solely 20% have adopted AI in some parts of the organisation, and only 5% have it extensively deployed and this mainly accounts for the largest companies (p. 5). The fact that AI diffusion in firms is so low despite its apparent benefits leads to the question what encourages companies to adopt the technologies and what hinders them from doing so.

In this context, it is essential to mention that literature provides numerous studies on, for instance, AI as a persuasive business model (Valter, Lindgren, & Prasad, 2017/2017), its influence on management (Kolbjørnsrud, Amico, & Thomas, 2017), the adoption of information and communication technologies, though in rural areas and without focus on AI (T.-K. Yu, Lin, & Liao, 2017), and AI in particular (technical) fields (Beam & Kohane, 2016; Liebowitz, 2001; Wollenberg & Sakaguchi, 1987). One study undertaken by *Accenture* (2019) on behalf of the Austrian Federal Ministry of Digital and Economic Affairs sheds light on AI from a practical, societal and economic perspective. The focus, however, lies on the future vision for the Austrian society and economy, describing possible impacts on these areas. It does not examine concrete factors relevant for AI adoption for companies.

Additionally, the technology consulting firm *Deloitte* (2019) published a qualitative research, in which 100 executives have been interviewed on the state of AI. The results offer some useful indicators of aspects concerning deployment of AI technologies in business, which can help in identifying possible drivers and barriers to adoption. Notwithstanding, the focal point is set on Germany and due to the exploratory nature of the research, the deployment indicators are not high in number, thus incomplete, and not yet quantitatively tested.

The most promising study for AI research in Austria which potentially includes some favouring or hampering factors is a research undertaken by the *Austrian Institute for SME Research* on the current state of AI in Austria (KMU Forschung Austria, 2019a). However, the study is still being conducted and will not be published before August 2019.

In brief, research on concrete motives for and against AI adoption in business, particularly in Austria is still is very limited or non-existent. Therefore, it is reasonable to consider this thesis a preliminary study in which the focus is laid on the main generic drivers and barriers to AI adoption in Austrian companies. Since the field of Artificial Intelligence is – even if reduced to the area of strategic management – utterly extensive, further research is necessary for a more complementary grasp of AI and its impact on business and society. Ideally, future studies can build upon the findings of this contribution.

1.3 Research Questions and Structure of Thesis

In order to contribute to the research gap identified in chapter 1.2 two research questions are asked.

1. What are the drivers to AI adoption in Austrian companies?
2. What are the barriers to AI adoption in Austrian companies?

To answer those questions, several steps are taken. First, the theoretical construct of Artificial Intelligence is broken down by examining and comparing existing definitions in literature in chapter 2.1. Then, for a more comprehensive understanding of the research field, chapter 2.2. delineates the historical development of AI, which shows to have led to a split of AI into several research subfields and technologies.

A deeper look into the respective technologies contributes both to further clarify what AI is composed of and which use it can have for companies. Therefore, the most prevalent technologies are depicted in chapter 2.3.

Based on this knowledge, a coherent and well-informed review of literature and use cases on relevant driving and impeding forces to AI adoption is conducted in chapter 2.4. Building upon on these findings, the respective drivers and barriers are identified, hypotheses are formulated, and a research model is developed.

The research approach is presented in chapter 3, and the model’s variables and the corresponding hypotheses are tested empirically by applying adequate statistical methods in chapter 4. The results of the statistical analysis are discussed in chapter 5, thereby answering the research questions. Additionally, both implications for business and limitations on the study find their place in this chapter.

Lastly, the conclusion summarises the thesis' findings in chapter 6.

2 Literature Review

2.1 Definition

Two problems have to be considered when it comes to breaking down what was first coined "artificial intelligence" by John McCarthy and his colleagues in *A proposal for the Dartmouth summer research project on artificial intelligence* in 1955 (McCarthy, Minsky, Rochester, & Shannon, 2006). The first difficulty presents itself when some of the numerous definitions of AI are considered as will be demonstrated below. The second issue in defining AI is that it is not a specific technology but that it serves as an umbrella term for a broad collection of concepts, approaches, and technologies, which is discussed in chapter 2.2.

One of the fathers of AI, John McCarthy, defines AI very generally as "the science and engineering of making intelligent machines, especially intelligent computer programs" (McCarthy, 1993). A similar definition is provided by Haugeland (1987) who declares that AI is "the exciting new effort to make computers think" with the goal to create "*machines with minds*, in the full and literal sense" (p. 2 [emphasis in original]). Yet, both definitions lack any further explanation of "intelligence" or "mind".

Other definitions are a little more specific by relating intelligence to human intelligence. Kurzweil (1990) denotes AI as "[t]he art of creating machines that perform functions that require intelligence when performed by people" (p. 14). Equivalently, Tanimoto (1990a) affirms that AI is "a field of study that encompasses computational techniques for performing tasks that apparently require intelligence when performed by humans" (p. 6). Simmons and Chappell (1988) share this view and state: "The term artificial intelligence denotes behavior of a machine which, if a human behaves in the same way, is considered intelligent" (p. 14). According to these three definitions AI is, to put it in simple words, a machine or a system that thinks like a human and consequently acts like one.

This view on AI has not changed in essence in the past decades, which becomes apparent from a look at technology-related platforms like *Certes Computing Limited*: "It summarises the efforts to make computers think the way we think, to be able to simulate human cognitive thinking and decision-making, leading to human-like actions, and ultimately to be better and faster at problem-solving than we are" (n.d., 2018). According to *Analytics Insight* (2018) "Artificial Intelligence is the simulation of human intelligence but processed by machines, mainly computer systems" (Uj, 2018). The following table summarises the definitions provided.

Table 1: Definitions of Artificial Intelligence

Author	Definition of AI
McCarthy (1993)	"the science and engineering of making intelligent machines, especially intelligent computer programs"
Haugeland (1987)	"the exciting new effort to make computers think" with the goal to create "*machines with minds*, in the full and literal sense"
Kurzweil (1990)	"[t]he art of creating machines that perform functions that require intelligence when performed by people"
Tanimoto (1990)	"a field of study that encompasses computational techniques for performing tasks that apparently require intelligence when performed by humans"
Simmons and Chappell (1988)	"The term artificial intelligence denotes behavior of a machine which, if a human behaves in the same way, is considered intelligent"
n.d. (2018)	"It summarises the efforts to make computers think the way we think, to be able to simulate human cognitive thinking and decision-making, leading to human-like actions, and ultimately to be better and faster at problem-solving than we are"
Uj (2018)	"Artificial Intelligence is the simulation of human intelligence but processed by machines, mainly computer systems"

Source: Own table

What becomes evident from these definitions is that "artificial" refers to the fact that the action or thinking is not done by humans but by computer programmes or machines (Wirth, 2018, p. 436) or, in other words, that the source of the intelligence involved is not natural. Interestingly, all the definitions have in common that they use some form of "intelligence" without further delineating this term. This is due to the fact that there is no generally renowned definition of intelligence (Simmons & Chappell, 1988, p. 14; Wirth, 2018, p. 436) which is another reason for the difficulty in defining AI. Fetzer (1990) therefore comes to the conclusion that "[o]ne of the fascinating aspects of the field of artificial intelligence (AI) is that the precise nature of its subject matter turns out to be surprisingly difficult to define" (p. 3).

Still, all the above-mentioned definitions impart a general idea of what AI is. Taking the above-mentioned definitions into account, and trying to circumvent the problematic term of intelligence, in this study the definition of AI is considered to be a collection of methods and technologies which use data to learn, i.e., to improve and adapt itself to changing environments and to solve tasks autonomously, i.e., without constant guidance of a user.

The following chapter provides a short insight into the historical development of AI. This, on the one hand helps get a better understanding of the concept, and, on the other hand, provides an explanation for the second difficulty in defining AI mentioned at the beginning of this chapter.

2.2 Historical Development

The second difficulty when explaining AI alluded to in chapter 2.1 is the split into diverse subfields during its development. As mentioned before, John McCarthy and his colleagues labelled the field of study of intelligent machines as *Artificial Intelligence* in 1955, however, the first work acknowledged as AI was conducted already in 1943 (Russell & Norvig, 1995, p. 16). Based on these endeavours a period of enthusiasm and high expectations in the 1950s and 1960s gave birth to pioneering approaches and technologies in the areas of mathematics, logic, knowledge representation and reasoning, neural networks, and language processing. Fruits of these efforts resulted in problem-solving programmes, for example one playing checkers participating in professional competitions, one solving prominent mathematical theorems, and one imitating conversations in natural language using predetermined parts of sentences. Notwithstanding, these systems were only capable of solving problems in strongly limited areas. When confronted with additional or broader problems, which went beyond the input provided manually, they failed (Russell & Norvig, 1995, pp. 17–21).

One example for these limits is the machine translation of the sentence „the spirit is willing but the flesh is weak" into Russian, which has been retranslated as "the vodka is good but the meat is rotten" (Tecuci, 2012, p. 169). The reasons for failure were threefold. First, the AI systems did only possess very limited amounts of knowledge even in the fields where they were applied. Second, they did not dispose heuristic techniques to narrow down complex problem spaces. Third, basic structures of intelligent behaviour were not yet sufficiently known in order to automate them (Tecuci, 2012, p. 170).

Continuing with this example of language processing, the knowledge base of the AI system was represented by word-by-word translations and some English and Russian syntactic rules. However, to correctly understand and interpret language, knowledge about words and syntax is not enough. A much larger, interrelated, and more complex understanding about morphology, semantics, intonation, context etc. is necessary. Additionally, there are exponentially growing combinations to assemble words to phrases. This amount of knowledge could not be captured by machines, heuristic procedures for the reduction of possible solutions could not be programmed, and (human) cognitive functions for the accomplishment of such tasks could not be fully understood and thus not be imitated.

Therefore, many real-world problems could not be tackled, which led to disillusionment and large-scale reduction of public and private funds for AI research projects during the late 1960s (Russell & Norvig, 1995, pp. 20–21). The research groups were forced to specialize in smaller areas, and a lack of investors and general interest ended interdisciplinary exchanges on AI in the form of joint conferences and journals to a large extent (Tecuci, 2012, p. 170).

The result was a split into different coexisting research areas leading to the evolvement of specialized know-how. This development in combination with the enormous increase in computing and storage capacities, and the size and availability of data entailed the design of more useful machines (Minsky, 1990, p. 5; Tecuci, 2012, p. 170). One instance of such ground-breaking technologies are *expert systems*, or *knowledge-based systems* (Kurzweil, 1990, pp. 283–294). These programmes have access to highly specialised knowledge of a certain area and are able to make meaningful statements using logical rules, a capability previously reserved for humans (Metaxiotis & Psarras, 2003).

The consequence of this specialisation was an emergence of different subareas or „microworlds" (Russell & Norvig, 1995, p. 19), such as knowledge representation, game playing, theorem proof, planning, probabilistic reasoning, machine learning, natural speech recognition, robotics, neural networks, and genetic algorithms (Russell & Norvig, 1995, pp. 22–23; Tecuci, 2012, p. 170). Considering this spectrum, it becomes obvious why defining AI is difficult. The first successful commercialisations of such specialised AI systems took place in the 1980s and have slowly but steady evolved until the present day (Russell & Norvig, 1995, p. 24).

In order to get a clearer and more profound understanding of AI, and hence, of which benefits it could bring to companies, the most important underlying technologies will be depicted in more detail in the subsequent chapter.

2.3 AI Technologies

2.3.1 Knowledge Representation

Generally, a differentiation is made between data and information with the latter being the analysed output of the former. In AI, there is a third state, "knowledge", which is a more general kind of information (Tanimoto, 1990b, p. 115). Knowledge in a machine can be seen as "the internal representation of its external environment" (Tecuci, 2012, p. 170), which contains facts, procedures, models and heuristics that serve as the basis for problem-solving and logic reasoning. Most of knowledge representation methods are based on logic and include production rules, ontology, inclusion hierarchies, mathematical logic, frames, scripts, semantic nets, constraints or predicates, and relational databases (Tanimoto, 1990b, pp. 115–159). No technique has shown to be optimally suited for representing knowledge but have their respective advantages and downsides either in representing objects and states, or processes and relations. For this reason, *complementary approaches* are often chosen. For example, in order to represent a chair standing in a room, ontology and production rules can be integrated (Tecuci, 2012, pp. 170–172). The representation would be of a kind of:

chair = subgroup of *furniture*; *floor* = lowest part of *room*; ➞ chair *standing on* floor

This approach combines a description and categorisation of the objects and their interrelation. The logic rule implies that the floor as the lowest part of the room cannot stand on the chair but vice versa. According to Ginsberg (1994), the "intended role of knowledge representation in artificial intelligence is to reduce problems of intelligent action to search problems" (p. 107). In other words, research on knowledge representation should advance up to a point, where a reliable knowledge base is given, and focus can be set on how to extract information from this base (see chapter 2.3.3).

2.3.2 Planning

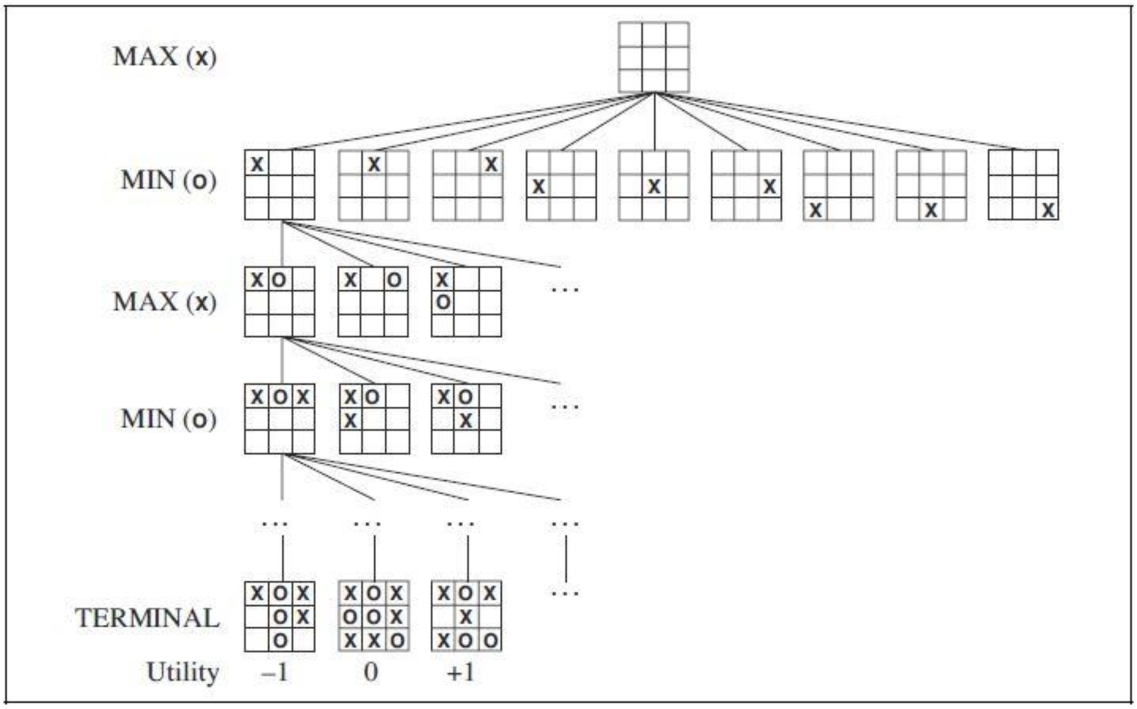
Before getting to search problems, planning will be addressed firstly because it comes one step earlier in the order of problem-solving. The objective of a plan is to create a procedure or instruction within a so-called *configuration space* to solve a certain task (Tanimoto, 1990b, p. 202). An example is to put a dirty plate into the dishwasher. The configuration space is the kitchen, and the task is solved when the plate is placed correctly in the dishwasher machine. A plan to do so could look like this: The subject must grab the plate with its hands, walk around the table towards the dishwasher, open it, pull out one of the trays, look for a free spot, and place it vertically in the tray. Albeit this procedure seems simple at first glance, one must be aware that a machine has to take plenty of sub-operations and hence, millions of alternative ways into account to reach this goal, even if only the ones with the minimal number of steps are considered. Depending on where the subject stands in the kitchen, it could first open the dishwasher and then walk to the table or take another way around the table or both, it could open another tray or choose a different free spot etc. Considering each possible operation and its respective variations lead to what is called a "*combinatorial explosion*" (Russell & Norvig, 1995, p. 21) of possible sequences of operations. Therefore, *hierarchical methods* are used, which group certain steps to one *macro-operator*, by that, reducing the number of operations (Tanimoto, 1990b, pp. 202–206).

Planning is closely related to search, yet, the latter can be considered the execution of the former (Ginsberg, 1994, pp. 289–290).

2.3.3 Search

In accordance to what Ginsberg (1994) remarked (chapter 2.3.1.), most of AI systems are built around search methods. Many computer programmes need to seek through a predetermined way of complex nets of knowledge, states and conditions in order to find certain information or to reach a "goal position". Such a net can be described as a graph of nodes and edges where the former represent a certain state and the latter the relation between them. The whole set in which the search takes place is called *state space*, comparable to the aforementioned configuration space (Tanimoto, 1990b, pp. 171–172). Further, the kind of search method is critical for a programme's success. For simple problems exhaustive techniques which go through every possible solution may be appropriate. A very simple example would be: *How many possibilities exist to put four books in an order that is different each time*? The mathematical solution would be $n!$, hence 24. A search algorithm would generate a state space in form of a game tree in which each possible combination is delineated. This kind of search is called *blind search* since the algorithm does not "see" where it goes until it reaches its goal (Ginsberg, 1994, pp. 49–52), i.e., that no other position of books is possible and the final number of different positions is 24. The following figure shows a partial game tree for the game of tic-tac-toe, which has *9!* possible solutions.

Figure 1: Partial Game Tree for the Game of Tic-Tac-Toe



Source: Russell and Norvig (1995, p. 163)

However, as soon as problems become more complicated this method would take years even for computers with state-of-the-art processing capacity. Taking the game chess as an illustration, after the first move of each player, 400 different positions must be calculated. After 12 moves this number rises to a quintillion of possible positions (nodes) (Hulick, 2016, p. 10). That is why in this case a *heuristic search* method has to be applied. This technique uses or general knowledge (such as the size of the board and the number of fields) or special information about the problem (such as known, “best” moves), thereby reducing the search space to an area where the solution most probably will be found (Tanimoto, 1990b, pp. 188–190). Since the goal is not to find any position but the best one, a large part of positions can be excluded from search due to low estimated probability of success. In 1997, IBM’s programme Deep Blue defeated the world’s chess champion using heuristic search (Hulick, 2016, p. 12).

2.3.4 Logic Reasoning

Logic reasoning in computers is generally based on mathematical logic and logic applying algorithms, including *propositional calculus* of the kind: If a dog is a mammal, and a mammal is an animal, then a dog is an animal. However, this kind of deduction is limited when it comes to less general statements or questions. *Why is a dog a mammal*? A propositional calculus could not answer the question as it can only describe an object as it was defined before. Therefore, another approach called *predicate calculus* is used for more complex matters. It is able to depict the inner structure of a statement and the characteristics of an object by manipulating its objects and predicates, thereby deducing logically (Tanimoto, 1990b, pp. 225–273). For instance, a machine may find the answer to the mentioned question by including the predicates that a dog does not lay eggs and has a steady body temperature throughout the year and consequently must belong to the group of mammals.

2.3.5 Probabilistic Reasoning

In practice, problem solving often includes incomplete and unprecise knowledge. Weather forecasts or medical diagnosis are examples, where, due to lack of knowledge, logic inferences come to its limits. Although a human being has incomplete, unprecise und uncertain knowledge he/she is able to develop and apply methods such as generalisation and approximation that help him/her take the right decision. The same methods can be used in AI systems by employing *probabilistic reasoning* and *decision theory* (Tanimoto, 1990b, pp. 283–286). An intelligent system could be programmed according to *Bayes' law*, which allows to calculate the probability of an event depending on the occurrence of related conditions (Tecuci, 2012, p. 171). By way of illustration, the probability of a patient having cancer depends to a high degree on certain symptoms and whether he/she suffers from them or not. An intelligent system could recognise the related symptoms and calculate the likelihood that these leading to cancer (see also chapter 2.4.2.1).

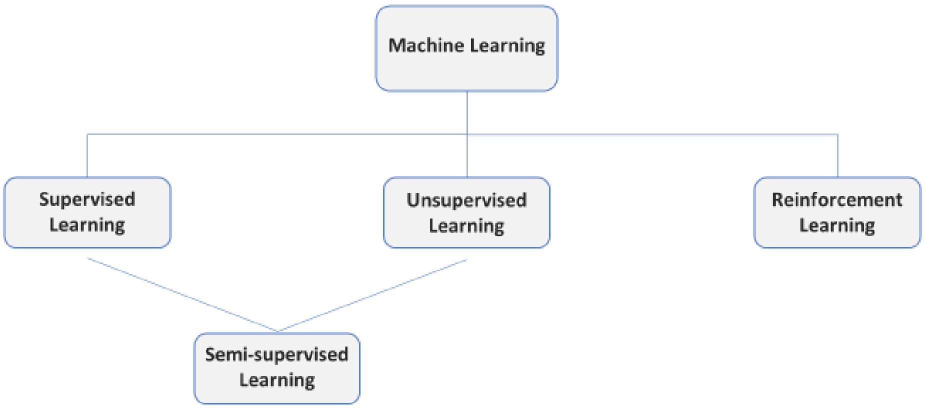
2.3.6 Learning

The field of automated or machine learning concentrates on self-improvement of a system. According to Hulick (2016), "[m]achine learning happens when a program changes itself so it can perform better in the future" (p. 15). In particular, one can speak of "learning" when a programme improves its working method or increases its knowledge base. Another focus is laid upon the automation of knowledge acquisition as it is costly to incorporate expert knowledge manually and to represent it in a form which allows the system to draw inferences. Research in this field aims at developing systems which are enabled to acquire knowledge, find patterns in data, and to build up its internal representation completely on their own. There are two generic procedures for machine learning – *numerical* and *structural* – or a combination of both (Tanimoto, 1990b, pp. 331–340). The former method involves algorithms which create threshold values that allow the programme to differentiate between objects, such as a banana and an apple by means of its length in centimetres. The structural approach deals with concepts, relations, quantities, and graphs. It would distinguish the fruits rather by their colour than by numerical values. By being given large quantities of examples a system improves its performance (Tecuci, 2012, pp. 173–176).

