Artificial Intelligence and its Impact on Innovation - Assessment of AI’s Readiness and Future Role in Innovating

MASTER THESIS

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<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>AGI</td>
<td>Artificial General Intelligence</td>
</tr>
<tr>
<td>TRA</td>
<td>Theory of reasoned action</td>
</tr>
<tr>
<td>TPB</td>
<td>Theory of planned behavior</td>
</tr>
<tr>
<td>ATT</td>
<td>Attitude</td>
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<tr>
<td>SN</td>
<td>Subjective Norms</td>
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<td>PBC</td>
<td>Perceived Behavioral Control</td>
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<tr>
<td>IT</td>
<td>Information Technology</td>
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<tr>
<td>I1 – I6</td>
<td>Identification of Interviewees</td>
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<tr>
<td>ML</td>
<td>Machine Learning</td>
</tr>
<tr>
<td>DL</td>
<td>Deep Learning</td>
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<tr>
<td>RoI</td>
<td>Return on Investment</td>
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<tr>
<td>R&amp;D</td>
<td>Research and Development</td>
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<td>PoS</td>
<td>Point of Sale</td>
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Abstract

Due to the presence of adequate computing power, sophisticated algorithms and the accessibility to vast amounts of data, narrow artificial intelligence (AI) has substantially gained ground over the past years. Prior studies have therefore investigated into first AI use-cases as well as into how organizations can drive the adoption of AI. However, no insights have been provided regarding AI's potential impact on a company's innovativeness. It is for this reason that this study uses a mixed-method approach to assess AI's potential and future role in the innovation process. More precisely the focus is set on two different aspects. Firstly, it is examined, which organizational and individual factors influence an individual's intention to use artificial intelligence technologies when innovating. Theory of planned behavior (TPB) is therefore applied to an AI adoption context. Secondly, quantitative research is conducted to investigate into AI's future role within the area of innovation. In particular, it is assessed which kinds of tasks within the innovation process are expected to be most enhanced by AI as well as which AI systems or tools are most suitable for being applied when innovating. In the end, 'levels of autonomous innovating' are assigned to the overall innovation process and each innovation task, to provide a picture of AI's expected role in innovation. These levels include AI's degree of autonomy in executing the tasks, the expected degree of required human monitoring as well as the expected degree of autonomous decision-making.
Introduction

1.1 Problem Statement & Research Gap

History of Artificial Intelligence (AI) research has been a roller-coaster ride. First research into AI had already been conducted in the 1940s and 1950s with the foundation of the Artificial Intelligence Laboratory at MIT and works on self-learning software at IBM. In 1956 AI was founded as an academic discipline. Nevertheless, in the 1970s and 1990s funding for further research slumped as backers were tired of waiting for practical AI applications and cut appropriations for further work (Negnevitsky, 2002). Hence, Artificial Intelligence research preceded another ‘AI Winter’ until the 21st century as growing computer power, more sophisticated algorithms and huge amounts of generated data convinced investors that it was practical and profitable (Buchanan, 2005). Still, AI has not yet experienced wide-scale commercial deployment. Despite significantly growing investments in AI over the past years, the adoption level of AI in organizations is expected to be low in 2018 (Ransbotham et al., 2017). Many recent studies have therefore investigated the factors that facilitate or impede the adoption of AI within organizations. Furthermore, AI use-cases for many parts of the organization, such as production and maintenance, marketing and sales, customer experience, and R&D were identified (McKinsey, 2017). However, very little was investigated into AI's potential to enhance an organization's innovativeness. The latter fact and the urgent need of companies to permanently innovate to survive in highly competitive markets, highlight the relevance of this topic. Innovating promises long-term success, higher growth rate, and survival on the market (Chefis et al., 2006). Nonetheless, it has not been investigated yet into how AI can influence the future innovation process.

The aim of this master's thesis is therefore to provide a comprehensive picture of the current and future role of AI in the area of innovation. In this regard, three different levels of readiness are tackled. Firstly, an individuals' readiness to use AI when innovating is researched. Secondly, the technological aspect of AI is covered by investigating different types of AI technologies as well as by taking a closer look at specific innovation tasks that AI algorithms may be able to enhance. Thirdly, organizational aspects related to the adoption of AI in the area of innovation are examined.
1.2 Research Question

The described problem statement leads to the formulation of the following research question. The research question and its sub-questions determine the framework of this thesis.

“What is AI’s future role in innovating?”

a) Which aspects influence an employee’s intention to use AI when innovating?

b) What innovation tasks have the highest potential for being impacted by AI?

c) Which AI technologies are most promising for being applied to innovation?

d) What is the expected degree of automation of AI concerning completing tasks and making decisions?

1.3 Contribution

This study contributes to current research by combining two highly relevant topics, narrow artificial intelligence, and innovation. AI research has become more and more critical over the past years, as overall technological improvements led to specific use-cases that could for the first time be deployed at wide-scale. Innovation has always been considered an essential part of an organization, as it highly contributes to the overall success of a company. However, it has not yet been investigated how AI as a tool may influence the way organizations innovate. The aim of this study is, therefore, to contribute to existing literature with new findings and insights in this regard. Its goal is to provide a first comprehensive picture about AI's potential for being applied within the area of innovation. Furthermore, aspects of the individual as well as organizational level are identified that may facilitate or impede an employee's readiness to use AI technology when innovating. The results of this thesis should give indications about the direction in which further research and developments in this area could go. They do so by assessing which innovation tasks have the most potential for being enhanced by AI, by examining which AI tools are most promising for adding value to the innovation process and by investigating into the expected degree of autonomy AI may exhibit in the future.

1.4 Structure

This thesis consists of several different sections to guarantee a clear structure as well as a consistent threat. The introduction provides a first understanding of the problem statement,
research gap and the contribution of this study. The introduction is followed by a literature review part that presents an in-depth foundation of the theoretical background of this thesis as well as reflects the authors reasoning processes. After that, a description of the research context, applied methodology, used research model as well as data collection and analysis, is given. Chapter four shows the results of the empirical part of this study by combining the findings of the hypotheses testing, the descriptive analytics, and insights from the interviews. The discussion part then answers the research question. Last but not least managerial implications are given, limitations are highlighted, and directions regarding further research are provided.
2 Literature Review

2.1 Artificial Intelligence (AI)

2.1.1 Definition

A proper definition of the term Artificial Intelligence (AI) is crucial to get a better understanding of the research object. Historically, AI has been explained alongside four different dimensions: thinking humanly, acting humanly, thinking rationally and acting rationally. Already in 1978 Bellman defined AI as "[The automation of] activities that we associate with human thinking, activities such as decision-making, problem-solving, learning." Winston (1992) described AI as "The study of the computations that make it possible to perceive, reason, and act." Six years later Poole et al. (1998) claimed that “Computational Intelligence is the study of the design of intelligent agents.” (Russell et al., 2010)

Nowadays, the term Artificial Intelligence is much more extensive and complex. It appears as a combination of the statements named above. Hence, a current definition is that AI generally refers to the ability of machines to exhibit human-like intelligence or behavior, such as ‘learning’ or ‘problem-solving’ (Press, 2017). The Oxford English Dictionary refers to Artificial Intelligence as "[AI is] the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision making, and translation between languages."

For the sake of completeness, it is also necessary to take a look at the different categorizations of AI. As organizations often mix and match several technologies to create solutions for individual problems within a company, it is difficult to classify AI precisely. Nevertheless, literature mentions four different dimensions alongside which AI technologies can differ: Strong vs. Weak AI and Narrow vs. Broad AI. While strong AI technologies try to simulate human reasoning, weak AI technologies are systems that behave like humans (Vorhies, 2016). Furthermore, AI technologies are narrow if they perform lots of limited and narrowly defined tasks, the same tasks that humans perform. Broad AI in return is a system which can be applied to many context sensitive situations in which it can mimic human activity or decision making (Vorhies, 2016). As a result AI research is split into two significant research areas: On the one side there is weak and narrow AI, and on the other side there is strong and broad AI, also called Artificial General Intelligence (AGI). The current focus in economic research is on weak and narrow AI technologies, because they have near-term business potential, while broad and strong AI has yet to come (Ransbotham et al., 2017). For this reason, the focus of this study is on weak and narrow AI technologies. It is the nature of narrow AI to perform somewhat limited and
specific tasks, which makes it so suitable for organizations to use it within single processes or process steps, in particular projects or their product and service offerings (Ransbotham et al., 2017). Hence, in case of narrow AI, Artificial Intelligence is often rather seen as automation of decision-making as opposed to intelligence. It is about learning about multiple areas and then making human-like decisions, but in a much quicker, more reliable and more accurate manner (Awadallah, 2017). Therefore, AI is capable of impacting any function where humans make repeatable decisions. This fact means that AI gives organizations the opportunity to automate some jobs or areas by taking over some of the presumably dull and unpleasant current tasks (Ransbotham et al., 2017). As a result, this allows human workforces to shift their focus of attention into more innovative, creative and customer-centric areas. In this regard, Atif Rafiq, CIO and CDO of Volvo, agreed that "AI assists humans to unlock human potential, allowing them to focus on higher and higher value tasks and activities (Capgemini, 2018)." As a consequence of this development, some old job profiles disappear while new ones emerge. So, AI will not simply replace work. It is expected to transform the way value is created at a fast pace (Floridi, 2017). Since the very dawn of automation, every category of automation eliminates jobs and creates jobs. It has always displaced people, but it has simultaneously also created new opportunities. Hence, "AI is just one in a long line of automation technologies" (Chen, 2017). The following subsection discusses, which narrow AI technologies are currently the most promising ones across different industries.

2.1.2 Narrow AI

At the core of every narrow AI technology is logic, if-then rules, decision trees, or machine learning algorithms (Knoll, 2018). Depending on the chosen approach, those technologies are either focused on the automation of activities or try to exhibit human-like intelligence. Figure 1 gives an overview of the current state of AI technologies. It shows how different approaches, main areas, and sub areas are interrelated and for which specific outcomes they are most suitable for (Jeffs, 2017). The basis of all of the listed technologies is algorithms. An algorithm is a sequence of instructions or a set of rules that are followed to complete a task (BBC, 2018). Therefore, algorithms are typically used in mathematics and computer science to solve a class of problems. They do so by performing calculations, data processing, and automated reasoning tasks (Rogers, 1987). In narrow AIs those algorithms are very task specific and do not generalize. Hence, an algorithm used to predict whether a patient is going to get a specific type of cancer does not work when giving product recommendations based on historical purchase data. Thus, the degree of suitability of a specific technology highly varies, depending on the
The goal of this study is to investigate into the types of AI technologies that are currently most suitable or have the highest potential for being used within the innovation process of companies.

**Figure 1. Artificial Intelligence - Automated Intelligence (Jeffs, 2017)**

In 2017 the most relevant narrow AI technology systems across different industries were robotics and autonomous vehicles, computer vision, natural language, virtual agents and machine learning (McKinsey Global Institute, 2017).

While the first four key technologies are commonly classified as AI, machine learning constitutes an exception. Machine Learning (ML) can instead be seen as a Technology Foundation (Capgemini Digital Transformation Institute, 2018). Hence, ML algorithms form the core of many other technologies, but cannot be classified as AI technologies per se. Figure 2 is a graphical presentation of some of the most relevant terms in current AI research. While Artificial Intelligence is the umbrella term and includes any technique that enables computers to mimic human intelligence using logic, rules, decision trees, and machine learning, ML itself is currently the most promising subset of AI (Knoll, 2018).
Figure 2. AI Umbrella (Digital Nebula, 2018)

Machine Learning includes complex statistical techniques that enable machines to improve at tasks with experience (Knoll, 2018). Hence, the performance of algorithms improves as they are exposed to more and more data over time. So, the more historical data available to learn from, the more accurate will their predictions be (Mohri et al., 2012). Here, experience refers to the past information available to the algorithm, which typically takes the form of electronic data, collected and processed by the organizations’ data governance systems. These data can be in the form of a digitalized human-labeled training set, or other types of information obtained via interaction with the environment (Mohri et al., 2012).

Hence, a significant advantage of ML is that algorithms can learn from data without relying on rule-based-programming (Pyle, 2015). Those algorithms can handle the unmanageable volume and complexity of the big data that the world is currently swimming in, which makes them indispensable in the future. They can yield insights that human analysts can’t see on their own and make predictions with ever-higher degrees of accuracy (Pyle, 2015). A breakthrough in ML was in 2007, when Fei-Fei Li, the head of Stanford's Artificial Intelligence Lab, gave up on trying to program machines to recognize objects. Instead, she began to label millions of raw images and feeding them to computers. Analogously to how children learn, namely through repetition, she fed thousands and thousands of images that a child may encounter by age three to the computer. As a result, the machine could shape its own rules for deciding whether a particular set of digital pixels was, in fact, a specific object (Pyle, 2015).

The latter process is what research currently describes as training AI or training algorithms. However, unlike children, who can make sense of things rather quickly, algorithms need
hundreds of thousands of data to learn from. Such training data is often scarce and therefore expensive.

Nevertheless, this need for vast amounts of data to learn from makes machine learning algorithms suitable for being applied to extensive data sets. They can detect patterns and learn how to make predictions and recommendations by processing data and experiences, rather than by receiving explicit programming instructions (Chui et al., 2018). Also, the algorithms respond and adapt to new data and experience in real-time, which makes them valuable for organizations from a strategic perspective.

Of value for organizations are also the different types of analytics which ML algorithms can perform: descriptive, predictive, and prescriptive analytics (Chui et al., 2018). While descriptive analytics has a rather low degree of complexity and is already heavily employed across all industries, the primary focus of machine learning is on predictive and prescriptive analytics. Predictive analytics anticipate what is going to happen and is inherently probabilistic. Prescriptive analytics additionally provides recommendations on what to do to achieve goals (Chui et al., 2018). Besides the different types of analytics ML algorithms offer, they can also be differentiated by the learning they are using. AI research distinguishes between supervised learning, unsupervised learning, and reinforcement learning (Chui et al., 2018).

The majority of practical machine learning uses supervised learning. In supervised learning “an algorithm uses training data and feedback from humans to learn the relationship of given inputs to a given output” (Chui et al., 2018). More precisely, it can be described as a process in which you have input variables (x) and an output variable (Y), and you use an algorithm to learn the mapping function from the input to the output. Hence, the goal is to approximate the mapping function so well that, in case of new input variables (x), you can predict the output variables (Y) for that new data (Brownlee, 2016). The term ‘supervised' is used because the process of an algorithm learning from the training dataset can be thought of as a teacher supervising the learning process. So during the learning process, the algorithm iteratively makes predictions on the training data but is corrected by the supervisor, who knows the correct answer. Learning typically stops when the algorithm achieves an acceptable level of performance (Brownlee, 2016). Given the definition of supervised learning, this type is most suitable when organizations know how to classify the input data and the type of behavior they want to predict, but they need the algorithm to calculate it for them on new data (Chui et al., 2018). To explain it on the example of predicting housing prices, we can say that a human labels the input data as 'time of year', 'interest rates', and more, and defines the output variable as 'housing prices'. Now in case of supervised learning, the algorithm is trained on the data to find the connection between the
input variables (time of year, interest rates) and the output (housing prices). Once that algorithm is sophisticated enough, it is applied to new data in order to make predictions (Chui et al., 2018). The other dominant type of machine learning is unsupervised learning. In that case, an algorithm explores input data without being given an explicit output variable (Chui et al., 2018). Hence, the algorithm receives unlabeled data and infers a structure from that data to learn more. The algorithm is able to identify groups of data that exhibit similar behavior. This makes unsupervised learning suitable for organizations that do not know how to classify their data and want the algorithm to find patterns and classify the data for them (Chui et al., 2018).

Furthermore, unlike supervised learning, there is no teacher and no correct answers. Hence, algorithms get no human support and are left to their own devices to discover and present the new structure in the data (Brownlee, 2016). The two most frequent unsupervised learning problems are clustering and association. In clustering, you want to discover the inherent groupings in your datasets, such as grouping customers by their product preferences. Many online-shops are using such cluster behavior prediction to make purchase recommendations based on preferences of other customers with similar attributes (Chui et al., 2018). An association rule problem is “where you want to discover rules that describe large portions of your data, such as people that buy X also tend to buy Y” (Brownlee, 2016).

A highly researched subset of machine learning is deep learning. It is capable of processing an even more extensive range of data sources than conventional machine learning and requires fewer data preprocessing by humans (Chui et al., 2018). It requires larger amounts of data but is able to produce more accurate results than traditional ML approaches. Figure 3 shows the % reduction in error rate achieved by deep learning compared to traditional ML methods. It achieves an impressive reduction in error rate of 25-41% depending on the subarea it is applied in (Chui et al., 2018).

![Figure 3. Deep Learning vs. Traditional ML (Chui et al., 2018)](image-url)}
This performance improvement results from the use of neural networks in which the data is processed. They are called neural because they present similarities to the human brain. Therefore, analogously to what our brain does, those networks ingest vast amounts of input data and process them through multiple layers. At each layer, they learn increasingly complex features of the data (Chui et al., 2018). As a consequence, the network can make assumptions about the data, learn if its determination is correct and then use the learned to make determinations about new data. Currently, the most promising area of application for deep learning is image recognition, as figure 1 also highlights. Once the algorithm learns how a specific object looks like, it can recognize the object in new images.

The following subsection discusses, which narrow AI technology systems are currently the most promising ones across industries and which ones have the potential for being used within the innovation process of an organization.

2.1.3 AI and its Areas of Application

As mentioned above, some of the most relevant AI technology systems across industries are robotics and autonomous vehicles, computer vision, language, and virtual agents (McKinsey Global Institute, 2017). This is supported by the amounts of external investments AI-focused companies received in 2016. Figure 4 shows investors’ focus on technology category in $ billion. It is visible that machine learning, with its subset deep learning, received the highest amount of financial attention in 2016. As technology foundation, it is the basis of many other technology systems. This is highlighted as ML’s circle is overlapping with all the other technologies. The second highest amount invested by external stakeholders was into AI-companies that are focused on computer vision. This aligns with previous assumptions that deep learning has the most significant influence on recent developments in image processing. Natural language received the third highest degree of attention from external investors in 2016. Natural language processing (NLP) includes sub-areas like text-to-speech, speech-to-text, language translations or voice recognition, which is currently used in virtual assistants (Jeffs, 2017).

Another key technology that is commonly classified as AI is the so-called Biometrics Intelligence (Capgemini, 2018). It deals with the measurement of characteristics of human expressions and physical states to understand emotions, intentions, age, and more. (Capgemini, 2018). Hence, Biometrics is particularly suited for identification. Fingerprints, facial measurements, and even the way humans walk – all of these characteristics and more are unique to each human individual. Algorithms can identify those characteristics, which makes
Biometrics particularly suitable to be applied to identity verification systems (Biometrics, 2018).

Similar to Biometrics is Affective Computing, sometimes also called Artificial Emotional Intelligence (el Kaliouby, 2017). The primary motivation for the research in that area is the ability to simulate empathy. The machine should be able to interpret the emotional state of humans, adapt its behavior to them, and give an appropriate response to those emotions (Diamond, 2003). To recognize human emotions, affective computing makes use of deep learning algorithms that are capable of identifying patterns in the way humans are speaking, reacting, their facial expressions, as well as biological data such as pulse, body temperature, and more, when feeling particular emotions (Caridakis et al., 2006).

Text mining, roughly equivalent to text analytics, is another area that massively benefitted from the latest developments in AI. It is the process of deriving valuable information from text. This information is mostly derived through the devising of trends and patterns through the application of various statistical methods (Feldman et al., 2006). So the overarching goal of text data mining is to turn text into data for analysis. This is done through the application of natural language processing (NLP) and other analytical methods (Indurkhya et al., 2010). Typical Text
mining tasks include text clustering, text categorization, sentiment analysis, document summarization, concept/entity extraction, and entity relation modeling (Srivastava et al., 2009). The fact that text data mining is retrieving high-quality information from text, which usually refers to some combination of novelty, relevance, and interestingness, makes this technology suitable for being used within the innovation process. Identifying trends and patterns more accurately, for example, most likely results in a lower product failure rate. Nevertheless, the difference between theory and practice is often enormous. Therefore, the later parts of this thesis discuss, which innovation tasks can be most enhanced by AI, as well as whether organizations already recognize AI's potential for being used when innovating.

