Bachelorarbeit
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How does Artificial Intelligence impact on the economics of work?

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Abbreviations

AI	Artificial Intelligence
ANN	Artificial Neural Network
DL	Deep Learning
GTLRM	Grounded Theory Literature Review Method
IT	Information Technology
ML	Machine Learning
RBTC	Routine-Biased Technological Change
SLR	Systematic Literature Review

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1 Introduction

During the last years the importance of Information Technology (IT) systems in companies has become a key factor of success. Companies are forced by market mechanisms to reduce costs by implementing better algorithms for automating tasks (Brynjolfsson & McAfee2015, p. 9). Until recently these algorithms needed to be codified step by step using if-conditions and loops, which made it difficult to automate complex behavior. Due to the fast development in data, algorithms, networks, cloud and the exponential growth of computing power, breakthroughs have been reached in the field of Artificial Intelligence (AI) allowing to execute more complex tasks (Brynjolfsson & McAfee, 2017, pp. 95-108).

The use of AI is seen as the next industrial revolution. Recently Aritficial Neuronal Networks (ANN) are trained using Machine Leaning (ML) techniques to perform tasks that were not thought to be programmable before (Autor, 2014, p. 8). Additionally many trained ANNs have already shown that they can overtake professional humans in intricate tasks (Andreopoulos and Tsotsos, 2013, p. 827). Although there is no sign of any Artificial General Intelligence (AGI)[1] to be released in the near future, these AI systems[2] already raise concerns about the future of human labor and employment (Frey & Osborne, 2013, p. 1). Scientists do not have a homogeneous attitude towards the changes that will be driven by the increasing use of AI systems. Agrawal, Gans and Goldfarb (2017, p. 1) argue that the costs of 'prediction' will fall. Acemoglu and Restrepo draw a comparison to elapsed industrial revolutions regarding occupations that will become destinct and jobs that will be invented through technology enabled possibilities (2017b, p. 1). Frey and Osborne researched on job tasks and which occupational groups might be fully automatable with actual types of AI (2013, p. 44).

This leads to the research problem: There is no overview that includes the opinions that were published in 2017 and puts them into perspective with articles from the years before.

One striking question is whether intelligent machines will be able to perform every task better and faster than any human could do. Apart from this there is a high potential to increase overall productivity and welfare by using AI technology which drives development and research (Acemoglu & Restrepo, 2017b, p. 34).

Generally there are two parties on the job market, companies and workers. The key driver for companies is to implement AI to gain first mover advantages and not

[1] Here, the same as "Singularity".

[2] An IT system/robot that is controlled by an AI.

to loose the race against their competition (Brynjolfsson & McAfee2015, p. 9). On the one hand companies need an answer to the question what an investment into AI systems will entail as to calculate a trade-off between high investments and a final reduction of costs (Pratt, 2015, pp. 57-58). When labor is cheaper than implementing another AI they need to hire staff and when technical solutions offer a competitive advantage against human labor they need to fire (Pratt, 2015, pp. 57-58). The key driver for human workers regarding AI is to stay employed. They need to know whether their job will still be done by humans in the future and how the involving tasks might change. In case their job can be fully automated, human workers need to know what they can do to stay employed in a different job.

As mentioned before there are some articles that have been published during the last year that answer the concerns in different ways. Although systematic reviews enable to "speed up theoretical progress in the IS field" (Wolfswinkel, Furtmueller, and Wilderom, 2013, p. 2) there is no article that compares those new publications. This is the research problem for this thesis.

This document will provide an overview on actual research regarding the impact of AI on the labor market. Additionally it will compare different opinions and implications that the automation of tasks by AI systems will have and its influence on the economics of work.

To meet the expectations and to provide a profound thesis, the following three research questions shall lead the way to answer the overall title question "How does AI impact on the economics of work?":

1. "Which kind of tasks can now be automated that were not computable without ANN?"

2. "Where is the boundary of actual AI executing tasks or how can human labor stay ahead of the automation wave?"

3. "Does AI influence the way job acquisition will be done?"

Apart from company owners and workers the audience for this literature review is thought to come from economics, informatics or any other interested people.