In the last decades, researchers have made huge progress in artificial neural networks. This method is inspired by the human brain. An example is a child, which is shown different animals in a book by its parents. They tell the child that this specific animal is a cat, that is a horse and so on until it is able to recognise the animals by itself. Moreover, it learns to generalise the patterns so that it can identify cats and horses, which it has never seen before. This is possible thanks to billions of neurons linked with trillions of connections that receive data (e.g., visual, auditive, physical) as input, process the information and produce output such as thoughts, emotions and movements. The same is done with machines. They receive large amounts of training data and a target function which shall be maximised (Scherk et al., 2017, pp. 16–20). After giving the programme millions of cat pictures and a prescription of how a cat looks like (target function) the system "learns" the patterns which are characteristic for a cat. By improving its recognising skills, it eventually is able to detect a cat among different animals in a picture. This technique to learn is called *supervised learning* meaning that the output is already known, and that the way of achieving the desired output ("the correct answer") is explicitly prescribed.

Additionally, there are three other types of machine learning (Figure 2). The second one is *unsupervised learning*. In this case, no training data and neither the "right" output, nor a rule to get to the output, nor any correlation between input and output is provided. The system must find patterns by itself only with the help of its inherent logical operations. Imagine a person who has never heard of football before and watches a game for the first time. Although he has no clue what the rules and the objective are, after some time he will develop at least a basic understanding of the game, e.g. that the ball is supposed to be put in the goal to score. A third approach combines both supervised and unsupervised mechanisms. This *semi-supervised learning* system is fed with some data, for example the correct output but then has to find out the best way to get there without any predetermined rules. Fourth, *reinforcement learning* trains algorithms by rewarding or penalising the output. Apart from a specific (problem) environment, no rules are given. The programme tries out different ways with different results and gets rewarded when the output is desired and punished if not, comparable to training a dog.

Figure 2: Types of Machine Learning



Source: Own figure

In the context of neural networks, it is crucial to introduce the most promising approach called *deep learning* (Wolf, 2018, pp. 8–13). It basically uses the same techniques as mentioned above but possesses multiple layers with more neurons and connections. Just like in a human brain, the connections (synapses) between the neurons are strengthened if and until a desired output is obtained, thereby finding the best way to achieve a certain goal (Hulick, 2016, pp. 16–20). Consequently, the feature extraction and steps of processing data are developed completely autonomously by the system. This way, the analysis is split into many different levels, where only one main task is executed per level which increases speed and accuracy. As the procedures of analysis are chosen by the system itself once it is initiated, deep learning systems have a very high degree of autonomy, needing less input from developers (Scherk et al., 2017, p. 18).

2.3.7 Natural Language Processing

In order to understand natural language in spoken or written form a programme must be able to perform a set of tasks (Ginsberg, 1994, pp. 351–376). First, it has to separate bits of language into sequences of sentences and words (*signal processing*), which is relatively easy in written but more difficult in spoken form. In a next step, morphology and syntax, i.e., the structure of words and phrases must be analysed. “Arthur asks James” and “James asks Arthur” consist of the same words, however, the order of words plays a role. Understanding the syntax of a text reduces the possible number of meanings which, in turn, decreases necessary processing capacity of a programme. Further, *semantics*, i.e., the meanings of words, are crucial for understanding (Tanimoto, 1990b, p. 380). Yet, words with ambiguous meanings represent a difficulty, for instance, in “Maria likes red nails” it is not clear whether she refers to finger nails or nails to put in a wall. Finally, the context, or, as called in linguistics, *pragmatics* are indispensable to comprehend a language. These difficulties are tried to come by with large amounts of training data and machine learning techniques to discover patterns in the language.

Once a system is able to understand a language in the indicated way, it can also generate reasonable sentences. This permits a machine to give its answers not only in programming language but in natural language, thereby vastly broadening the possible uses for organisations, in particular for human-machine interactions. The techniques utilised to conduct these processes are drawn from the research areas already mentioned above, such as logic applying algorithms, decision theory, and structural methods (Tecuci, 2012, pp. 176–177).

2.3.8 Computer Vision

One goal of AI systems is that information is not only obtained passively through their developer but that those systems gain information actively through sensory inputs. Processing visual inputs can significantly help a programme learn about its domain which makes computer vision a key area in AI research (Tanimoto, 1990b, p. 437). Yet, what is natural to human beings is a true challenge for machines. Problematic issues include the amount of data of which photographs or pictures are comprised and the *visual noise* such as blurry edges, dust or reflections, which distort information. Besides, the transformation of a three-dimensional reality into a two-dimensional picture and the understanding of a scene’s meaning, which necessarily presupposes knowledge of the objects’ mutual relation and interaction represent difficulties. What research does in order to tackle these obstacles, is analysing an image in several stages, starting with smallest bits of information and ending with the interpretation of large objects’ relations (Ginsberg, 1994, pp. 324–325). This still remains the most difficult part of computer vision (Tecuci, 2012, p. 177).

More recent approaches imitate the visual system of primates. In 2015, a team of the University of Toronto equipped a neural net with a mechanism reproducing human sight, thereby allowing the algorithm to solely look at the most relevant parts of a picture. By combining the information, the system could complete its internal representation of a scene a lot faster and more reliably (Wolf, 2018, p. 12).

2.3.9 Expert Systems

The idea of *expert systems*, or *knowledge-based systems* is that an expert's specific knowledge and his/her reasoning capabilities in a certain domain are represented in a programme in order to solve problems. The two main components are a knowledge base and an *inference machine* (Zwass, 2016). The former can be a collection of facts, production rules (e.g., "if-then" rules), semantic nets or frames etc. acquired from human specialists in a certain domain. The latter is a procedure using rules of logic and probabilistic inference networks, which generate interpretations, evaluations, and decisions based on existing knowledge (Tanimoto, 1990b, pp. 523–524). Usually, there is also a natural language interface which enables communication with users that are not computer literate (Ginsberg, 1994, p. 385). Expert systems constitute one of the most applied AI technologies (Metaxiotis & Psarras, 2003, p. 361).

2.3.10 Robotics

Robotics per se represents an own field of science which studies robots (Siciliano & Khatib, 2008, pp. 1–4). A robot can act autonomously in a real-world environment by following a programmed sequence of steps. Yet, no intelligent action is involved, since it always repeats the same task until it is reprogrammed to do something else (Owen-Hill, 2017). An artificially intelligent robot is a machine which includes some of the abovementioned technologies such as planning, machine learning or computer vision, which enable it to interact "intelligently" with its physical surroundings (Hulick, 2016, pp. 67–88). The most common apparent example is a self-driving car.

Whilst two decades ago the vast majority of robots were used in the manufacturing industry (Nof, 1999, pp. 3–18), nowadays, thanks to integrated AI applications, intelligent robots are on the rise and can be found in almost every industry reaching from surgical (Grespan, Fiorini, & Colucci, 2019) to space operating (Floreano & Wood, 2015) up to entertainment robots (Hulick, 2016, pp. 79–90).

Concluding, these technologies represent the main components of AI. The following table depicts the methods indicated above as well as its respective definition and possible fields of application.

Table 2: Overview of AI Technologies

Technology / Method	Definition	Application Field (Example)[2]
Knowledge Representation	"the internal representation of its external environment" (Tecuci, 2012, p. 170)	Information providing systems; Diagnosis of medical condition
Planning	Create a procedure or instruction within a *configuration space* to solve a certain task (Tanimoto, 1990b, p. 202).	Gaming; Driverless vehicles
Search	Seek through complex nets of knowledge, states and conditions (*state space*) in order to find certain information, i.e., to reach a "goal position".	Navigation systems; Supply chain efficiency
Logic Reasoning	Reasoning based on mathematical logic and logic applying algorithms.	Expert systems; Automated computation
Probabilistic Reasoning	Reasoning based on generalisation and approximation such as heuristics to overcome uncertainty.	Sales forecasting; Weather forecast
Learning	Procedures to improve working method and/or increase knowledge base.	Process optimisation of any kind; Image recognition
Natural Language Processing	Capture and use of natural language by machines.	Chatbots; Language translation
Computer Vision	Gain information through visual sensory inputs.	Identification systems; Autonomous drones
Expert Systems	Representation of and access to expert knowledge of certain domain.	Telemedicine; Educational/teaching systems
Robotics	Machine able to interact "intelligently" with its physical surroundings.	Warehouse automation; Surgical assistance

Source: Own table

As mentioned before, the split of the research areas induced the development of expertise in each domain. What is important to acknowledge is that breakthroughs in science and economy in the

[2] Since many applications use several methods at the same time, the fields mentioned represent possible examples, which can also be assigned to other methods.

1980s such as commercial expert systems that could be successfully marketed led to a new era of interest in AI that is still present today. Consequently, the researcher's mindset of investigating solely in their own isolated fields of study has changed, once again promoting an integration of the subfields for mutual advantages (Russell & Norvig, 1995, pp. 24–27; Tecuci, 2012, p. 170). Nowadays, AI can be called an interdisciplinary research which is rooted in and overlaps with "not only all the computing disciplines, but also mathematics, linguistics, psychology, neuroscience, mechanical engineering, statistics, economics, control theory and cybernetics, philosophy, and many others" (Tecuci, 2012, p. 168). Therefore, AI technologies can find applications in basically all industries as will be shown in the subsequent chapter.

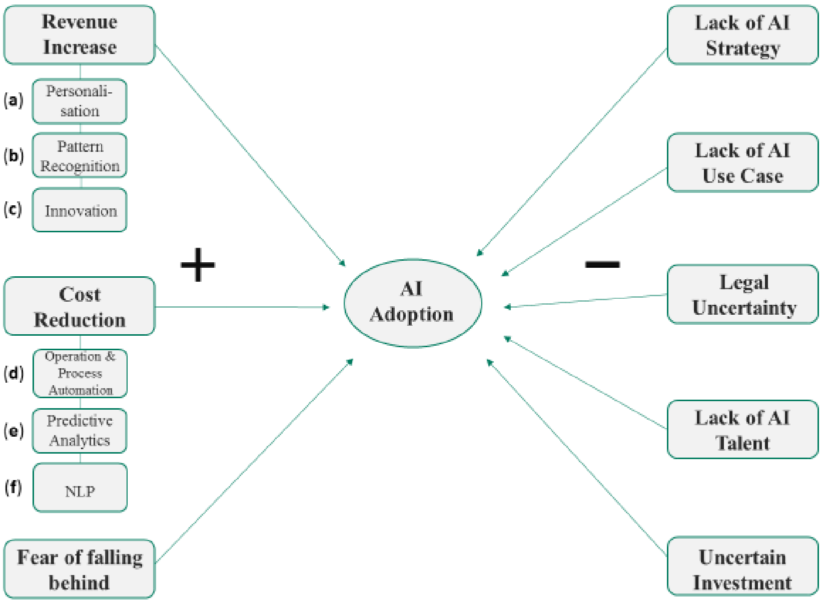
2.4 Hypotheses

In chapter 1.1 the strategic impact of AI on the macro- and meso-level has been pointed out leaving no doubt about the importance for companies to embrace the technology. It has also been shown that in spite of managers' concordance with the notion of creating competitive advantage through AI, few firms have adopted any AI technology. This discrepancy induces to take a closer look and get a clearer understanding of the underlying principal driving and impeding forces to AI adoption in Austrian companies. By reviewing literature and concrete AI use cases, several factors are identified to be either drivers or barriers, and corresponding hypotheses are formulated. Before going into detail, the research model is presented in order to provide an overview.

2.4.1 Research Model

Assembling the drivers and barriers to one construct generates the following research model. The driving forces, i.e., variables that are assumed to exercise a positive effect (+) on AI adoption are pictured on the left-hand side. Hampering factors, which presumably have a negative effect (–) on the dependent variable are found the right-hand side.

Figure 3: Research Model



Source: Own figure

2.4.2 Drivers

2.4.2.1 Revenue Increase

Pertinent literature, articles and case studies provide numerous examples across all industries and functions of how artificially intelligent programs can help raise revenue as delineated in the following.

A major driver of revenue is product and service personalisation (a)[3]. According to a global study, AI technologies enable firms to "continually deliver more tailored and personalised services" (MIT Technology Review Insights, 2018, p. 29) and 90% of global executives indicated that their firms use AI solutions to improve customer experience. Indeed, AI technologies make "hyper-personalization" (Gonfalonieri, 2018) possible including not only personal and transactional data (name, gender, purchase history etc.) but also behavioural and real-time data. This entails gains on an unprecedented scale for firms in all sectors. Benefits stem from highly customised product and service recommendation systems, digital ad placements, marketing campaigns, dynamic pricing, product design, enhanced user experience and so on, leading to a better customer engagement, loyalty and brand relationship (Reavie, 2018). According to Gartner research, companies which engage in intelligent personalisation will outsell companies that do not do so by 20% (Kihn, 2015). One example is the Netflix recommender system which is based on intelligent algorithms scrutinizing members' historical and real-time search and consumption data. The programme allows Netflix to customise the page experience and movie

[3] The letters (a), (b), (c), and (d) correspond to the research model presented in chapter 2.4.1.

recommendation to each individual's needs and preferences (Gomez-Uribe & Hunt, 2016, p. 15), thereby retaining old members and attracting new ones. The Netflix Vice President of Product Innovation and the Chief Product Officer state that they "think the combined effect of personalization and recommendations save [them] more than $1B [dollar] per year" (p. 7).

As explained in chapter 2.3, particularly machine learning and deep learning approaches are able to recognise patterns (b) in vast quantities of data where humans do not. Further, they can turn it into useful information which would – if at all possible – take an excessive amount of time for a human. The following example outside of the realm of business illustrates this. One study conducted at the laboratory at the NYU School of Medicine used a neural network which was fed with 800.000 images of lungs with and without cancer (World Intellectual Property Organization, 2019, p. 103). After two weeks of training its effectiveness was tested and with 97% accuracy and much less time spent on the diagnoses compared to experienced pathologists the programme performed better than the human experts. Furthermore, it was able to detect patterns of genetic mutations in the patient's DNA which the doctors were not aware of, and which could predict if lung cancer was likely to occur with an accuracy rate of 80%.

Turning to more business-related applications, the customer relationship management platform *ZenDesk* reported excessively high costs for advertising their solutions via pay-per-click and search engine marketing leads (Faggella, 2017). The reason was that their customer audience was too broad, and the product placement could not be tailored to specific needs. With the help of a deep learning marketing automation platform they could detect patterns in contact data and subsequently categorise customers in a way that allowed for a specified targeting. The result was an increase of four times the lead volume, thereby shrinking cost-per-lead and raising the number of products sold. Similarly, numerous other use cases of customer segmentation through AI technologies exist (Brenner, 2019; Y. Kim & Street, 2004; Sarkar, Bali, & Sharma, 2018).

Another example which shows that not only the tech giants like Google, Amazon and Facebook can effectively employ Artificial Intelligence is the case of the German online merchant *Otto* (The Economist, 2017). The company has the problem of selling millions of products from many different brands which it cannot hold in stock. This makes it almost impossible to ship various items from one order within the two critical days in which customers are likely to retain the orders. Otto consequently deployed a deep learning algorithm analysing roughly three billion past transactions and 200 parameters including past sales, clicks on Otto's website and weather conditions. The algorithm detects patterns among billions of seemingly unrelated data points and is, thus, able to predict what customers will purchase one week before they do so. Due to its accuracy rate of 90%, Otto allows the software to autonomously buy 200.000 products per month in advance. This whole process takes place without human interaction and instead of emotional decision-making based on “gut-feeling”, objective and data driven knowledge is optimally utilised. The system allows the retailer to ship several items from different brands within two days. As a consequence, its surplus stock declined, and product retention increased significantly. Let away high initial implementation costs, this approach could be applied anywhere. For instance, even a small hairdresser could have relevant variables such as fashion trends, demographic numbers, weekday and weather forecast analysed and make accurate predictions on how many hair cutters should be staffed each day.

Moreover, intelligent data analytics and its ability to identify patterns are used to create internal benefits in the form of *people analytics* as many use cases show (Koester & Tintman, 2019; Leonardi & Contractor, 2018; Shrivastava, Nagdev, & Rajesh, 2018). Organisations analyse their employees and their networks based on the large data volumes they create each day via e-mails, chats, file-sharing, virtual team activity etc. They take this data to report, calculate, and comprehend employee performance and improve their business by adapting staff planning, recruiting, compensation and retention plans (Collins, Fineman, & Tsuchida, 2017).

Although most of the currently deployed AI technologies perform repetitive, rule-based tasks, “AI is not only about process automation, but is also used by companies as part of major product and service innovation” (c) (Bughin et al., 2017, p. 14). Indeed, creativity and innovative spirit in machines is being developed enabling machines to create even art (Landwehr, 2018, pp. 68–76). Artificially intelligent systems are, for example, capable of generating new marketing insights solutions and strategies (Li, 2000; Wirth, 2018). Cockburn, Henderson, and Stern (2018) argue that AI may be used as a “method of invention”, thereby exercising great impact on innovation, particularly for commercial actors. Clearly, existing products and services can be tremendously improved through AI as was shown in this chapter, and this fact alone can motivate managers to embrace the related technologies. Yet, Ransbotham, Kiron, Gerbert, Reeves, and Spira (2018) expect considerable impact of AI in all major industries already within five years including not only changes in existing businesses but also the emergence of completely new business models (pp. 6–12). Likewise, according to Purdy and Daugherty (2016), AI enables organisations to “propel innovations” (pp. 12–15). One example is the company *Lifegraph* which developed a smartphone app that claims to deliver a “clinically proven migraine forecast” (Lifegraph, 2019). By exploiting machine learning and smartphone technologies, the app gathers and monitors behavioural and other data such as insights on sleep, physical activity and weather to forecast migraine attacks. This service is new in such a way that a relatively accurate (70%) and personalised medical diagnosis and prediction is made available to an end customer via smartphone app. Prior to that, a visit at a doctor’s surgery including extensive examinations were necessary, usually not even yielding such precise forecasts. This business model has only become possible through the integration of AI. Other examples include *Enlitic* who streamline radiologists' workflows and ameliorate healthcare diagnosis in an unknown way utilising deep learning techniques (Enlitic, 2019), and the technology company *Equifax* which developed a new intelligent analytics tool called *Ignite*. It is labelled a "revolutionary portfolio of premier data and advanced analytics solutions", which due to the integration of AI enables the firm to offer new products, for instance, in credit risk decisioning (Equifax, 2019).

Summarising, it can be stated that the deployment of Artificial Intelligence can very likely lead to a revenue boost in all industries across the value chain as shown above. Countless use cases show the potential benefits of AI implementation and thus, it is assumed that it represents a driving force for firms to adopt AI. Therefore, the subsequent hypothesis is developed.

> H_1: The opportunity to increase revenue by implementing and using AI technology has a positive effect on AI adoption.

Further, complementary information about the respective function, which is expected to lead to the rise in revenue, yields more profound insights about the motivational factors. The ways presented, namely personalisation (a), pattern recognition (b), and innovation (c) can be respectively seen as independent reasons for managers to deploy AI. Therefore, these more concrete explanatory arguments are queried in the survey.

2.4.2.2 Cost Reduction

The deployment of AI technologies allows for heavy cost savings in almost all businesses. Rao and Verweij (2017) argue that AI has huge potential in cutting costs in the medium and long run. However, already at the current stage of development the intelligent technologies are able to do so, mainly by automating operations and processes (d) (Rao & Verweij, 2017, pp. 15–17), which represents the largest area of AI applications at present-day. The authors provide several use cases in their research paper where process automation led to significant cost reductions. For instance, an AI bot developed by an insurance company conducted process claims automatically, thereby trimming processing time from several days or months to just three seconds (p. 9).

Scanning academic literature and business cases for the existing possibilities of AI to optimise processes reveals uncountable further examples (McAfee & Brynjolfsson, 2017, pp. 7–8). One illustrative case is the online supermarket *Ocado* which implemented a completely automated warehouse of the size of several football fields (Clarke, 2018a). The whole ordering, picking and packing process is automated, assembling a 50-item order in a matter of few minutes, a number unachievable for any human. Similarly, the supermarket chain *Morrison* optimised its stock replenishment system with the help of machine-learning techniques, "reducing costs and stock levels" and shelf gaps by 30% (Juhr-De Benedetti, 2017). Also, *Amazon* could decrease its operating expenses by 20% due to deploying intelligent robots in their fulfilment centres (E. Kim, 2016). Overall, an extensive research executed in the retail industry calculates a $ 340 billion dollar cost saving for retailers by 2022 if AI is implemented across the value chain (Jacobs et al., 2018). Similar numbers can be achieved in other industries, since automation is able to reduce costs in many domains such as for transactions (Birkinshaw, 2018), manual labour (Bughin et al., 2017, p. 42), or administrative tasks (Thomas Davenport & Ronanki, 2018, p. 110).

The ability to forecast certain events using artificial intelligence represents a significant cost saver in business. Taking the example of sales, Syam and Sharma (2018) depict the effect of machine learning and AI on personal selling and sales management and foresee a "sales renaissance" (p. 135). They argue that the ways to simulate the whole sales process with AI algorithms and models have become considerably more elaborate allowing salespeople to anticipate risks and resource wasting actions (p.145). Hence, expenses can be reduced significantly. Other examples include an intelligent fast sales forecasting model for the dynamic fashion industry (Y. Yu, Choi, & Hui, 2011) or an artificial, fuzzy neural network which is able to significantly improve sales forecasting methods in any domain by beating the conventional statistical methods in prediction accuracy (Kuo, Wu, & Wang, 2002). Apart from the AI-based forecasting abilities in the sales area, predictive analytics (e) has huge potential also in almost any other domain. Machine learning techniques, which analyse all relevant stock-related data, make it possible to predict stock market prices in such a way that it greatly outperforms any traditional statistical and technical method (Magesh & Swarnalatha, 2019; Nann, Krauss, & Schoder, 2013). Costly procedures to scan and analyse the market can thereby be trimmed substantially. In Jordan, loan defaults occur increasingly. This represents a major problem for commercial banks. The implementation of a multi-layer artificial neural network tool, which analyses client data, can accurately predict a loan applicant's probability to pay back the credit, thereby significantly cutting the costs of those who deploy the technology (Eletter, Yaseen, & Elrefae, 2010). The prediction of a patient's future health applying a Bayesian multitask learning approach used by clinics (Lin, Chen, Brown, Li, & Yang, 2017) is another example. This approach helps hospitals undertake preventive care for people with chronic diseases which constitutes superior and cheaper treatment than medicating them when the effect of a disease already occurs.