After getting an impression about what technologies are the most promising ones, it is interesting to take a look at what exact benefits AI technologies can offer to organizations. Recent studies have identified four different ways in which AI can create value across an organization's value chain: Project, Produce, Promote, Provide (McKinsey Global Institute, 2017). Project and Promote are these two areas it will be focused on. 'Project' refers to AI's ability to better project and forecast to anticipate demand, optimize R&D, and improve sourcing. Promote is about promoting product or service offerings with the right message, at the right price, and to the right target customers (McKinsey, 2017).

*Projection* and forecasting is the first area in which AI can create value. Better and more accurate forecasts allow organizations to optimize supply chain management and design better offerings. Furthermore, it can discern trends and patterns that can be acted on. Hence, trend and demand forecasting are powerful tools that allow minimizing waste of inventory, but also anticipating soon-to-be-popular products or customer needs (McKinsey, 2017). The recent insights are especially valuable for future product or service innovations, as 79% of 1000 surveyed companies confirmed that AI is bringing new insights and better data analysis to the organization (Capgemini, 2017). Furthermore, over 70% confirm that AI is making their organization more creative by automating some of the repetitive tasks, as well as helps them to make better decisions (Capgemini, 2017).

In the area of Innovation, decision making is especially important for organizations' R&D departments. In this regard, AI can support researchers in assessing whether a prototype would be likely to succeed or fail in the market-and why (McKinsey, 2017). Moreover, AI can help to overcome difficult challenges engineers and researchers are currently facing. Consumers' increasing taste for customization and sharp growth in demand, in combination with heavy budget constraints, require R&D teams to improve their productivity and efficiency.
Furthermore, limits on the number of designs that can be tested, often restrict the predictability of product performance (McKinsey, 2017). In this regard, AI-driven technologies can help deliver more efficient designs than were previously achievable by eliminating waste in the design process. Besides, innovations’ time-to-market can be remarkably reduced, as AI facilitates faster process cycle times and an increased focus on real-time negotiations and other interactions (McKinsey, 2017). The usage of AI in R&D processes is estimated to result in productivity gains of 10 to 15 percent. Also, AI-based approaches could reduce time to market by 10 percent or more (McKinsey&Company, 2017).

The second area of application that is important in the context of this thesis is Promote. AI is used in marketing activities to provide new or old products at the right price, with the right message, to the right target groups (McKinsey, 2017). As customers continuously redefine value by comparing prices online, today's requirement of intelligent price management is very high. In this regard, AI can help organizations to price their goods or services dynamically. Depending on different variables like demand, customers willingness to pay, competitors' pricing strategies, the day of the week, time of day, and many more, AI automatically adjusts its optimal price for a good (McKinsey, 2017). Furthermore, machine learning can help to determine which customers are the most profitable. Clustering allows identifying groupings in your data sets, such as groups of high-value customers that share particular attributes. Hence, algorithms offer the possibility to apply the derived patterns onto new data sets and therefore to identify customers who share the attributes of previous high-value customers (Power, 2017).

Online, a focus on the most valuable customers, combined with dynamic pricing, can lead to a 30% growth in sales (McKinsey, 2017). Offline, at the Point of Sale (PoS), AI can help optimize, update, and tailor promotions and displays to each shopper in real time, as customers smartphones are targeted as part of retailers' omnichannel sales strategies. Again, when customizing the discounts and displayed offerings, AI can make sense of variables like previous purchases, age, web browsing habits, and more, to tailor offerings to every single individual. As a consequence, this kind of insights-based selling can increase sales by 1 to 5 percent (McKinsey, 2017). Other studies support these numbers. More than 750 of 1000 surveyed companies reported that the implementation of AI increased sales of traditional and new products by more than 10% (Capgemini, 2017). Furthermore, 68% could notice an increase in inbound customer leads (Capgemini, 2017), as AI is able to analyze thousands of campaign variables to identify what worked and what did not (Power, 2017). Valuable for the area of innovation is the fact that AI can drive sales of new products too. As Marketing and Selling are parts of a multidisciplinary, integrated Innovation Process (Langdon, 2014), it is also vital to
the success of a product or service innovation that it targets the right customers, with the right message, at the right time. As for roughly 42% of start-up fails, no real market need for the innovated product or service is the reason that they fail (Patel, 2015), better predictions, forecasts, clustering of valuable consumer groups and customizable offerings enabled through AI, can help to remarkably reduce product failure rate.

2.1.4 Synthesis

This chapter aims to provide insights into the field of Artificial Intelligence. The focus of this thesis has been set on narrow AI. Hence, algorithms that are very task specific and do not generalize. The reason is that they have near-term business potential (Ransbotham et al., 2017) and are capable of radically impact organizations’ offerings as well as processes. Often, machine learning with its sub-set deep learning acts as a technology foundation for several other key technologies that are commonly classified as AI (Capgemini, 2018). ML algorithms are codes that can learn over time. So the more data they have to learn from, the more accurate they become (Mohri et al., 2012). The process of feeding an algorithm with such data is commonly described as training an algorithm. Machine learning is particularly suitable for predictive and prescriptive statistics, forecasts, as well as for technologies that are based on image recognition (Jeffs, 2017).

AI has four ways it can create value across an organization's value chain: Project, Produce, Promote, Provide (McKinsey, 2017). As this thesis investigates into the adoption of AI within the area of innovation, the focus primarily lies on Project and Promote. Project refers to the ability of AI to make accurate projections and forecasts, as well as to discern trends and patterns from data. This is extremely valuable in the area of Research and Product Development. Hence, trend identification and identifying what worked out in the past and what did not provides valuable information that could reduce market uncertainties and therefore reduce an innovation's chance of failing. Also, to successfully bring a new product to the market, it is necessary to promote the offering with the right message, at the right price, and to the right target customers (McKinsey, 2017). In this regard, AI can support an insight-based selling that is enabled through optimizing and customizing of an organization's marketing activities.

The most relevant AI technology systems focused on in this study are Robotics, Computer Vision, Language, Virtual Agents, and Affective Computing. Furthermore, use-cases notably enabled through latest developments in machine learning were added: Prediction, Recommendation, Text Mining, and Clustering.
Recent studies found out that organizations are still missing significant opportunities by ignoring the "low-hanging fruit" (Capgemini, 2017). This means that many companies are jumping straight onto the high complexity/high benefit use-cases. Thus, they are focusing on very challenging use-cases, instead of those areas of application for AI that are not only easy to implement but also have a high benefit upside (Capgemini, 2017). Figure 5 shows the distribution of AI use-cases by benefits (horizontal axis) and complexity (vertical axis). In this figure, the different use-cases are categorized by the above-mentioned AI technology systems that this study focuses on. For the context of this study, only the high-benefit use-cases are highlighted. Hence, the ‘Need to Do’ and ‘Must Do’ quadrants show those use-cases that are expected to have the highest potential to be applied within the area of innovation.

Figure 5. Distribution of use-cases by benefits and complexity (Ad. from Capgemini, 2017)
2.2 Innovation

2.2.1 Definition

As one of the aims of this thesis is to investigate the potential of AI for being applied in the area of innovation, this section briefly discussed some essential terms. Schumpeter (1934) described Innovation as "Creative destruction in which old ways of doing things are destroyed and replaced by new ways." Already in the first half of the 20th century, he argued that innovation substantially drives economic development and that innovating must be an essential part of any organization that seeks to make a profit (Schumpeter, 1934). The latter statement is even truer in today's fast-changing economic environment. Especially in the era of "digital disruption" organizations must innovate and adapt to continuously changing and growing consumer needs or they die (Maranville, 1992). In fact, while successful companies lasted an average of 67 years in the 1920s, they typically exist for only 15 years today (Williams, 2013). To stop that downward-trend, companies need to innovate. This is commonly achieved by developing more effective processes, products, services, technologies or business models. Nevertheless, not every innovation has to be revolutionary in its field. Therefore, literature distinguishes between different types of innovations that vary in their impact and scope. Radical and incremental are the most commonly used terms when speaking about different types of innovations. Incremental innovation includes exploiting and upgrading a current technology (Gatignon et al., 2002). Hence, in incremental innovations, organizations utilize or enhance their current core competencies or capabilities to serve already existing markets (Nagji, 2012). It concerns existing products, services, and processes whose performance has been significantly upgraded to meet changing customer needs (Nemet, 2009). Currently, incremental innovation is the most dominant form of innovation. The reason is its steady growth potential and relatively low risk. Still, at some point, incremental changes are not enough to sustain viability for a business. Even though most growth can be achieved through a steady stream of incremental innovation, it is necessary to opt towards radical and disruptive innovations too to ensure a balanced innovation portfolio (Nagji, 2012). Radical innovations interrupt current technologies (Dosi, 1982) and have a significant impact on a market and on the economic activity of organizations in that market. Hence, radical innovations are able to change the structure of a market, create new markets or render existing products or business models obsolete. Due to their disruptive nature, they also come with a much higher degree of risk and resistance to it, which typically results in a slow rate of adoption. Therefore, in this context, the use of Artificial Intelligence within the innovation process, for
one thing, may improve the performance of incremental innovations even further. By providing more insights, more accurate forecasts and identifying more suitable target customers, AI can drastically enhance the value that is created by incremental innovations. Secondly, the support of AI technologies when innovating may encourage organizations to radically innovate more often, as AI is able to deliver much more accurate analysis than previously used methods and therefore to reduce the risk of failure. However, the risk of failure includes not only market failure, but also a technological failure of the innovation (Martin, 2017). One of the most prominent risks organizations take in the innovation process is whether or not the new product also works once it is launched in the real markets. Therefore, organizations usually carry out trials on a smaller scale to test the product's effectiveness. Closely aligned with market failure is also the challenge of redundancy. As trends in the markets are continuously changing, it is possible that an innovation, which is profitable today, may already be redundant tomorrow. To be that step ahead of competition there is the necessity for continuous research on how to improve the innovations, as well as for proper monitoring of global trends and the factors influencing them (Martin, 2017). Hence, due to AI's ability to handle enormous amounts of data, to discern trends and patterns from them and to improve forecast accuracy, AI may be an appropriate tool to tackle the challenge of redundancy too. Furthermore, as AI technologies facilitate faster process cycle times and reduce an innovation's time-to-market (McKinsey, 2017), also the risk of draining out the organization resources can be drastically reduced. Often, returns that innovations generate are long-term, which frequently leads to abortion of a product or idea once it is perceived to be non-profitable (Martin, 2017). Here, AI can help as it improves and accelerates the innovation process and therefore reduces costs. Those faster process cycle times, in turn, lead to faster Returns on Investment (RoI), which result in a lower rate of innovation abortion.

Summing it up, there are some general challenges that organizations have to face within the innovation process:

- Market failure
- Technological failure of the innovation
- Financial strain
- Redundancy

AI can support organizations in tackling all of the problems named above. However, whether or not organizations recognize AI's potential of influencing the various tasks of the innovation process, is discussed in the later parts.
2.2.2 Innovation Process

To successfully be innovative, robust organizations need a clear innovation process. The innovation process is defined as a structured strategy that ensures that an organization idealizes an innovation and sticks to it until its successful implementation (Martin, 2017). It structures and systematically implements the development of new products, services or business models (Hengsberger, 2017). An extensive corpus of literature exists on innovation processes describing the stages of the process from the first idea to final commercialized product (Rothwell, 1992). Different innovation process models have evolved in six generations. They range from simple linear models to more complex interactive models. Table 1 shows the development of innovation models over time (du Preez et al., 2008).

<table>
<thead>
<tr>
<th>Model</th>
<th>Generation</th>
<th>Characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology push</td>
<td>First</td>
<td>Simple linear sequential process, emphasis on R&amp;D and science</td>
</tr>
<tr>
<td>Market pull</td>
<td>Second</td>
<td>Simple linear sequential process, emphasis on marketing, the market is the</td>
</tr>
<tr>
<td></td>
<td></td>
<td>source of new ideas for R&amp;D</td>
</tr>
<tr>
<td>Coupling model</td>
<td>Third</td>
<td>Recognizing interaction between different elements and feedback loops between</td>
</tr>
<tr>
<td></td>
<td></td>
<td>them, emphasis on integrating R&amp;D and marketing</td>
</tr>
<tr>
<td>Interactive model</td>
<td>Fourth</td>
<td>Combinations of push and pull models, integration within firm, emphasis on</td>
</tr>
<tr>
<td></td>
<td></td>
<td>external linkages</td>
</tr>
<tr>
<td>Network model</td>
<td>Fifth</td>
<td>Emphasis on knowledge accumulation and external linkages, systems integration</td>
</tr>
<tr>
<td></td>
<td></td>
<td>and extensive networking</td>
</tr>
<tr>
<td>Open Innovation</td>
<td>Sixth</td>
<td>Internal and external ideas as well as internal and external paths to the</td>
</tr>
<tr>
<td></td>
<td></td>
<td>market can be combined to advance the development of new technologies</td>
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Table 1. Innovation Models Over Time (du Preez et al., 2008)

The first and second generation models are linear models and explain the innovation process as either pushed by technology or science or pulled by market needs (Varjonen, 2006). The third generation model is a coupling model that integrates the influence of technological capabilities and market needs within the framework. Although this approach contains some feedback loops, it is mostly a sequential model with limited functional integration (Rothwell, 1995). One of the most well-known sequential innovation process models is the Stage-Gate model by Cooper (1990). As the name indicates, this model divides the innovation process into stages with defined gates, which act as decision points between the stages. Hence, at the end of each stage, there is a stage-gate where it is decided whether the previous task or stage was satisfactorily completed or not. The project continues to the next stage as soon as it is reviewed.
as positive (Cooper, 1990). Thus, these continuous feedback loops after each stage ensure a better quality of the innovation process, but they simultaneously make the innovation process slow and inappropriate for anticipating radical innovations (Martin, 2017).

As sequential models lack some functional integration, the *fourth generation* innovation process model was developed. This model, which follows an interactive approach, views the innovation process as parallel activities across organizational functions (Rothwell, 1995). These organizational functions vary depending on the model and its context but can range from Marketing, R&D, Product Development, Parts Manufacture, to Manufacture (Rothwell, 1995). However, these interactive models do not explain the whole innovation process. Concerning the latter aspect, *fifth generation* innovation process models were developed that try to explain the complexity of the whole innovation process. Those network models originated in the 1990's, and their primary characteristics are the effective communication with the external environment and the influence this external environment has on the organization's innovation process. Hence, innovation happens within a network of external and internal stakeholders (du Preez *et al.*, 2008) that is enhanced through effective communication between them. However, fifth generation models are mainly considered closed networks of innovation. This consideration originates from the fact that traditionally new development processes and the marketing of new products took place within the organization's boundaries (du Preez *et al.*, 2008). So, in closed innovation systems, ideas are typically generated internally and in secrecy by an organization’s employees (Docherty, 2006).

On the contrary, the new *sixth generation* models can be considered as open innovation models. They are also network models, but instead of being only focused on internal idea generation and development, they actively combine internal and external ideas as well as internal and external paths to the market. Hence, one of the most obvious benefits of open innovation is the much more extensive base of ideas and technologies from which organizations can draw (Chesbrough, 2003). Furthermore, organizations recognize the potential of open innovation to explore new growth opportunities at a lower risk. They use networked or webbed communities of different stakeholders such as consumers, suppliers, and more, as open and collaborative vehicles to generate new ideas, while simultaneously strengthening their relationship to them, as stakeholders can create value for organizations through collaboration and co-creation. Moreover, in open innovation systems, AI technologies can create additional value by substantially supporting employees in analyzing the received input from stakeholders. On open innovation platforms, for example, AI algorithms may be able to browse through the enormous amounts of ideas provided by consumers and cluster them based on various situational
variables. Furthermore, machine learning algorithms may be able to discern some trends and patterns from historical data, which could help to evaluate whether new ideas have the potential for being a success on the real markets or not.

To summarize, most of the previously mentioned innovation process models, despite their different advantages and disadvantages, do have some steps or stages in common. They involve: a) idea generation and identification, b) concept development, c) concept evaluation and selection, d) development and e) implementation (du Preez et al., 2008). Nonetheless, for this thesis, it is not focused on the stages that AI can impact, but rather on the more specific innovation tasks within those stages, whose performance AI is able to enhance. As a consequence, some of the stages named earlier are broken down into single innovation tasks, while others are merged.

Idea generation and identification (a) is broken down into market research activities, which are crucial to determine what the market needs, and idea generation itself. Hence, market research activities that AI can substantially improve are:

- Technology scouting
- Identification of needs, trends, and patterns

Technology scouting is typically considered an element of technology management but can in the broader context also be seen as a part of an organization's corporate foresight activities (Rohrbeck, 2010). It includes steps like the identification of emerging technologies, the acquisition of technologies, and the channeling of technology-related information into an organization (Rohrbeck, 2010). Spitsberg (2013) even applied Technology scouting as an element of an open innovation approach. They claim that a broader awareness of technology and market trends can itself become a powerful source of differentiating and new ideas. Hence, technology scouting as a task within the innovation process may be critical for enabling a collaborative cross-functional ideation process (Spitsberg, 2013).

Additionally, idea generation itself is added to the list of innovation tasks:

- Idea generation

Concept development (b) and concept evaluation and selection (c) are merged and broken down into the following task:

- Idea selection and decision making
Furthermore, as the focus of this stage is to transform ideas into workable concepts, to evaluate those concepts as well as to model and prototype them to determine its feasibility (Wycoff, 2003), another innovation activity this study focuses on is Prototyping. The term Prototyping, in this thesis, includes the steps of build, learn, and measure. Eric Ries (2011) first came up with this approach as part of the Lean Startup Methodology. The lean startup method aims to provide a scientific approach to new product development at maximum acceleration. This is accompanied by the goal to support entrepreneurs in creating and managing startups and getting the desired product to customers' hands faster (Ries, 2012). To do so, startups should draw on the Lean Startup Process whose aim is to minimize the total amount of time through the loop. Figure 6 shows the learn-build-measure loop.

The build – measure – learn feedback loop is a core component of the Lean Startup methodology. This process is characterized by continuous feedback from and communication with consumers. The first step typically involves figuring out the problem that needs to be solved with the new product. This stage is followed by the development of a minimum viable product (MVP).

Figure 6. The Lean Startup Process (Ries, 2011)

“The MVP is that version of a new product which allows a team to collect the maximum amount of validated learning with the least effort” (Ries, 2011). In other words, the minimum viable product is used to test a specific set of hypotheses, with the goal of proving or disproving them as quickly as possible (Ries, 2011). This testing is done through multiple approaches. The most important hypotheses tested, typically involve question like "what will the customer care about?" and "How will they define quality?". This feedback is used in a next step to enhance the product from the MVP to an ideal. It often requires multiple attempts until the organization reaches a decision point, where it has to choose whether to reject the idea or to stick with it (Ries, 2012). Finally, the last step is defined by the decision to preserve or pivot the idea. If the organization keeps learning from the continuous feedback and testing loops and keeps
processing towards the ideal product it is meaningful to stick to the product. However, if a company does not further improve, drastic change may be mandatory. In case an organization decides to pivot, the whole process starts at its initial step again (Ries, 2012).