The next section will cover the Literature Search containing the used sources, the Search Strategy for the research questions, the Search Results as well as the Data Extraction. After that in section 3 the findings summarized and put in contrast in a discussion (section 3). In section 4 the Conclusion will finally answer the research questions. Last in section 5 an Outlook will be presented including future research fields.

2 Literature Search

This section will describe the method of research used to find the sources which are used in the following chapters. To create a structured, detailed and repeatable Literature review, the eight stages "Systematic Literature Review" (SLR) scheme (Figure 1) from Okoli and Schabram (2010, pp. 6-7) is used.

The SLR scheme will be described until the next paragraph (Okoli & Schabram, 2010, pp. 6-7). The first stage is included in the introduction of this document and defines the research problem as well as the research questions. The second stage covers the definitions for a repeatable research, which is represented by the whole chapter two (Literature Search). In the third stage the databases and the search strings will be shown including the number of found articles by the queries. Following in the practical screen (stage four) the by the queries found articles will be reduced to those that matter regarding the quality characteristics. Additionally articles that are linked over references, that seem essential and meet the criteria will be added to the literature selection of articles. In stage five the selection will be examined on their content and put into a concept matrix (Webster & Watson, 2002, p. xvii) for a better overview and to prepare a well structured summary. After that the findings will be sorted (stage six) by different characteristics like content, scope or the release date (year), to prepare for a structured synthesis (stage seven), that will generate the striven value and both answer the research question and solve the research problem.

Figure 1: Literature Search Process

The last stage is covered by the final chapter of this document "Summary".
According to the eight stages (Okoli & Schabram, 2010, pp. 6-7), the chapter "Sources" will define the characteristics of important database sources and interesting articles. After that an appropriate search strategy will be defined to meet the research questions with useful search terms and a suited period of time. Thereby it is necessary not to reduce the scope dramatically as different views on the topic shall be contained in the results. Last it is reasonable to give an overview of the search results numbering relevant and not relevant documents by every step and to list the important results regarding their characteristics (year, review, content).

2.1 Sources

To find as many useful articles as possible the web application "LitSonar" from the University of Cologne is used. It provides the possibility to search in multiple common used databases (EBSCO (Business Source Complete & Academic Search Complete), IEEEXplore, ProQuest, ACM Digital Library, ScienceDirect & AISeL) simultaneously. With multiple databases the literature review will not be dependent on a single search engine algorithm and articles which might not be found by one Database are found in another.
The topic of this document has multiple influence factors which need to be covered by selecting appropriate Baskets of Journals. First there is a technical component like new algorithms etc. in the field of Information Systems (IS). This will be met by the "Senior Scholars' Basket of IS Journals", the "AIS Toplist" and "VHB-JOURQUAL 3". Second there is a business aspect as AI will reshape companies. To cover this part of business economics the baskets "Handelsblatt (BWL)", "VHB-JOURQUAL 2.1 (Electronic Commerce)" and "VHB-JOURQUAL 2.1 (Marketing)" are used. Third this technical improvement might have such a strong force that it will impact macroeconomics and will reshape the labor market or even force governments to become active. Due to this the baskets "Handelsblatt (BWL)" and "VHB-JOURQUAL 2.1 (ABWL)" are searched, too. These baskets ensure that the scope of each search will fit the requirements of this thesis. Please note, that the philosophical part will be neglected. The in the next step defined search queries take the full range of the mentioned databases and baskets of journals.
The newest wave of technological engineering is related to Artificial Neuronal Networks with Deep Learning (DL). The first systems solving complex tasks like

speech recognition appeared in 2009 (LeCun, Bengio and Hinton, 2015, p. 439). Hence, the literature search uses a primary search period of 17 years from 2000 to today (2017) to cover initial researches on this first step.

In advance to this thesis four documents have been read to gain some experience for choosing appropriate search strings.

(1) Brynjolfsson & McAfee (2017)
    Book: "Machine, Platform, Crowd: Harnessing Our Digital Future"

(2) Acemoglu & Restrepo (2017b)
    Journal Article: "THE RACE BETWEEN MACHINE AND MAN"

(3) Frey & Osborne (2013)
    Journal Article: "Future of Employment"

(4) Agrawal, Gans & Goldfarb (2017)
    Journal Article: "Prediction, Judgment and Uncertainty"

The found keywords ("AI" / "machine intelligence") are represented by the phrase "artificial intelligence". Keywords like ("work" / "task" / "job") are represented by the phrase "labor". These two phrases build the core of every search and are combined with the keywords "economy", "education", "employment", "prediction" and "automation".