Another major specific measure for cost-cutting is natural language processing (NLP) (f) which is more profoundly depicted in chapter 2.3.7. One way to let NLP do the work for which organisations otherwise have to pay a lot more, is extracting information from unstructured data. Whilst statistical algorithms are very good at finding patterns and information in structured (e.g., numerical) data, they fail when examining social media content, emails or customer conversations. Doing so manually is prohibitively expensive (Tecuci, 2012, pp. 173–176). In order to incorporate knowledge from free text sources, NLP offers not only a far more economic, but also high-quality solution (Abramowicz, 2007). The extracted information from, for example, a sentiment analysis of customer opinions or language translation can be used to improve business (Singh, 2019).

However, due to its relatively easy applicability, the most used NLP-based technology are chatbots. These programmes are able to understand and express natural language and can, combined with a profound knowledge base, deliver satisfying answers to most queries (Hulick, 2016, pp. 7–12; Tecuci, 2012, p. 177). Chatbots can be implemented in all industries and are usually used for communication in contact centres with end users since by replacing or supporting customer service agents they offer an enormous cost savings potential, despite the initial implementation costs (Thorne, 2017). For instance, *IBM*'s *Watson Assistant* helped the American software company *Autodesk* decrease per-query costs of up to 200%, improve response-time and increase the number of resolved customer support queries (Reddy, 2017). In total, customer service expenses dropped by 30%.

Summing up, "by deploying the right combination of AI technologies, producers can boost efficiency, improve flexibility, accelerate processes, and even enable self-optimizing operations" (Küpper et al., 2018, p. 3) and in this way diminish costs excessively. Due to these promising possibilities the following hypothesis is formulated.

> H_2: The opportunity to reduce costs by implementing and using AI technology has a positive effect on AI adoption.

In this case, too, the three most applied cost saving approaches, i.e., operation and process automation (d), predictive analytics (e) and natural language processing (f), are queried in the survey to gather a more profound understanding of the underlying motivational factors.

2.4.2.3 Fear of Falling Behind

Lastly, one other aspect, which drives managers to deploy AI technologies, and which cannot be put into the categories of revenue increase or cost reduction, is the fear to technologically fall behind competitors. Mahidhar and Davenport (2018) argue that contrary to other upcoming technologies where it was reasonable to wait for further developments, it is a "bad idea" to wait to implement AI. Although real-life benefits through AI are reported only since a few years, the foundational technology has continuously been developed for decades as was also shown in chapter 2.2. With the improved processing and memory capacities available nowadays, AI can be deployed anywhere across sectors and business functions. However, it takes time, sometimes up to several years, to integrate the AI application in the respective business model or system (Mahidhar & Davenport, 2018).

Additionally, independent large-scale global studies of both the *MIT Sloan Management Review* in collaboration with the *Boston Consulting Group* (Ransbotham et al., 2017), and

Capgemini (Westerman, Tannou, Bonnet, Ferraris, & McAfee, 2012) each clustered companies into groups depending on their degree of digitization. They both have in common that they identified one leading group of organisations which vigorously take up digital transformation and, most importantly, actively collect and use data to enhance business, and others that fall behind these terms. Bughin et al. (2017) state that these companies which lag in data usage and AI adoption already at present time will have even greater difficulties in catching up later (p. 14). The CEO of the AI solutions start-up *Satalia* describes the apprehension which managers may have in this context: "There's this fear factor that if you're not on the AI bandwagon, then you're going to lose out to competitors that are going to be eating your market, because they're using technologies to make decisions faster and better than you" (Cameron & Unger, 2018). The awareness of firms' managers that embracing AI too late might result in an irremediable disadvantage against their competitors could urge them to adopt AI, leading to the following hypothesis.

> H_3: The fear of falling behind in terms of technological adaption has a positive effect on AI adoption.

2.4.3 Barriers

Undoubtedly, the adoption of new technologies and AI in particular offers numerous advantages for a company. Nevertheless, there are several reasons of why an organisation may not be able or willing to implement AI technologies. In this study, five major barriers have been identified by examining literature and use cases, which are depicted below.

2.4.3.1 Lack of AI Strategy

One basic prerequisite for adopting new technologies is a clear strategy. In order to be able to benefit from artificial intelligence, companies must first and foremost understand what AI is, decide to act upon it (Westerman et al., 2012, p. 20) and draw a coherent roadmap for why, when, where and how they deploy the technologies (Küpper et al., 2018, pp. 11–14). It must be in line with the firm's strategic goals, business model, and overall digital strategy, taking into account both the existing pain points which shall be tackled as well as the impact on business and stakeholders. Additionally, there must be a person or a team responsible for the effective rollout of a strategy. The head of *Daimler* Strategy puts it this way: "Having a strategy in place [...] is the key lever to implement AI technologies to improve existing processes along the entire value chain as well as developing new products and services to delight our customers" (Ransbotham et al., 2018, p. 10). However, if a clear vision of AI is missing, in other words, with no or just a diffuse AI strategy in place, a company is unlikely to adopt AI at all. This induces the succeeding hypothesis.

H_4: The lack of a clear AI strategy has a negative effect on AI adoption.

2.4.3.2 Lack of AI Use Case

Apart from having a holistic strategic perspective on AI employment, executives must know what AI is capable of and what it can do for them. It must be clear in which concrete cases AI can bring an improvement, be it in automating production processes, in forecasting staff requirements or in customising the clients' shopping experience. The respective applications (use cases) differ in each business and have to be identified across all functions and processes. Research shows that companies do have difficulties in identifying the use cases (Bughin et al., 2017, p. 20; Ransbotham et al., 2017, p. 7) with "just 17 percent of respondents say[ing] their companies have mapped out where, across the organization, all potential AI opportunities lie" (McKinsey & Company, 2018, p. 4). For instance, a sportswear manufacturer could improve its business with AI by leveraging a highly accurate customer segmentation. Nonetheless, if the managers of the firm, for whatever reason, do not recognise this or any other AI use case, they will not have any need to adopt the technology. Similarly, AI does not yet offer solutions to every kind of business. Thus, at the moment, for some there will be no practical use at all. Consequently, the following is hypothesised.

H_5: The lack of a clear use case for AI technologies has a negative effect on AI adoption.

2.4.3.3 Legal Uncertainty

Even if an AI strategy and use cases exist, a firm may stall or impede the implementation due to unclear legal regulations. Setting up programmes which more or less autonomously collect, consolidate, and analyse data and take their own decisions includes many risks. Which data is collected? Does it meet data protection regulations? What happens if a decision taken by a machine leads to a negative outcome for the firm or the customer? The most discussed example is a driverless car equipped with artificially intelligent applications hitting a person. Who exactly is responsible for the consequences? Many other questions regarding contracts and liability, intellectual property and human rights still remain unanswered to a great extent (Beauchemin, 2018). Yet, legal uncertainty hampers innovation in general (Deutscher Industrie- und Handelskammertag, 2018, p. 1) and AI diffusion in particular (Bundesministerium für Verkehr, Innovation und Technologie & Bundesministerium für Digitalisierung und Wirtschaftsstandort, 2018, p. 14). Due to ambiguous legal regulations, managers might reject deploying AI technologies. This results in the consequent hypothesis.

H_6: Legal uncertainty has a negative effect on AI adoption.

2.4.3.4 Lack of AI Talent

A major challenge is finding people capable of implementing AI. They must possess the necessary technical skills to engineer artificial neural networks, create algorithms, and align it with an organisation's IT-infrastructure and keep everything going after deployment (McKinsey & Company, 2018). Yet, since "[d]ata science and AI lie at the most overheated end of the software engineering spectrum, and there is a massive shortage of graduates and postgraduates emerging with the necessary skills" (Clarke, 2018b), the latter become very rare to find. The introduction of a Bachelor's and Master's Programme on AI at the *University of Linz* is an answer to the lack of AI talents but it still remains one of very few offers in Europe (JKU Linz, 2019). According to Sepp Hochreiter, companies offer students and assistants annual salaries as high as 1.8 million to work for them (Innerhofer, 2018). Hence, the next hypothesis states that many firms will not be able to find or pay skilled workers, which are critical for any successful AI implementation.

H_7: The lack of adequately skilled personnel for AI implementation has a negative effect on AI adoption.

2.4.3.5 Uncertain Investment

New technologies often imply high costs for implementation and acquisition of know-how. This can be considered a significant obstacle to embrace AI particularly for small and medium-sized enterprises (Bundesministerium für Verkehr, Innovation und Technologie & Bundesministerium für Digitalisierung und Wirtschaftsstandort, 2018, p. 14) as a firm must always undertake a cost-benefit consideration. Costs are not only restricted to monetary value, for instance, for the software but also include time spent, opportunity costs, expenses for persuasive efforts to align stakeholder interests etc. In accordance with this notion, Bughin et al. (2017) who surveyed company executives find "that one of the biggest barriers preventing them from further adoption of AI was the uncertain return on investment" (p. 35). Indeed, in the course of digitalisation, organisations have particularly many competing investment priorities and investing in one area always means to trim expenditures in another. Thus, at relatively high initial costs and only uncertain benefits, companies may opt to not invest in AI at all or in other projects. This idea is captured in the hypothesis below.

H_8: Uncertain investment has a negative effect on AI adoption.

2.4.4 AI Adoption

All the variables presented above are measured against the dependent variable AI adoption, i.e., whether a firm has adopted AI or will do so in the near future. As technologies develop and change rapidly, the “near future” in this case is limited to a maximum of two years. The adoption could be further differentiated into different levels, for instance, by distinguishing the deployed AI technologies based on the degree of intelligence (Scherk et al., 2017; Wirth, 2018). In this case however, this distinction is not made, since the focus of this research lies on finding out if AI is or will be implemented, and why. The goal is to generate initial tendencies, and more a nuanced mapping of AI technologies is left to further studies.

Both the identified drivers and barriers do certainly not include all possible motivating or impeding reasons companies might have for AI implementation. Further, possible moderating or mediating variables are not included in the framework. Firstly, this is due to the fact that this study aims at presenting a generic, industry-independent picture of the most important drivers and barriers to AI adoption in Austria which can serve as a basis for further research, and secondly, the inclusion of more variables would go beyond the scope of a master’s thesis.

3 Methodology and Research Design

The objective of this research is to deliver answers to the two research questions stated in chapter 1.3 by testing the hypotheses formulated in chapter 2.4.

Despite the fact that the notion of AI has existed for almost seven decades, real-world problems can be tackled successfully only since a few years. This is why AI is considered to be still in its infancy (Bünte, 2018, p. 31; Doelfs, 2018). Even in the realm of strategic management, research has focused mainly on specific issues. A comprehensive, general examination of both driving and inhibiting forces to AI adoption, particularly for Austrian companies, is missing. This study aims at filling this research gap by trying to find evidence for why or why not Austrian companies deploy AI systems. In order to deliver these insights, an approach is chosen that is both descriptive and explanatory (Saunders, Lewis, & Thornhill, 2016, pp. 174–177). On the one hand, the study delineates the current state of AI adoption, i.e., whether firms have adopted AI or not, and where. On the other hand, it seeks to identify and empirically confirm reasons which explain the relationship between the independent and the dependent variable. Researchers apply either experimental or statistical methods in order to measure the impacts of predictor variables on target variables (Zikmund, 2010, pp. 59–60).

3.1 Method

Factors which encourage or hamper companies to implement AI are merely covered in academic research, which makes it hard to relate this study to prior research methods. Several business consulting firms have done their own studies on particular aspects of AI adoption but firstly, they do not comprise the spectrum of variables which are of interest in this study and secondly, they do not share the research process but only present the results. Apart from that, Hermeier, Heupel, and Fichtner-Rosada (2019) investigate the influence of digitalisation on the workplace, where amongst others they apply a quantitative method in the form of a survey using a five-point-Likert scale to assess managers' judgement on how much certain digital trends, including AI, will have an impact on their organisation (pp. 276–277). Similarly, researchers examining the impact of digital technologies on controlling in Swiss firms employ a questionnaire with a seven-point-Likert scale to ask CFOs to evaluate the technologies' repercussion on their companies (Keimer & Egle, 2018).

None of these studies is directly comparable to this research, however, using surveys in the form of questionnaires, and, in particular, applying a Likert scale seems appropriate to obtain a valid estimation of managers' opinion towards the impact of certain technologies.

One study, which is being conducted by the Austrian Institute for SME Research, and which could be taken into account for orientation and comparability with this research examines the current state of AI in Austria (KMU Forschung Austria, 2019a). However, at the time of conducting the research, the study has not been published yet.

This research follows a deductive approach, i.e., a theory is developed and then tested analysing the data gathered (Saunders et al., 2016, p. 166). As the goal of this thesis is to draw a general picture of motivating and impeding forces to AI adoption independent from specific geographical, industry or organisation structure characteristics, the research is designed to be broad rather than specific. Hence, a quantitative research strategy is applied, as it allows to reach a greater number of respondents (Saunders et al., 2016, pp. 165–168). In contrast to in-depth interviews with comparatively few participants from specific companies, a survey devised for a wide-ranging target group is used, thereby favouring a more general view. This approach is also in accordance with the aforementioned studies on the impact of digital trends on companies (Hermeier et al., 2019; Keimer & Egle, 2018).

Surveys have become increasingly popular amongst academic studies since they offer various advantages (Saunders et al., 2016, pp. 177–183). Firstly, they permit a standardisation of collected data which is convenient for data analysis and useful for comparability. The data can be analysed employing descriptive and inferential statistics. Secondly, a vast population can be attained at relatively low cost and effort.

For this research it is reasonable to create an online-survey. In addition to the aforementioned general benefits of a survey, an online version involves further advantages. The data will be examined using the software *IBM SPSS Statistics* and as the results of the survey will already be stored digitally, the transfer, analysis and interpretation of data is facilitated. What is more, online-surveys support both adjustments of items depending on answers given before and filter-questions, thereby showing only the relevant questions to each individual respondent, which diminishes the dropout rate.

With 88.7% of Austrian households and 99.6% (2018) of Austrian companies having access to internet, Austria belongs to the countries with the highest internet penetration rates in the world (Statistik Austria, 2019a, 2019b). Therefore, conducting an online-survey and sending out the link to the questionnaire via e-mail is considered both to be reasonable and an efficient method to reach a meaningful number of valuable responses.

As stated above, this research is considered both descriptive and explanatory. Therefore, on the one hand, the survey's questions are designed in such a way that they grasp the respondents' attitudes towards driving and impeding forces to AI adoption (chapter 3.2). Descriptive statistics will subsequently reveal differences and similarities in the phenomena examined (chapter 4.1). On the other hand, inferential statistics may explain cause-and-effect-relationships of the variables in question (Saunders et al., 2016, p. 439) (chapter 4.2). This method allows to generate valuable findings on AI adoption in Austria.

3.2 Composition and Structure of the Questionnaire

The purpose of a questionnaire in quantitative research is to collect the necessary data in a structured and standardised way from which the desired information can be derived (Reinecke, 2019, pp. 720–721). In chapter 3.1 it was mentioned that no prior survey has been found, which can be directly compared and applied to this study.

One additional way to find existing questionnaires and coding schemes is to search in pertinent handbooks such as in Bruner (2017) or in databases like the *UK Data Service* collection where numerous surveys, variables, scales and questions are provided (UK Data Service, 2019). Yet, no appropriate questionnaire or scale, which would fit the topic, was found there either. Consequently, there are no empirically tested and validated questions or scales which can be taken for the questionnaire of this thesis (Reinecke, 2019, pp. 721–722).

Since this research is conducted in the realm of strategic management, general methods of business research can be utilised instead. Saunders et al. (2016)) and Zikmund (2010) present several types of questions and make suggestions on how to design a questionnaire in business research.

Generally, it is necessary to achieve a good balance between breadth of data and shortness of a questionnaire. Closed questions offer the advantage that they can be answered quickly, that they do not require much cognitive effort for the respondent and that the answers can be easily compared (Saunders et al., 2016, p. 452). In particular, rating questions, which include a Likert-style rating are mainly used in this questionnaire, trying to get reliable and valid responses (Reinecke, 2019, pp. 721–722). In order to avoid a common tendency of respondents to select a neutral "in-the-middle" option when unsure (Raab-Steiner & Benesch, 2018, p. 60), a four-point rating scale is employed, forcing the subject to choose one side. However, a "not applicable" (= -1) option is included as in some cases this will certainly be the legitimate answer and a non-inclusion may lead to frustration and a subsequent cessation. The answer options range from "strongly disagree" (= 1) on the left to "strongly agree" (= 4) on the right, whereas the two intermediate options (= 2; 3) are not labelled in order to keep the layout simple (Saunders et al., 2016, p. 458).

Zikmund (2010) underscores the importance of the visual presentation of web-based questionnaires (pp. 356–360). Accordingly, the questionnaire was designed in such a way that it is intuitive to use, easy to follow and visually plain. The web-based survey tool *ScoSci Survey*, which is used for this study, offers various features to design the questionnaire in an appealing way. The design is also appropriate for usage with smartphones.

In order to assure that the questionnaire fulfils the criteria on coherence, comprehensibility, technical feasibility, design, and duration, researchers strongly recommend to trial-run the questionnaire before going into the field (Raab-Steiner & Benesch, 2018, pp. 63–64; Saunders et al., 2016, pp. 473–474; Zikmund, 2010, pp. 361–362). In a first stage, both business students and managers, totalling 10 people, were given the questionnaire under direct observation and were asked to express their thoughts when filling it out. Based on this feedback, unclear or misleading questions or answer options were amended. In a second stage, the redesigned questionnaire was sent out in pretest-mode to another 24 people resembling the target group, allowing participants to make comments on each question. The answers then were incorporated where appropriate. The final questionnaire will be delineated in the following.

The first page of the questionnaire is a welcome text which thanks the respondent for participation, providing information on the time it takes for completion and on confidentiality. Most importantly, AI is defined and explained with short examples so that everyone has the same understanding of the theoretical concept of AI (Fowler, 2006, p. 13; Saunders et al., 2016, p. 407).

The first question asks about the participant's general knowledge about AI (item 1). Saunders et al. (2016) note that answers can be contaminated, for instance, when subjects do not have sufficient knowledge of the topic (p. 442). As a consequence, they respond arbitrarily, thereby adulterating the data. Hence, this first question was included in order to better assess answers given and, if necessary, to rule out uniformed responses when analysing the data.

The second and third question collect information on the first two variables *revenue increase* (H_1) and *cost reduction* (H_2), i.e., whether AI systems represent an opportunity for the respondent's company to increase its revenue and to reduce its costs (item 2 and 4). Both items are filter questions. If a participant agrees to some extent (answer options 2, 3, or 4) that AI can boost revenue or diminish costs he/she will be asked which technological function is most likely to do so (items 3 and 5). These questions are not directed at explaining the relationship between the variables directly but to deliver deeper insights on what could drive AI adoption. The technological functions presented were chosen by analysing the literature in chapter 2.4. If the respondent finds that a function is missing, he/she is given the chance to add it in the input field provided. If, however, he/she strongly disagrees with the statements mentioned above, there is no point in asking about the functions likely to entail the effect. On the contrary, it would discourage the respondent and lead to a higher dropout rate.

For each of the variables *fear of falling behind* (H_3), *lack of AI strategy* (H_4), *lack of AI use case* (H_5), *legal uncertainty* (H_6), *lack of talent* (H_7), and *uncertain investment* (H_8), two questions were designed. How the respective concepts are defined, is outlined in chapter 2.4. The two items per variable aim at extracting the necessary information taking into account possible third variables as much as possible without unnecessarily extending the questionnaire's length.

For instance, in the case of H_3, item 6 accounts for the participant's general attitude towards technological trends, i.e., whether he/she fears that slow adaption causes competitive disadvantage. If this "fear factor" is not present at all, it is likely that it will not be given for AI technologies either (asked in item 7), thereby delivering a possible explanation for when a low or no effect on the dependent variable is measured. In any case, answers to question 7 can be better interpreted when considering responses to question 6, thus they complement each other. This logic also applies to the items 10 and 11 (*lack of AI use case*) and items 12 and 13 (*legal uncertainty*).

The concepts *lack of AI strategy, lack of talent,* and *uncertain investment* are covered by the question pairs 8 and 9, 14 and 15, and 16 and 17, which also respectively complement each other. For example, an AI strategy involves both a coherent long-term roadmap (asked in item 8) and a responsible team or person dedicated to its successful rollout (asked in item 9). Both elements must be given so that an AI strategy can be considered to be in place. Again, this rationale also applies to the variables *lack of talent* and *uncertain investment*, which ask about the availability of skilled personnel and the investment attractivity for AI systems. Internal consistency of the items, i.e., whether they complement each other, will be measured by Cronbach's alpha (Saunders et al., 2016, p. 451) in chapter 4.2.

All the above-mentioned variables are measured on a four-point-Likert scale, which enable the participants to express finer shades of opinion rather than just yes or no. Included graphics visually make clear the ascending (dis-)consent with each statement, diminishing cognitive effort and consequently the dropout rate.

After the participant has filled in questions 1 to 17, item 18 represents the dependent variable *AI adoption*. It can be answered on a nominal scale with no (= 0) or yes (= 1) which makes it a discrete, dichotomous (binary) variable (Field, 2013, p. 182). As remarked in chapter 2.4, no distinction of degrees of adoption is made in this study.