To summarize, within the Build-Measure-Learn loop, a company's effectiveness when developing a new product is determined by its ability to ideate, quickly build a minimum viable product (MVP) of that idea, to measure its effectiveness in the market through testing of hypotheses and in the end to learn from that experiments. Hence, this loop is a continuous learning cycle of turning ideas into products, measuring consumers' behaviors and reactions against that products, and finally deciding whether to pivot or persevere the idea (Maurya, 2012). Speed is thereby the main ingredient of this approach. Luckily speed is what Artificial Intelligence excels at. As AI technologies are capable of processing enormous amounts of data at the higher speed and better performance than previous methods, thus are providing better and faster analysis, they are suitable for supporting organizations' decision making in each of the three stages of the loop. For this reason, within this study, prototyping, as well as concept testing are also treated as single innovation tasks that AI could impact:

- **Prototyping** *(Build-Measure-Learn)*
- **Concept testing**

As far as the two last phases of the innovation process development (d) and implementation (e) concerns, they were broken down into two last innovation tasks. Given that tasks within the development stage (d) are partly overlapping with what The Lean Startup approach offers, a remaining aspect worth mentioning is the design process for a product. In this regard, AI offers a whole new area of application, called generative design. Generative design software, which is based on machine learning algorithms, can offer huge benefits concerning providing a wider range of design options, making impossible designs possible and optimizing for materials, costs and manufacturing methods (Autodesk, 2018). Hence, advanced algorithms as well as cloud computing, allow designers to give input parameters such as the manufacturing method, cost constraints, and materials. The software then explores all the possible permutations of a solution and quickly generates design alternatives. It continuously tests and learns from each iteration what works and what does not, thus being able to prove which designs perform best (Autodesk, 2018). Due to its potential of exploring huge amounts of design possibilities at a fast pace, Generative Design is used in various design fields such as architecture, engineering, art and product design. Thus, it is also investigated whether organizations recognize AI’s potential in the area of design or not:
Generative design

When talking about the implementation phase (e), the aim is to exploit and generate more value from the product solution (du Preez et al., 2008). This is done by achieving sales targets for the new product. Hence, by offering the product at the right price, with the right message, to the right target groups (McKinsey, 2017). Marketing activities are what AI can drastically enhance, by pricing products dynamically, identifying the most profitable customer groups and customizing promotions.

As Marketing can be considered as a part of a multidisciplinary, integrated innovation process (Langdon, 2014), it is also treated as an innovation task that AI could be able to impact in the future.

Marketing

2.2.3 Synthesis

This chapter aims to provide essential definitions of innovation as well as to give an overview of different types of innovations and how AI technologies can influence them. Incremental innovation and radical innovation are these terms that are most commonly used in this area. While incremental innovations focus on enhancing already existing products (Gatignon et al., 2002), radical innovations strive to disrupt markets with new-to-the-market innovations at a higher risk (Dosi, 1982). The performance of both types of innovation can be drastically enhanced through AI, as it is capable of precisely forecasting demands and trends, enable faster process cycle times and ultimately reduce the overall risk of failure.

Besides, this chapter defines the innovation process and provides an overview of the development of the innovation process over time. Those innovation process models range from simple linear models to increasingly complex interactive models. Nonetheless, despite their different approaches, they do have essential steps of the innovation process in common: idea generation and identification, concept development, concept evaluation and selection, development, and implementation (du Preez et al., 2008). In this chapter, these stages of the innovation process are broken down into single innovation tasks as they may be used in multiple different stages of the innovation process. Therefore, it is investigated whether organizations recognize AI's potential for being applied in the following innovation tasks or not:
- Technology scouting
- Identification of needs, trends, and patterns
- Idea generation
- Idea selection and decision making
- Prototyping (Build-Measure-Learn)
- Concept testing
- Generative design
- Marketing

2.3 Theory of Planned Behavior

2.3.1 Theoretical Background

As the aim of this study is not only to assess the potential of AI to influence organizations’ innovativeness, but also to investigate into individuals’ intention and readiness regarding the adoption of AI within the area of innovation, the theory of planned behavior (TPB) will be taken as a theoretical framework.

Icek Ajzen first proposed the theory of planned behavior in 1985 in addition to the theory of reasoned action (TRA), which he developed alongside Martin Fishbein in 1980. In TPB, Ajzen extended TRA by adding a new component, ‘perceived behavioral control,’ to improve its predictive power. Hence, TPB aims to predict an individual intention to engage in a particular behavior under certain circumstances, such as a specific time and place. Figure 7 shows how the different constructs of TPB are interrelated.

Figure 7. The Theory of Planned Behavior - TPB, (Ajzen, 1991)
The framework posits that individual behavior is driven by behavioral intentions. Behavioral intentions, in turn, are a function of three determinants: an individual’s attitude, subjective norms, and perceived behavioral control (Ajzen, 1991). The foundation of the latter three determinants is an individual’s beliefs. Literature claims that human behavior is guided by three kinds of consideration: behavioral beliefs, normative beliefs, and control beliefs. ‘Behavioral beliefs’ lead to an unfavorable or favorable attitude towards the behavior. ‘Normative beliefs’ result in subjective norms; and ‘control beliefs’ provoke perceived behavioral control (Ajzen, 2002).

Attitude toward behavior (ATT) is the first construct, which influences behavioral intention and consequently also an individual’s likelihood of displaying the researched behavior. It refers to the degree to which a person has positive or negative feelings of the behavior of interest (Ajzen, 1991). Attitude is determined by the total set of accessible ‘behavioral beliefs’ that link the behavior to various outcomes and evaluate them. Hence, the evaluation of each outcome in combination with the individual’s subjective probability that the behavior also produces that outcome, essentially contributes to the attitude of a person towards a behavior (Ajzen, 1991).

Subjective Norms (SN) relate to person’s perception of the social environment surrounding the behavior and how this social environment, primarily composed of relevant groups of others such as friends, colleagues, parents, etc., as well as society, judges this particular behavior (Amjad et al., 2009). In other words, an individual’s ‘normative beliefs’ that it should or should not perform a certain behavior as well as judgments of significant others (e.g., friends, parents, colleagues) against that behavior, influence an individual's behavioral intention (Ajzen, 1991).

Perceived Behavioral Control (PBC) is the variable that Ajzen added to their theory of reasoned action, to enhance its predictive power. PBC originates from self-efficacy theory (Bandura, 1977) and can be understood as an individual's perceived ease or difficulty of performing the particular behavior (Ajzen, 2002). Like attitude as well as subjective norms, also perceived behavioral control is determined by a set of accessible beliefs, called ‘control beliefs.’ These control beliefs are an individual's beliefs about the presence of factors that may impede or facilitate the performance of the behavior. Hence, PBC increases when individuals perceive that they have more resources available and have the confidence of executing given behavior (Ajzen, 2002). So, if a sufficient degree of actual control over the behavior is given, PBC does not only affect behavior indirectly through behavioral intention but also has a direct influence on the behavior (see Fig. 7). In this regard, Ajzen claimed that PBC moderates the effect of intention on behavior in a way that a favorable intention produces the behavior only when the
PBC is strong.

Behavioral Intention (BI), as shown in the TPB model (Fig. 7), is an immediate antecedent of behavior. As discussed before, it is influenced by the attitude toward behavior (AB), subjective norms (SN) and perceived behavioral control (PBC) and gives therefore an indication of an individual’s readiness to perform a given behavior (Ajzen, 2002). Furthermore, it represents a person's motivation in the sense of her or his conscious plan or decision to perform a certain behavior (Connor et al., 1998). Therefore, also in this case it can be said that the stronger an individual’s behavioral intention is, the more likely it is that the behavior will also be executed.

Behavior acts as the dependent variable of the original TPB model. It can be seen as an individual's observable response in a given situation with respect to a given target.

2.3.2 Synthesis

The aim of this chapter is to provide a clear description of the theoretical framework that the first part of this study applies, in order to make sense of an individual’s intention to use AI when innovating. The theoretical background of TPB (Ajzen, 1985) was discussed and explanations for each of the five original constructs were provided. Thus, the three independent variables of Attitude (ATT), Subjective Norms (SN) and Perceived Behavioral Control (PBC) are each determined by underlying beliefs about the behavior, that ultimately also influence the intention toward executing that behavior. However, not the entire model that was demonstrated in figure 7 was applied to the context of this study. Which aspects were included and which were not relevant for purposes of this thesis, is explained in chapter 3.

2.4 Readiness

2.4.1 Theoretical Background

Given that ‘behavioral intention’ indicates an individual's readiness to execute a certain behavior, the research is partly framed around the concept of ‘readiness.’ Therefore, it is necessary to provide an explanation of the term ‘readiness’ and discuss its use in different technological and organizational contexts. ‘Readiness’ refers to the state of being fully prepared for something. The concept has already been applied in several contexts including strategic change, organizational behavior as well as management of technology (Ramaseshan et al., 2015). In the context of strategic change Kaplan and Norton (2004) explain the concept of "readiness as the extent to which organizational assets, processes, and activities indicate that
the organization is ready to move from a current state to a new desired state.” In organizational behavior literature, Eby et al. (2000) investigated readiness relative to organizational members' attitudes and beliefs about imminent change by taking into account the factors that can foster or influence transformative change. In the context of technology, readiness has been defined as an individual’s propensity to embrace or use new technology for accomplishing goals in private life as well as in working life (Parasuraman et al., 2015).

These varying conceptualizations of ‘readiness’ in literature, make it necessary to contextualize ‘readiness’ in an organization's AI setting. Readiness, as understood in an organizational behavior context, is already covered by the Theory of Planned Behavior framework. This framework is used to investigate into whether individuals within an organization are ready to execute a particular behavior or not and to what extent their behavioral intention is influenced by factors like their attitude toward that behavior, subjective norms or perceived behavioral control (Ajzen, 1991). The behavioral intention, in context of this thesis, is defined as the usage of AI technologies when innovating.

In addition to an individual’s readiness to use AI when innovating, it is also of interest to discuss readiness in the context of technology. Not only as an individual’s tendency to use new technology for accomplishing goals in life (Parasuraman et al., 2015) but also as a technology’s readiness of being able to perform its respective tasks. In this regard, the following subsection will discuss an approach, whose aim is to establish different levels or stages for a technology. As that technology, namely autonomous driving, is classified as an AI technology system, it poses the potential to draw analogies between it and the usage of AI in Innovation.

2.4.2 Levels of Autonomous Driving

Autonomous vehicles is one of the six AI technology systems that received the highest amount of external investments in 2016 (McKinsey Global Institute, 2016). It includes manned or unmanned vehicles that are able to sense its environment and to navigate without human input (Gehrig et al., 1999). These vehicles do so, by making use of various technologies such as GPS, radar, laser light, odometry as well as computer vision (Lassa, 2013). The latter technology, computer vision, is commonly classified as AI, as its basis are machine learning or deep learning algorithms that are able process and recognize objects in images.

In 2014 the International Society of Automotive Engineers (SAE International) published a classification system for autonomous driving vehicles. It is based on six different levels that differ by the degree of human driver intervention and attentiveness required.
- **Level 0**: Automated warning systems that can momentarily intervene, but that have no vehicle control. Human driver still needs to perform all aspects of the dynamic driving task.

- **Level 1**: The human driver and the system share control of the vehicle. Driver is typically either steering or controls speed. The other part is executed by the system. Nonetheless, the driver must be ready to retake full control at any time.

- **Level 2**: Driver assistance systems are taking control of the vehicle and are capable of steering, accelerating, and braking. Still, the driver must monitor the driving process and be ready to intervene at any time.

- **Level 3**: The driver can turn his/her attention away from the driving tasks. The systems are able to react to immediate situations that, e.g., require emergency braking. Still, when the vehicle signals to do so, the driver must be prepared to intervene within some limited time.

- **Level 4**: The fifth level can also be considered as “mind off” level. If a vehicle is capable of level 4 self-driving, no driver attention is ever required for safety. The driver may as well go to sleep or leave the driver’s seat.

- **Level 5**: All driving modes are fully automated. No human intervention is ever required.

These six levels of autonomous driving range from ‘no automation’ to ‘full automation’. While in the levels of zero to two the human driver monitors the driving environment, within the levels of three to five the automated driving system monitors and judges the driving environment itself (SAE International, 2014).

### 2.4.3 Levels of Autonomous Innovating

Analogously to how SAE International defined different levels for autonomous driving, this subsection comes up with levels that appear suitable to describe the future state of artificial intelligence in innovation. Those levels are closely aligned to the stages of autonomous driving and include variables such as the degree of human intervention and the degree of autonomy in executing innovation tasks. These levels were developed to get a clearer picture of how organizations and its employees evaluate AI’s potential and technological readiness for being used within the innovation process. To test the levels, it is asked for the expected role that AI will play within innovation and for which level of autonomy AI is expected to reach within a time frame of five to ten years.
### Table 2. Levels of Autonomous Innovating (Adapted from SAE International, 2014)

<table>
<thead>
<tr>
<th>Level</th>
<th>Name</th>
<th>Narrative Definition</th>
<th>Execution of Innovation Task</th>
<th>Monitoring of Task Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Assistance</td>
<td>AI assists humans in executing the innovation task. It accelerates and improves the performance of the job but does not perform or decide on its own.</td>
<td>Human</td>
<td>Human</td>
</tr>
<tr>
<td>2</td>
<td>Split Innovating</td>
<td>Innovating is split between human and AI. AI performs one task, while the employee focuses on another one.</td>
<td>Human and AI</td>
<td>Human</td>
</tr>
<tr>
<td>3</td>
<td>Partial Automation</td>
<td>AI will act semi-autonomous. It will perform multiple tasks within the innovation process, but requires continuous human monitoring.</td>
<td>AI and Human</td>
<td>Human</td>
</tr>
<tr>
<td>4</td>
<td>Conditional Automation</td>
<td>AI will innovate autonomously and perform every relevant task on its own. Only requires human assistance in certain emergency situations and upon AI’s request to intervene.</td>
<td>AI</td>
<td>Rare human monitoring</td>
</tr>
<tr>
<td>5</td>
<td>Full Automation</td>
<td>AI will innovate completely autonomous. No human intervention needed.</td>
<td>AI</td>
<td>No human intervention</td>
</tr>
</tbody>
</table>

#### 2.4.4 Synthesis

This chapter should give the reader an overview of the term ‘readiness.’ In general, it refers to the state of being fully prepared for something (Ramaseshan et al., 2015). Nonetheless, definitions of ‘readiness’ vary, depending on the context in which the term is applied. For the purpose of this thesis, readiness is discussed in an organizational behavior and technological context. As readiness, in an organizational behavior context, refers to members’ attitudes and beliefs towards change or a particular behavior (Eby et al., 2000), the theory of planned behavior (Ajzen, 1991) is applied as a framework.

To tackle the aspect of technological readiness, levels of automation for AI in Innovation were developed. These levels aim to facilitate the assessment of the future role that AI is going to play in the area of innovation. Furthermore, these levels (see table 2) should help to provide a first impression of how sophisticated and well-advanced AI is expected to be in the future. They do so by supporting people in judging AI’s technological progress based on variables like the
required degree of human monitoring and the expected degree of autonomy in executing innovation tasks. The ‘Levels of Autonomous Innovating’ (see table 2) are derived from the levels of autonomous driving that were introduced in 2014 to classify driving vehicles (SAE International, 2014).
3 Research Design

The previous chapter provided most essential aspects of literature regarding narrow AI, its areas of application and benefits. Additionally, most relevant innovation tasks, Theory of Planned Behavior and the term ‘readiness’ was discussed. This chapter now describes in what ways the research questions have been addressed. Hence, the following subsections describe the research context, methodology, research model, sample, data collection and data analysis.

3.1 Research Context

The findings of the empirical part of this study contribute to the overall goal to assess the current and future state of AI in Innovation. On the one hand, this is tackled by applying the Theory of Planned Behavior (TPB) framework to the context of AI adoption in the area of innovation. TPB is used to point out the main drivers that influence an employee's readiness to use AI technology when innovating. Doing so, it includes aspects like an individual's attitude towards using AI, social reactions that may result from the adoption of AI as well as the presence of factors that facilitate or impede the adoption of AI in Innovation. On the other hand, within the empirical part, it was focused on the assessment of AI's potential for being used when innovating. The potential was examined by investigating those AI technologies that are expected to be most suitable as well as into the various innovation tasks that may be impacted by AI. Besides, ‘levels of autonomous innovating’ were developed as a tool to assess the degree of technological progress that AI is expected to reach within the next five to ten years.

Within the first section of this study, two identical questionnaires were developed. One survey was created in English, while the other one was developed in German. The translation of the questionnaire was important to be able to address not only German-speaking participants but also employees from organizations that are operating in other countries. These questionnaires were the central data collection method and had the aim to provide an overall picture of the state of AI in innovation.

In the second part of the study, six qualitative interviews were conducted to gain additional insights into this topic. The six participants were all familiar with the topic AI, as these interviews were run at the first German 'KI Konferenz,' organized by EUROFORUM and Handelsblatt, that took place from the 15th to 16th of March in Munich. The interviewees were working for organizations that operate in various industries, such as healthcare, finance, consulting, and airline. One participant was part of an AI-Startup. Hence, they have contributed with their experience and provided insights regarding their organization's use of AI, the
advantages, and challenges that AI brought for their companies as well as how they think Artificial Intelligence is going to impact the way value is created within their company.

### 3.2 Methodology

Within this thesis, a mixed-method approach has been chosen to provide an answer to the research question and its subparts. The advantage of a mixed-method approach is that it provides the possibility to draw on the unique strengths of both qualitative and quantitative methods. Despite drawing on the limitations of both types too, it provides a more complete understanding than would be possible using only one approach. In case of this study, the phase of data collection has not been sequential, but concurrent, as the qualitative part was mainly seen as a means to enrich the results from the quantitative study. Hence, this thesis is primarily based on a positivistic worldview. From an ontological perspective, this means that a universal reality exists, which is apprehensible and independent of individuals. From an epistemological perspective, positivism implies that findings are correct and that knowledge is based on the falsification of hypotheses. Hence, a deductive approach was used. Theory and literature about the current state of AI and its adoption were reviewed. From the literature review, a suitable model, namely the Theory of Planned Behavior model, was chosen and used as a theoretical framework. The model was adapted to the context of AI in Innovation and led to the formulation of corresponding hypotheses. After the quantitative data collection via standardized questionnaires and the analysis of the results, these hypotheses were either confirmed or rejected. A quantitative/conclusive research design was chosen to do so. Additionally, descriptive research was conducted to gather information about characteristics or factors related to the adoption of AI technology in organizations, the suitability of specific AI technologies for being used in innovation tasks and the future role of AI in the area of innovation. The descriptive part did not claim to explain causal relationships between variables. It instead had the purpose of providing an overview of many relevant context-related aspects by using frequencies, averages or other descriptive statistics. The qualitative part of the research, namely the conduction of six semi-standardized interviews, served as a means to add some in-depth information and personal experiences to the results of the quantitative study. They had the purpose of enriching the descriptive results, as they can provide further insights into the reasons why participants answered as they did.
| Research | Method                | Analysis                                | Goal                                           |
|----------|-----------------------|-----------------------------------------|                                                |
| Quantitative | Questionnaire         | Inferential Statistics (Correlation, Regression) | Hypotheses-Testing; Testing relationships between variables of the TPB research model. |
|          |                       | Descriptive Statistics                  | Providing descriptive information about the current and future state of AI in Innovation. |
| Qualitative | Semi-standardized Interview | Thematic Content Analysis               | Providing additional in-depth information that supports the creation of an overall picture of AI in Innovation. |

**Table 3. Overview of the Research Design**

Table 3 provides an overview of the applied research design, including used methods, performed data analyses, and intended goals. The subsequent sections of this chapter go further into detail and provide accurate descriptions for each of these parts.

### 3.3 Research Model

To make sense of an individual's and organization's readiness to adopt AI when innovating, a research model was developed. The theoretical framework, which was adapted to the context of this thesis, was the Theory of Planned Behavior framework that Icek Ajzen first proposed in 1985 (see chapter 2.3).

For the following research model, the original constructs of **Attitude (ATT)** toward a behavior, **Subjective Norms (SN)**, **Perceived Behavioral Control (PBC)** and **Behavioral Intention (BI)**, were retained and adapted to the Artificial Intelligence context. Furthermore, two additional constructs were added that are also expected to influence an individual's readiness or intention toward a particular behavior. It is a person's **Involvement** as well as **Competence**. However, **AI Involvement** and **AI Competence** were not treated as single constructs but integrated into the original constructs of ATT and PBC.

This study uses the TPB model for predicting the readiness and intention of individuals to use AI technologies when innovating. The exact model and its constructs are shown in figure 8. It is composed of three independent latent variables and one dependent latent variable. The dependent variable is **Behavioral Intention (BI)**. It defines people’s intended usage of AI in the area of innovation.
**Attitude (ATT)** toward use refers to the degree to which a person has positive or negative feelings about using AI within the innovation process. This includes an individual’s attitude regarding AI’s usefulness, potential or meaningfulness. Ajzen (2002) divided Attitude into two subconstructs, called Affective Attitude and Instrumental Attitude. Affective Attitude, on the one hand, indicates whether an individual likes or dislikes the behavior. Instrumental Attitude, on the other hand, describes whether an individual believes that the behavior is beneficial (Ajzen, 2002). The construct of **AI Involvement** was added as a third subcategory of **Attitude**, as affective attitude and instrumental attitude overlap content-wise with what the expression Involvement is connected with. The term involvement originates from psychology where it is mainly used in marketing to indicate a person's involvement in an event, product or object. Involvement thereby includes aspects such as the degree of importance and benefit the object presents for the individual as well as the dedication or commitment a person shows for a specific topic, object, behavior (Esch, 2006). As a result, Involvement in context of this study indicates an individual's interest and dedication for AI. Involvement was measured by asking for a person's willingness to engage in discussions about AI, to permanently monitor AI's latest developments and to actively work in AI projects.