The following table shows the search strings with their number of results.

Search String	**Results**	**Date**
artificial intelligence AND labor AND economy	42	04.12.2017
artificial intelligence AND labor AND education	31	04.12.2017
artificial intelligence AND labor AND employment	79	04.12.2017
artificial intelligence AND labor AND prediction	28	04.12.2017
artificial intelligence AND labor AND automation	130	05.12.2017
SUM	310	

Table 1: Query and Search Results

The results are listed before any adjustments, like filtering duplicates, have been made.

The individual preferences of each search can be accessed in a separate Excel sheet which documents the results in detail.

2.2 Search Strategy

Unfortunately it cannot be guaranteed that only important articles will be found by the initial queries and that all the essential articles will be found through the database search. Thats why the results need to be filtered first. To get a homogeneous quality and not to be dependent on the mood of any researcher the selection process needs to be defined and standardized, which shall be ensured by using the "Grounded Theory Literature Review Method" (GTLRM) with its five steps scheme (Wolfswinkel et al. , 2013, p. 2-9). The scheme is shown in Figure 2. The GTLRM scheme will be described until the next paragraph (Wolfswinkel et al. , 2013, p. 2-9).

The first three steps reduce the number of relevant articles. The fourth adds articles to the selection. In the last step the content of the final sample is structured and presented.
At the beginning there are X articles which are listed from the different queries and duplicates are filtered out ($X \geq A$). After that in step two the articles are screened based on their title and abstract ($A \geq B$). In the last filtering step the full text is used to define whether an article is important or not ($B \geq C$). The fourth step looks for influencing articles both forward and backward from references ($C \leq D$). If there were new articles coming up in the actual iteration of the four steps, there will be another round of filtering (input: $X = D$). If there was no new article, D equals the final number.

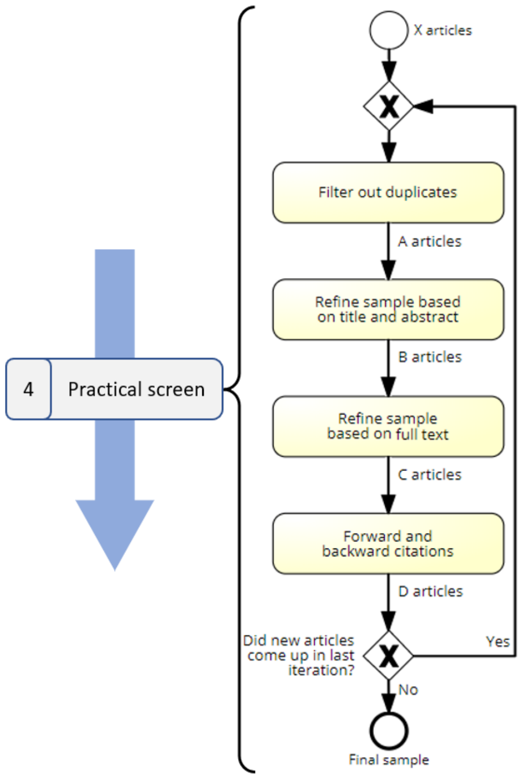

Figure 2: Grounded Theory Literature Review Method

Whereas step one and four are trivial, there needs to be a clear rule set for step two and three to ensure that only high quality literature such as peer reviewed articles will be used to prevent that high quality articles will not be lowered in their importance due to opinions from low quality publications. The 5th step will be represented by the section "Search Results".

The criteria for this literature review are defined as follows:
(1) Aspects of AI influencing the labor market
(2) Definitions of at least one of the following:
  (a) Benefits of AI labour
  (b) Benefits of human labour
  (c) Influence on the general labor market
  (d) Focus on multiple occupations
(3) The article must be "peer-reviewed". Second choices are conference papers and book chapters.
(4) The article must be out of a scientific journal OR meet at least basic requirements like citations and grounded (mathematical) reasoning.