The following two questions (item 19 and 20) are optional open questions allowing the surveyed to express additional thoughts or arguments on why or why not his/her company implements AI. This is important as it provides the chance to add aspects which may not have been covered in the questionnaire and to obtain an increased understanding of the reasons.

The subsequent four items (21 to 24) collect meta-data on the companies' location (federal state), industry, number of employees, and annual revenue. With this information, a more nuanced picture of AI adoption in Austria can be drawn. The criteria on these variables are adapted from the Economic Chamber of Austria (WKO, 2017). Although the Economic Chamber's proposed categories for the number of employees end with > 250, categories of between 249 and 1000, and > 1000 employees were added, since it allows for a more precise observation. The variables *location* and *industry* are measured on a nominal scale, since no rank order is given, whilst, *number of employees* and *revenue* represent ranked ordinal data (Saunders et al., 2016, p. 499). The meta-data will provide further insights on possible influencing factors such as company size or location.

The last item asks the interviewee whether he/she wants to receive the thesis' results when finished, which represents the incentive offered in the invitation mail (more in chapter 3.3).

Depending on the respondent's reading speed and choice in the filter questions, the completion of the questionnaire takes between 5 and 10 minutes. The questionnaire itself was written in English, which certainly decreases the response rate as potential interviewees may not be able or willing to do it in English. However, since both the model and the hypotheses are formulated in English, and since Saunders et al. (2016, p. 464) and Zikmund (2010, p. 363) mention issues such as misinterpretation and misleading expressions when (back-)translating questionnaires, English was chosen as the survey language. The questionnaire can be found in Appendix A.

3.3 Sample Design and Data Collection

Häder and Häder (2019) argue that a total census, i.e., collecting data from the whole population excludes certain errors, which can occur in sampling, and therefore, the results are more reliable and precise (pp. 333–334). However, Stein (2019) points out that the great financial, personnel and time-consuming burden in many cases speaks against a total census (p. 136). In this study, the aim is to gather information on the broadest spectrum of companies possible, therefore, the target population includes all companies of any size and industry in Austria. According to the Economic Chamber of Austria the number of Austrian firms mount up to 525.956 in 2018 (WKO, 2019a). Collecting data from every single company is impossible in the context of a master's thesis. For this reason, sampling, i.e., a selection of a reduced number of elements or cases, which ideally represent the total population, is applied.

According to Häder and Häder (2019), in *simple random sampling* all elements have a known, equal chance of being elected (p. 334). This means that *probability sampling* can be applied to ensure a valid representation of the targeted population. Furthermore, it can be considered the best way to exclude selection bias and although sampling errors cannot be fully avoided, the confidence interval can be calculated more precisely (Saunders et al., 2016, pp. 287–289).

In order to be able to make statistical inferences from a sample which are generalisable, a *sampling frame*, i.e., a complete list of all elements of the target population is necessary (Saunders et al., 2016, p. 277). The list, which is most appropriate for this study taking into account the resource constraints, is the database of the Economic Chamber of Austria. It is possible to retrieve data on every company listed in its database (550.958 listings), which is publicly accessible on its homepage[4]. Unfortunately, the list cannot be downloaded. The company data can, thus, solely be accessed on the platform itself where it is not possible to arrange the list in a certain or random order so that simple random sampling could be applied.

Yet, with the help of a web scraping tool it was possible to randomly choose company listings and extract email addresses. In this context, Saunders et al. (2016) emphasise that a researcher should be aware of the currency of databases as many are only updated occasionally, and the targeted subjects may change their email addresses (pp. 278–279). Indeed, not all organisations share their email address on the platform, and not all addresses were reachable as will be further discussed in chapter 4.1.1.

This implies that, if scientific rules are applied strictly, simple random sampling as defined by Häder and Häder (2019) is not given. Rather, it can be considered a mix of random and *haphazard* sampling (Saunders et al., 2016, p. 304) where the latter is a *non-probability sampling* technique

[4] Database available at https://firmen.wko.at/Web/SearchComplex.aspx.

used when a complete sampling frame is missing and elements are chosen due to their availability, i.e., whether an email address is provided or not. Saunders et al. (2016) point out that a combination of methods is common and accepted (p. 276). The results, however, lose the ability to be generalised.

Notwithstanding, statistical inferences are not imperative to answer the research questions. The objective of this study is not to display the whole population but to obtain enough evidence to find influencing factors to AI adoption. With the methods chosen this is possible and therefore, this approach is suitable to deliver these insights.

It is crucial to mention that the obtained results might be subject to self-selection bias. More precisely, those who are already interested in AI might be rather prone to partake in the survey than those who do not have an interest in or are unaware of this technological trend.

To determine the sample size, Borg (2000) published a useful table (p. 144). At a 95 per cent confidence level ($\alpha = 0{,}05$), which is usually used for management studies (Saunders et al., 2016, p. 280), a margin of error of 5% and a total population of N = 525.956, a sample size of 384 is needed in order to achieve statistical significance.

Since the respondents are managers or people with strategy-relevant knowledge of their organisation who usually lack time, it is difficult to incentivise them to participate in a survey for a master's thesis. Moreover, the email addresses collected are most of the time designed for general inquiries of the type *companyname@info.at* which will further reduce the number of responses. Hence, a response rate of 0,5% – 2% is assumed which results in 76.800 (for a 0,5% response rate) and 19.200 (for a 2% response rate) companies to be asked to engage in the survey, if 384 valid responses were to be attained. It is not possible to obtain such a high number of email addresses considering the resource constraints of a master's thesis.

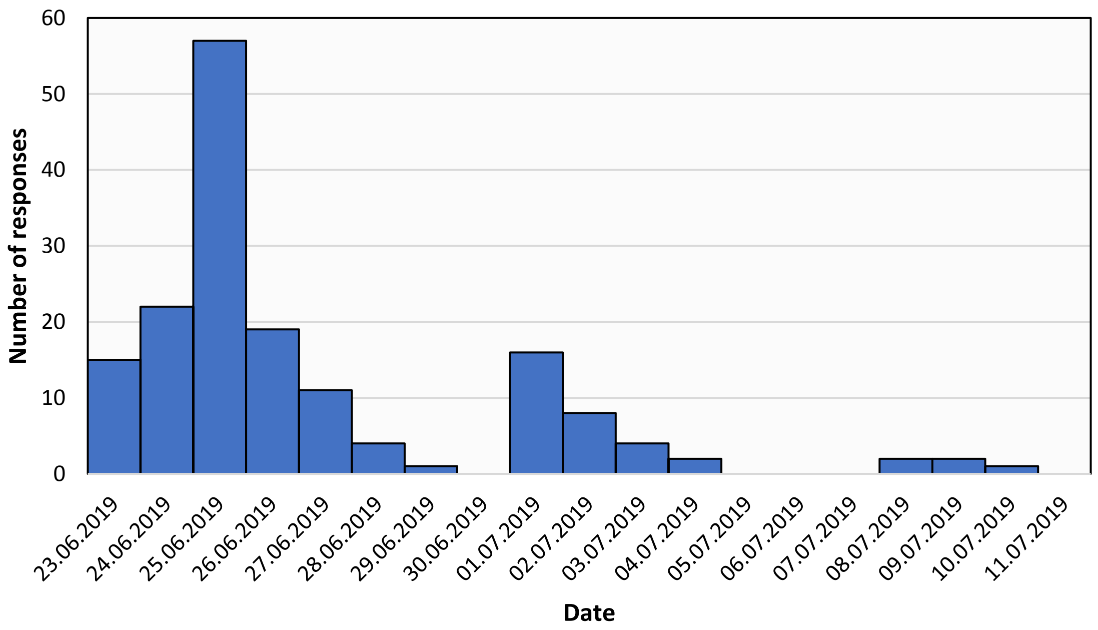
Still, 12.023 email addresses of companies could be collected on a random basis, fulfilling the above-mentioned criteria of being distributed over any industry, company size and location within Austria. Given that for example only 1% would answer the questionnaire, this would yield 120 valid responses which would, although statistically not relevant, suffice to generate initial findings.

In order to obtain as much data as possible, i.e., to achieve a high number of participants, an invitation email has been formulated. It represents the first point of contact for the queried where they will decide whether they participate in the survey or not. Therefore, the text should be chosen carefully, being polite and clear, without any grammar mistakes. It should not be too long and explain the purpose and context of the survey, how the participant can contribute, how much time it will take and how the data will be treated (Saunders et al., 2016, pp. 468–478).

These criteria were taken into account and a carefully written invitation email was drafted. The head of the text asks to further the email to an executive manager of the firm. Contrary to the survey itself, the invitation was written in German since the target group is located in Austria and, although it informs that the questionnaire is in English, the language barrier leading to instant dropout might be diminished. Zikmund (2010) further points out that the interviewees should obtain an incentive to increase the response rate (p. 216). Since the target group are managers, the only incentive that could be offered was to send them the study's results as it may be of interest for their company.

The emails containing the invitation and the link to the questionnaire were distributed to the 12.023 email addresses collected. Saunders et al. (2016) suggests 2-6 weeks to complete data collection for web and mobile questionnaires (p. 441). The survey distribution started on 23 June 2019 and ended on 11 July 2019. The survey was sent out in several waves within a few days, since the integrated email client of SosciSurvey allows only a limited number of dispatched emails per day. The following graph (Figure 4) shows the survey's return distribution in the course of time.

Figure 4: Survey Return Distribution



Source: Own figure[5]

[5] For all the following tables and graphs, which are own representations based on the data collected, no source is indicated.

4 Results

In this chapter the data collected will be analysed and turned into information, from which conclusions can be drawn in order to answer the research questions.

After describing the sample and its characteristics, Cronbach's alpha is used to assess the questionnaire's internal reliability. If the items turn out to be reliable, they will be transformed into cumulated, single variables. Thereupon, a chi-square (χ^2) test is applied to check whether the respective independent variables (IV) significantly correlate with the dependent variable (DV) or not. In a next step, the strength and direction of possible correlations between the IVs and the DV is examined by applying both Cramer's V and a rank-biserial correlation.

4.1 Descriptive Statistics

4.1.1 Data Cleaning

Before the analysis, the data undergoes some cleaning. From the 12.023 email addresses 919 were faulty and did not receive the invitation email. From the 11.104 recipients 454 started to fill in the questionnaire out of which 290 stopped before completing it. Although data has been collected from them until abortion, this data will not be taken into account. This is due to the fact that the missing values would distort the results when comparisons based on accumulated values of the variables are made. Thus, 164 completed questionnaires remain.

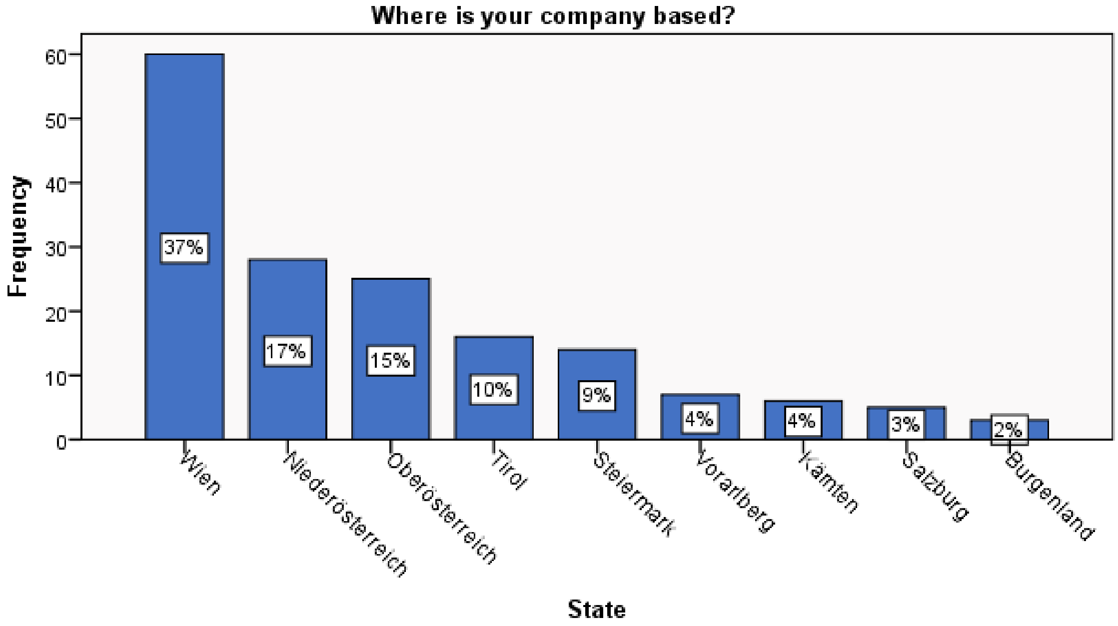
As expected, the response rate is as low as 1,36% (for fully completed questionnaires) and statistical significance with p = 0,05 is not given. Still the number suffices to draw initial inferences.

Each time when a respondent selected the “Not applicable” option the value is defined as -1 and will not be included in the analysis of the respective item, which is why the number of cases n varies in the sub-analyses. Apart from that, a thorough inspection of the data collected does not exclude any further data.

4.1.2 Sample Description

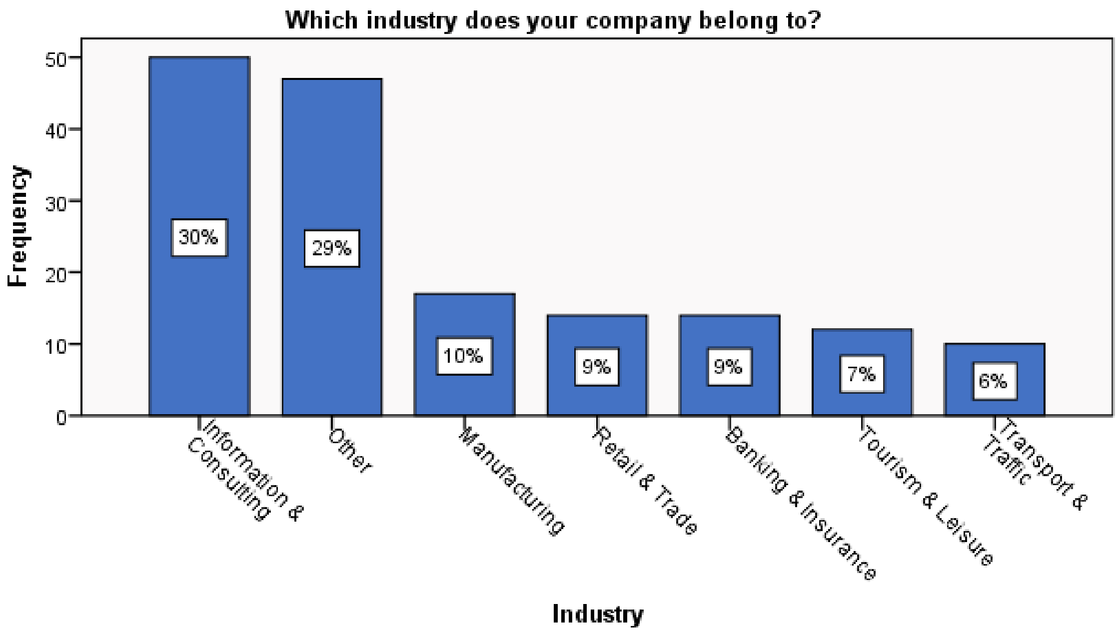
Of the 164 queried firms, the majority is based in the federal state of Vienna (*Wien*, 60), followed by Lower Austria (*Niederösterreich*, 28) and Upper Austria (*Oberösterreich*, 25). Although *Wien* is overrepresented and *Steiermark* is underrepresented, the ranking is similar to the population distribution in Austria (WKO, 2019c). Regarding location, the sample therefore can be considered relatively similar to the general population (Figure 5).

Figure 5: Respondents' Local Distribution



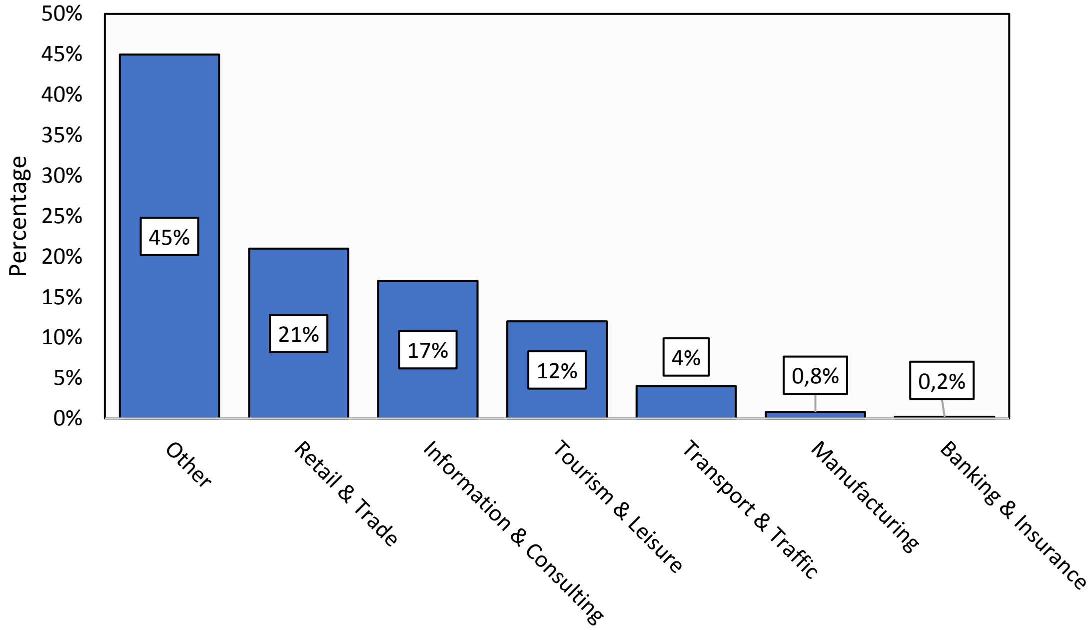
The data further reveals the number of the sample's firms per industry (Figure 6). With 50 responses most of the companies surveyed belong to the information and consulting industry. Almost as many (47 responses) indicated the category *Other* where a specification was required. Some did not sort their industry in one of the categories provided despite they might fit, for example, one participant indicated "wholesale" which could have been marked as *Retail & Trade*. Apart from that, the sectors vary from "Architecture" to "Elderly Care" to "Technology Company" (see Appendix 7.2). Apart from that, no distinctive feature can be observed in *Other*.

Figure 6: Respondents' Industry Distribution



Comparing the sample with the Economic Chamber's statistics of the distribution per sector of the 525.956 Austrian companies (Figure 7) shows that the sample is not representative of the Austrian sector distribution (WKO, 2019a). Particularly the industries of information and consulting, manufacturing, and banking and insurance are strongly overrepresented, whilst the sectors belonging to the category *Other* and the industry of retail and trade are underrepresented. One explanation could be the self-selection bias mentioned in chapter 3.3, according to which firms, that are active in information processing are more interested in or aware of AI, rather take part in the survey than others.

Figure 7: Industry Distribution in Austria

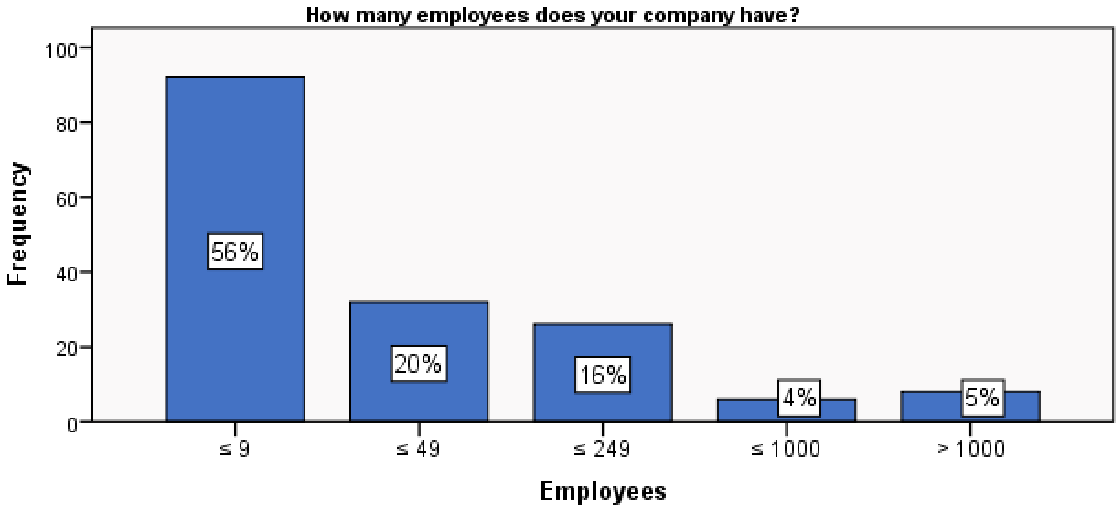


Source: Own figure, data from WKO (2019a)

In spite of 99.7% of Austrian companies belonging the group of small and medium sized enterprises (SME) (KMU Forschung Austria, 2019b), a more detailed view on company size, i.e., number of employees and annual revenue, can uncover relevant information.