Previous studies that applied the TPB model to the technology adoption context expected **Attitude** to have a positive and direct relationship to **Behavioral Intention**. Thus, also in this study, the latter assumption was made, which led to the formulation of the following hypothesis:

**Hypothesis 1 (H1):** **Attitude (ATT)** toward the use of AI in innovation positively and directly influences the **Behavioral Intention (BI)** to use AI when innovating.

**Subjective Norms (SN)** refers to an individual’s perception of how relevant groups of others, like top management as well as colleagues, judge his/her use of artificial intelligence when innovating. Aligned with previous assumptions in literature, also Subjective Norms are expected to have a positive and direct impact on a person’s intention or readiness to use AI. The second hypothesis is therefore also directly related to the classic TPB and is stated as follows:

**Hypothesis 2 (H2):** **Subjective Norms (SN)** positively and directly influence an individual’s **Behavioral Intention (BI)** to use AI when innovating.
The third independent variable is Perceived Behavioral Control (PBC). PBC reflects an employee’s perception of its individual ability to use and adopt AI. Furthermore, the construct includes an individual’s beliefs about the presence of factors that may impede or facilitate the performance of the behavior. Thus, the intention to use AI when innovating is expected to be influenced by people's perception of their ability to use AI as well as by organizational factors that are perceived to facilitate or hinder the application of AI within the innovation process. However, an individual's intention to use AI when innovating is expected to not only be influenced by people's perception of their own ability, but also by their actual technological skills. Therefore, the subconstruct of AI Competence was added as part of the original PBC construct. Competence in the context of AI refers to people's ability to effectively use AI, to train AI algorithms and effectively collaborate with machines and computers. It is expected that the higher a person's AI competence, the more likely he/she is to use AI in suitable innovation tasks. Consequently, also overall PBC is expected to influence people's behavioral intention directly:

**Hypothesis 3 (H3):** Perceived Behavioral Control (PBC) positively and directly influences an individual’s Behavioral Intention (BI) to use AI when innovating.
The following table provides an overview of the constructs and corresponding items utilized within the quantitative part of this study.

<table>
<thead>
<tr>
<th>Construct</th>
<th>Items</th>
</tr>
</thead>
</table>
| Attitude (ATT)                   | AI reduces market uncertainties  
I consider the use of AI in innovation as good  
I like discussing AI-related topics  
I am intensively working on AI projects  
I am intensively observing the development of AI |
| Subjective Norms (SN)            | Importance of top management’s opinion  
Importance of colleagues’ opinion  
Influence on your career |
| Perceived Behavioral Control (PBC) | I have adequate technological skills to implement AI in innovation  
I have adequate resources to implement AI in innovation  
I have an adequate position to drive the use of AI in innovation  
Perceived managerial support  
I am sure that I have the needed skills to use AI  
I am sure that I can train algorithms  
I am sure that I can work alongside machines |
| Behavioral Intention (BI)        | How extensively will your organization use AI in innovation? (5-10 y.)  
Organization’s intended strategic focus on AI in innovation (5-10 y.)  
Future role of AI in innovation process of your organization (5-10 y.)  
Organization’s resource allocation to AI in innovation (next 5-10 y.)  
Likelihood of using AI when innovating  
Plan to initiate further steps within the next 12 months to use AI  
AI will become an integral part of the innovation process (5-10 y.) |

Table 4. AI use constructs and items

The findings of the model testing are presented in chapter four. The next subsection continues by providing information about the sample.
3.4 Sample

3.4.1 Sample Survey

In total, an amount of 163 respondents have answered at least the first three questions of the quantitative survey. 66% of these respondents (n = 108) did take the entire questionnaire and could, therefore, be included when applying inferential statistics. In addition to those respondents who took the survey online, three relevant questions were posed to participants of an AI conference via TED poll. 106 participants of the conference answered the question regarding their current use of AI in innovation. 116 was the number of respondents that rated AI's potential for innovating and 86 people shared their opinion about AI's expected role in innovation.

Participants of the survey were primarily contacted via LinkedIn, as well as through distribution lists of Euroforum and Capgemini. People were chosen irrespectively of age, gender or nationality. Expertise-wise, during the acquisition it was focused on finding people that work in the area of innovation, have AI-related knowledge from positions as AI managers or experts, and on people working in general management.

3.4.2 Sample Interviews

Overall six interviews have been conducted. They took place on the 15th and 16th of March in Munich. The occasion was the first German 'KI Konferenz,' organized by Euroforum and Handelsblatt, in which, in one and a half days, guest speakers from all industries provided insights into the latest developments of AI and how their organizations are currently applying those technologies. As the interviews were conducted in between presentations and during smaller breaks, it was focused on keeping the conversations rather short. Hence, the interviews’ durations ranged from 9 to 22 minutes. The questions of the interview guideline were closely aligned with the aspects addressed in the quantitative survey, as the interviews were taken as a means to collect in-depth insights and personal experiences related to the adoption of AI in organizations.

The six participants were randomly chosen. They presented different degrees of knowledge about AI, as some of them had already applied some AI technologies within their companies, while others were still on the starting blocks. Nonetheless, all six interviewees were highly involved in this topic and had advanced as well as the expert knowledge they could share. The six interviewees work in five different industries and hold different positions within their organizations as well. A more detailed overview of the interviewees is provided in table 5.
<table>
<thead>
<tr>
<th>ID</th>
<th>Profession &amp; Industry</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Working for an IT company that processes health data – <em>IT/Health Care</em></td>
<td>14:24 min</td>
</tr>
<tr>
<td>12</td>
<td>AI expert in the area of Visual Computing; Founder of own AI-Startup that provides software and hardware solutions – <em>AI Startup</em></td>
<td>9:09 min</td>
</tr>
<tr>
<td>13</td>
<td>Management position in a big German bank - <em>Finance</em></td>
<td>12:48 min</td>
</tr>
<tr>
<td>14</td>
<td>VP of a global playing German Consulting Agency - <em>Consulting</em></td>
<td>21:14 min</td>
</tr>
<tr>
<td>15</td>
<td>Innovation Manager in one of the world’s leading providers of aircraft maintenance, repair, and overhaul services - <em>Aircraft</em></td>
<td>12:49 min</td>
</tr>
<tr>
<td>16</td>
<td>30 years of experience as a computer scientist; currently working for a consulting agency - <em>Consulting</em></td>
<td>13:28 min</td>
</tr>
</tbody>
</table>

Table 5. Overview of the Interviewees

3.5 Data Collection

3.5.1 Questionnaire

The first data collection method used to gather quantitative information was standardized questionnaires. The purpose of using questionnaires was to test and quantify the hypotheses derived from literature as well as to gather descriptive information about specific aspects that are related to AI's adoption and future role. In this regard, two identical questionnaires were created. One was formulated in German, while the other one was in English. It was decided to focus on two languages because this allowed the researcher to reach a bigger audience. Hence, the German questionnaire was provided to German-speaking participants coming from Germany, Austria, and Switzerland. The English version of the questionnaire was sent to people, who lived and worked in countries other than the latter three. While creating both questionnaires, significant focus was on a rigorous translation between the two languages, to guarantee that each respondent received the same stimuli. The results should be independent of the language in which the survey is taken.

The questionnaires were created and distributed electronically. Thus, the researcher provided participants with a description of the purpose of the study as well as the link to the respective questionnaire. The survey itself was created within ‘QGen,’ an online platform provided by ‘HYVE-the innovation company.’ QGen allowed to design the layout and to choose between different types of questions. Regardless of whether the questions were closed-ended or open-ended, the platform provided appropriate tools to complete the creation of the questionnaire. The user interface was thereby very intuitive and self-explanatory. Simple drag and drop options supported that experience.
The online questionnaire consisted of eleven pages. The first and last one included the starting page and the ending page, which were used to provide relevant information about this study. The other nine pages consisted of a total of 45 different questions. Each page covered a different subtopic and varied in its length. The first two questions of the survey had a single choice format, in order to get a first overview of the current adoption of AI in organizations. Single choice questions were also used towards the end of the questionnaire to gather socio-demographic information about participants. However, most questions were asked in the form of single select radio matrix questions and scaled questions. Previous to the creation of the questionnaire online, the questions and structure of the survey were designed within Microsoft Excel, to get a first preview of the survey instrument (see Appendix).

A five-point Likert scale was applied, as it allows to quantify and analyze the responses efficiently. Furthermore, scales allow for more comfortable coding, since a single number can be used to represent a participant's response. Hence, a Likert survey is typically a quick, efficient and also inexpensive method of data collection. However, as questionnaires often provide too few options, do not indicate why a person chose a particular answer or give no information about whether participants also understood the question that was being asked, it was decided on conducting some qualitative interviews too. The following subsection provides information about the qualitative research instrument used in this study.

3.5.2 Interviews

Interviews are the second data collection method used in this thesis. In this regard, six qualitative interviews were conducted. These semi-structured interviews were conducted face to face during the two days at the AI conference in Munich. Hence, on the 15th and 16th of March 2018 interviews were held within the Sofitel Munich Bayerpost Hotel. Breaks in between speakers and between different parts of the program were used to approach participants. The used interview guideline contained a specific amount of questions that were prepared prior to the interview. These questions had to be posed similarly between the different interviews. However, in semi-structured interviews, the interviewer can flexibly react to answers and ask non-prescribed questions as well. Therefore, it is not necessary to strictly follow the interview guideline or the predefined order of questions. What indeed should be taken into account, is that the researcher is asking open-end questions. In this regard, the interviewer has to pose questions in a way that they avoid simple yes or no answers and simultaneously avoid any biases. Standardized interviews aim to gain in-depth information on a specific subject. This can best be done if the researcher avoids leading questions and does not
influence the answers (Bryman et al., 2011). However, the interviewer has the freedom to use perpetuating questions to keep the interviewee on the right track. Moreover, not every question has to be asked. If the interviewee has already sufficiently answered certain aspects within other questions, the researcher does not have to jump back to that topic, unless he/she wants some additional information in this regard. Therefore, the interviewer aimed to focus on the appropriate manners when conducting the interview, such as flexibly reacting to answers of participants, asking open-end questions and avoiding leading questions that may result in biased answers.

3.5.2.1 Interview Guideline

To give the interviews a structure and to obtain relevant information, an interview guideline was developed. The questions were posed in German, as all six participants are German natives. Literature suggests that interviews should be held in that language that the participants feel most comfortable in expressing themselves in. Hence, it was decided against an interview in English, as the absence of appropriate English skills, may have led to challenges in expressing the right thoughts and ultimately to influenced results.

The questions within the interview guideline were open-ended, and their primary purpose was to contribute information about the current state of AI as well as the future potential of AI for being used when innovating. As the interviews should provide additional insights into the results of the survey, the guideline was closely aligned with the elements that the questionnaire addressed. Hence, the interview guideline provided 14 pre-set questions to ensure that essential aspects are covered (see Appendix). However, the order in which the questions were asked varied from interview to interview, as the researcher reacted to answers flexibly and tried to keep the flow high. Furthermore, throughout the interview, an enabling technique was used. Such techniques typically have the purpose to enable the respondents to communicate things to the researcher by projecting their underlying beliefs and attitudes regarding the issues of concern. Thus, in the context of the thesis, a graphical presentation of the levels of autonomous innovating were presented. These levels had the aim to trigger responses from the interviewees' side, thereby covering how they estimate AI's degree of technological progress in the area of innovation within the next five to ten years. The specific interview guideline is listed in the appendix.
3.6 Data Analysis

3.6.1 Questionnaire

Inferential as well as descriptive statistics have been applied to analyze the results of the questionnaires. Some questions had the purpose of providing descriptive information, while others were included when testing the proposed hypotheses of the research model. Thus, reliability analysis, correlation analysis, as well as regression analysis were used to examine the effect and causal relationships between variables of the model. It was decided on just including constructs of the reviewed theory, as this was the primary goal of the first part of the study. However, exploratory factor analysis (EFA) could have been applied, to identify additional factors among all variables of the survey, which could have lead to a higher proportion of explained total variance.

Concerning the second part of the quantitative study, descriptive analytics have been applied. Thus, means and frequencies were used to draw comparisons between different categories of one or multiple variables. Also, throughout the findings section, graphical illustrations of the results have been provided, which allowed for higher comprehensibility and greater comparability of outcomes. At the end of each subsection in chapter 4, differences in results between various organizational maturity clusters have been displayed. However, no real cluster analysis was conducted within the statistical software SPSS. Instead, participants were divided into five different organizational clusters based on their degree of AI usage within the innovation process (see chapter 4.2.2.1).

3.6.2 Interviews

The data analysis method used to analyze the qualitative data of the empirical part of this study is thematic content analysis. Content analysis is a general term for a number of different strategies that are used to analyze text. It includes coding and categorizing approaches to determine trends and patterns of words used, their structures, their frequency and their relationships (Powers et al., 2006). However, in this thesis, it is not focused on the latter elements. Instead, thematic analysis was used as an independent qualitative descriptive approach. It can be described as a "method for identifying, analyzing and reporting patterns (themes) within data" (Braun et al., 2006). Hence, the application of thematic analysis includes the search and identification of common themes that extend across an entire interview or a set of interviews (DeSantis et al., 2000). So the basic process of thematic analysis is coding. Coding
can be described as labeling the content of the interview to construct categories. This categorization then helps to generate findings and results.

In this study, the six face-to-face interviews have been recorded and afterward transcribed. The 84 minutes of audio data resulted in 24 pages of data volume. While conducting the interview, participants often used ordinary language or did not fully complete their sentences. In these cases, those parts of the interview were transcribed in an understandable and structured manner, to avoid any difficulties when proceeding to the data analysis stage. It was thereby highly focused on maintaining the meaning of the statements.

Before coding the data, the transcripts of the interviews have been reviewed multiple times to gain a deeper understanding of the content. Afterward, a code-book was used to identify themes and categories. As coding is a continuous process, this was repeated multiple times. Hence, new categories were iteratively added to the code-book until no new insights emerged. Thus, theoretical saturation was reached. While completing the code-book, statements of participants were simultaneously translated into English, as this facilitated the interpretation and discussion of the results.
4 Findings

Within this fourth chapter, the findings of the quantitative, as well as qualitative study, are presented. Initially, findings regarding the used research model are defined. Inferential statistics were applied to analyze the data and to test the hypotheses. The second section provides an overview of AI's future role in the area of innovation by applying descriptive statistics. Throughout the findings section, the results of the quantitative survey instrument are supplemented by the findings of the qualitative interviews, in order to go in-depth and provide additional insights. Thus, the results are supported by direct and significant quotes. The interviewees' statements have been interpreted in English during the coding process, paying particular attention to keeping the meanings behind them.

4.1 Research Model

This section covers the findings of the model testing. Various statistical methods are applied to discover relationships between variables. Thus, it is tested whether the research model is suitable to investigate into people’s intention to use AI within the area of innovation, how the proposed variables correlate and also whether the outlined hypotheses (see chapter 3.3) can be confirmed or rejected.

4.1.1 Sample Statistics

A total of 163 participants have contributed to this study by taking the survey. 66 % of these (n=108) have fully completed the questionnaire. As a consequence, only these 108 questionnaires were included when applying inferential statistics such as correlation or regression analysis. When using descriptive statistics at a later stage, all given answers were taken and used for purposes of interpretation.

The sample distribution (n=108) indicates a significant proportion of respondents (n=102) who are male (94%). However, for this study, it is assumed that gender does not significantly impact an individual's intention to use AI when innovating. The age of participants ranged from 22 to 70 years with a high share being between 33 and 53 years old (72.1%). One-third of the respondents work for organization's whose primary industry is technology, media or telecommunication (n=36). Other 30 participants work for companies, which provide professional services (n=16) or operate in the industrial sector (n=14) (see figure 9).
Within their companies, 41% of the respondents (n=44) have a top-level management job, which means that they are part of the c-suit and hold different positions, such as c-level executive, president, senior VP, director, and more. 37 participants (34%) answered that they are part of the middle management, which forms the second largest category of this sample. Individuals in both of these levels are expected to have firm decision making power within their companies, which makes them valuable contributors to this study. Nonetheless, it was not solely focused on higher level managers. As one goal of this study is to provide a comprehensive overview of AI’s potential in the area of innovation, lower tier managers as well as office workers, who are likely to work with AI closely, were expected to make insightful contributions with their expertise as well. Thus, low-level managers (n=15) and respondents without any management position (n=12) account for a cumulated proportion of 25% of the total sample.

In addition to the position within organizations, information about the respondents’ primary functional affiliation has been collected. The three most significant categories were general management (n=25), R&D and product development (n=24), and IT (n=14).

### 4.1.2 Reliability Tests

The internal reliability of the three measurement instruments was evaluated by using Cronbach’s Alfa. Typically, a Cronbach’s Alfa value above 0.7 is seen as acceptable (Blanz, 2015). Cronbach’s alfa values for attitude (0.884), subjective norms (0.702) and perceived
behavioral control (0.884) reveals an at least satisfactory reliability of the constructs. Hence, as all individual construct reliability tests reported scores above 0.7, all constructs can be considered as reliable.

### 4.1.3 Correlation Analysis

The Bravais-Pearson correlation measures the linear relationship of two at least interval scaled variables. The resulting Pearson correlation coefficient indicates the extent to which two variables co-vary. Thus, literature speaks of a positive correlation between two variables if high (low) values of one variable come along with high (low) values of the other variable. On the contrary, it is spoken of a negative correlation if high (low) values of one variable come along with low (high) values of the other one. However, in both cases, an undirected linear relation is examined. This means that there is no dependent or independent variable. Thus, correlation analysis measures the strength of effects between variables but makes no statement about causal relationships.

<table>
<thead>
<tr>
<th>Correlations</th>
<th>ATT</th>
<th>SN</th>
<th>PBC</th>
<th>BI</th>
</tr>
</thead>
<tbody>
<tr>
<td>BI Pearson’s correlation</td>
<td>.608**</td>
<td>.592**</td>
<td>.539**</td>
<td>1</td>
</tr>
<tr>
<td>Significance (2-tailed)</td>
<td>.000</td>
<td>.000</td>
<td>.000</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>108</td>
<td>108</td>
<td>108</td>
<td>108</td>
</tr>
</tbody>
</table>

**. The correlation is significant at the 0.01 level (2-tailed).

Table 6. Correlations

Correlation analysis shows that ATT, SN, as well as PBC, significantly correlate with BI at the 0.01 level. As the correlation coefficients for all three variables are positive, it means that the higher the attitude, subjective norms, or perceived behavioral control, the higher is also behavioral intention. This assumption can also be made the other way round, as Pearson correlation analysis does not indicate the direction of the relationship.

The correlation coefficient does also indicate how strong the relationship between two variables is. Typically, \( r < 0.3 \) indicates a weak effect, \( r < 0.5 \) indicates a moderate effect and \( r > 0.5 \) indicates a strong effect between two variables (Cohen, 1992). Thus, in case of this model, as all coefficients are above the 0.5 threshold, the analysis indicates that ATT, SN, and PBC and behavioral intention positively, strongly and significantly correlate.

Furthermore, correlation analysis was used to test for discriminant and concurrent validity. Discriminant validity means that the intercorrelations of the three independent variables are
significantly less than 1. This is an indication that each variable is also a distinct factor. For concurrent validity to occur, the correlations between the independent variables and the dependent variable must be positive and significantly high. As table 6 shows, discriminant validity can be confirmed as the inter-construct correlations between the independent variables (ATT, SN, PBC) are significantly below 1. Concurrent validity can be confirmed too as the correlations between the single independent variables and the dependent variable are higher than the inter-correlations between the independent variables. The only exception is that the r between PBC and SN is marginally higher than the correlation between PBC and BI (difference of 0.003). All correlations are significant at the 0.01 level.