Notice for the Search:
First, the influencing articles both from forward and backward are not necessarily required to meet the time slot (2000-2017) given into the queries. Nevertheless recent articles are more likely to fit in the scope due to the rapid technological change.
Second, "peer-reviewed" articles are counted with a high reliability. Conference papers and books are accounted for the least acceptable source to ensure the overall quality criteria.

To increase the transparency of this document, Figure 3 delivers an example for the filter and screening process of the article "Why are there still so many Jobs?" (Autor, 2015). The article is referenced as "input".

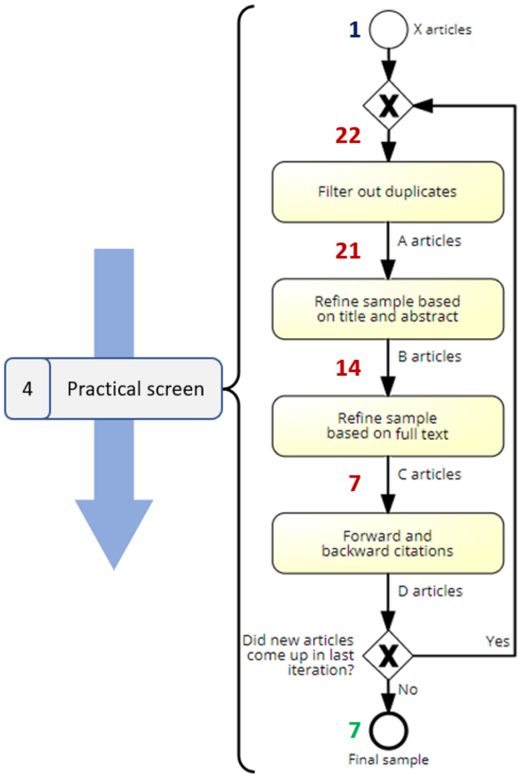

Figure 3: One Article, multiple Rounds (GTLRM)

In the references there are 21 new interesting articles. Including the input, 22 articles need to be filtered on duplicates. One was a duplicate to the complete database query sample and is therefore sorted out of the sample. After reading the abstracts 14 articles were left. The full text screening left six new articles, which led to the final sample of seven articles. Further forward and backward search rounds are not shown to reduce complexity.

For the full range of articles this process is shown in Figure 4. The queries delivered 310 articles, which could be reduced to 140 by filtering out duplicates. By screening title and abstract 80 articles were left. After reading the full text only 24 articles stayed in the scope. Although there were little more than ten articles that were found by forward and backward citations, most did not come up with new ideas to enrich the literature search. So the final sample comprises 34 articles. There are more articles that are cited especially for niche knowledge. Those resulted in single searches with special scopes to provide profound and detailed knowledge. The searches are documented in the Excel sheet (”AdditionalArticles”).

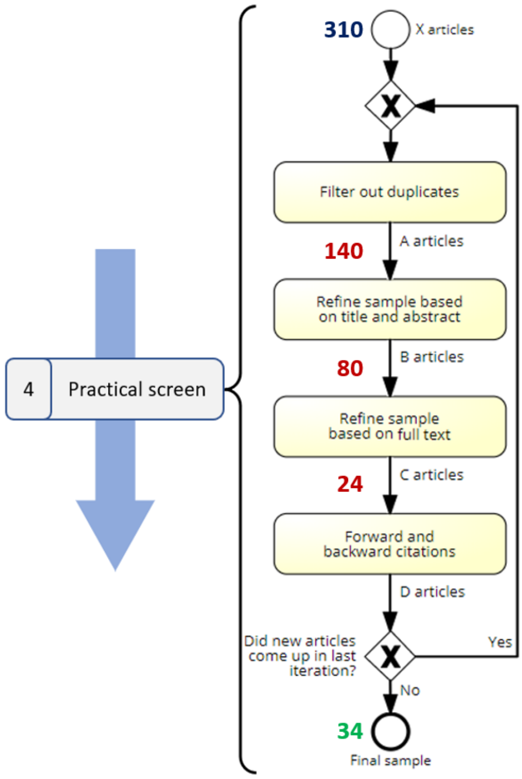

Figure 4: All Articles, one Round (GTLRM)

2.3 Search Results

The results from the database query have been screened on a clear position towards AI and labor as well as its influence on economy, education, employment, prediction and automation. This chapter represents the fifth stage ”Quality Appraisal” of the SLR (Okoli & Schabram, 2010, pp. 25-29). First it contains a concept matrix (Webster & Watson, 2002, p. xvii). Second the distribution of the literature in year, research field and kind of sources is expounded.