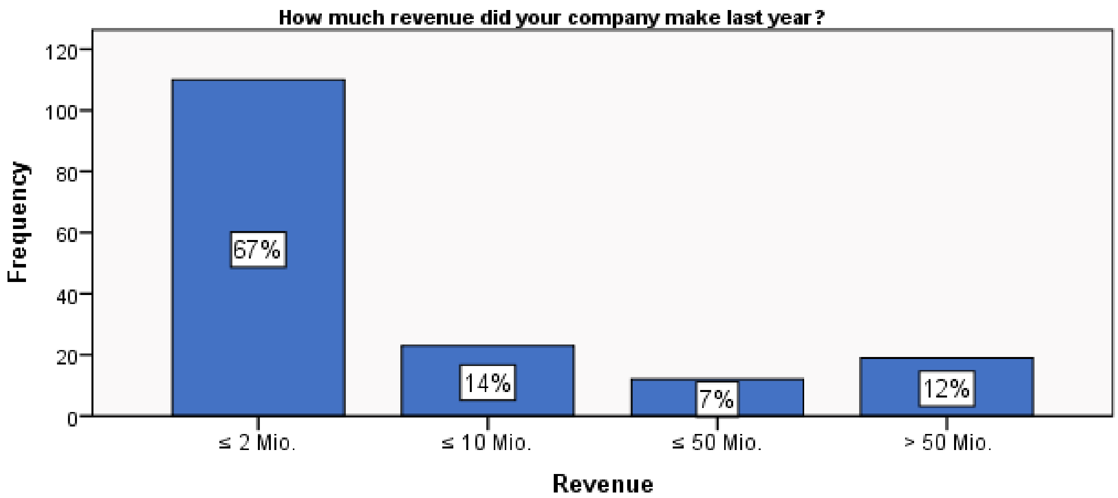
The vast majority of firms (92) reports having a maximum of 9 employees, followed by 32 companies indicating employing between 10 and 49 people, and 26 employ between 50 and 249 workers (Figure 8). Only six organisations have between 250 and 1.000 and eight more than 1.000 employees.

Figure 8: Respondents' Headcount Distribution



Equally, most companies declare a revenue of less than €2 million during the past year, which is the minimum category proposed by the Economic Chamber, i.e., those are most likely (if also having less than 9 employees) micro-enterprises (Figure 9). Together with 23 firms indicating annual revenues between €2 million and €10 million, and 12 assigning themselves to the category of between €10 million and €50 million, 88.4% do fulfil the revenue criteria for SMEs. This does not come unexpected, since the bulk of Austrian companies are in fact SMEs. Still, 19 firms make more than €50 million of revenue per year. Crossing the data of *number of employees* and *revenue* (see Appendix 7.4) reveals that 13 companies do not belong to the group of SMEs, which accounts for almost 8%. Hence, large companies are overrepresented as according to KMU Forschung Austria only 0.3% of Austrian firms are large (KMU Forschung Austria, 2019b).

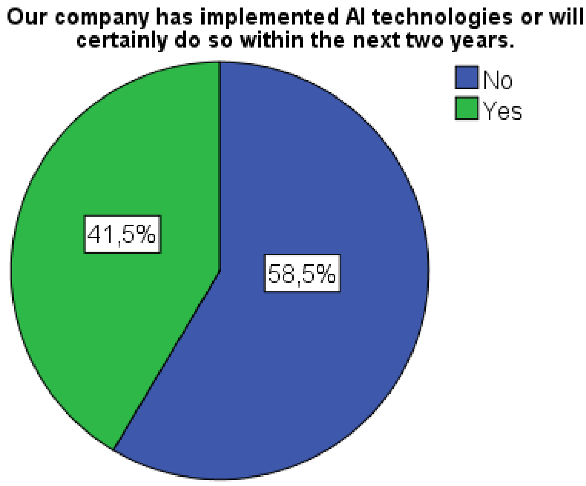
Figure 9: Respondents' Revenue Distribution



4.1.2.1 AI Adoption

Regarding the DV, the data shows a total rate of AI adoption of 41.5% (Figure 10). This can be considered surprisingly high when relating to the 20% rate found by Ransbotham et al. (2017). Yet, direct comparison may not be appropriate, since the mentioned study measured levels on a global scale without any focus on Austria. For this study, it means that 68 out of 164 organisations already have implemented some kind of AI technology or will certainly do so within the next two years (see Appendix 7.5). Due to the comparatively small sample size, one cannot infer that the AI adoption rate in Austrian companies indeed mounts up to over 40%. This high level could in part be explained with the overrepresentation of large companies, which are more prone to implement AI systems (Ransbotham et al., 2017, p. 5). Further descriptive analysis of the data will, amongst others, reveal if there is a correlation between company size and AI adoption rate.

Figure 10: AI Adoption Rate



In order to gather more detailed information, consolidated groups per federal state, industry, annual revenue and number of employees are created. The latter two will be presented first, as to answer the question whether a correlation between AI adoption and company size can be assumed. Figures 11 and 12 display the adoption rate per number of employees and per annual revenue, respectively.

First of all, firms with less than 9 employees and less than €2 million in revenue predominantly do not adopt AI. What can be considered remarkable is that respectively one third and one quarter of these small firms still deploy AI technologies.

AI implementation in organisations of the intermediate categories is, generally seen, balanced, yet, with a tendency to non-adoption. As expected, there seems to be a positive correlation between company size and adoption rate, since all of the firms with over 1000 employees and two thirds of those with an annual revenue above €50 million indicated to adopt AI. However, this correlation is not as sharp as expected, which is due to the relatively high adoption rates also in smaller companies.

Figure 11: AI Adoption per Employee Category

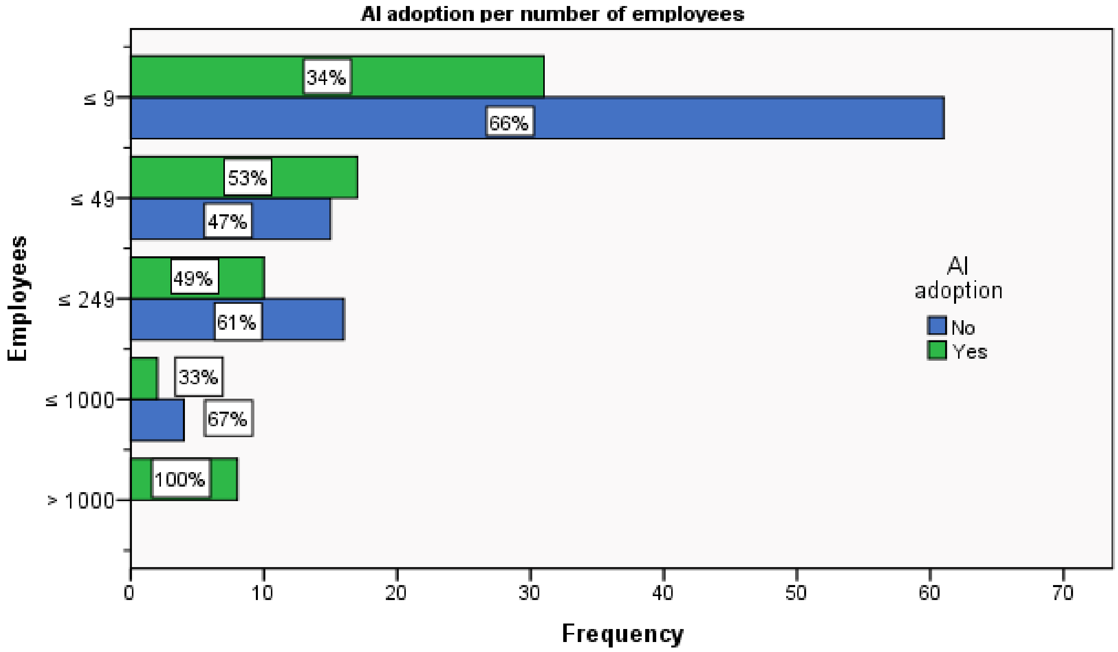
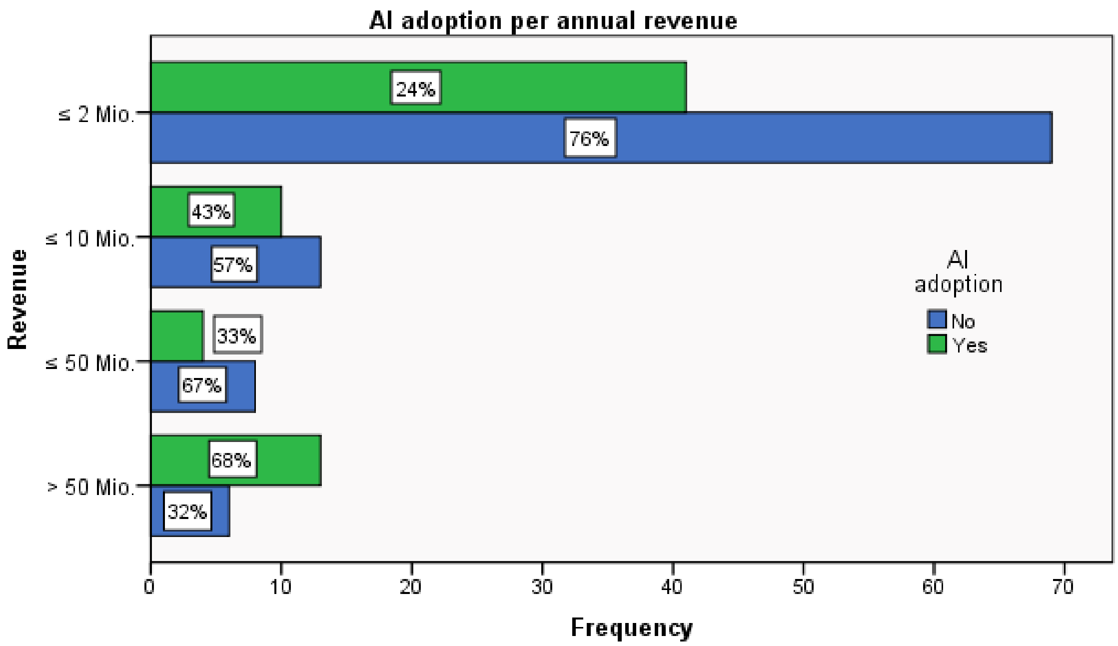


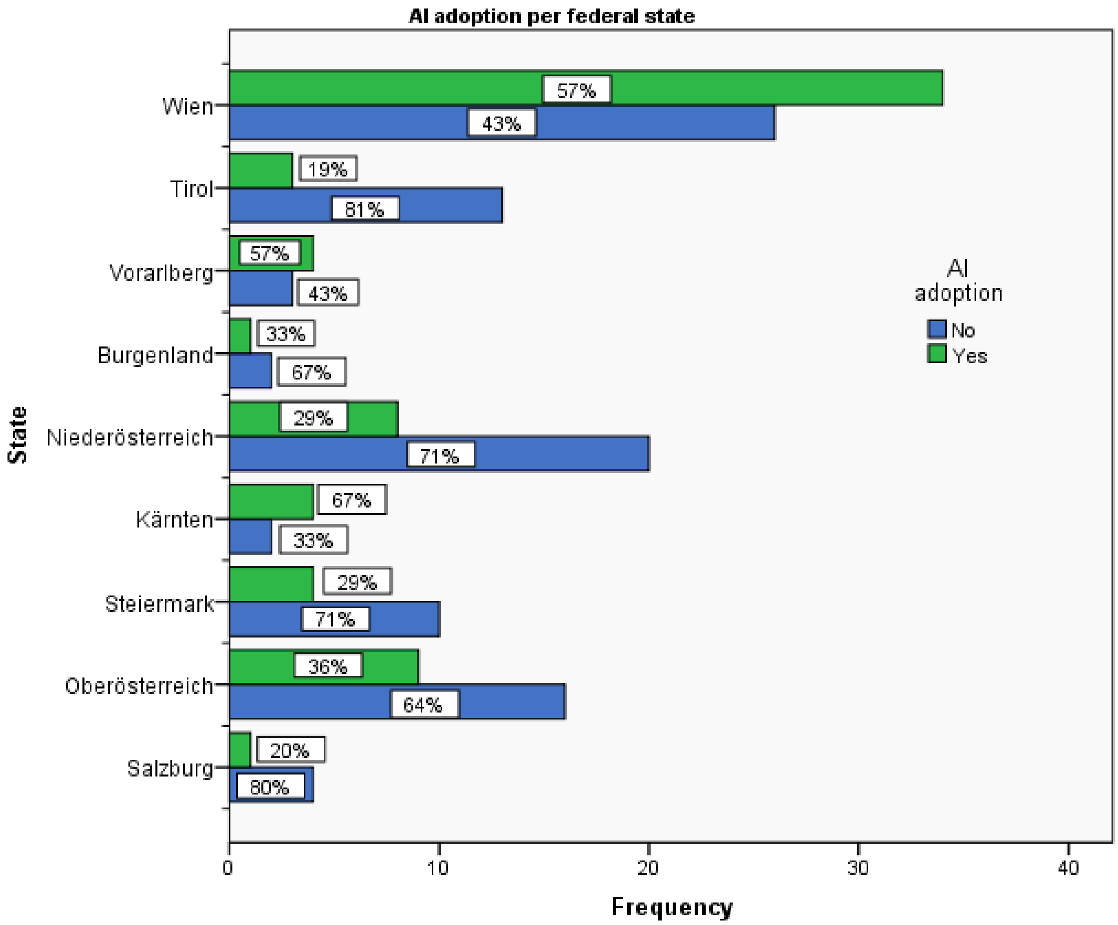
Figure 12: AI Adoption per Revenue Category



Grouping the adoption rate with federal state shows that in *Wien*, *Vorarlberg*, and *Kärnten* more firms adopted AI than not (Figure 13). The highest rates of non-deployment can be found in *Tirol* and *Salzburg* where roughly 80% report not having implemented AI.

Apparently, *Wien* possesses structures which increment awareness and encourage implementation of AI compared to other states. As *Wien* is also the capital of Austria with more than one fifth of the overall population and the highest density of companies and universities in the country (WKO, 2019b) this conclusion is reasonable.

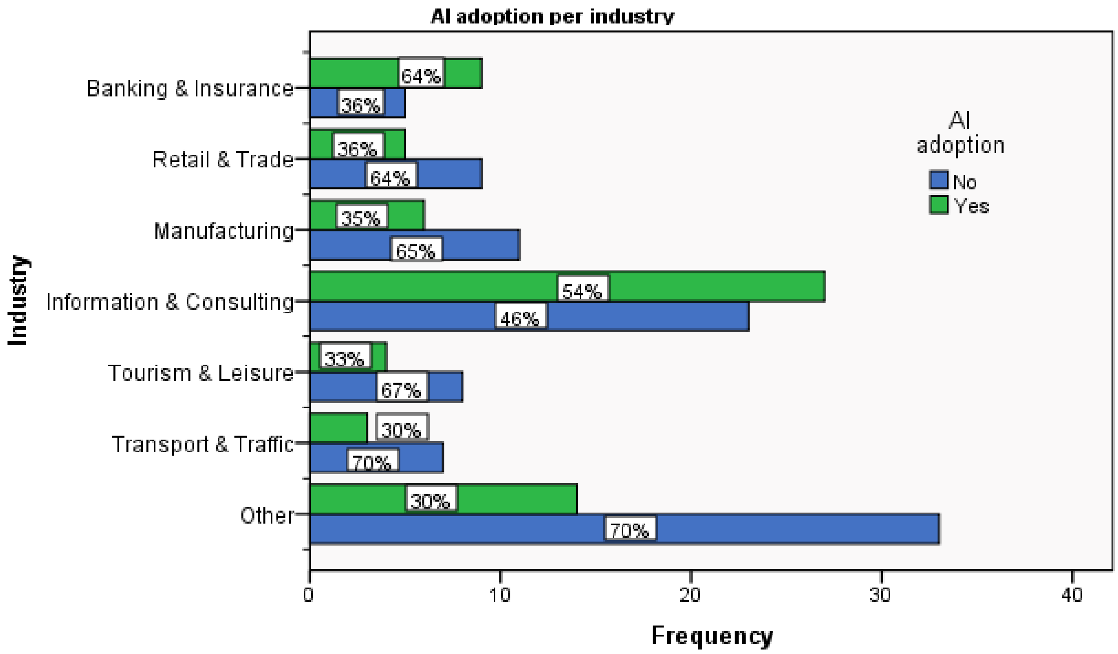
Figure 13: AI Adoption per Federal State



AI adoption per industry (Figure 14) shows that the sector with the greatest rate of adoption (64%) relative to non-adoption (36%) is banking and insurance. Together with the information and consulting sector, these two are the only ones where more companies implement AI than not. In all other industries roughly two thirds of firms do not deploy AI.

Hence, according to this sample, AI systems seem most attractive to the banking and insurance, and the information and consulting industry.

Figure 14: AI Adoption per Industry



4.2 Inferential Statistics

Before investigating correlations between the constructs representing driving and hindering forces and the DV, the internal reliability of the questionnaire is tested. In other words, it is checked if those questions which are combined as a scale to assess a certain construct are consistent in explaining it (Saunders et al., 2016, p. 451).

For each variable of the questionnaire explained by more than one item, i.e., *fear of falling behind*, *lack of strategy*, *lack of use case*, *legal uncertainty*, *lack of talent*, and *uncertain investment*, the items' internal reliability is tested. Cronbach's alpha, α, is the appropriate indicator of the internal reliability and also indicates whether items should be dropped in order to increase reliability (Field, 2013, pp. 673–681). The core of the formula for Cronbach's alpha consists of the average correlations of all items on the scale. It is essential to mention that the α score increases with the number of items of a scale and vice versa, hence, with only two items per scale as is the case in this questionnaire, Cronbach's alpha yields a conservative measure.

Additionally, the correlation measures of Spearman's rho and Kendall's tau, τ, which are applicable for the non-parametric, ranked data being present in this case, are calculated to obtain a very sound assessment of the meaningfulness of the items (Field, 2013, pp. 179–182) .

The following table summarises the number of valid cases, Cronbach's α, the correlation coefficients of Spearman's rho and Kendall's τ and its respective significance *p* for each of the items for the above-mentioned variables.

Table 3: Internal Reliability

	N	Cronbach's α (2 items)	Kendall's τ	*p* (τ)	Spearman's rho	*p* (rho)
Fear of falling behind	150	0.734	0.518	0.000	0.576	0.000
Lack of strategy	130	0.853	0.682	0.000	0.74	0.000
Lack of use case	149	0.586	0.329	0.000	0.371	0.000
Legal uncertainty	129	0.822	0.63	0.000	0.689	0.000
Lack of talent	133	0.562	0.262	0.001	0.303	0.000
Uncertain investment	135	0.554	0.192	0.011	0.215	0.012

The α values for *fear of falling behind, lack of strategy*, and *legal uncertainty* are above 0.7 and below 0.9 and therefore indicate a very good reliability. Also, their correlation coefficients are all positive, strong and highly significant. The constructs *lack of use case*, *lack of talent*, and *uncertain investment* have an α of 0.586, 0.562, and 0.554 which are slightly below the accepted threshold of 0.6. However, as mentioned above, the measure tends to be conservative when only 2 items constitute the scale. This in combination with the positive, relatively strong, and significant correlation coefficients makes it reasonable to assume an acceptable reliability. Accordingly, no variables must be dropped.

In a next step, the item variables are transformed via an averaging function creating the new, cumulated variables or constructs. Due to the averaged values new proficiencies of 1.5, 2.5, and 3.5 are generated for all multi-item variables from Table 3. The increase in number of proficiencies compared to variables *revenue increase* and *cost reduction*, where the four original proficiencies remain, does not make any difference for the subsequent correlation test.

In order to find out whether there is a bivariate, significant correlation between the ordinally ranked IVs, i.e., the drivers and barriers, and the nominal, dichotomous DV, i.e., AI adoption, a chi-square, χ^2, test is applied. Practically speaking, the chi-square test takes into account the data's frequencies observed and measures the probability that the data has been gathered by chance, i.e., under the null hypothesis, or not. Values of significance, *p*, below 0.05, or 0.01 therefore mean that there is a 95% , or 99% chance that the data has not been collected by chance and that the null hypothesis should be rejected and the alternative hypothesis should be accepted (Field, 2013).

Furthermore, the strength of the respective correlations is evaluated using measurements appropriate for the given scales, more precisely, Cramer's V and Spearman's rank biserial correlation coefficient, r_s (Schirmer & Blinkert, 2009). The former can only assume positive values, which means that it does not measure the correlation's direction. Nevertheless, it is included in this case, since on the one hand it offers a fair assessment of correlation strength and on the other hand it can serve as a double check of correlation. The more important measurement is the rank biserial correlation coefficient r_s which assumes values between -1 and 1 with 1 indicating a perfect positive correlation and vice versa. Therefore, apart from denoting the strength of correlation it indicates its direction. According to Cohen (1992) values of $r_s = 0.1$, $r_s = 0.3$, and $r_s = 0.5$ indicate a weak, intermediate, and strong correlation.

Before computing the correlations, one must be aware that the questions capturing the barriers were articulated in the same way as the ones relating to the drivers. In other words, the respondents who chose high values (3 or 4) positively relate to the concept measured. For instance, for *lack of strategy* this means that respondents selecting high values agree or strongly agree with having an AI strategy in place. For Spearman's correlation coefficient this would result in a positive relationship between lack of strategy and AI adoption, although it actually is negative. In order to obtain the correct sign when calculating the correlation, the variables for the barriers are reversed, so that 1 becomes 4, 2 becomes 3 and so on. In spite of still having the same information of the data, the variables in the table will – as a matter of form – receive the addition *rev* for "reverse"[6].

From the results of these calculations the hypotheses formulated in chapter 2.4 are accepted or rejected.

The table below shows the results of the χ^2-test, Cramer's V, the rank biserial correlation coefficient r_s and the respective significance, *p*, of each IV in relation to AI adoption. For clearer appearance, the green rows represent the drivers, the red rows the barriers.

[6] In the following, the variables will for appearance's sake continued to be called by their original name, i.e., without the addition *_rev*.