4.1.4 Regression Analysis

After confirming the internal reliability of the constructs as well as validities, multiple regression analysis can be used to test, whether there is a relationship between multiple independent variables and one dependent variable. So, in this study's case, it was tested whether there is a relationship between attitude (ATT), subjective norms (SN), and perceived behavioral control (PBC) and behavioral intention (BI). Table 5 shows the SPSS output for the multiple linear regression analysis.

The model summary indicates an $R^2$ of 0.502 and adjusted $R^2$ of 0.488. This coefficient of determination, called ‘R squared,’ indicates the proportion of variance in the dependent variable
(BI) that can be explained by the independent variables (ATT, PBC, SN). Thus, in the above case, an adj. R² of 0.488 means that 49% of the total variance in Behavioral Intention can be explained by the three independent variables of the proposed model.

To assess whether the overall regression model is significant or not, an F-test was conducted. This test examines whether the prediction of the dependent variable is improved if independent variables were added or not. Hence, the F-test demonstrates if the model can offer any explanatory contribution. Table 6 shows that the model is significant (F(3,104) = 34.948, p = .000), which is a prerequisite for further analysis.

While ANOVA showed that the overall model is statistically significant, table 9 demonstrates now, whether the single regression coefficients have a significant influence on the dependent variable. To test the significance, SPSS conducts a t-test for each of the regression coefficients.

<table>
<thead>
<tr>
<th>Model</th>
<th>Sum of Squares</th>
<th>df</th>
<th>Mean Square</th>
<th>F</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>53,309</td>
<td>3</td>
<td>17,770</td>
<td>34,948</td>
<td>.000</td>
</tr>
<tr>
<td>Unstandardized Residual</td>
<td>52,879</td>
<td>104</td>
<td>,508</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>106,188</td>
<td>107</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>Unstandardized Coefficients</th>
<th>Standardized Coefficients</th>
<th>T</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Constant)</td>
<td>-829</td>
<td>.481</td>
<td>-1,724</td>
<td>.088</td>
</tr>
<tr>
<td>ATT</td>
<td>.554</td>
<td>.132</td>
<td>.355</td>
<td>4,208</td>
</tr>
<tr>
<td>SN</td>
<td>.429</td>
<td>.132</td>
<td>.288</td>
<td>3,250</td>
</tr>
<tr>
<td>PBC</td>
<td>.209</td>
<td>.083</td>
<td>.216</td>
<td>2,528</td>
</tr>
</tbody>
</table>

Table 9. ANOVA

Table 10. Regression Coefficients
Table 7 shows that the t-tests for the regression coefficients of ATT ($t = 4.208$, $p = .000$), SN ($t = 3.250$, $p = .002$) and PBC ($t = 2.528$, $p = .013$) are significant at the 0.05 level. However, the regression coefficient of the constant is not significant, as $0.088 > 0.05$.

Beta values (see table 9) are the standardized regression coefficients. Typically it is said that the higher the betas, the more of an effect independent variables have on the dependent variable. Consequently, it can be said that the larger the beta, the larger the t-value and lower the p-value.

Attitude ($\beta = .355$) has the strongest effect on Behavioral Intention, while PBC has the weakest ($\beta = .216$). All effects are significant though.

### 4.1.4 Hypothesis Testing

The original research model proposed in this study (see chapter 3.3) included three essential assumptions that wanted to be examined. These assumptions were formulated within the hypotheses:

**Hypothesis 1 (H1):** Attitude (ATT) toward the use of AI in innovation positively and directly influences the Behavioral Intention (BI) to use AI when innovating.

**Hypothesis 2 (H2):** Subjective Norms (SN) positively and directly influence an individual’s Behavioral Intention (BI) to use AI when innovating.

**Hypothesis 3 (H3):** Perceived Behavioral Control (PBC) positively and directly influences an individual’s Behavioral Intention (BI) to use AI when innovating.

Regression and correlation analysis was conducted to test the hypotheses. The adjusted $R^2$ and standardized regression coefficients for the single relations are shown in figure 10.

H1 stated that Attitude toward use has a positive and direct relationship with Behavioral Intention. This hypothesis was accepted as the regression coefficient of ATT is significant at the 0.01 level. The standardized regression coefficient $\beta$ is 0.36, which indicates that Attitude towards the use of AI has a positive, direct yet moderate effect on the intention to use AI when innovating.
H2 stated that Subjective Norms have a positive and direct influence on Behavioral Intention. The regression coefficient $\beta$ of SN is 0.29 and is significant at the 0.01 level. H2 was therefore accepted too.

H3 expressed the assumption that Perceived Behavioral Control positively and directly influences Behavioral Intention. The $\beta$ of PBC has a score of 0.22 and is significant at the 0.05 level. Thus, also the last hypothesis was accepted. However, although H3 was accepted, among all three independent variables, PBC was the lowest contributor to BI.

In conclusion, it can be said that the proposed model afforded good prediction of intention to use AI when innovating, accounting for 49% of the variance. Moreover, the regression coefficients showed that each of the theory's constructs made moderate but significant contributions to the prediction of the usage intention of AI within the area of innovation.
4.2 Artificial Intelligence – Status Quo

This section covers the gathered insights regarding AI’s status quo within organizations. Particular attention lies on the current degree of AI adoption within the innovation process and on the discussion of benefits and challenges that the implementation of AI brings with it. Additionally, a picture of companies' strategic focus in this context will be provided. To provide a comprehensive overview, descriptive statistics were applied and supplemented by direct quotes of interviewees. This style of interpretation will be applied throughout the entire findings section.

4.2.1 Current Adoption of AI

The degree of AI adoption within organizations was initially examined, to get a first overview of the current state of AI in 2018. The results are shown in figure 11.

![Current Usage of AI](image)

**Figure 11.** Current Adoption of AI [in % of respondents] (n = 163)

The highest proportion of participants has not yet adapted AI within its organization but plans to do so in the future (31%). This result closely aligns with results of the AI study conducted by BCG in 2017 (Ransbotham et al., 2017). They also confirmed a share of 32% for companies that had not yet adopted AI but had plans to do so (see fig. 12). In this study, only 7% of all respondents indicated that their organization has not yet adopted artificial intelligence and also has no intention to do so. Comparing it with results of the previous study (see fig. 12), a strict downward trend in this regard can be noticed. This decrease in the number of participants who
resist adopting AI may be the indication for an increased understanding and acceptance of AI that has happened over the course of the past year. This tendency can be recognized across all of the results. While in 2017, about one quarter (23%) of all organizations have adopted AI so far (see fig. 12), the results of this study show that over one third (17%+17%) of the participants have adopted AI in 2018 (see fig. 11). Despite the fact that the results of both studies cannot be directly compared, due to their difference in the number of respondents, the outcomes of this study demonstrate a clear tendency towards an increasing degree of AI adoption.

![Figure 12. Adoption level of AI (Ransbotham et al., 2017)](image)

The qualitative part of this study supports this assumption too. All six interviewees reported different degrees of AI adoption within their organizations, ranging from having first plans, through conducting single pilot projects, to having AI incorporated in offerings or processes.

"We have not yet adopted AI." (I 3)

"[…] operationally in a very early stage. However, we are more advanced from research and strategic perspective." (I 1)

"[…] not long ago, we started to test six AI use-cases in pilot projects." (I 5)

"AI for us is a means to an end. It is part of our portfolio, in which we, e.g., prototypically enter projects with our customers […]" (I 6)
4.2.2 Current Adoption of AI in Innovation

After getting a first impression of the overall degree of AI adoption, figure 13 shows how extensively organizations are already using AI within their innovation process.

Analogously to previous results, also in the context of innovation, the highest share of participants (31%) has not yet adopted AI in Innovation but has plans to do so in the future (n = 50). 41 respondents work for companies that have already partially applied AI in some tasks within the innovation process or single pilot projects. This accounts for 25% of the overall respondents. The share of companies who have already incorporated AI in some process steps or have extensively adopted AI within innovation is with a cumulated percentage of 28, 6% lower than the result shown in figure 11. In comparison to the overall adoption of AI, the share of companies who have not adopted AI within innovation and have no interest in doing so has more than doubled. It increased from 12 respondents (7%) to 27 (17%) respondents. This development is an indication for lack of understanding of AI's role within the innovation process. Previous studies so far have not covered how AI can be used to enhance a company's innovativeness and what suitable use-cases for doing so would be.

This assumption is reflected in the outcomes of the interviews too. Only one out of six interviewees is using AI as a means to enhance other companies’ innovativeness. The other five participants had not yet applied AI technology when innovating.
"We do not use AI in this regard" (I 2)

"We use AI to create first models based on historical data. Their purpose is to validate what has been reasoned within the creative process or shortly tested in real life." (I 6)

4.2.2.1 Potential of AI in Innovation

To make results comparable and to highlight differences between various groups better, the respondents were categorized by their degree of AI adoption in Innovation.

<table>
<thead>
<tr>
<th>Degree of AI Adoption in Innovation</th>
<th>Cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extensively Incorporated in processes</td>
<td>Adopters (Ext.) (15%)</td>
</tr>
<tr>
<td>Incorporated in some processes</td>
<td>Adopters (Part.) (12%)</td>
</tr>
<tr>
<td>Partially applied in pilot projects</td>
<td>Pilots (25%)</td>
</tr>
<tr>
<td>Not adopted, but planning to do so</td>
<td>Passives (31%)</td>
</tr>
<tr>
<td>Not adopted and no interest</td>
<td>Resisters (17%)</td>
</tr>
</tbody>
</table>

Table 11. Organizational Maturity Clusters [in %] (n = 163)

Irrespective of their different degrees of AI adoption within the innovation process, each group also varies in its opinion about AI’s overall potential to impact the way their company innovates. Results show an overall mean of $\bar{\phi} = 3.99$ for AI's expected potential in the area of innovation. As in the questionnaire, a 5-point Likert scale was applied, a mean of 4 indicates that respondents on average rate AI's potential as high. However, the standard deviation of 1.202 indicates that the actual expected potential on average deviates by 1.2 points from the average of $\bar{\phi} = 3.99$. Figure 14 highlights this discrepancy between the different clusters (see table 10). It is visible that the higher the degree of adoption, the higher is also rated AI's potential for enhancing a company's innovativeness. Resisters, those who have not adopted AI and also have no interest or plans in doing so, present an average of $\bar{\phi} = 2.52$ (see fig. 14). Compared to Adopters, which present means above the value of 4.75, the difference between both of these clusters is very high ($\Delta > 2.2$).
During the AI conference, the same question was asked to people of the audience. Results of the TED poll align with outcomes of the survey. Out of a total of 116 participants, 34% each (n = 40) evaluated AI's potential in innovating within the next 5 to 10 years as high or very high. Qualitative results show that most interviewees would rate the potential for artificial intelligence in the area of innovation as high, but are not able to state specific use-cases or how this high potential will manifest in the future.

Two interviewees mentioned particular use-cases in this regard. They expect AI to influence the area of Corporate Foresight, as well as see AI as a means to combine different assets within an organization.

- Corporate foresight

"[...] it is not possible for a corporate foresight department or innovation manager to process all the information and to check them on their relevance. This is definitely a good operational purpose for AI." (I I)
• Combining assets

"A company has three important assets. [...] a customer base, [...] data and employees, viz. certain skills. The interesting question is to integrate these assets into the innovation process, and also how this is done. However, this happens very rarely. AI can help in this regard, but not entirely solve that problem." (I 4)

4.2.3 Advantages of AI

This section covers what benefits AI may bring to organizations and how they respectively rate them. Previous research identified various aspect whose performance AI may be able to enhance. Within the quantitative survey, it was tested for the relevance of these aspects.

![Benefits of AI](image)

**Figure 15.** Overall average per benefit (n = 136)

4.2.3.1 Increase in Efficiency

Results indicate that an overall increase in efficiency (\( \bar{\phi} = 4.02 \)) is what most organizations expect AI to provide (see fig. 15).
"A big topic, of course, is the internal increase in efficiency. Regarding production processes as well as administrative processes." (I 5)

Efficiency can be defined as "(a system or machine) achieving maximum productivity with minimum wasted effort or expense" (English Oxford Dictionary, 2018). Thus, given that efficiency is a comprehensive term, a great variety of different factors influences it. Which specific factors are often connected to efficiency in the context of AI, will now be discussed.

- **Objectivity**

Interviewees indicated that the provided objectivity of AI is a huge benefit. The technology system thereby ignores subjective influences such as emotions or people’s preferences and solely decides based on objective evaluation criteria.

"An artificial intelligence is objective, without letting emotions influence its decisions." (I 1)

"[...] the validation, to take a closer look at the designed model on an objective level." (I 6)

- **Availability**

The big difference between an AI and a human employee is that the AI can perform its tasks regardless of the time of the day or the place it is needed.

"[AI] is 24/7 available [...]" (I 1)

- **Consistency**

Interviewees also reported that AI, unlike humans, is consistent in its results, which is another contributing factor for an overall efficient innovation process.

"[...] the same Input does always lead to the same result." (I 1)

- **Accuracy**

Accuracy is also at what AI excels at. Machine learning and deep learning algorithms in particular, often outperform traditional methods. They can drastically reduce the error rate in specific areas (Chui et al., 2018) and thus contribute to an overall increase in efficiency.

"[...] can achieve results faster and more accurately than with traditional methods." (I 3)
• Speed

Interviewees claimed that AI could provide enormous benefits through the speed in which it is analyzing the data. This faster processing of data leads to reduced process cycle times, which in turn increases productivity and overall efficiency.

"[can process bigger data volumes] much much faster." (I 1)

"[…] may it be things like voice commands, instead of completing paperwork within the workshop. I really think you can save a lot of time like this." (I 5)

• Automation

Automation can be seen as the most significant contributor to an increase in efficiency. The literature review, as well as the results of the study, show that one of the most valuable benefits of AI is its ability to automate some of the unpleasant and undemanding tasks. In the past, human employees had to invest enormous amounts of time to complete routine tasks that did not require any expertise. Nowadays, AI may be able to take on these unsatisfying tasks and perform them in a much faster, more accurate and more reliable way. This is what increases the overall internal efficiency of an organization. Not by replacing humans, but by shifting their know-how into areas where it is needed.

"An advantage is that we support humans in completing their tasks with AI. A big media company, e.g., in the past had to keyword millions of images by hand. This task was very repetitive and time-consuming. […] This is where we can position ourselves. Not by substituting humans […]" (I 2)

"In the future humans will not have to do analysis and develop scenarios anymore." (I 3)

"Where we as humans will probably be able to completely withdraw from in the future, is the question who analyzes, develops scenarios and delivers the results." (I 3)

"[…] use AI or some types of bots to replace the monotonous and non-value creating working tasks through automation." (I 5)

"If this all can be provided by just pressing one button, I could focus on other working tasks. Thus, I see AI as a big chance." (I 5)
"I see huge potential there because everyone that sits in front of a PC and follows certain rules can easily be integrated within an automation process. [...] So basically, the automation, which we have always had at the assembly line, is transferred to computer workspaces. This starts with the fact that I can semantically analyze emails. I use methods of machine learning, namely natural language processing, to derive structured data from unstructured sources. These data are then sent to rule-based robots that process the information." (I 6)

- **Scaling**

The last aspect that was mentioned within the context of efficiency improvement is scaling. Due to its objectivity, speed, ability to process enormous amounts of data, accuracy, and availability, AI can be considered as a scaling element.

"AI for me is a scaling element. It can help to scale and broaden the process. (I 4)

**4.2.3.2 Forecasts of future needs and trends**

According to the respondents, the use of AI within the innovation process allows to better forecast future needs, trends, and requirements. With an average of $\bar{\theta} = 3.75$, it is the benefit that was rated second highest (see fig. 15). Qualitative results support this tendency as interviewees highlight the importance of AI's ability to predict and derive patterns by processing vast amounts of structured and unstructured data.

- **Data Volume**

Machine learning and deep learning algorithms excel at processing vast amounts of data at a fast pace.

"[AI] can process much bigger data volumes [than a human could]" (I 1)

"We have an enormous amount of data about our customers, their financial behavior and also about the financial markets." (I 3)

"I am convinced that AI can analyze a much bigger data volume than a human could." (I 3)

- **Prediction and pattern recognition**

These machine learning algorithms learn from historical data in a supervised or unsupervised way, which allows for clustering or association techniques. These techniques are aimed at
discovering the inherent groupings in datasets, in order to use that information for making predictions (Chui et al., 2018).

"[...] with the help of AI we strongly go into the direction of predictive models, customer behavior models, to use historical data to create first profiles." (I 6)

"I think AI can help us to display the reaction of one party on another better. [...] how customers react to institutional investors, to changes in the market and why/how the markets react to investment behaviors of customers." (I 3)

"[...] and to predict the behavior of market players." (I 3)

"I also think that AI will be able to simulate and play through scenarios better than any human. [...] it is about going through different scenarios in order to provide different alternatives to the investor." (I 3)

**4.2.3.3 Decision making and idea selection**

With a mean of $\bar{\varnothing} = 3.73$, the 136 respondents above-average agree with the assumption that the usage of AI technology within the innovation process, improves decision making and idea selection (see fig. 15).

Interviewees within the qualitative part of this study, mentioned ‘decision making support’ as a benefit of AI too. AI’s suitability in this regard mainly derives from its objective nature. Often results derived from an analysis that was performed by AI, are used as a means to justify future investment decisions.

"[...] provides better quality in supporting decisions." (I 6)

"[AI] also helps to get a higher security of investment for customers. Also to convince the executive board to enter that topic and to do it." (I 6)

“An innovation is often an investment decision, and political aspects normally influence such investment decisions. So every tool that can neutralize decision making can help a lot. Also, AI in this regard can play a big role, because I agree on a system and let that system have a certain freedom in decision-making." (I 4)
4.2.3.4 Comparison between organizational maturity clusters

The graphical representation of the averages for each benefit shows clear differences among organizational clusters. While the three most important benefits stay the same across all categories, the mean values for each cluster vary. Adopters rate the overall increase in efficiency highest. With a mean of $\emptyset = 4.5$, this benefit is by far the most valuable aspect AI can provide for those companies that are already adopting AI to a certain extent (see fig. 16). However, a clear difference can be noticed regarding the second and third highest rated benefits. While both Adopter clusters (Ext. + Part.) on average rate the improved decision making and idea selection as more valuable, Pilots and Resisters on average saw AI’s ability to forecast future needs and trends as more beneficial.

![Figure 16. Average assessment of benefits [per organizational cluster] (n = 136)](image)

Moreover, a considerable discrepancy can be noticed among the height of the averages for each cluster. Those companies that have already gained some experience with artificial intelligence, on average rate its benefits much higher. Adopters (Ext.) on average agreed 0.89 points stronger that AI leads to an increase in efficiency than Resisters. Adopters (Ext.) and Resisters massively vary in their opinion on the other advantages too. The difference in the average of $\Delta = 0.97$ for the aspect that AI leads to a greater variety of ideas is another sign for the discrepancy between clusters. These variations in values are expected to be mainly caused by a disparity in know-how and experience with AI.
To take a look at where the disparities between clusters originate from, and what barriers organizations have to overcome to adapt AI in Innovation successfully, the next subsection will cover the most common challenges connected to the use of narrow artificial intelligence.

### 4.2.4 Barriers and Challenges

The adoption of new technologies does not come along without some major barriers and challenges an organization has to overcome. Figure 17 shows the result of the quantitative study. Overall average values within this part of the study range from 2.31 to 3.39, which can be considered as rather low compared to previous results.

![Figure 17. Average assessment of AI challenges and barriers (n = 136)](image)

#### 4.2.4.1 Great Effort

That the adoption of AI within the innovation process requires great effort, is what respondents on average rated highest ($\bar{\theta} = 3.39$). 33% of respondents highly agree (value = 4) with that statement ($n = 45$).

Qualitative results indicated what aspects, in particular, contribute to the perception that the adoption of AI requires much effort.
• **New Roles**

Interviewees indicated that a significant challenge in adopting AI is the fact that employees, as well as managers, need to be aware that their role within the company will change and lead to a new self-image. Some new job profiles will emerge, while others will disappear due to the automation of tasks through artificial intelligence.

"I think the biggest challenge will be to find a new self-image of our role in the production, in the consulting process, …" (I 6)

"It will be a challenge [for managers] to recognize that they need to train new behaviors and develop new skills that employees need to have." (I 3)

"To prepare humans that AI is something that will change their self-perception." (I 3)

"I am sure that especially within the financing sector many managers have not yet dealt with AI. In this regard, much educational work is still required." (I 3)

• **Choice of technology and training data**

For companies, another challenge that is often resource and time consuming is the choice of the proper technology and training data. It is often difficult to agree on the right type of AI algorithm or even neural network. The framework has to be suitable for the desired use-case and trained accordingly on data.

"At the beginning, the choice of technology was a big issue. It took us a while until we had determined a neural network framework" (I 1)

"One challenge for sure was to put together the training data to form a ground-truth, from which it is possible to train neural networks" (I 1)

"A neural network itself is not intelligent. It only becomes intelligent through the transfer of know-how from the human's side. […] Only then an AI can become so intelligent that it can support us." (I 2)

"Datasets alone don't make the model intelligent. […] Only through knowhow-transfer by a human expert, I as an AI data scientist, can build something useful out of it." (I 2)
Lack of understanding and transparency

As it is with every new technology or massive change within an organization, there are always doubts and resistances in people's minds that have to be overcome. Proper change management is what is needed in this regard. Thus, management is required to create a proper understanding of AI throughout the entire organization. Furthermore, interviewees claim that by increasing the transparency of such technologies and by making them tangible, it is possible to take employee's fear and consequently to drive the implementation of AI.

"The biggest barriers are still a lack of understanding and knowledge [about AI]. For many people, AI is still astonishing. They almost consider it as sorcery, because they do not know what exactly happens." (I 6)

"I think there is not enough information and transparency regarding decisions on this topic. [...] people cannot really grasp it. [...] (I 6)

"[...] It was about audit processes, fully automated, by using AI, more precisely a deep learning system. How can I know now, how the AI came to those results? As an auditor, I have a burden of proof. How can I prove now how a self-learning system came to its results? I can only see the output. [...] We will have to answer that questions somehow to provide that proof of transparency." (I 6)

"I think the biggest challenge is that organizations cannot grasp AI. They say they want to use AI, but don't know how it is done. The first reaction [...] often is that they get a CTO/CDO, give him a lot of money and he/she should do the rest. [...] So what primarily happens is a relabeling, which means that coming investments are set in the context of AI in order to get more funding. However, this is not working. There will be no change. [...] AI should not be seen as an end in itself, but rather as an enabler." (I 4)

"This taboo word of 'AI,' that futuristic vision that sometimes seems to be very dark, needs to be made tangible for people that are scared of it. If we build robots [...], we give them names. We personify them, to demystify AI."

4.2.4.2 Incremental Innovations

Descriptive statistics show that incremental innovations, with an average of $\bar{\phi} = 3.19$ are seen as the second highest challenge among the mentioned aspects. More precisely, 58 respondents (43%) strongly agree (value $\geq 4$) that the usage of AI within the innovation process only leads
to incremental innovations based on already existing solutions, rather than leading to radical innovations. This results can be partly explained by the fact that AI is particularly suitable to identify patterns in historical data. As a consequence, the systems have the capability to identify and to judge what worked out in the past for the own company or competitors. This information, in turn, is especially valuable when working on an incremental innovation, whose original goal is to enhance already existing products or services, to meet continuously changing customer needs. Radical innovations, however, require a much higher degree of creativity. However, creativity, according to the interviewees, will strictly remain a human domain.

"I think the creative part will luckily still be a human domain. I think an AI system will not be able to generate ideas by itself." (I 6)

"I do not see potential in idea generation, as idea generation [...] requires a high degree of creativity." (I 1)

4.2.4.3 Difficulties in data governance

Respondents indicated that the usage of AI within the innovation process leads to difficulties in data security, data privacy, and data ownership. With an average of $\Phi = 3.04$, it presented the third highest value among the mentioned aspects. The distribution between the frequencies for each value is relatively equal. 33% of respondents ($n = 45$) did not agree with the latter assumption (value $\leq 2$). 26% of the participants ($n = 35$) rated the challenge of data governance as medium-high (value = 3). However, 41% ($n = 56$) indicated that they still see proper data governance as a real challenge for their organizations (value $\geq 4$). As respondents answered relatively different from each other, it will be examined at a later stage, if this circumstance can be explained by taking a look at the different organizational maturity clusters. Also results from the qualitative study show that data governance and data security are aspects that cannot be neglected.

"[...] have to operate everything that is related to AI on-premise. We cannot use cloud-services [...] We do not do it because of data security concerns." (I 1)

"We have an enormous amount of data about our customers, their financial behavior and also about the financial markets." (I 3)
4.2.4.4 Missing technological skills

When asking whether organizations think that the absence of required technical skills is a significant barrier when adopting AI in innovation or not, they did not agree with it at all. 52% of respondents indicated that they do not think that missing technological skills is one of the main issues for their companies when adopting AI (value $\leq 2$). As a consequence, results indicate a mean value of $\overline{\phi} = 2.6$. However, 37 respondents (27%) still reported that the adoption of AI within the innovation is not possible for them, because their companies do not have the required technological skills. Results from the qualitative study also support this statement. They did not only report great effort in choosing the right technology and data framework (see chapter 4.2.4.1) but do also see employees as an essential asset when it comes to technological expertise.

- Employees

"Staff is also an important topic, as there are very few specific education programs in this area." (I 1)

"[a challenge is the] acceptance of the workforce. The tolerance threshold for mistakes that the AI makes is very very low." (I 1)

"[it is a question] of school education or education at universities." (I 3)

"[...] programming was opened to a much bigger crowd. [...] I do not need that one specialist can code in 300 programming languages and knows how to build machines by himself any longer. Rather I need people that are capable of combining the business context, the socio-cultural context, and some IT-Know-How." (I 4)

4.2.4.5 Not advanced enough yet

Almost 60% of all respondents ($n = 80$) indicated that they think that AI algorithms are currently advanced enough for being applied within innovation tasks (value $\leq 2$). On the contrary, 14% think that the use of AI within the innovation process is not possible, because AI technologies are not sophisticated enough yet (value $\geq 4$). As more people believe in AI’s sophisticatedness than doubt it, the mean value $\overline{\phi} = 2.4$ is below the middle value (3). This fact indicates the overall tendency that organizations indeed believe that AI algorithms are sophisticated enough yet for being applied, but that there are some company-specific use cases in which AI’s error rate is still too high. Statements from interviewees confirm this assumption.
• **High error rate**

"I think it was highlighted today. AI has still a relatively high error rate. That is why I think that you should not let AI make relevant decisions autonomously." (I 3)

### 4.2.4.6 Overly rational decision making

Concluding, it was asked whether participants think that the usage of AI would lead to overly rational decision-making practices. Literature and experts mentioned the concern that blind faith in technology's rationale may lead to ethical issues, especially if human beings are directly involved. E.g., How can a dismissal be justified, if it happened on the basis of an analysis of uncountable variables, processed by AI? In many cases, it is still not possible to reproduce how the neural network learned and came to its output. However, respondents were not concerned about this issue, as the mean of $\bar{\theta} = 2.31$ is the lowest among the examined aspects.

Interviewees, in turn, stated some negative aspects regarding AI's rational and objective nature.

• **Logic**

"AI is inferior to humans in things that have to do with recognizing logical relationships in patterns." (I 2)

• **Can’t account for individual preferences**

"[to make decisions] depending on their preferences, which the AI does not know [...]" (I 3)

"We often have many different investors sitting at one table, and everyone has different preferences." (I 3)

Overall results show that AI's objectivity, on the one hand, can be a massive benefit concerning the justification of all kinds of decisions (see chapter 4.2.3.1). On the other hand, blind faith in AI's rational decision making may lead to difficulties, when it comes to excluding individual preferences, and human emotions or cognitive processes. Thus, in the end, it comes down to the degree to which organizations let AI systems make decisions autonomously. When using AI as a means of supporting decisions, not much of a problem will be caused. Nonetheless, as soon as companies allow AI to make crucial decisions on its own and blindly trust the system, a call for more transparency will emerge. The next sections will discuss this issue, by assessing the expected degree of autonomy for AI in innovation. Additionally, results regarding the most suitable innovation tasks and AI technologies will be shown.
4.2.4.7 Comparison between organizational maturity clusters

A comparison of the results between clusters shows that the averages of four of the five clusters align with the results of figure 17 (n = 136). Great effort, difficulties in data governance and incremental innovation are the three aspects that almost all clusters agreed highest on. The only exception is the category of Resisters. On average they agreed most (∅ = 3.3) on the fact that AI in its current state, is not sophisticated enough for them to use it within their innovation process. The reverse trend can be noticed for the other clusters. The higher the degree of adoption of AI, the less they see the low technological sophistication as a barrier.

**Figure 18.** Average assessment of challenges and barriers [per organizational cluster] (n = 136)

What also aligns with previous assumptions is the fact that those clusters that have not yet adopted AI, namely Resisters and Passives, agree much higher than others on the aspect that they lack the required technological skills. Furthermore, a discrepancy between the height of averages for each cluster can be noticed. While Adopters (Ext.) agreed on the three aspects mentioned earlier as their highest barriers, Resisters, and Adopters rated all aspects substantially higher or lower than the other clusters. The highest differences between Adopters (Ext.) and Resisters can thereby be noticed between the mean for missing technological skills (Δ = 1.15), overly rational decision making (Δ = 1.01), and for the assumption that AI is not advanced enough yet (Δ = 1.6).
### 4.2.5 Strategic Focus

This section covers the results regarding the question, which aspects organizations focus most on when thinking about implementing AI technology within the innovation process. Figure 19 demonstrates overall averages. The values for the mentioned aspects are close together. The range between the lowest value (\( \bar{\phi} = 3.54 \)) and the highest (\( \bar{\phi} = 4.01 \)) is at 0.47. This result indicates that overall the level of agreement throughout the various aspects is very similar. However, whether there are some apparent differences between organizational clusters or not, will be examined in a later subsection.

![Figure 19. Strategic focus in planning to adopt AI in innovation (n = 112)](image)

### 4.2.5.1 Data

Results from the quantitative study show that regarding the implementation of AI within the innovation process, participants (n =112) on average agreed most with the statement that they think about which data are available for use (\( \bar{\phi} = 4.01 \)). The highest proportion of respondents (n = 47) strongly agreed (value = 5) that their organization is concerned about what kind of data appears to be most suitable for being used within innovation. Qualitative results support this tendency. One of the interviewees’ most stated requirements for AI to work, was a suitable amount of data in combination with the right type of data.

"The organization needs to have sufficient data to train its neural network." (I 1)
"I think one of the biggest requirements [...] is the topic of data quality. We have enormous amounts of data, but they are in some cases not in the right format in order to be further processed." (I 5)

"I need to have a big pool of critical relevant data." (I 6)

4.2.5.2 Most valuable use cases

A comparison of the averages shows that the second highest focus is on identifying the most valuable use cases for AI within the area of innovation ($\bar{\phi} = 3.9$). 73% of all respondents at least strongly agreed (value $\geq 4$) that one of their biggest priorities in the adoption of AI is the identification of use cases that generate value as well as allow to capture that value. Interviewees made some statements in this regard as well. Thus, organizations should not just invest into AI, for the sake of using AI as a marketing tool. They are rather well-advised to start small, identify specific use cases, collaborate, but most importantly to also capture the value they generated.

- Capture the value

"I think a challenge will be to determine what added value AI brings to an organization. [...] I think that too many companies within their innovation process too heavily rely on taking a lot of money and investing it in some startups. It is then tried to integrate those startups somehow. [...] But the challenge is not to build such labs or to invest in startups, but to bring the outputs of those labs back into the organization." (I 4)

4.2.5.3 Problem solving

With an average of $\bar{\phi} = 3.87$ problem solving resulted in being the third highest priority, when it comes to the adoption of AI within innovation. Despite the fact that problem-solving can be related to finding appropriate use cases, there is still a slight difference in meaning. However, results from the qualitative interviews indicate that it is not enough to purely identify problems for whose solution AI may be suitable for. An organization's overall corporate strategy needs to be aligned in a way that it enables to approach AI step-by-step and to enhance a risk-taking culture.
• Corporate strategy

"[...] but then I need a clear corporate strategy. I take that strategy and do not formulate it for the next five years, or the next three years, but I rather decide on half-year goals and allow every department to work with their key results towards that goal. These goals must or can be enabled through AI then." (I 4)

"So for AI I would rather suggest that the company sets goals, but then allows each department to run their own small AI initiatives or use-cases. I give them space and also allow that some of them fail. And those use-cases that were successful at a small scale are then made big by making substantial investments." (I 4)

• Communicative and open culture

"[...] is the involvement of employees and cultural change. I need to create a corporate culture that enhances, allows, encourages digital transformation. AI is a part of it, but not the only one." (I 4)

"A lot has to do with how I lead my employees, how I allow them to make mistakes and also how I incentivize [the adoption of new technology]." (I 4)

"It is also important [...] to have a very good communication right from the start. To make AI touchable and to invite people as well as critics to be a part of it. These are the basic formulas." (I 6)

4.2.5.4 Algorithms and tools

When thinking about using AI in specific innovation tasks, it is inevitable to properly decide on those algorithms or tools, which are most suitable in this regard. Participants of the quantitative study agreed with this statement too. The highest proportion of respondents (n = 41) indicated that their opinion strongly aligns (value = 5) with the statement that their focus when adopting AI is on identifying and using the right algorithms and tools, to gain the most value out of the planned AI initiatives. 31% of respondents (n = 35) shared the same opinion (value = 4), which leads to an overall average of $\bar{\emptyset} = 3.82$. However, distribution of frequencies indicates that a fairly high amount of people (19%) do not see the choice of the right tools as that much of an issue for their companies (value \leq 2). Thus, to make sense of this result, it will be taken a closer look at how the averages between organizational clusters vary.
4.2.5.5 Resources and skills

The last result that is discussed in this regard is that companies, when intending to adopt AI within the innovation process, rigorously think about what resources and skills are required to guarantee a successful implementation. Figure 19 shows that respondents agreed with this statement by giving on average $\bar{\theta} = 3.72$ points out of a maximum of 5. So overall 65% of the respondents ($n = 73$) at least agree ($\geq 4$) with the fact that their organization's focus is on being aware of required resources as well as skills. Skill mostly refers to technological skills of employees, as results of the qualitative study can confirm. Concerning resources, interviewees mentioned that an adequate and consistent IT infrastructure is a prerequisite for employees to work efficiently and for allowing the whole organization to collaborate cross-departmental.

- Talent

"[... ]talents that want to engage in that topic." (I1)

"[... ] programming was opened to a much bigger crowd. [...] I do not need that one specialist is able to code in 300 programming languages and knows how to build machines by himself any longer. Rather I need people that are capable of combining the business context, the socio-cultural context, and some IT-Know-How." (I4)

"One the one hand we, of course, try to build our AI competencies internally. [...] Good people do not just grow on trees [...]." (I5)

- Infrastructure

"[... ] need to make big investments into infrastructure. May it be GPU's that provide high computational power or overall data governance." (I1)

"An additional topic is our IT-landscape. [...] In the course of a centralized IT strategy it is tried to bring everything down to a common denominator." (I5)

"[it is important] to set up a clean data-governance for such projects [...] to guarantee a high degree of transparency and data security." (I6)

"The only thing where I really need an overarching framework is the topic of data. I believe that for proper data-governance a data framework has to be pushed through. [...] have to do
that top-down to guarantee a standardization, moving away from these single, separated data silos."

4.2.5.6 Comparison between organizational maturity clusters

When intending to use AI within the innovation process, we think about ...

![Figure 20. Average strategic focus [per organizational cluster] (n = 112)](image)

Figure 20 shows how the averages across the five different organizational maturity clusters vary. The figure was scaled onto the values, to better highlight differences and facilitate interpretation. Thus, despite the impression that the differences between averages within the clusters seem to be substantial, in fact, they are rather small.

Nonetheless, as it was already the case with previous results of the quantitative study, there is a reasonably significant difference between organizational clusters, when it comes to the overall height of averages. The graphical representation of the results shows that the higher the degree of adoption within a company, the higher it is also on average agreed on the importance of the mentioned strategic aspects. Numbers confirm that assumption. While the lowest mean of Adopters (Ext.) is on $\bar{\phi} = 4.56$, Resisters on average even disagreed on some aspects ($\bar{\phi} = 2.56$). Worth mentioning is also that the different clusters have also varying priorities when it comes to the intended adoption of AI within innovation. While Adopters (Ext.) on average think most about which problems AI can solve ($\bar{\phi} = 4.83$), Pilots, Passives, and Resisters are most concerned about which data are available for use ($\bar{\phi} = 4.45$, $\bar{\phi} = 3.58$, $\bar{\phi} = 3.38$). Adopters
(Part.), on average, think most about what specific algorithms and tools appear to be suitable to further drive the adoption of AI within their company's innovation process ($\bar{\theta} = 4.38$).
4.3 Artificial Intelligence – Future Role in Innovation

This last part of the findings section covers the results regarding AI's technological readiness for being applied to the innovation process. AI's future role is discussed by interpreting the outcomes of the quantitative survey. Focal points are thereby the discussion of which AI technologies appear to be most suitable for being used when innovating as well as to take a look at what innovation tasks, in particular, AI may be able to enhance. In the end, it is covered how AI's future role will look like, by assessing its expected future degree of automation in completing tasks and making decisions.

4.3.1 Innovation Process

Within literature review section it has already been discussed how the innovation process, for purposes of this study, was split into single innovation tasks (see chapter 2.2.2). As AI technologies excel at solving all kinds of problems, it was decided not to observe the innovation process as a whole, but to separate it into various innovation tasks instead. The potential for the following innovation-relevant tasks is discussed: a) Technology scouting, b) identification of needs, trends, and patterns, c) idea generation, d) idea selection and decision making, e) concept testing, f) marketing, g) prototyping and i) Generative Design.

Results of the quantitative survey show that respondents rate the importance of AI for the single innovation tasks as high (see fig. 21). The mean for each of the tasks is above the value of 3.1, which indicates that on average each of the innovation tasks appears to be at least suitable for being enhanced by AI. With an average of $\varnothing = 4.00$ the identification of needs, trends, and patterns was rated highest when it comes to AI's expected importance in that area. The second and third ranks go to concept testing ($\varnothing = 3.88$) and prototyping ($\varnothing = 3.77$), innovation tasks that are directly related to product development (Ries, 2012).
Identification of needs, trends, and patterns

The literature review has shown that narrow AI, more precisely machine learning algorithms, are particularly suitable for predictive and prescriptive analytics. They can detect patterns and learn how to make predictions and recommendations by processing data and experiences (Chui et al., 2018). The results of the quantitative study align with theory. With an average of $\bar{\varnothing} = 4.00$ respondents indicated that the usage of AI is most important, when it comes to identifying changing market needs, new trends or when companies aim to detect patterns in the data to customize their offerings even better. 77% of all respondents stated that AI's analytic nature makes the technology at least important (value $\geq 4$) for identifying relevant trends and patterns within historical data. The resulting predictions and recommendations, in turn, can be used to enhance product development. Results of the interviews support the outcomes of the survey. Interviewees see the area of prediction and pattern recognition as particularly suitable for AI too. Thus, some of them are already applying AI for the purposes mentioned above.

"[...] as well as in the area of the identification of trends and needs." (I 1)

"[...] definitely for identifying market needs and trends." (I 6)
"[...] with the help of AI we strongly go into the direction of predictive models, customer behavior models, in order to use historical data to create first profiles." (I6)

"I think AI can help us to display the reaction of one party on another better. [...] how customers react to institutional investors, to changes in the market and why/how the markets react to investment behaviors of customers." (I 3)

4.3.1.2 Concept testing & Prototyping

Concept testing and prototyping are collectively discussed in this section, as quantitative results are very similar and both aspects are content-related. Prototyping within this thesis includes the steps of building, measuring and learning, which are in line with Eric Ries’ Lean Startup Methodology (2011). As concept testing is part of this build-measure-learn loop, its results will not be separately discussed.