Table 4: Independent Variables' Correlation to AI Adoption

	n	χ^2	p (χ^2)	Cramer's V	p (V)	r_s	p (r_s)
Revenue increase	146	52.150	0.000	0.598	0.000	0.597	0.000
Cost reduction	144	15.983	0.000	0.333	0.001	0.302	0.000
Fear of falling behind	150	49.907	0.000	0.577	0.000	0.572	0.000
Lack of strategy_rev	130	50.199	0.000	0.621	0.000	-0.671	0.000
Lack of use case_rev	149	45.026	0.000	0.55	0.000	-0.509	0.000
Legal uncertainty_rev	129	22.747	0.001	0.42	0.001	-0.399	0.000
Lack of talent_rev	133	12.824	0.025	0.311	0.025	-0.293	0.001
Uncertain investment_rev	135	17.202	0.009	0.357	0.009	-0.282	0.001

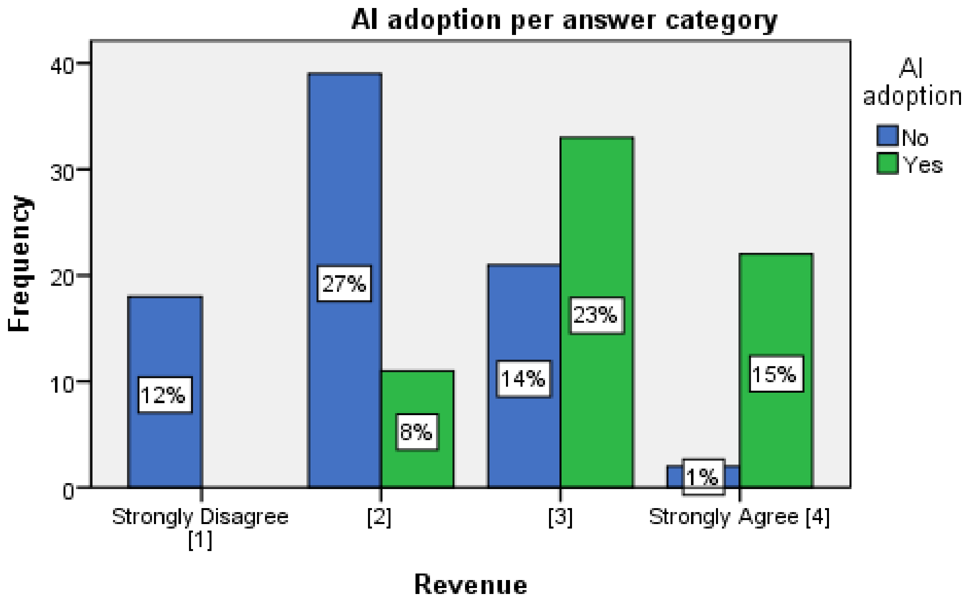
First and foremost, all the correlations are significant with $p < 0{,}05$. Further, a comparison of the correlation coefficients shows no noteworthy differences, so the strength of the respective correlations can be considered meaningful. The requisite values for further analysis are all given, thus focus will be placed on the rank biserial coefficient.

4.2.1 Drivers

4.2.1.1 Revenue Increase

Regarding the drivers, *revenue increase* yields a highly significant, positive correlation with AI adoption ($r_s = 0.597$, $p = 0.000$, $n = 146$). This means that those who chose high values for the opportunity to increase revenue tended to also indicate that they have implemented AI or will do so within the near future. The following graph (Figure 15) serves as an example for this tendency, which in different proficiencies also exists for the other correlations. The graph shows the rate of AI adoption per answer category, where the data labels express the percentage of the $n = 146$ responses given. For instance, 15% of all respondents strongly agree that AI can increment their company's revenue and they also adopt AI. Conversely, 1% of those indicating to strongly agree with this statement do not deploy AI.

Figure 15: AI Adoption per Answer Category for Revenue Increase, n = 146

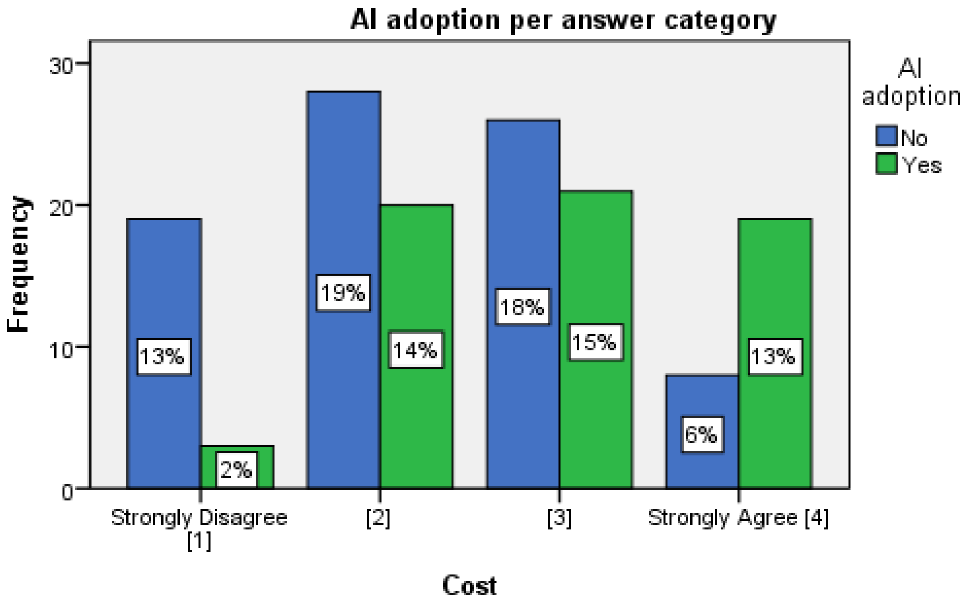


The chi-square test (χ^2 = 52.150, p = 0.000, n = 146) implies that the null hypothesis, i.e., that a potential revenue increase has no effect whatsoever on AI adoption, must be rejected and the alternative hypothesis must be accepted. Along with the positive and highly significant r_s of 0.597 it can be inferred that the opportunity to increase the company's revenue by deploying AI technologies represents not only a very strong, but the strongest driving force to AI adoption. Therefore, H_1 is accepted.

4.2.1.2 Cost Reduction

The significant chi-square test (χ^2 = 15.983, p = 0.000, n = 144) for the *cost reduction* variable indicates that a correlation with the DV is present. As expected, the correlation is positive, however, it is not that strong (r_s = 0.302, p = 0.000, n = 144). In practical terms, it means that respondents who perceive AI as a potential cost saver tend to deploy such technologies, though, not as much as those who see it as a revenue booster. Still, the analysis of the data suggests accepting H_2, as the opportunity to reduce costs drives people to deploy AI.

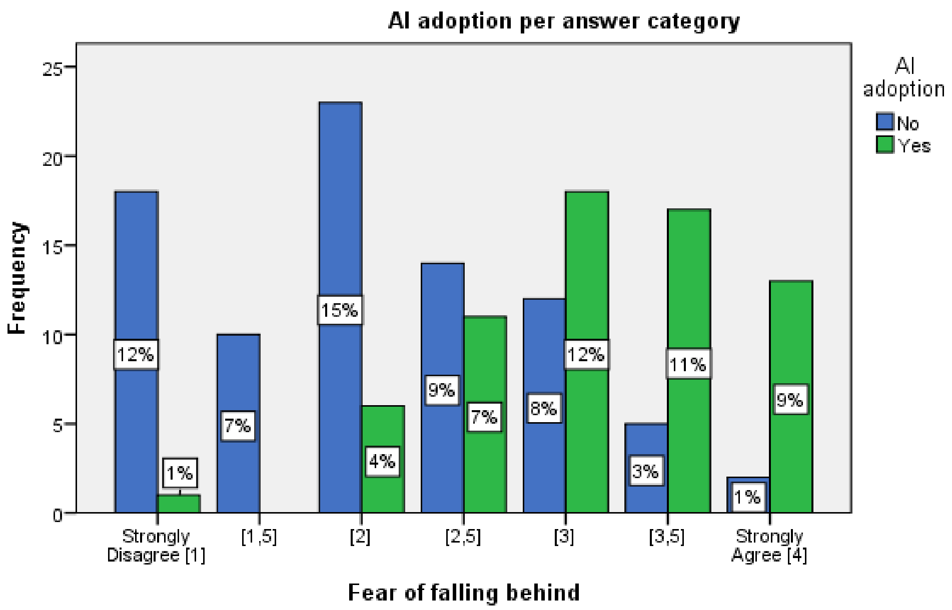
Figure 16: AI Adoption per Answer Category for Cost Reduction, n = 144



4.2.1.3 Fear of Falling Behind

The last driver identified in chapter 2.4, which is the *fear of falling behind* in terms of technological, and in particular of AI advancements, turns out to be a motivating factor to employ AI almost as strong as the possibility to augment revenue (r_s = 0.572, p = 0.000, n = 150). The higher a manager's apprehension to miss out on the latest technologies the higher the rate of AI implementation. Consequently, the correlation analysis gives evidence to support H_3. The graph (Figure 17) showing the tendency includes the additional data labels which resulted from merging the items.

Figure 17: AI Adoption per Answer Category for Fear of Falling Behind, n = 150



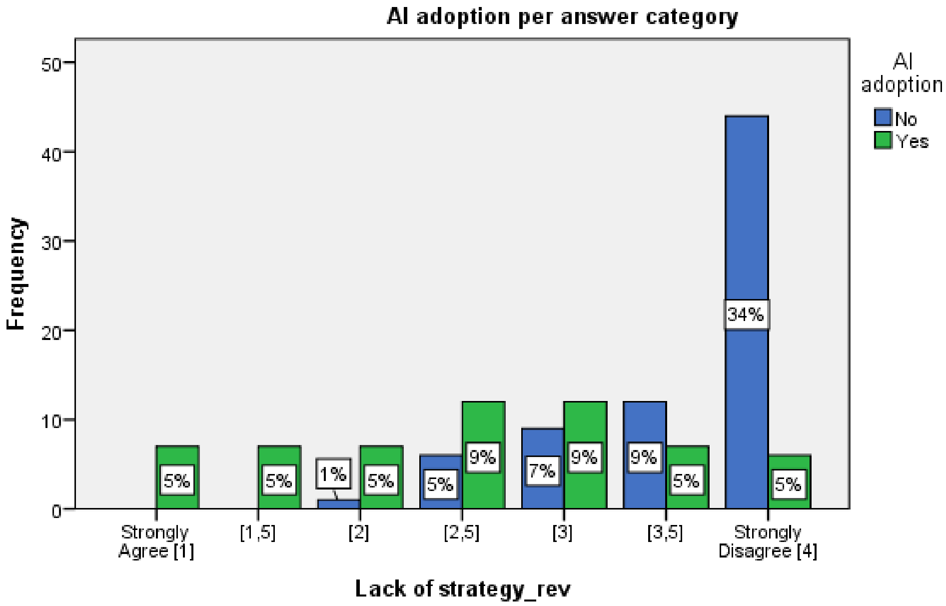
4.2.2 Barriers

Turning attention to the barriers, one can observe in Table 4 that all the values for the rank biserial correlation coefficient have a negative sign. This implies that the correlations to AI adoption are negative.

4.2.2.1 Lack of AI Strategy

The first barrier is *lack of strategy*. A significant chi-square test (χ^2 = 50.199, p = 0.000, n = 130) shows that this variable has an impact on the rate of AI adoption. Comparing its correlation with all the other correlations reveals that *lack of strategy* has the strongest influence on the DV. The rank biserial correlation coefficient of r_s = -0.671 (p = 0.000, n = 130) indicates that this impact is negative. In simple terms, this means that the more a company lacks a coherent long-term AI strategy, the less it adopts corresponding technologies. Therefore, the null hypothesis is rejected and the alternate H_4 is affirmed. According to the graph depicting the AI adoption per answer category, one must be aware that as the variables have been reversed, 1 now means “strongly agree” and 4 corresponds to “strongly disagree”.

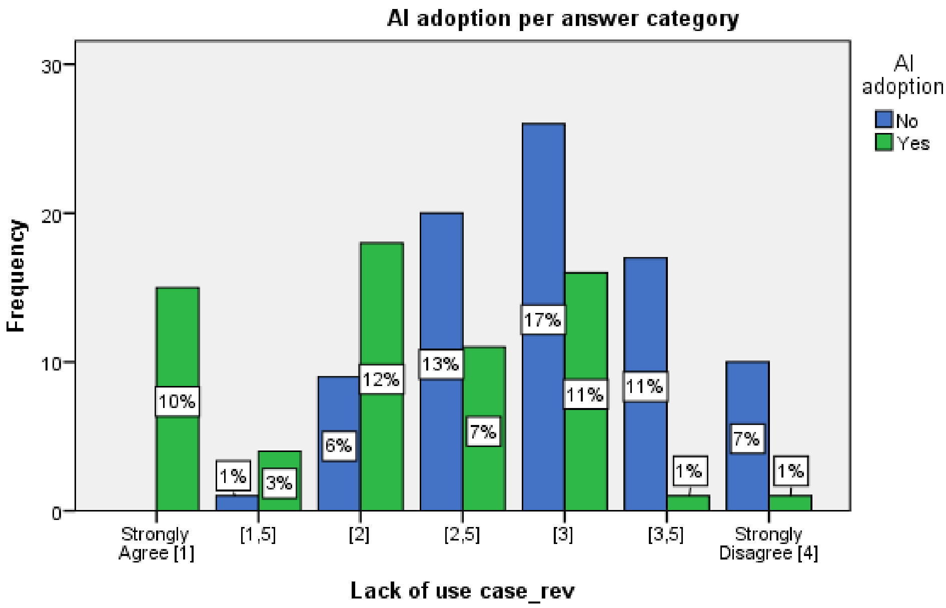
Figure 18: AI Adoption per Answer Category for Lack of Strategy, n = 130



4.2.2.2 Lack of AI Use Case

The second factor hampering AI implementation, *lack of use case*, has the second largest impact on the DV. With r_s = -0.509 (p = 0.000, n = 149), there is a significant, and strong correlation with AI adoption. Hence, one can conclude that where concrete use cases are not identified, companies hesitate to employ AI. Again, the results of the χ^2-test (χ^2 = 45.026, p = 0.000, n = 149) suggest dropping the null hypothesis and accepting H_5.

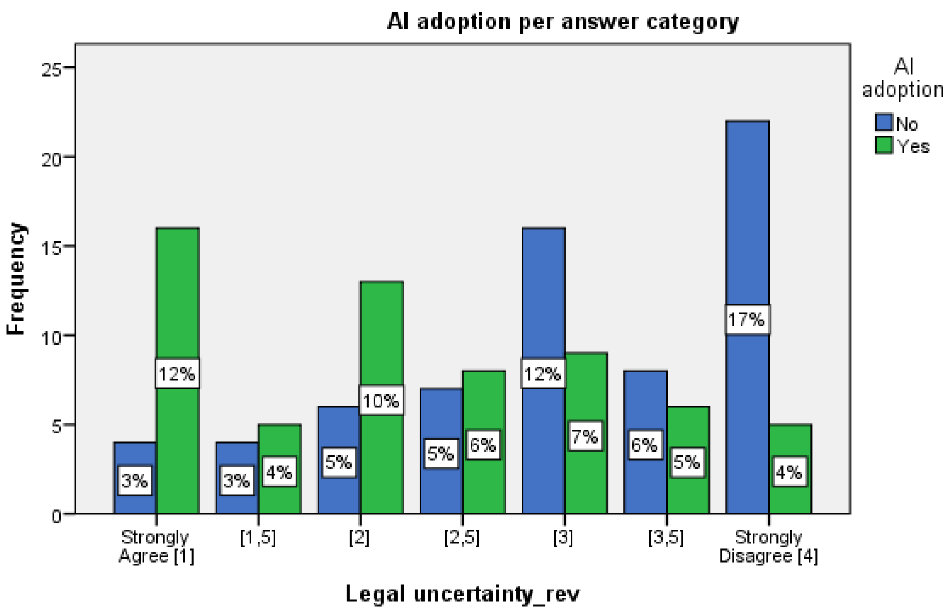
Figure 19: AI Adoption per Answer Category for Lack of Use Case, n = 149



4.2.2.3 Legal Uncertainty

Being unsure about the legal framework surrounding AI appears to significantly affect the DV (χ^2 = 22.747, p = 0.001, n = 129). The negative correlation can be considered intermediate (r_s = 0.399, p = 0.000, n = 129), so one can say that general and specific *legal uncertainty* indeed prevents organisations from deploying AI, though, lacking a strategy and use cases is substantially stronger in this regard. H_6 is therefore supported.

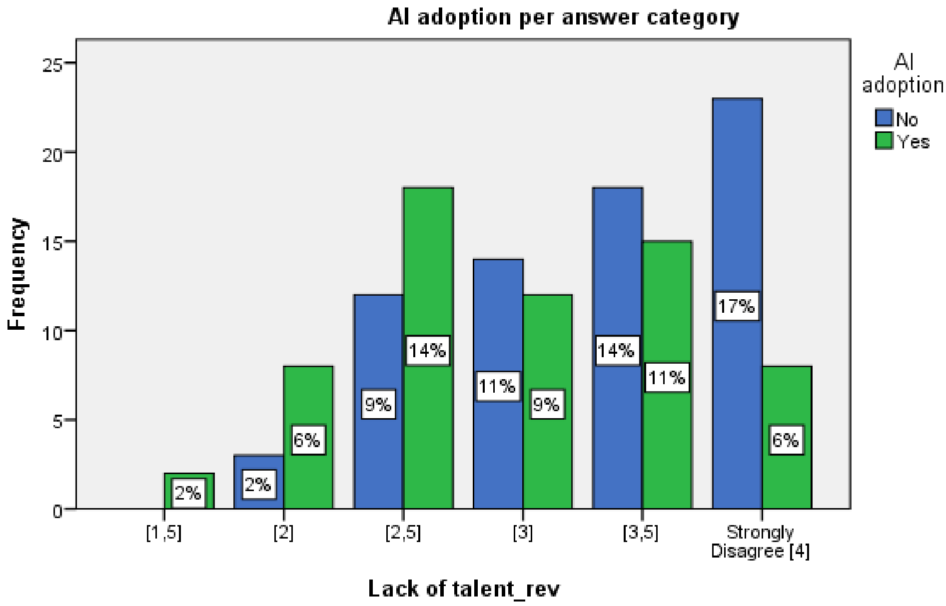
Figure 20: AI Adoption per Answer Category for Legal Uncertainty, n = 129



4.2.2.4 Lack of AI Talent

Although there is a significant effect on AI adoption (χ^2 = 12.824, p = 0.025, n = 133), the correlation of *lack of talent* is found to be somewhere between weak and intermediate levels, since r_s is slightly below 0.3 (r_s = -0.293, p = 0.001, n = 133) and Cramer's V a little above 0.3 (V = 0.311, p = 0.025, n = 133). Since the rank biserial correlation coefficient is more precise for the given scales and its significance level is still lower than the one of Cramer's V, a rather weak correlation is considered. Notwithstanding, not having and not being able to require enough skilled personnel to implement AI systems still impedes AI adoption, hence H_7 finds support.

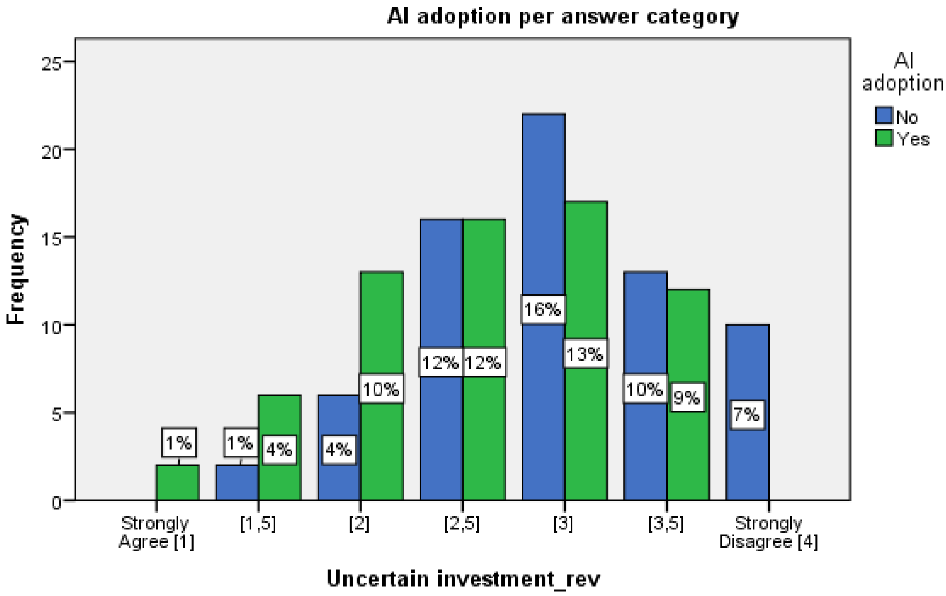
Figure 21: AI Adoption per Answer Category for Lack of Talent, n = 133



4.2.2.5 Uncertain Investment

The chi-square test shows that *uncertain investment* influences the decision to employ AI (χ^2 = 17.202, p = 0.009, n = 135). Yet again, Cramer's V = 0.357 (p = 0.009, n = 135) and r_s = -0.282 (p = 0.001, n = 135) show an intermediate and a weak correlation, respectively. Due to the same reasons as for the variable *lack of talent*, a rather weak correlation is assumed. This means that for AI implementation the uncertainty whether AI will yield a positive return or not does seem to play a role, though, not a big one. Evidence to reject the null hypothesis and support H_8 is still found.

Figure 22: AI Adoption per Answer Category for Uncertain Investment, n = 135



5 Discussion

In this chapter the research questions will be answered on the basis of the results found in chapter 4. Further, the implications for business are discussed and finally, this study's limitations are outlined.

5.1 Drivers

The first research question is:

1. What are the drivers to AI adoption of Austrian companies?

Drivers to adoption are factors, which encourage managers to embrace and implement AI technologies within their company. In chapter 2.4 three such factors were identified scrutinising existing literature, namely, the opportunity to increase revenue, the possibility to reduce costs, and the fear to technologically lag behind competitors.

5.1.1 Revenue Increase

To begin with, the statistical analysis of this study's data furnishes evidence that the most encouraging cause to employ AI is to boost revenue. The intelligent programmes, which are already available on the market enable many firms to have their data – be it on customers, employees or products – intelligently scrutinised and used. Thereby, organisations can, for instance, discover unseen sales opportunities. An analogy for a more intuitive explanation is a mine worker who does find some gold by digging with his classic mining implements. As the development of the instruments continues, a new tool enables him to dig deeper and wider into areas of the mine he never had reached before, sorting out the stones and bringing to light previously untouched gold veins. AI technologies represent such a tool capable of creating new value in previously undiscovered data structures.