Quantitative results indicate that concept testing, as part of the product development cycle, achieved an average of $\bar{\theta} = 3.88$. This means that a majority of respondents ($n = 83$) thinks that AI will be at least important (value $\geq 4$) in the future when it comes to testing ideas and concepts.

The average of $\bar{\theta} = 3.77$ for prototyping is slightly below the one for concept testing, but can still be considered as high. The highest proportion of respondents (36%) indicated that the use of artificial intelligence would be important (value = 4) when it comes to prototyping ideas and developing a first minimum viable product (MVP). Also, statements of interviewees could support these results. While the first interviewee, who works for an IT company, did not see much potential for AI to improve concept testing or prototyping, interviewee six, a consultant, has already used AI in this regard and could confirm its importance.

"Concept tests/Prototyping, I do not see much potential for AI there." (I 1)

"[We use AI] to validate what was reflected in the creative process and what may have already been tested in real life." (I 6)

"[...] we also use it in first small use-cases or prototypes in the MVP approach, where we develop such AI models with our customers and test them in real life." (I 6)
4.3.1.3 Technology scouting

As already discussed in chapter 2, technology scouting can be seen as part of an organization’s corporate foresight activities (Rohrbeck, 2010). Making foresight and predictions is what machine learning algorithms excel at. Thus, a broader awareness of technology and market trends through AI, can itself become a powerful source of new and differentiating ideas (Spitsberg, 2013). Respondents of the survey, as well as interviewees, share that assumption. 46 respondents (40%) think that AI will play an essential role in the future, when it comes to scouting new technologies, to channeling technology-related information into an organization or to scouting emerging market trends. 28 participants (24%) would even consider its impact as very important. With a mean of $\bar{\theta} = 3.72$, it is ranked fourth among the mentioned innovation tasks. However, the difference in averages between the different groups is not substantial.

"[...] definitely the topic of technology scouting." (I 1)

"[...] generative design and technology scouting are my top two." (I 2)

"The first topic that comes to my mind is scouting. I think that AI methods can help us to set our data into a relevant context. [...] The difficulty is not that the knowledge does not exist. The challenge is to identify the knowledge that is relevant to my organization and me. And this is what AI can do, as it can process enormous amounts of data and learn in the context of the organization." (I 4)

4.3.1.4 Generative Design

Generative design as a means to enhance product design reached an overall average of $\bar{\theta} = 3.58$. 41 respondents indicated that they consider AI’s potential in improving product design as high (value = 4). Generative design software, which is based on machine learning algorithms, is able to offer considerable benefits in terms of providing a more extensive range of design options and optimizing for materials, costs and manufacturing methods. In total, respondents recognize AI's potential in this regard, as only 14 out of 116 participants were considering the use of artificial intelligence within Generative design as unimportant (value $\leq 2$).

"Generative Design is a huge point for me." (I 2)

"I definitely think generative design has big potential." (I 6)
4.3.1.5 Idea selection and decision making

The importance of AI when selecting ideas and making decisions was rated second lowest among the proposed innovation task. However, with an overall average of $\bar{\theta} = 3.48$, a clear tendency is visible. Despite being considered as less important than the other aspects, the mean is still substantially above the neutral stance (value = 3), which indicates that a fair amount of respondents believes in AI's potential to identify and select those ideas that add the most value to an organization. Additionally, 62 respondents, which accounts for 53% of total responses, stated that they would consider the use of AI for selecting ideas and making decisions as important or very important (value $\geq 4$). These results are supplemented by statements of interviewees, who make the acceptance of AI’s autonomous decision making dependent on the degree of relevancy that the decision has.

"I would not let AI select and decide about ideas. There are few decisions at this stage anyway. Those can definitely make humans." (I 1)

Moreover, it was mentioned that AI is expected to have significant influence when it comes to evaluating ideas. Due to its ability to process vast amounts of data and to learn from them, a machine learning algorithm may be able to detect patterns in historical data that help to determine whether new ideas are likely to succeed or not.

"I think what an AI indeed may be able to do, is to rate [already formulated] ideas based on their chances of success. [...] To have a forecasting method that determines which ideas have prospects of success and which do not. (I 6)

Frequently, these evaluations can also serve as a means to neutralize conflicts of interests within organizations by providing an objective and neutral point of view.

"Valuations, I really see the potential for AI there. Once I have ideas, to evaluate them neutrally. Investments within a company are often politics. Viz. Innovation is often an investments decision, and political aspects normally influence such investments decisions. So every tool that can neutralize decision making can help a lot. So AI in this regard can play a big role because I agree on a system and let that system have a certain freedom in decision-making." (I 4)
4.3.1.6 Idea generation

Idea generation is the last innovation task to discuss. With an average of $\bar{\varnothing} = 3.15$, AI's importance in generating new ideas is rated lowest. The graphical representation (see fig. 21), although it is scaled on the values, to provide greater clarity when interpreting the results, shows an apparent gap between the first seven innovation tasks and idea generation. The numbers confirm this too. A total of 60% of respondents ($n = 70$) is either indifferent (value = 3) towards AI's usage within idea generation or thinks it is not important (value $\leq 2$) at all. Furthermore direct statements of interviewees confirm the assumption that AI is rather unsuitable in computing tasks that are connected to creativity and sense-making.

"I do not see potential in idea generation, as idea generation [...] requires a high degree of creativity." (I 1)

"I do not really see idea generation as suitable." (I 2)

"I think the creative part will luckily still be a human domain. I think an AI system will not be able to generate ideas by itself." (I 6)

4.3.1.7 Comparison between organizational maturity clusters

![Graph showing comparison between organizational maturity clusters](image)

**Figure 22.** Average importance of AI for each innovation task [per organizational cluster] ($n = 116$)
Figure 22 shows how each organizational maturity cluster on average rates AI's importance for the proposed innovation tasks. At first glance, it can be noticed that Adopters (Part.), Pilots and Passives demonstrate a somewhat similar height and distribution of values. All averages within these three clusters range from 3.11 to 4.00. Additionally, all three share the opinion that AI is most important when it comes to identifying needs, trends, and patterns. Values for Adopters (Ext.) and Resisters, however, massively vary from each other. While Adopters (Ext.) on average rate AI as important for all of the mentioned innovation tasks (min. $\bar{\phi} = 3.89$, max. $\bar{\phi} = 4.61$), Resisters’ opinions massively vary for each task. Thus, Resisters see the most potential in AI being used for predicting ($\bar{\phi} = 3.88$) and scouting ($\bar{\phi} = 3.38$). In line with the overall averages, Resisters also believe that AI is essential when it comes to testing concepts ($\bar{\phi} = 3.56$). Those companies that have already extensively adopted AI within innovation stated that the performance of prototyping ($\bar{\phi} = 4.61$) and concept testing ($\bar{\phi} = 4.56$) has most potential for being enhanced by AI.

The graphical representation clearly illustrates that idea generation, seen relative to the values of the other tasks, is rated as least important or even unimportant. While Adopters (Part.), Pilots and Passives see the application of AI when generating ideas as neither important nor unimportant, Resisters think that idea generation and artificial intelligence do not fit together ($\bar{\phi} = 2.44$). Adopters (Ext.) also think that idea generation, compared to all the other tasks, has the least potential for being impacted by AI.

### 4.3.2 AI Technology

This section aims to cover the question which AI technologies are most suitable for being utilized within companies’ innovation processes. In the literature review section (see chapter 2.1) it has already been discussed that the focus of this study is on narrow and weak AI technologies. Hence, AI in the form of algorithms, machine learning or deep learning algorithms, which present the foundation for many different AI technology systems. By reviewing recent studies (McKinsey, 2017; Capgemini, 2018) it was decided on nine different AI technology systems or techniques, whose potential for being applied within innovation, was examined within the quantitative part of the study: Robotics, Computer Vision, Language, Virtual Agents, Affective Computing, Predictions, Recommendations, Text Mining, and Clustering. The illustration of the results can be seen in figure 23. The latter figure was scaled onto the values, to provide a better overview and allow more straightforward interpretation.
Thus, even though differences between averages appear to be significant, the values occur close together.

**Figure 23.** Average potential per AI technology (n = 112)

### 4.3.2.1 Predictions

Results of the study show that the potential for using AI’s predictive power within the innovation process was on average rated highest (∅ = 4.46). This result aligns with the outcome of the previous part of the study, in which the identification and prediction of needs, trends, and patterns was considered as the innovation activity that is most likely to be enhanced by AI. 92% of respondents (n = 103) indicated that AI has high potential (value ≥ 4) for being applied to the innovation process when it comes to making predictions. Direct statements of interviewees support these results.

"[…] to recognize patterns […]" (I 3)

"[…] and to predict the behavior of market players." (I 3)

### 4.3.2.2 Language

The potential of Language, often also Natural Language Processing (NLP), was rated second highest (∅ = 4.39). The key technology of natural language is often divided into sub-areas such as chat bots or voice bots, speech recognition, natural language generation, or semantic technology (Capgemini, 2018). The latter sub-area may be particularly suitable for innovating.
as it provides context to decision-making by data analysis. The participants of the survey have also recognized the potential of this AI technology system. 90% of participants (n = 101) estimate the potential of natural language for innovating as high (value ≥ 4).

### 4.3.2.3 Computer Vision

Computer Vision achieved the same average score as natural language (∅ = 4.39). This AI technology system makes use of deep learning algorithms and neural networks for purposes of image recognition and classification. For the latter area of application, these neural networks are capable of analyzing images and videos and interpreting them autonomously (Capgemini, 2018). Thus, once the algorithm learned how a particular element looks like, it can recognize that element in new images or videos. 89% of respondents think that the mentioned ability is applicable to the innovation process and therefore rate its potential as high (value ≥ 4).

### 4.3.2.4 Recommendations

With an average of ∅ = 4.17, AI's analytic capability to make recommendations is ranked fourth among the mentioned technology systems. 91 respondents (81%) indicated that they expect recommendations to have high impact (value ≥ 4) in enhancing the innovation process. 11 participants were indifferent. They stated that machine learnings ability to apply prescriptive analytics is neither suitable nor unsuitable (value = 3) for being used when innovating. Prescriptive analytics refers to AI systems' capability to not only anticipate what is going to happen but also to provide recommendations on what to do to achieve goals.

### 4.3.2.5 Text Mining

Text mining can be considered as the process of deriving valuable information from text. This information is mostly derived through the devising of trends and patterns through the application of various statistical methods (Feldman et al., 2006). Thus, text mining as a tool for identifying future needs and trends is expected to have high potential in innovation (∅ = 4.16), when it comes to identifying relevant information in vast amounts of text. This information, in turn, can be used for purposes of decision-making, when it comes to selecting the most profitable ideas or to deciding on product attributes, which a new product needs to have, to increase its likelihood of being bought.

"I think where it would be suitable too, is the topic of patent screening. Hence, to have a look at what the other big competitors do. Going in the direction of Benchmarking. You can already
do that on your own by doing internet research, [...] but it takes too long. I thought about Internet-crawler [...] with text recognition and text mining." (1.5)

4.3.2.6 Clustering

Clustering is one of the more frequent unsupervised learning problems. In clustering, the scientist wants to discover the inherent groupings in the datasets, such as grouping customers by their product preferences. This area of application can, e.g., support companies in better targeting their marketing campaigns for new products and in identifying most profitable customers for them. Additionally, hierarchical clustering allows for informing product usage or development by grouping customers by their mentioned keywords in social media data (Chui et al., 2018). This can be used as a means to monitor and test customer feedback on product prototypes. Consequently, clustering seems to be an appropriate tool for prototyping or testing the reactions against the product or concept. Answers of participants reflect those assumptions too. With a mean of $\bar{\varnothing} = 4.10$ clustering is ranked sixth, but exhibits a value substantially above the neutral stance (value = 3). 76% of respondents ($n = 85$) take the view that clustering has a high potential for being utilized when innovating.

4.3.2.7 Comparison between organizational maturity clusters

[Figure 24. Average potential per AI technology [per organizational cluster] ($n = 112$)]

The comparison between organizational maturity clusters clearly illustrates that respondents in each cluster have their own perception of what AI technology has the most potential within
innovation and which ones seem not to be suitable (see fig. 24). Adopters (Ext.) that is who has already extensively applied AI within innovation processes or process steps, rate the potential of clustering on average as highest ($\bar{\theta} = 4.78$). The shared second place is taken by text mining, predictions, and language with an average of $\bar{\theta} = 4.72$ each. Thus, this average-based ranking of Adopters (Ext.) aligns with assumptions from literature and previous studies that machine learning's predictive and prescriptive nature allows more rigorous forecasts, monitoring, and valuations through analysis.

The low averages of clustering and text-mining for Resisters can be explained by the fact that respondents within this cluster lack expertise in this area as well as understanding of these tools. The categories of robotics and affective computing were excluded from interpretation as four out of five clusters estimated their potential substantially lower than the potential of the other AI technologies.

### 4.3.3 Levels of autonomous innovating

This last chapter of the findings section discusses the results regarding AI's expected degree of autonomy and required human monitoring when executing innovation tasks. In order to pursue this matter, participants were first asked to assess AI's future role in innovating by indicating the expected level of automation that AI will reach within the next five to ten years. The levels of autonomous innovating (see chapter 2.4.3) were therefore used as an assessment tool for investigating into AI's expected degree of autonomy within the innovation process, as well as a tool for examining how the future collaboration between human and AI would look like.

Secondly, participants were asked to assign a level of autonomous innovating for each of the innovation tasks (see chapter 4.3.1). Levels of autonomous innovating were described as following:

- **Level 1: Assistance** - AI assists humans in executing the innovation task. Human execution & human monitoring.

- **Level 2: Split innovating** - Innovating is split between human and AI. AI performs one task, while the employee focuses on another one. Execution by human and AI, but human monitoring.

- **Level 3 – Partial Automation** - AI will act semi-autonomous. It will perform multiple tasks within the innovation process but requires continuous human monitoring.
• **Level 4 – Conditional Automation** - AI will innovate autonomously and perform every relevant task on its own. Only requires human assistance in certain emergency situations and upon AI’s request to intervene. AI does the execution of tasks and only requires sporadic human monitoring.

• **Level 5 – Full Automation** - AI will innovate completely autonomous. No human intervention needed.

Results for the overall expected role of AI within the future innovation process are demonstrated in figure 25.

![Figure 25. Expected level of autonomous innovating for the overall innovation process (n = 116)](image)

The graphical illustration clearly shows that a high proportion of respondents (89%) expects AI’s technological progress to reach a point within the next 5 to 10 years, at which it will either play an assisting role, take over certain tasks, or act semi-autonomously. Thus level 3 (n = 38), level 2 (n = 36), and level 1 (n = 29) are these levels of autonomous innovating that, according to respondents, are most likely to be reached within the future innovation process.

Level 4 and level 5, considering current developments in the area of AI, are still seen as too optimistic. Only 14 of 116 respondents think that AI will able to reach the fourth or fifth level in innovating. However, it is tough to predict future technological developments. One discovery
may be able to trigger developments within multiple other areas and lead to unexpected progress.

Results of the TED poll, which was conducted in Munich, are almost consistent with outcomes of the survey. The highest proportion of the audience at the AI conference expects AI to reach level 3 (n = 32). However, there is a slight mismatch of opinions, when it comes to level 2 and level 1. A higher amount of people share the opinion that AI will play a supportive role (level 1), rather than a collaborative one (level 2). Still, the difference in headcount is so marginal that it does not lead to any significant changes if both results of the polls are summed up.

4.3.3.1 Level 3 – Partial Automation

Partial Automation is what one-third of all respondents (33%) expect AI to reach within the next 5 to 10 years. Thus, AI is expected to be capable of innovating semi-autonomously. Suitable AI algorithms will perform multiple tasks within the innovation process autonomously but will require continuous human monitoring. Additional outcomes of the quantitative study show that respondents expect AI to reach level 3 in innovation tasks such as concept testing, Generative Design, prototyping, identification of needs, trends and patterns, and technology scouting.

Figure 26. Expected level of autonomous innovating for innovation tasks (n = 116)
Among the innovation tasks that were discussed in previous subsections, Concept testing, Prototyping, and Generative Design are those three that are most expected to reach level 3 within the next 5 to 10 years. Level 3 was also assigned to the identification of needs, trends, and patterns. However, the illustration (see fig. 26) clearly shows that a high proportion of respondents (n = 29) believe that AI's capability to identify and predict future needs and trends is already advanced to such a degree, that, within the next 5 to 10 years, it will able to act autonomously, requiring human intervention solely in emergency situations (level 4).

Direct statements of interviewees support quantitative results. All six interviewees expected AI’s role within the future innovation process to be either supportive (level 1), collaborative (level 2) or expected AI to innovate semi-autonomously, but under constant human supervision (level 3). In the latter regard interviewees stated:

"At the moment I would say level 2. However, if you say 5 - 10 years, I am sure that we will reach level 3. That AI will act semi-autonomous, but that we still need continuous human monitoring." (I 3)

"I think it depends on the task. If the task is easy and has no big value behind it, then AI may be able to act and decide autonomously." (I 5)

4.3.3.2 Level 2 – Split Innovating

31 % (n = 36) of respondents expect AI’s future role within innovation to be collaborative. Thus, they think that innovating will be divided between human and AI. While AI performs tasks of an analytical kind, the employee can simultaneously focus on duties that require creativity or human reasoning. However, despite the fact that the execution of tasks will be carried out by employees as well as AIs, the supervision of AI’s outputs or performance will still be in human hand. Additional outcomes of the quantitative study show that respondents expect AI to reach level 2 in tasks that are related to the selection and generation of ideas. Figure 27 shows respondents’ evaluations.
Results show that there is the tendency of respondents to assign level 2 to those innovation tasks that deal with ideas and how they are best generated and selected. The fact that the degree of autonomy of AI when it comes to generating and selecting ideas as well as making decisions is estimated lower than for other innovation tasks aligns with previous results of the study. The overall potential of the latter two tasks for being impacted by AI was on average rated lowest too. As a logical consequence, respondents do not rate AI's future degree of autonomy in executing these tasks as equally high as in the other parts of the innovation process. Concerning level 2, interviewees acknowledged the fact that AI is able to take over some of the unqualified and unpleasant tasks and therefore allows for splitting of responsibilities.

"[...] unqualified tasks, like entering data [will be taken over by AI]" (I 1)

"Work for humans will be relocated to more qualified tasks, like monitoring and specialist tasks." (I 1)

"[...] things that were previously done by humans will then be prepared by machines." (I 1)

4.3.3.3 Level 1 – Assistance

Autonomous innovating level 1 can be considered as the stage in which AI is used as assistance system to complete tasks. Thus, AI serves as a tool which is capable of accelerating and improving the execution and performance of innovation tasks, but that is not able or allowed to perform or decide on its own. Results of the survey indicate that 29 participants (25%) estimated that AI's future role in innovating within the next years would be supportive. This result heavily aligns with direct statements from the qualitative study. Concerning AI's future role,
interviewees stated that the more creative the task gets, the more human skills will be required. Furthermore, they saw AI today and in the nearer future as a tool. Thus, as it is with every tool, they have a supportive character.

"Within the next five years, I see AI on level 1. AI will support humans in completing tasks. With a slight chance to reach level 2." (I 1)

"I think that within the next 5-10 years AI will only be an assistance system. [...] AI will not be able to make decisions autonomously. That is my experience." (I 2)

"[tools] have always had a supportive character. [...] Always keeping in mind that AI should serve the human." (I 3)

"[…] as a tool for supporting decisions or making suggestions, or as a help in executing certain tasks that are mechanically and ergonomically not so comfortable. AI can definitely support there." (I 5)

"The more creative the task gets, the more human skills will be required. In this case, AI will only be able to assist." (I 6)

### 4.3.3.4 Comparison between organizational maturity clusters

This last section, for exploratory purposes, will discuss how the assessment of AI’s future role within the overall innovation process varies, depending on organizations’ current degree of AI adoption within innovation. Figure 28 shows a comparison between organizational clusters.

The graphical representation of the results shows that Resisters expect AI to reach a maximum of level 3. The highest share of Passives expects AI’s future role to be collaborative (level 2). Pilots, as well as Adopters (Part.), expect AI to be so technologically advanced within 5 to 10 years, that it is capable of innovating semi-autonomously (level 3). Distribution-wise, Adopters (Ext.) is the most exciting cluster to take a look at. Participants in this cluster evaluated all five levels as realistic. However, in line with opinions of interviewees, the highest proportion of Adopters (Ext.) expect artificial intelligence to play an assisting role. Thus, as a tool that accelerates and improves the performance of tasks, but that is not able to decide on its own.
Figure 28. Expected overall level of autonomous innovating [per organizational cluster] (n = 116)
5 Discussion & Implications

This section aims to recap most important findings of this study and to connect it with theory. Thus, the research question and its sub-questions will be answered within this chapter by combining insights from the quantitative as well as qualitative part of this thesis.

“What is AI’s future role in innovating?”

a) Which aspects influence an employee’s intention to use AI when innovating?

To make sense of an individual's intention to use AI within the innovation process, the Theory of Planned Behavior framework was applied (Ajzen, 1991). It was therefore investigated into whether people's Attitude, Subjective Norms or Perceived Behavioral Control directly influence their intention or readiness to use artificial intelligence technologies within tasks of the innovation process. The findings demonstrate that the proposed model with its three independent constructs and the respective items is able to explain 50% of the total variance in Behavioral Intention. Literature does not give any information on the aspired value for adjusted R² and for what percentage can be considered as good or bad. It often depends on the case and context of the study. Given the fact that TPB has never been applied to the context of AI adoption before and no similar studies exist to draw comparisons from, an adjusted R² of 50% can be considered as good. Moreover, the analysis demonstrated that all three proposed hypotheses could be confirmed. Thus, Attitude, Subjective Norms and Perceived Behavioral Control have a significant yet moderate impact on people's intention to use AI within innovation. Results indicate that among the three independent variables, Attitude towards the use of AI has the strongest effect on intention to use AI. Thus, if people can be convinced that the application of AI within the innovation process is beneficial and provides substantial advantages for the organization as well as for the working experience of employees, they are expected to be more willing to use AI when innovating. Furthermore, findings show that people's involvement in AI, as part of their overall Attitude, does also contribute to their readiness to use AI. For practitioners, this finding means that it all starts with people or talents that have the right mindset. Thus, recruiting talents from other organizations or universities (Ransbotham et al., 2017) that are already highly involved into the topic of AI or want to engage in it, most likely also drives the adoption of AI within the innovation process of your company. Recent studies have also mentioned on-the-job training of employees as an approach to building
AI-related skills (Ransbotham et al., 2017). However, results show that companies must be careful concerning choosing those employees that also have the willingness to dive into this topic. "Talents do not just grow on trees" (I 5), and their training often comes along with high effort and investments.

When it comes to recruiting and training the right individuals, it is not only their Attitude and Involvement toward AI that should influence an organization's HR decisions. Results of the model testing indicate that also people's perception of their individual ability to use and adopt AI impacts their willingness to apply AI within innovation. Moreover, the construct of PBC includes an individual’s beliefs about the presence of factors that may impede or facilitate the performance of the behavior (Ajzen, 1991). For companies that want to drive the adoption of AI within their innovation process, this means that the more an employee perceives that he/she is capable of utilizing AI in a meaningful fashion, the higher is his/her intention or willingness to do so. This finding at the same time implies that the more AI-related skills a person has, the higher is also its intention to make use of those capabilities at the workplace. On the contrary, the literature indicates that, even if employees are capable of using AI when executing innovation tasks, there is still the possibility for the presence of organizational factors that negatively influence their behavioral intention to do so (Ajzen, 1991). Results support this assumption. Organizational aspects such as having adequate resources, the required technical skills or the right position within the company, turned out to have a significant yet moderate impact on people's intention to use AI when innovating. Thus, to drive the adoption of AI within innovation, it is recommended to keep the presence of impeding factors as low as possible. Having the right corporate culture is a first step in doing so. Engaging with past literature and in line with results of this study, an open and communicative culture that provides space for errors and encourages an open mindset (Saunila et al., 2013), is a prerequisite for digital transformation to succeed. Thus, a company culture that enables digital transformation is most likely also expected to lead to a lower perception of the presence of impeding factors and ultimately drives overall AI adoption.

Regarding Subjective Norms, results of the model testing show that individuals are more likely to use AI if groups of relevant others judge the behavior as good or advantageous. Thus, in an organizational context, it was examined whether top-management or colleagues judge the usage of AI as beneficial. Furthermore, it was expected that the employee's perception of AI's impact on its future career, influences its intention to use AI too. Thus, results indicate that the more supportive and enthusiastic top management and colleagues are, and the more beneficial AI is
expected to be for one’s career, the higher is also that person’s intention to use artificial intelligence when innovating.

In the following, a final summary of the results of the model testing and its meaning for companies is provided:

- Following the TPB framework, people’s *Attitude* toward the usage of AI has the highest effect on their intention to do so. Thus, in line with theories from change management, companies would be well-advised to make sure that the planned adoption of AI within the innovation process is communicated in a clear and positive fashion (Kotter, 2002). Employees must be made aware that the adoption of this new technology is advantageous for themselves as well as for the entire organization.

- Involvement, as part of overall Attitude, influences behavioral intention as well. Concerning the latter, companies within their recruiting and training activities should focus on those talents that show a high degree of involvement into AI and willingness to engage in that topic.

- When building AI-capabilities, it is not only about finding people with an adequate mindset but also about scouting those talents that exhibit the required skillset. To drive the adoption of AI, people are needed that combine the business context, the socio-cultural context, and some IT-Know-How. The latter presence of a skillset is essential, as results show a positive and direct relationship between people's perception that they possess the required skills to use AI and their actual intention to make use of AI.

- Moreover, behavioral intention is influenced by an individual's perception of the extent to which he/she has access to the means of control. Thus, people sensitively react to aspects that they perceive as compounding. A way to avoid employee's perception of the presence of obstacles in their ways is to allow for an agile, open and communicative culture. Thus, a company culture that allows employees to make mistakes and enables digital transformation, of which AI over the past years became a part of.

- Last but not least, the latter culture should enhance communication between different parties, as well as allow for proper incentivization. As employee’s intention to use AI when innovating is partly influenced by whether the behavior is approved or performed by important others, an open and supportive culture, in which managers act as role models, can substantially influence people’s behavioral intention. Concluding, the organization may establish proper incentivization systems, to make employees notice that their efforts in using AI are judged as favorable and may positively impact their career.
The following part will provide a summarizing overview of AI's future role in innovating. Quantitative and qualitative findings, which were comprehensively discussed in chapter 4, are therefore used to portray respondents evaluations regarding most suitable innovation tasks and AI technologies, as well as AI's expected degree of autonomy. For the sake of clarity, the overview is divided into an overall section that covers the results of all respondents, and subparts that answer the research questions from the perspective of each organizational maturity cluster.

b) What innovation tasks have the highest potential for being impacted by AI?

c) Which AI technologies are most promising for being applied to innovation?

d) What is the expected degree of autonomy of AI concerning completing tasks and making decisions?

Table 12 demonstrates which innovation tasks the entirety of respondents and each organizational cluster evaluates as having the highest potential for being impacted by AI. The ranking is thereby based on their averages. Parts highlighted in green show those tasks that are evaluated best. The red parts show the two innovation tasks that are rated lowest relative to the others.

<table>
<thead>
<tr>
<th>Org. Cluster</th>
<th>Ranking for the innovation tasks</th>
</tr>
</thead>
</table>
| All respondents | 1. Identification of needs, trends, and patterns  
| | 2. Concept testing  
| | 3. Prototyping  
| | 4. Technology Scouting  
| | 5. Marketing  
| | 6. (Generative) Design  
| | 7. Idea selection and decision making  
| | 8. Idea generation |
| Adopters (Ext.) | 1. Prototyping  
| | 2. Concept testing  
| | 3. Identification of needs, trends, and patterns  
| | 7. Idea selection and decision making  
| | 8. Idea generation |
| Adopters (Part.) | 1. Identification of needs, trends, and patterns  
| | 2. Technology Scouting  
| | 3. Prototyping  
| | 7. Marketing  
| | 8. Idea generation |
Results of the study show that the three innovation tasks that are expected to be most impacted by AI within the next years are the identification of future needs, trends and patterns, concept testing, and prototyping. These three innovation tasks, although their ranking could easily be interchanged, were consistently evaluated as most promising across all organizational maturity clusters. Similar tendencies can be reported for those tasks within the innovation process that were rated lowest concerning their potential of being enhanced by AI. Idea selection and decision making and idea generation were consistently rated lowest across all five organizational clusters. This aligns with results of the qualitative study, in which interviewees stated that they do not expect AI's potential to be high for tasks that require creativity and human reasoning, such as generating new ideas, making important decisions or selecting ideas based on the inclusion of interpersonal aspects. However, results show that they do see the potential for AI in selecting ideas, if no political aspects influence decision making and algorithms are given space to objectively analyze historical data and identify patterns that allow determining whether new ideas are likely to succeed or not.

The following table summarizes results regarding the question, which AI technology or area of narrow artificial intelligence is most likely for being put to use within the innovation process. Similarly to the previous table, results for each organizational maturity cluster as well as the entirety of respondents will be listed.

<table>
<thead>
<tr>
<th></th>
<th>Pilots</th>
<th>Passives</th>
<th>Resisters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1. Identification of needs, trends, and patterns</td>
<td>1. Identification of needs, trends, and patterns</td>
<td>1. Identification of needs, trends, and patterns</td>
</tr>
<tr>
<td></td>
<td>2. Prototyping</td>
<td>2. Concept testing</td>
<td>2. Concept testing</td>
</tr>
</tbody>
</table>

**Table 12. Summary of rankings for innovation tasks [based on averages]**
### Table 13. Summary of rankings for AI technology [based on averages]

Table 13 shows that consistently throughout four out of five organizational clusters, Predictions, Language and Computer Vision are considered as these AI areas that have the highest potential of affecting the future innovation process. However, those companies that have already extensively adopted AI in some processes or process steps of the innovation process considered
the technique of clustering, the area of text mining and AI's ability to make predictions as most promising for being used. This mismatch can be explained by assumptions made in previous studies that AI technologies are often overlapping and therefore hard to categorize (McKinsey, 2017). Thus, text mining for example often applies natural language processing (NLP), which can at the same time be considered a part of 'language' (Indurkhya et al., 2010). Virtual Agents, Robotics and Affective Computing, are those categories that are expected to have the least potential when it comes to innovating.

The last aspect to be discussed in this thesis is the expected future role and therefore the degree of autonomy that comes along with implementing AI within tasks of the innovation process. Concerning the latter, table 14 shows those three levels of autonomous innovating that were rated as most realistic for being reached by AI within the next 5 to 10 years. The highest proportion of respondents of the questionnaire indicated that level 3, partial automation, is the degree of autonomy they expect AI to have. Accordingly, also the highest share of participants of the AI conference in Munich, who answered the question via TED poll, indicated that AI will be able to act semi-autonomously, but would require continuous human monitoring (n = 32).

<table>
<thead>
<tr>
<th>Level of autonomous innovating</th>
<th>Innovation task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 3 (n = 70)</td>
<td>- Concept Testing</td>
</tr>
<tr>
<td></td>
<td>- Generative Design</td>
</tr>
<tr>
<td></td>
<td>- Prototyping</td>
</tr>
<tr>
<td></td>
<td>- Identification of needs, trends, and patterns</td>
</tr>
<tr>
<td></td>
<td>- Technology Scouting</td>
</tr>
<tr>
<td>Level 2 (n = 56)</td>
<td>- Idea selection and decision making</td>
</tr>
<tr>
<td></td>
<td>- Idea generation</td>
</tr>
<tr>
<td>Level 1 (n = 50)</td>
<td>- Marketing</td>
</tr>
</tbody>
</table>

Table 14. Levels of autonomous innovating for each innovation task [based on frequencies]

Overall results of this study show that most participants consider autonomous innovating level 3 as most realistic for being reached by AI. Respondents of the survey, as well as participants of the TED poll, share this opinion. However, expectations for level 2 and level 1 are relatively close together. While among respondents of the questionnaire the second most frequent answer was level 2, participants of the conference saw AI rather as a supporting tool (level 1).
Regarding the question, which degree of autonomy AI will reach within each of the innovation tasks, it was assigned a higher level of autonomous innovating (level 3) to those innovation tasks that were also expected to have an overall high potential for being enhanced by AI. Thus, in tasks such as the identification of needs, trends and patterns, concept testing, prototyping, technology scouting and generative design, participants expect AI to act semi-autonomously. AI algorithms will primarily perform those tasks that require their prescriptive and predictive analytic capabilities. Thus, they are most valuable when it comes to processing vast amounts of data, identifying valuable patterns and applying these insights to new data sets or cases, to make predictions and recommendations on how to best succeed. However, level 3 indicates that humans will thereby not blindly trust the AI system, but continuously monitor the execution of the tasks as well as judge the outputs of the analysis. People are not yet willing to let AI decide on relevant aspects on its own, as the technology in some areas is not advanced enough yet or the basis of decision making in some cases has to not only consist of objective and rational analysis, but also of interpersonal and political aspects.

Consistent with previous results of this study, respondents assign level 2 to those tasks within an innovation process that were rated lowest, when it comes to their suitability for being enhanced by AI. Thus, in tasks like idea selection and decision making, and idea generation people expect their relationship with AI to be collaborative (level 2). This means that human and AI split the execution of the task, but AI at no time has the power to act or make decisions autonomously. Idea generation, idea selection, and decision making are activities that require a certain degree of creativity and human reasoning, which AI cannot yet deliver. Thus, AI algorithms are not able to automate those steps within the innovation process that require domain-specific know-how, creativity or interhuman capabilities. They instead are suitable for automating administrative and analytical tasks, where repeatable decisions can be made, in order to increase an organization's overall efficiency, and enhance employees experience at the workplace by taking over unqualified and unpleasant tasks.
6 Conclusion

It is hard to predict how the future role of narrow artificial intelligence within the innovation process is going to look like. However, outcomes of the study indicate that the degree to which AI will autonomously act and decide strongly depends on the type of task it is used for. Thus, consistently throughout different organizational maturity clusters, AI is expected to have the most potential as well as the highest level of autonomy in those tasks that allow for an objective and neutral analysis. The application of predictive and prescriptive analytics is expected to be most valuable in tasks such as the identification of needs, trends and patterns, concept testing, and prototyping. Concerning the latter three tasks, the AI technology systems that were rated most valuable for being used when innovating are language and computer vision. In detail, AI techniques such as clustering and text mining are expected to enhance AI’s ability to make valuable predictions that ultimately improve the performance of the innovation process.

Concerning AI’s expected degree of autonomy, those companies that have already adopted AI within innovation as well as those organizations that are planning to do so, anticipate AI to reach level 1 to level 3 within the next five to ten years. Thus, it is expected that AI either plays an assisting (level 1), a collaborative (level 2), or a semi-autonomous role (level 3). AI will be a supportive tool or execute a few specific tasks when it comes to innovation tasks that require creativity and human reasoning. Thus, AI’s potential as well as degree of autonomy is rated lower for tasks like idea selection and decision making, and idea generation, which are typically human domain. In turn, level 3 is anticipated for those tasks, in which repeatable decisions based on rational analysis and processing of data can be made.

6.1 Managerial Implication

The insights presented in this thesis provide practitioners the opportunity to enhance their knowledge of artificial intelligence. Aspects were mentioned that would be likely to influence employee’s willingness and intention to adopt AI when innovating. This information especially helps those organizations that plan to drive the adoption of AI in the nearer future. Furthermore, results regarding most suitable innovation tasks and AI technologies are provided. They give a first direction of which process steps within the innovation process could be tackled. By discussing AI’s future role in innovating, the topic of artificial intelligence should be made more graspable for employees as well as managers and help to reduce fears and uncertainties of how the future collaboration between human and computer will look like. Furthermore, outcomes of this thesis are not industry-specific and can, therefore, be applied to many different contexts.
6.2 Limitations

While this study provides relevant findings, which are on the one hand new to literature and on the other hand will provide a clear direction for companies, there are also some limitations and consequently possibilities for further research. Despite time constraints and difficulties in finding appropriate participants for this highly specific topic, the sample size for the quantitative questionnaire as well as the interviews can be considered as satisfactory but could have been higher, in order to guarantee an even better validity and reliability of the results. Also, concerning the qualitative interviews, a geographical limitation was given, as interviewees were only German-speaking and of Austrian or German nationality. Concerning the application of the TPB framework within the context of AI, an explained variance of 50% can be considered as good but leaves room for improvement. As the usage of AI within processes of a company is not only influenced by intentions of those individuals who make use of the AI, but also by decisions of the company as a whole, further research that not only includes individual perceptions (TPB), but also the broader organizational context, can improve predictability of an organization's intention to use AI even further. Concerning AI’s potential for innovating, the results of this study can serve as a basis for further research that investigates into the exact AI algorithms that can be used within each of the innovation tasks. Furthermore, this research could be expanded, by identifying first specific AI use cases in service and product development that organizations could run in the form of pilot projects, to approach this highly relevant topic.
Bibliography


Interview Guideline


In diesem Sinne bedanke Ich mich herzlich, dass Sie sich zu diesem Interview bereiterklärt haben. Die Befragung wird ca. 15 Minuten lang dauern. Ist es in Ordnung für Sie, dass ich unsere Konversation aufnehme? Selbstverständlich werden die gesammelten Daten streng vertraulich behandelt und nur in Rahmen dieser Masterarbeit verwendet. Haben Sie noch weitere Fragen bevor wir loslegen?

Ice- Breaker Questions:

1) Zu Beginn des Interviews möchte ich Sie bitte sich kurz vorzustellen. In welcher Industrie ist Ihr Unternehmen tätig und was ist Ihre Position darin?
2) Welche Erfahrungen haben Sie bisher mit künstlicher Intelligenz gemacht?

KI in Ihrer Organisation:

3) Wie intensiv nutzt Ihr Unternehmen derzeit KI?
4) Wie intensiv nutzt Ihr Unternehmen derzeit KI beim Innovieren?
5) Wie würden Sie das Potenzial von KI fürs Innovieren in Ihrem Unternehmen innerhalb der nächsten 5-10 Jahre bewerten?

Chancen und Risiken:

6) Welche Vorteile bringt die Verwendung von KI (beim Innovieren) Ihrer Meinung nach mit sich?
7) Welche Nachteile, Herausforderungen oder Barrieren verbinden Sie mit der Nutzung von KI? (im Innovationsbereich)
Einstellung gegenüber KI im Innovationsbereich:

8) Welches ist Ihre persönliche Einstellung gegenüber der Verwendung von KI? (Wie erachten Sie den Einsatz von KI?)


Potenzial von KI innerhalb des Innovationsprozesses:


11) Welche Rolle wird KI innerhalb der nächsten 5-10 Jahre beim Innovieren spielen? D.h. wie autonom glauben Sie wird KI künftig beim Innovieren agieren?
   (Level 1: KI wird assistierend wirken
   Level 2: Innovieren wird zwischen KI und Menschen aufgeteilt – der Mensch entscheidet
   Level 3: KI wird teil-autonom handeln, erfordert aber kontinuierliche menschliche Überwachung
   Level 4: KI wird autonom agieren und erfordert lediglich menschliche Unterstützung in bestimmten Notfallsituationen
   Level 5: KI wird vollständig autonom agieren - Kein menschliches Eingreifen erforderlich)

12) Welche KI Technologiesysteme nutzt Ihr Unternehmen derzeit oder plant sie zu nutzen? Welche davon haben Ihrer Meinung nach das größte Potenzial beim Innovieren eingesetzt zu werden?

Voraussetzungen für KI:

13) Welches sind Ihrer Meinung nach die wichtigsten Voraussetzungen, die ein Unternehmen erfüllen muss, um KI erfolgreich beim Innovieren zu nutzen?

14) Wie wird sich in Zukunft Ihrer Meinung nach die Zusammenarbeit zwischen Mensch und Maschine gestalten? Welche Vorteile als auch Nachteile könnten daraus resultieren?
Affidavit

I hereby declare that this Master’s thesis has been written only by the undersigned and without any assistance from third parties. I confirm that no sources have been used in the preparation of this thesis other than those indicated in the thesis itself.

This Master’s thesis has heretofore not been submitted or published elsewhere, neither in its present form, nor in a similar version.

Place

Date

Signature