The frequency tables below (5, 6, 7) display the respondents' assessment of which function is most likely to lead to an incremented revenue.

Table 5: Frequency Table for Personalisation

Personalisation (customise products / services)					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	26	15.9	20.6	20.6
	2	33	20.1	26.2	46.8
	3	45	27.4	35.7	82.5
	Very likely	22	13.4	17.5	100.0
	Total	126	76.8	100.0	
Missing	not answered	2	1.2		
	System	36	22.0		
	Total	38	23.2		
Total		164	100.0		

Table 6: Frequency Table for Pattern Recognition

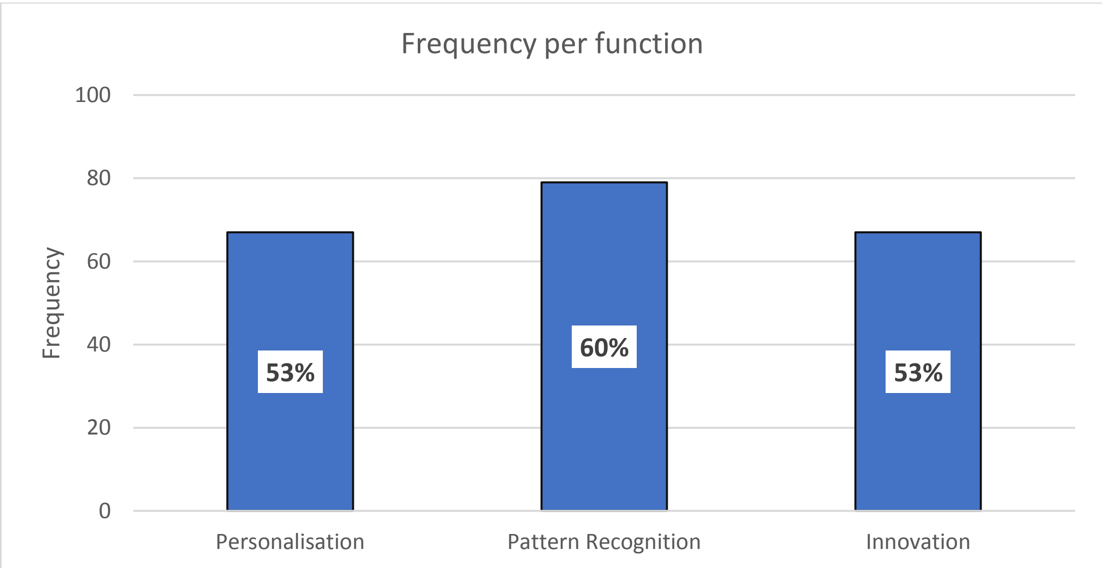
Pattern Recognition (identify useful patterns in large data sets)					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	17	10.4	13.5	13.5
	2	30	18.3	23.8	37.3
	3	48	29.3	38.1	75.4
	Very likely	31	18.9	24.6	100.0
	Total	126	76.8	100.0	
Missing	not answered	2	1.2		
	System	36	22.0		
	Total	38	23.2		
Total		164	100.0		

Table 7: Frequency Table for Innovation

Innovation (improve existing products / services or create entirely new ones)					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	15	9.1	11.9	11.9
	2	44	26.8	34.9	46.8
	3	43	26.2	34.1	81.0
	Very likely	24	14.6	19.0	100.0
	Total	126	76.8	100.0	
Missing	not answered	2	1.2		
	System	36	22.0		
	Total	38	23.2		
Total		164	100.0		

Since $n = 126$ is the same for each function, a direct comparison between the functions is possible. To obtain an understanding for which functions were most often elected to be likely to entail a revenue increase, the values for 3 and 4 (likely and very likely) are merged to one category respectively. This results in the following graph where the percentage is not absolute but relates to the frequency within the respective category.

Figure 23: Frequency per Function for Being Likely & Very Likely to Lead to Revenue Increase, n = 126



From the numbers it can be inferred that both *personalisation* and *innovation* are seen to likely or very likely offer possibilities to raise a firm's revenue in more than half of the cases. The greatest chances are granted to *pattern recognition* being elected by 60% of respondents. Indeed, a growing number of patents are filed in the areas of machine learning and deep learning, which enable to analyse ever greater amounts of data (World Intellectual Property Organization, 2019), thereby finding patterns, which remained hidden before.

The promising possibilities of AI usage probably are the reason for why *revenue increase* represents the strongest driving force.

5.1.2 Cost Reduction

Moreover, the opportunity to reduce costs is, statistically seen, also a stimulating factor. Correlation analysis has shown that the impact on AI adoption was only at an intermediate level, which signifies that it is not as motivating as a possible revenue increase or the fear to miss out on technological trends. This is surprising as literature and use cases offer numerous examples for the immense cost reducing opportunities lying in the application of AI systems (Bughin et al., 2017; Thomas Davenport & Ronanki, 2018; E. Kim, 2016).

Going into detail, the subsequent tables (8, 9, 10) depict the frequencies of responses estimating the probability that a certain AI function induces cost reductions.

Table 8: Frequency Table for Operation and Process Automation

Operation and Process Automation (automate and improve processes or administrative tasks)					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	18	11.0	14.8	14.8
	2	36	22.0	29.5	44.3
	3	33	20.1	27.0	71.3
	Very likely	35	21.3	28.7	100.0
	Total	122	74.4	100.0	
Missing	System	42	25.6		
Total		164	100.0		

Table 9: Frequency Table for Predictive Analytics

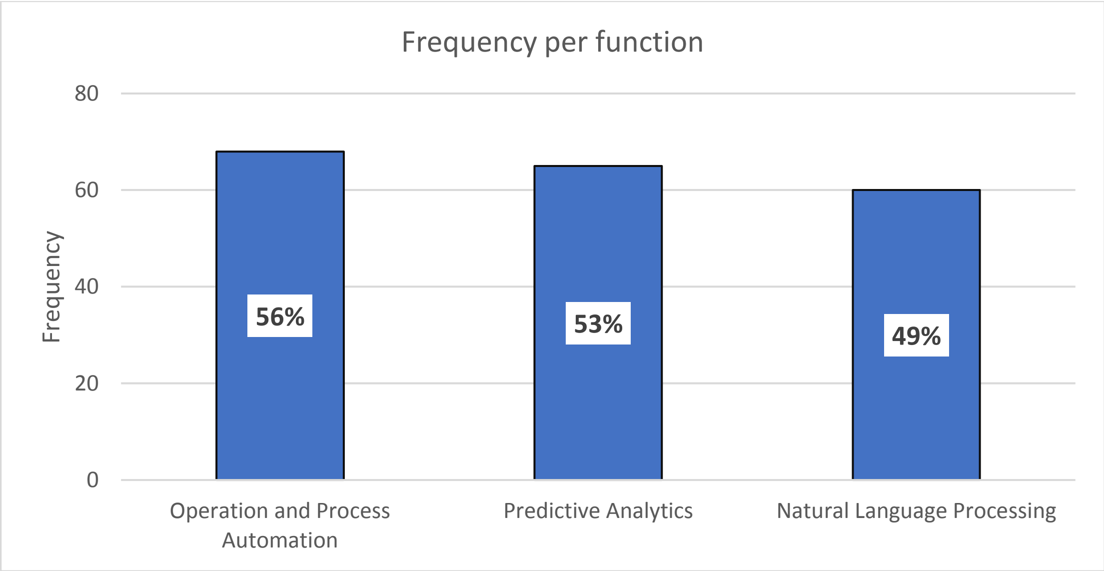
Predictive Analytics (analyse data to forecast events, e.g. sales, stock or staff requirements, etc.)					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	18	11.0	14.8	14.8
	2	39	23.8	32.0	46.7
	3	42	25.6	34.4	81.1
	Very likely	23	14.0	18.9	100.0
	Total	122	74.4	100.0	
Missing	System	42	25.6		
Total		164	100.0		

Table 10: Frequency Table for Natural Language Processing

Natural Language Processing (text/speech understanding, chatbots, etc.)						
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Very unlikely	23	14.0	18.9	18.9
	2	39	23.8	32.0	50.8
	3	35	21.3	28.7	79.5
	Very likely	25	15.2	20.5	100.0
	Total	122	74.4	100.0	
Missing	System	42	25.6		
Total		164	100.0		

With $n = 122$ being equal for all functions the same comparison as for revenue increase, visualised in the following graph (Figure 24), can be made.

Figure 24: Frequency per Function for Being Likely & Very Likely to Lead to Cost Reduction, n = 122



The strongest effect through AI to diminish costs is expected by the automation of operations and processes. As found by Rao and Verweij (2017) *operation and process automation* currently indeed represents the largest area of AI applications. Intelligent systems can replace workers doing particularly repetitive, time-consuming tasks such as in administration (Thomas Davenport & Ronanki, 2018) or manual warehouse organisation (Juhr-De Benedetti, 2017), which ideally are freed for more creative exercises.

Slightly more respondents chose *predictive analytics* to be likely or very likely to cut their costs than *natural language processing* techniques. Still, half of the queried think that both functions enable them to do so.

NLP technologies, for example, are well-developed and relatively easy to apply in the form of chatbots (Abramowicz, 2007; Hulick, 2016). Besides, they present immediate effects, since a large part of customer queries can be handled by them, thereby decreasing personnel, time and money spent on this behalf. Therefore, NLP could serve as a gateway technology to AI, showing businesses how AI can work and what effects it entails.

Undoubtedly, the increasing opportunities to cut down costs attract firms to deal with and eventually implement AI.

5.1.3 Fear of Falling Behind

Lastly, the fear of falling technologically behind competitors has a very strong impact on whether firms adopt AI or not. As correlation analysis has demonstrated, the influence is almost as high as the chance to augment revenue. The "fear factor " as described by Cameron and Unger (2018) therefore can be considered an external force, which is not to be underestimated.

AI is a buzzword filling the media and business congresses and speakers do not get tired to emphasise how fast AI technologies evolve. Truly, intelligent software solutions and machines based on AI develop exponentially (Spektrum, 2018), in parallel to increasing processing and memory capacities. Of course, many areas, also in business, cannot be effectively tackled by AI yet, but this not what is communicated.

Ransbotham et al. (2017) and Westerman et al. (2012) point out how digital leaders outperform competitors. Clearly, no one wants to become what they term "digital laggards" losing competitiveness in the market.

Consequently, it does not come unexpected that statistical results signal that the higher the apprehension to miss out on competitors in terms of technological adaption the higher the rate of AI implementation.

What is more, is that the questionnaire provided open questions to get a better grasp of why or why not managers employ AI. The full list of comments can be found in Appendix 7.3.

Examining the comments on what speaks in favour of adoption does not yield insights on an unconsidered driver. The most often mentioned AI function to improve business is (administrative) process automation

Summarising, the strongest factor to drive AI adoption in Austria is the opportunity to increase revenue, followed by the fear of falling behind in terms of technological adaption, and the possibility to reduce costs.

5.2 Barriers

The second research question is:

2. What are the barriers to AI adoption of Austrian companies?

Barriers to adoption are factors, which discourage managers to embrace and deploy AI systems within their firm. Literature review led to the identification of five inhibitors, which are lack of strategy, lack of use case, legal uncertainty, lack of talent, and uncertain investment.

5.2.1 Lack of AI Strategy

The first barrier identified in chapter 2.4 is at the same time the strongest. The negative correlation between a lack of strategy and AI adoption yielded the highest coefficient of all variables. Subsequently, it is fair to say that a clear strategy is key to a successful AI deployment. This requires a thorough understanding of AI technologies in the first place, but also includes the ability to map out exactly where the organisation wants to move and how AI can help going there. If AI is employed it must be concordant with the business model and the overall digital strategy and should be clearly communicated to all stakeholders impacted. When AI solutions are introduced on a great scale, there must be a person or team dedicated to the successful rollout, otherwise unclear responsibilities may entail a costly negligence of an effective implementation.

Summarising, without a clear and consistent AI strategy, a fruitful deployment is most likely not going to happen.

5.2.2 Lack of AI Use Case

One of the most crucial questions for firms is what AI can do for them. If no use case can be identified, there is no need to act on this behalf. This, in turn, presupposes that companies' managers know what AI is generally capable of, and which solution specifically fits their business. The application spectrum of AI is vast, and becomes broader every day, however, it is difficult to distinguish between the different functions that AI can fulfil, let away the puzzling number of providers of such solutions. Additionally to a lacking identification of potential use cases, it must be emphasised that AI by far does not (yet) offer solutions to most businesses, particularly to small ones. An excerpt from the comments, which will be analysed in more detail later in this chapter, evinces this aspect: "*I am a Dance und Fitness Trainer with no use of technology except of playing music.*" AI at its current state of development certainly is not of any practical help for a one-man dance and fitness trainer.

The rather high frequencies of answers indicating that the respondents do not really know what AI is generally capable of and where exactly AI solutions may improve business in relation to the

AI implementation rate (Figure 19) perfectly illustrate that a lack of use cases is present and a strong barrier to adoption.

5.2.3 Legal Uncertainty

Since Artificial Intelligence necessarily comprises the processing of (personal) data, legal issues are inevitably involved, when implementing such technologies. Hence, not being aware of the general legal framework surrounding AI leads to uncertainty of what to take care of, and consequently to avoidance of AI. Particularly, when business-specific AI solutions are considered to be deployed, ambiguous regulatory constraints, including questions of data protection or of responsibilities for decisions taken by a software, represent a tremendous risk. A company without the legal knowledge or the possibility to acquire such expertise will in most cases refrain from employing AI. The statistical analysis supports this claim, yet, legal uncertainty does not seem to play such a big role as a lack of strategy or use cases.

5.2.4 Lack of AI Talent

The massive shortage of personnel capable of developing and implementing AI as highlighted by Innerhofer (2018) or Clarke (2018b) does, according to the present sample, represent a significant barrier. This is due to the fact that certain skills are necessary to engineer the requisite IT-infrastructures, to create intelligent algorithms and apply neural networks to business-specific needs. As already mentioned, AI has existed for decades but only in the past years real-world issues can be effectively tackled. For this reason, there are almost no educational programmes available to increase the number of graduates skilled in the realm of AI. The university of Linz in *Oberösterreich* is the only educational institution in Austria and one of the few in Europe to have introduced a graduation programme for Artificial Intelligence starting in autumn 2019 (Johannes Kepler Universität, 2018). This is a good starting point, however, much more must be done to raise the number of AI researchers and practitioners if Austria and Europe do not want to be left behind China and the USA, which have many more AI talents at their disposal (Thomas H. Davenport, 2019).

It must be said, that contrary to expectations, the correlation to AI adoption measured is close to intermediate levels, yet, still assumed rather weak. In other words, the lack of talent does not prevent firms to embrace AI as much as the other impeding factors presented here.

5.2.5 Uncertain Investment

The last barrier that was investigated upon is the uncertain investment that comes with the deployment of AI systems. Apart from some attention-attracting examples such as IBM’s Deep Blue or Google’s self-driving car, AI has not been implemented on a large scale (Ransbotham et al., 2017). Therefore, few references, particularly for SME's, exist to get a notion of whether and how AI can improve business, and even less of how much it will cost them. It can be stated that there is a lack of references that SMEs can compare to. For these companies that means the following. On the one hand, it is certain that the implementation of new technologies always involves costs, on the other hand it is unsure whether the costs incurred really bring about the hoped-for benefits. For other investments – be it the acquisition of a new high-tech agricultural vehicle or faster processors for the employees' computers – certainly also include risks, but the chances of success can be assessed relatively easy due to existing references.

Subsequently, the ambiguity involved diminishes the number of companies adopting AI. Similar to the barrier of lack of talent, the correlation is rather weak meaning that uncertain investment is considered a significant barrier, though not a very strong one.

5.2.6 Comments

When scanning and sorting the comments, the barrier most often mentioned is a lack of use case. This is because on the one hand, some respondents apparently do not know what can generally be done with AI. An example is "*As a service company it is difficult to implement AI*." It does not become clear why this is the case, since in general, service firms are perfectly suited for deploying AI. Such a comment thus indicates a lack of knowledge about AI. On the other hand, comments like "*Can't figure out any use of AI in a small restaurant / butchery on the countryside*" express the above-mentioned lack of AI solutions due to its relatively early stages of development.

Moreover, one topic in particular, which has not been considered in this study, stands out. Several comments point out social issues, which can be interpreted as negative bias, including fear of AI. The statements "*Useless scrap for a workshop.*", "*A handcrafted workshop does not require AI. We use our brain.*" or "*Wir brauchen keine künstliche Intelligenz, da diese keine ethischen Werte hinterlegt hat*"[7] express this kind of social rejection, which could represent another significant barrier to AI adoption.

To sum it up, the strongest barrier to AI adoption in Austria is lacking an AI strategy. Not having clear use cases for AI technologies hinders companies almost as much. Legal uncertainty constitutes a barrier of intermediate strength. Both the lack of AI talents, and an uncertain investment represent impeding forces to AI adoption, yet, they seem to be less meaningful to managers than the aforementioned barriers. An analysis of respondents' comments indicates another potential impeding force, namely social rejection.

[7] Own translation: "We do not need artificial intelligence, since it does not comprise ethical values"

5.3 Implications

Artificial Intelligence undeniably has the potential to be a game-changer for most industries. The highly alluring opportunities that AI technologies bring with them are already observable in some concrete cases as shown in chapter 2.4. Significant efficiency and quality improvements along the whole value chain can be attained, leading to enormous revenue increases and cost reductions, and subsequently to more profitable companies. Taking into account existing literature and the empirical results of this study it can be stated that most managers in Austria agree that AI can be favourable to them. Further, the analysis provides support to the claim that those that implement AI do so because they grant the technologies high chances to augment their revenue or reduce their costs or both. In the light of the positive effects of AI, the third, external factor, that drives managers to deploy the intelligent systems, namely the fear to not be able to catch up with the competitors, can be considered a beneficial phenomenon for the diffusion of AI.

Nevertheless, there are still many that do not believe in the benefits of AI and show themselves reluctant to this trend. One reason certainly is because AI still has no practical use case for some businesses, particularly very small ones. Contrary to this view, a thorough examination of the technologies reveals that, in theory, they can be applied profitably almost anywhere, even if it only overtakes administrative tasks. This underestimation, which makes many firms think that AI cannot bring them any advantage leads to the second reason for hesitation to embrace AI.

The analysis of the comments has revealed an anxiety of AI, which, in turn, is founded in a lack of knowledge of these technologies.

An implication of this finding is that both companies and politics must enhance society's knowledge of digitalisation in general, and AI in particular. It is crucial to increase information offers about these topics in order to foster awareness and comprehension of AI, its underlying technologies, and what it can and cannot do. By that, the fear of AI can be taken, and once society is ready to embrace it, large-scale implementation in companies, but also in the public sector is possible.

In this context, it is also important to take the risks of AI into account. They include ethical issues, such as job replacements or social discrimination by algorithms, and ideas on morality (Bostrom & Yudkowsky, 2014).

All the identified barriers in chapter 2.4 turned out to be significant. As far as a lack of strategy and use cases are concerned, the responsibility lies within the organisations themselves. The managers in charge of running the firms must, if benefitting from AI is desired, inform themselves and their employees about AI in general and the specific tasks it can do for them. A sound understanding of its potential is as crucial as is a clear long-term roadmap, which explicitly depicts where the company is supposed to go with AI. As the implementation is an iterative process, concrete milestones and performance measurements must be developed so that the AI-induced improvements can be monitored and evaluated over time. Not conforming with these conditions will most likely prevent AI adoption in the first place or lead to a failure in execution.

The remaining barriers are influenced externally. Certainly, companies can increase their knowledge about legal regulations of AI, search more actively for AI talents, and try to find comparable references of firms investing in AI. Notwithstanding, these factors are to a great extent determined by external structures, which involve politics and society. As pointed out in the *Artificial Intelligence Mission Austria 2030*, precise and transparent laws and rules must be implemented, and a regulatory framework for orientation needs to be provided in order to stimulate AI adoption (Bundesministerium für Verkehr, Innovation und Technologie & Bundesministerium für Digitalisierung und Wirtschaftsstandort, 2018).

Equally, research has shown that companies have difficulties in finding adequate personnel for AI deployment. There is a severe deficiency in educational programmes in Austria to provide students with the necessary skills to be capable to develop and implement AI systems. Apart from specialised courses for ongoing experts, basic knowledge and skills should be taught already in school and other educational institutions in order to prepare people to deal with AI systems and also to fill the shortcoming of personnel at organisations.

In the course of further development of AI and subsequently of application possibilities for a broader spectrum of firms, reference cases will come with time. Still, politics is required to generate incentives for organisations to take on AI as soon as possible so that Europe's AI engine can finally gain momentum in the face of China and the USA. One way to do so could be to subsidise AI technologies especially for SMEs, which represent the backbone of the Austrian economy. Additionally, the government should increase public spending in research projects and start-ups dealing with AI. This would encourage all kinds of businesses to embrace AI and strengthen Austria's and Europe's global competitiveness.

It is decisive to put these measures into practice fast and to follow an integrated approach, i.e., involving the economy, politics, and the civil society in the discussion and decision processes. This way, a sustainable, beneficial, and healthy AI adoption can take place in Austria.

5.4 Limitations

After discussing the results of the synthesis of literature review and empirical analysis, this chapter takes into account limitations of this study.

First of all, the choice of a quantitative approach in contrast to a qualitative method has the downside that the latter can yield more in-depth information about managers' reasons to deploy AI or not. This would allow a more precise description of drivers and barriers of a certain kind of companies, for instance, of a particular size, industry, or structure. However, the ambition of this thesis was to generate a general view on the underlying drivers and barriers, which can be applied to any kind of company independent of its particular characteristics. A quantitative approach was therefore more appropriate. Future studies could use the findings of this research to test whether the drivers and barriers also hold in firms of specific traits or categories.

Second, while an online survey enables a researcher to reach a greater number of respondents at relatively low cost, it comes with some disadvantages. The downsides of a survey include potential misunderstandings, respondents not stating their true opinion, and the researcher designing the questionnaire based on his own experiences and expectations. Despite strong efforts to minimise those risks, biased results cannot completely be ruled out.

Further, although the link to the questionnaire was sent out to specific email addresses, the high number of recipients did not permit to directly address them with names. Thus, the impersonalised email may have led some to reject to click on the link. Additionally, the recipients were, if not managers themselves, asked to forward the email to a company manager. This represents another burden, since the email could more easily be lost on its way. Still, this measure was necessary, as it was important to have the questionnaire filled out only by people responsible and aware of the strategic situation of their firm.

Moreover, due to the research being conducted completely in English this was also the language chosen for the questionnaire, although the mother tongue of the target population is German. The language barrier certainly entailed many dropouts. Yet, a sufficient number of responses to discover initial tendencies could be collected and no (back-) translating issues distort the results (Saunders et al., 2016; Zikmund, 2010).

Third, the results of the survey lose their ability to be generalised to the total population. This is in the first place because the Economic Chamber's data base, i.e., the sampling frame, is not complete, hence, not all companies had an equal, known chance of being elected. Consequently, non-probability sampling including haphazard sampling had to be applied. Besides, considering the total population of more than half a million companies in Austria, the sample size is not big enough to reach statistical significance at a 95 per cent confidence level. To increase the sample size, measures such as collecting more email addresses, and personalising the content should be adopted. Taking into account the resource constraints of a master's thesis, the approaches taken are appropriate and beyond that, accepted in academic research (Saunders et al., 2016).

Another reason for the limitation of a generalisation of the results lies the fact that the survey is prone to self-selection bias. Firms, that already are aware of the topic of AI might be more willing to partake in the survey than those who are not leading to a skewed representation.

Fourth, certainly not all driving and impeding forces were identified, and possible moderating and mediating variables were not included in the research model. In concrete, the analysis revealed one barrier that was not accounted for, but which seems to play a significant role, namely, *social acceptance* of AI. If people reject the idea of an artificial mind, this clearly impacts their readiness to deploy AI technologies. In this context, it would also be interesting to uncover the underlying reasons for accepting or rejecting AI.

Notwithstanding, the purpose of this preliminary research was to generate initial findings of what encourages and hampers AI adoption, and the research questions could be answered. Future studies can build upon these findings and include more or different variables and deepen the insights about AI adoption in companies.

6 Conclusion

This study has delivered some initial insights of reasons that facilitate or obstruct the adoption and use of AI technologies in Austrian companies. First, a thorough literature review on Artificial Intelligence was conducted, including definition approaches, the historical background and the underlying technologies. Further, investigating literature and existing use cases made it possible to detect concrete drivers and barriers to AI adoption.

The findings of the empirical, quantitative analysis indicate that the identified encouraging and impeding forces are valid. According to this study, both the opportunity to increase a company's revenue via pattern recognition, customisation, and innovation and managers' fear to not be able to catch up with AI when not embracing it now, have the strongest positive effects on AI adoption. Also, the possibility of reducing costs by applying machine learning to automate operations and processes, predictive analytics, and natural language processing turned out to be a decisive factor, though not as effective as the former two.

The investigation also unveils that lacking a clear AI strategy is the most pivotal barrier to implementation. Given that according to Ransbotham et al. (2017) more than 75% of executives expect benefits for their firm from AI, managers should develop a coherent long-term roadmap for AI implementation, and integrate it in the overall business strategy. Apart from that, many firms do not know how AI technologies can be of any use for them, which, in turn, can be attributed to a general deficiency in knowledge about AI. Unclear legal regulations, a shortage in AI experts due to insufficient educational programmes, and uncertain investment prospects because of too few reference cases, particularly for small firms, constitute further inhibitors. Since Austria's economy is made up mainly of SME's, it is even more important to increase awareness that AI systems can help improve even smallest businesses. Facilitating public policies should be introduced fast to counteract these barriers, and to support businesses in embracing AI.

Besides, the examination uncovered that social acceptance of artificially intelligent systems seems to be another significant variable that could be taken into account in further studies. This finding also reflects the importance of ethical considerations in the further development of AI, which must be taken seriously, since only a socially acceptable, integrated Artificial Intelligence can be successful for business and society in the long-run.

To sum it up, in the global race for AI leadership, Austria and Europe still lack behind. Since "this new era will have winners and losers" (Gerbert, Hecker, Steinhäuser, & Ruwolt Patrick, 2017), it is of greatest importance for organisations to include AI in their long-term strategy. Otherwise, they will lack growth and competitive advantage. Politics, the economy and society must assume responsibility and take action to generate conducing circumstances for AI adoption.

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Appendix

A Questionnaire

soSci
oFb - der onlineFragebogen

artificial-intelligence-thesis → base 27.06.2019, 11:45

Seite 01

Welcome!

Dear participant,

thank you for your time, it will take only **5-10 minutes**!

The following questions refer to **Artificial Intelligence** (**AI**), which here is defined as a **collection of technologies which use data to learn (improve and adapt itself) and to solve tasks autonomously (without constant guidance of a user)**.

AI can be implemented in software and in hardware. One example is a chatbot, which responds to questions of customers and which gives better answers each time because it learns from previous questions and answers.

Another example is a robot, which moves around in a warehouse, and which sorts products more efficiently each day by learning from and adapting to its environment. Many more applications with AI are possible.

Your answers are treated completely **confidentially** and no inferences to you or your company can be made.

Click the "Next" button to start!

Seite 02

1. How profound would you describe your knowledge of Artificial Intelligence?

No knowledge at all			Very profound knowledge

Seite 03

2. The deployment and use of AI technologies represent an opportunity for our company to increase revenue.

Strongly Disagree			Strongly Agree	Not Applicable

1 aktive(r) Filter

Filter T003/F1
Wenn eine der folgenden Antwortoption(en) ausgewählt wurde: **2, 3, 4**
Dann Frage/Text **T004** später im Fragebogen anzeigen (sonst ausblenden)

Seite 04

3. How likely do the following AI functions lead to an increase in revenue in your company?

	Very unlikely			Very likely
Personalisation (customise products / services)	○	○	○	○
Pattern Recognition (identify useful patterns in large data sets)	○	○	○	○
Innovation (improve existing products / services or create entirely new ones)	○	○	○	○
Other, please specify:	○	○	○	○

Seite 05

4. The deployment and use of AI technologies represent an opportunity for our company to reduce costs.

○	○	○	○	○
Strongly Disagree			Strongly Agree	Not Applicable

1 aktive(r) Filter

Filter T005/F1
Wenn eine der folgenden Antwortoption(en) ausgewählt wurde: **2, 3, 4**
Dann Frage/Text **T006** später im Fragebogen anzeigen (sonst ausblenden)

Seite 06

5. How likely do the following AI functions lead to a cost reduction in your company?

	Very unlikely			Very likely
Operation and Process Automation (automate and improve processes or administrative tasks)	○	○	○	○
Predictive Analytics (analyse data to forecast events, e.g. sales, stock or staff requirements, etc.)	○	○	○	○
Natural Language Processing (text/speech understanding, chatbots, etc.)	○	○	○	○
Other, please specify:	○	○	○	○

Seite 07

6. Generally, I believe that if our company does not adapt to technological trends in due time, it will suffer from competitive disadvantage.

○	○	○	○	○
Strongly Disagree			Strongly Agree	Not Applicable

7. Specifically, I believe that if our company does not adopt AI soon (within 2 years), it will have greater difficulties in catching up with the technology later.

○	○	○	○	○
Strongly Disagree			Strongly Agree	Not Applicable

8. Our company has a coherent long-term roadmap (strategy) for deploying AI technologies.

Strongly Disagree			Strongly Agree	Not Applicable
○	○	○	○	○

9. Our company has determined a responsible person / team for the AI rollout.

Strongly Disagree			Strongly Agree	Not Applicable
○	○	○	○	○

10. Our company has knowledge of what AI technologies are generally capable of.

Strongly Disagree			Strongly Agree	Not Applicable
○	○	○	○	○

11. Our company has clear use cases for AI technologies.

Strongly Disagree			Strongly Agree	Not Applicable
○	○	○	○	○

12. Our company is aware of the general legal regulations of AI technologies (data protection, liabilities, regulatory constraints / possibilities etc.).

Strongly Disagree			Strongly Agree	Not Applicable
○	○	○	○	○

13. Our company's legal department has sufficient knowledge of the specific legal framework of those AI technologies that are potentially usable for our organisation.

Strongly Disagree			Strongly Agree	Not Applicable
○	○	○	○	○

Seite 11

14. Our company has enough sufficiently skilled personnel to implement AI.

Strongly Disagree | | | Strongly Agree | Not Applicable

15. It is unproblematic to acquire adequately skilled personnel to implement AI.

Strongly Disagree | | | Strongly Agree | Not Applicable

Seite 12

16. Implementing AI technologies does not involve high costs for our company.

Strongly Disagree | | | Strongly Agree | Not Applicable

17. It is certain that the investment in AI will yield a positive return.

Strongly Disagree | | | Strongly Agree | Not Applicable

Seite 13

18. Our company has implemented AI technologies or will certainly do so within the next two years.

- No
- Yes

Seite 14

19. Do you have additional comments on why your company does/will deploy AI?

20. Do you have additional comments on why your company does/will not deploy AI?

21. Where is your company based?

- Salzburg
- Oberösterreich
- Steiermark
- Kärnten
- Niederösterreich
- Burgenland
- Vorarlberg
- Tirol
- Wien

22. Which industry does your company belong to?

- Banking & Insurance
- Retail & Trade
- Manufacturing
- Information & Consulting
- Tourism & Leisure
- Transport &Traffic
- Other, please specify:

23. How many employees does your company have?

- ≤ 9
- ≤ 49
- ≤ 249
- ≤ 1000
- > 1000

24. How much revenue did your company make last year?

- ≤ 2 Mio. €
- ≤ 10 Mio. €
- ≤ 50 Mio. €
- > 50 Mio. €

25. Do you wish to receive the results of the Master Thesis when it is completed?

- Yes, please enter e-mail address (will only be used to send results and will afterwards be deleted):
- No

Letzte Seite

Thank you very much for completing this questionnaire!

Your answers were transmitted, you may close the browser window or tab now.

Möchten Sie in Zukunft an interessanten und spannenden Online-Befragungen teilnehmen?

Wir würden uns sehr freuen, wenn Sie Ihre E-Mail-Adresse für das SoSci Panel anmelden und damit wissenschaftliche Forschungsprojekte unterstützen.

E-Mail: Am Panel teilnehmen

Die Teilnahme am SoSci Panel ist freiwillig, unverbindlich und kann jederzeit widerrufen werden.
Das SoSci Panel speichert Ihre E-Mail-Adresse nicht ohne Ihr Einverständnis, sendet Ihnen keine Werbung und gibt Ihre E-Mail-Adresse nicht an Dritte weiter.

Sie können das Browserfenster selbstverständlich auch schließen, ohne am SoSci Panel teilzunehmen.

B.A. Adrian Straub, Universität Wien – 2019

B Answers to Open Field of Question 22

Which industry does your company belong to?
Handwerk
Internet
Advertising & Communication
coaching
Medizin
trading stationayr + on Amazon + accounting for other companies
soziale Dienstleistungen
Biotechnology
Medical care
Construction
laboratory
Softwaredevelopment
call center
Construction
Service
Industrial Services
Architecture
real estate
Construction Industry
Education
Inspection
Real Estate
Medical services
Law
Counseling, Mediation
Goßhandel
E-Learning
Health care sector
Telecommunication
Verlag, Weiterbildung
media agency
Repair centre (electronics)
automotive information services
artisten, craftmen services concerning cleaning and grinding of stone and ceramic tiles
Health Care
Immobilienverwaltung
Building and costruction
Electronics, Engineering,Technology
Management for elevators
Elderly care
Software Development
Education

Sports & Art
Attorney
will not tell
Technology company
Medical

C Answers to Open Questions 19 and 20

Do you have additional comments on why your company does deploy AI?	*Do you have additional comments on why your company does **not** deploy AI?*
No	Ich bin ein Ein-Mann Betrieb im handwerklichen Bereich. Hier ist ai Maximal als plaungstool behilflich aber es geht um viel kreative Arbeit, die den Betrieb und die Persönlichkeit ausmacht, ne somit den Betrieb von anderen unterscheidet. Möglicherweise könnte für 0815 firmen ohne Kreativität so hier von Vorteil sein
This technology will change the world. As a CEO you have to adapt, or you will die.	
no	no
We are a very small company, so I am not sure if it is important for you.	I am not good with technical things, so I do not know how to use it. As our company is such small there are no ressources for another person to do it.
For the moment, introducing. AI will not bring much advantage for us, as we are in direct contact with our customers and the work we do is rather practical, whereby not many computer technology is required (besides basic administration).	See above
Not in strategic field of goal	
	we are a small handcraft company in the woodworking branch, we do a lot of "handwork" the evaluation of danger and chances needs to be done in the head of the emplojees. The trust of our custumors in the knowledge of our emplojees ist one of our USP´s. AI would probably built a barrier between our product (wich is founded on high quality handwork) and the custumors requirement and wishes on our product.

more freetime for me labor savings for me cost reduction employees	
We probably will not deploy AI in the next years, because our business is based on personal human contact.	Operational processes are largely automated, but individual customer needs have to met personally.
	Weil es in unserem Sektor derzeit keine Notwendigkeit dafür gibt.
to make decisions and processes easier	fear evetually
	I am a one Woman interior designer, AI is not what my customers would expect
Need to meet customer demand, keep up with competitors and to cut Costs.	
The primary use case for AI would be the collection and analysis of data related to our projects.	There is not enough data available to work with, as Information is not digitized yet.
	We use a C64 for Bookkeeping :-)
Machine translation has improved immensely over the past two years. Here's an example: Translation of 10 pages ranging from 1980 to present: 1980 (electric typewriters, paper dictionaries) 2 man days, 1995 (word processing) 1 man day, 2005 (word processing, dictation systems, dictionaries on CD): 6 hours, 2010 (word processing, dictation systems, online dictionaries, Google research function): 5 hours, 2019 (word processing, machine translation, online dictionaries, Google research function) 2 hours. Productivity in the translation sector has improved by several factors due to machine translation (AI), online dictionaries, research through Google. The work of a translator is moving more and more towards post-editing.	In view of the improvements made to Google Translate/DeepL, implementing AI is a no-brainer. Failure to implement AI would mean losing the race against the competition.
revenue	No
we won´t	AI does not work as good as a person in our company

AI is not a priority. We prefer safety and reliability of speed and comfort.	AI cannot drive our trucks in the forseeable future and while there might be a use in fleet management, AI won't be able to detect mechanical issues or navigate based on knowledge of the area without a massive database. Our company's data protection policy would also prohibit the use of such a database, even if it would increase profit. I would like to mention that we have a decentralized network, shielding individual departments from cyber attacks. AI would need some kind of access to all those systems via a network connection, defeating the purpose in the first place.
	The whole AI topic is still very young and needs more solid development
We are in a business field / activity, where AI can not help bcs has to be done manually and by humans (different services).	No
	We?re too small.
no	no
No	My business is a one-woman-bookshop.
	our industry relies heavily on trust and human interaction. So far, AI cannot replace that
No	No
We won´t deploy it.	My company works with people and their daily life issues/problems. No technology of the world can replace the feelings of a human being and real communication. As a mediatior and counselor I will not deploy AI technology. This would be the wrong way.
	company too small. investment very high. Boss believes in old fashioned ways.
	Wir nutzen kein KI und KI steht für uns auch nicht zur Debatte, da wir Produkte verkaufen und Servicedienstleistungen durchführen.
Since we are quite a small company, the costs would be relatively really high to implement AI. Due to this fact it is unlikely that AI will be implemented	No, only the size of the company (<20 employees)
to make the backoffice	it is a very individual handmade work.
no	no

Our company will deploy AI in the next 5 years from now	
	Can't figure out any use of AI in a small restaurant / butchery on the countryside
Useless scrap for a workshop.	A handcrafted workshop does not require AI. We use our brain.
No	No
no	we are a craftsmen company
Chatbot implementation	lack in ressources/manpower
no need yet	no
Insbesondere in der Verrechnung / Buchhaltung wird viel vollautomatisch erledigt. Wir warten auf die AI unserer verwendeten Verwaltungssoftware zur vollautomatischen Erkennung, Erfassung und Verbuchung von Eingangsrechnungen APPS und 24h OnlineZugriff auf Dokumente und weitere Infos wird von Kunden verlangt. Gewisse routine Anfragen (FAQS) könnten über AI abgefangen werden, sodass mehr Zeit für die eigentliche Kundenbetreuung bleibt	Bei der von uns verwendeten Hausverwaltungssoftware ist jedes neue Tool in der Lizenzierung recht kostspielig.
Not familiar with it	Lack of competences
NA	I'm a one man company with no use for automatization. You should select your target companies more carefully in order to get more meaningful responses. OK
I will not.	I produce unique products. Each is different.
	We are a rather small company where AI could possibly help in administrative tasks and data processing. The tasks are still very managable tough, so we don't think that the costs of implementing AI on those tasks would yield positive. Regarding customer service, we don't think that AI would do a better job than humans.
We use AI for cash transaction (i.e. ATM).	As a service company it is difficult to implement AI.
Um mit der Zeit zu gehen und die Kundenbetreuung noch gezielter und spezifischer durchführen zu können.	Not necessary in our business right now, not enough possibilties to implement AI efficiently.

Probably we will try to do it, if there is a strong connection for helping our business grow and help other people be more tuned with our business.	If we do not deploy AI it will be because we still late for some reason.
Main reason is to recognize behavior patterns of elderly and adapt our products ...	Mir wäre eine bessere Entwicklung der menschlichen Intelligenz ein großes Anliegen. Wir brauchen keine künstliche Intelligenz, da diese keine ethischen Werte hinterlegt hat. Diese Technologie führt zwar kurzfristig zu mehr Wertschöpfung und Gewinn für ein schmales Band von Branchen, wird uns gesellschaftliche aber in eine sehr gefährliche Situation bringen.
AI will change fundamental our processes regarding the ability for innovation, data driven analytics, customer behaviour and operations and the supply chain	Every firm which will not use AI will lag behind and loose ground against their competitors - in the end they will fail
No	No
	Overrated
May it could be possible to reduce human errors. It could be a loyal worker for a long time.	No
Please look at the next answer.	Our Company is working in the tertiary Sektor, epecially in coordinating Stakeholder-groups. Therefor we need not AI.
No	NO
no, it won't	I am a Dance und Fitness Trainer with no use of technology except of playing music.
The main core of our product relies on machine learning.	
well, I am working for a consulting company where we will hardly use AI within our own operations but we will deploy AI within our respective service offerings	
AI currently used only in cybersecurity for realtime UBA	no

D Frequency Tables for Transformed Multi-Item Variables

Fear of falling behind					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree [4]	15	9.1	10.0	10.0
	[3,5]	22	13.4	14.7	24.7
	[3]	30	18.3	20.0	44.7
	[2,5]	25	15.2	16.7	61.3
	[2]	29	17.7	19.3	80.7
	[1,5]	10	6.1	6.7	87.3
	Strongly Disagree [1]	19	11.6	12.7	100.0
	Total	150	91.5	100.0	
Missing	System	14	8.5		
Total		164	100.0		

Lack of strategy					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree [4]	7	4.3	5.4	5.4
	3,50	7	4.3	5.4	10.8
	[3]	8	4.9	6.2	16.9
	2,50	18	11.0	13.8	30.8
	[2]	21	12.8	16.2	46.9
	1,50	19	11.6	14.6	61.5
	Strongly Disagree [1]	50	30.5	38.5	100.0
	Total	130	79.3	100.0	
Missing	System	34	20.7		
Total		164	100.0		

Lack of use case					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree [4]	15	9.1	10.1	10.1
	3,50	5	3.0	3.4	13.4
	[3]	27	16.5	18.1	31.5
	2,50	31	18.9	20.8	52.3
	[2]	42	25.6	28.2	80.5
	1,50	18	11.0	12.1	92.6
	Strongly Disagree [1]	11	6.7	7.4	100.0
	Total	149	90.9	100.0	
Missing	System	15	9.1		
Total		164	100.0		

Legal uncertainty					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree [4]	20	12.2	15.5	15.5
	3,50	9	5.5	7.0	22.5
	[3]	19	11.6	14.7	37.2
	2,50	15	9.1	11.6	48.8
	[2]	25	15.2	19.4	68.2
	1,50	14	8.5	10.9	79.1
	Strongly Disagree [1]	27	16.5	20.9	100.0
	Total	129	78.7	100.0	
Missing	System	35	21.3		
Total		164	100.0		

Lack of talent					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	3,50	2	1.2	1.5	1.5
	[3]	11	6.7	8.3	9.8
	2,50	30	18.3	22.6	32.3
	[2]	26	15.9	19.5	51.9
	1,50	33	20.1	24.8	76.7
	Strongly Disagree [1]	31	18.9	23.3	100.0
	Total	133	81.1	100.0	
Missing	System	31	18.9		
Total		164	100.0		

Uncertain investment					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly Agree [4]	2	1.2	1.5	1.5
	3,50	8	4.9	5.9	7.4
	[3]	19	11.6	14.1	21.5
	2,50	32	19.5	23.7	45.2
	[2]	39	23.8	28.9	74.1
	1,50	25	15.2	18.5	92.6
	Strongly Disagree [1]	10	6.1	7.4	100.0
	Total	135	82.3	100.0	
Missing	System	29	17.7		
Total		164	100.0		

E Crosstabulation Employees and Revenue

Employees * Revenue_category Crosstabulation						
Count						
		Revenue_category				Total
		≤ 2 Mio.	≤ 10 Mio.	≤ 50 Mio.	> 50 Mio.	
Employees	≤ 9	86	4	2	0	92
	≤ 49	20	9	3	0	32
	≤ 249	3	10	7	6	26
	≤ 1000	1	0	0	5	6
	> 1000	0	0	0	8	8
Total		110	23	12	19	164

F Frequency Table AI Adoption

AI Adoption					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	96	58.5	58.5	58.5
	Yes	68	41.5	41.5	100.0
	Total	164	100.0	100.0	