To ensure the quality and purposiveness of the articles the concepts are listed into a concept matrix. The concept matrix is a table which provides the general concepts that are delivered by the found articles (Webster & Watson, 2002, pp. xvi-xvii). It shall prepare for the data extraction in the chapter summary and help to better compare concepts instead of just summarizing the literature (Webster & Watson, 2002, pp. xvi-xvii). The found categories "Automation", "Artificial Intelligence (AI)", "Impact of AI on the Labor Market" and "Human Role" including their concepts are explained as follows.

1. Automation
   The category of automation is split into the concepts "Today" and "Near Future". The first concept represents facts form the last years in regard to automation and the development of work life. The second concept faces the development that might show up in the next five years.

2. Artificial Intelligence (AI)
   This category consists of the concepts "New Influence Factor", "Range of Influence" and "Border of Influence". The first category shows the new possibilities that AI-Systems bring to business. The second category describes how much impact this factor might have. Last the borders that seem to exist for an even broader impact are demonstrated in category three.

3. Impact of AI on the Labor Market
   The impact on the labor market is also split into three concepts ("Growing Market", "Equilibrium" and "Shrinking Market"). They shall benchmark whether new influencing factors lead towards more employment, to a massive unemployment or to something in between.

4. Human Role
   The last category takes a look at the "Skill Set & Education" that enable human workers to stay ahead of the automation and which market regulations could lead to an equitable distributed wealth between AI owners and simple workers?

For both writer and reader of the literature research it is desirable to identify those authors/articles which are deeply involved in this research area. Hence it gives a first glimpse of the core articles and the influencers of the field. Presumably those are the most cited articles, too. Therefore the more concepts are provided by an article, the higher the article is rated in its importance for the liteature search. In the concept matrix the importance is represented by "Hits".

There are nine concepts in sum. Hence an article has a high importance, if it contains six or more concepts. The share of important articles is six out of 35 which equals 17.14 %.

Following, the concept matrix is presented (Figure 5). It contains the articles represented by Author and Year and shows on which pages the single concepts can be found in each text.

Category		Automation		Artificial Intelligence (AI)			Impact of AI on Labor Market			Human Role	
Concept		Today	Near Future	New Influence Factor	Range of Influence	Border of Influence	Shrinking Market	Equilibrium	Growing Market	Skill set & Education	
Author	**Year**										Hits
Acemoglu and Restrepo	2017a		p. 32				p. 33				2
Acemoglu and Restrepo	2017b		p. 29	p.34		p. 4		p. 3			4
Aghion, Jones and Jones	2017			p.34				p.6	p. 41		3
Agrawal, Gans and Goldfarb	2017	p. 1	p. 1	p. 21	p. 21	p. 22	p.22		p. 9	p. 23	**8**
Akst, Daniel	2013			p. 12	p. 12		p.11			p. 13	4
Andreopoulos and Tsotsos	2013			p. 827	p. 873	p. 827			p. 884		4
Arntz, Gregory and Zierahn	2017		p. 0						p. 0	p. 6	3
Autor, David	2014	p. 8	p.39			p. 41	p. 14	p. 10	p. 14	p. 37	**7**
Autor, David	2015	p. 5	p. 4	p. 6	p. 9	p. 26			p. 12	p. 26	**7**
Bessen, James	2016	p. 30	p. 30		p. 31				p. 2		4
Borenstein, Jason	2010			p. 31			p. 31	p. 31			3
Brynjolfsson and McAfee	2015		p. 9				p. 11		p. 10	p. 12	4
Brynjolfsson and McAfee	2017	p. 16-17	p. 24	p. 58	p. 71	p. 85-86	p. 99	p. 101-102	p. 125	p. 125-126	**9**
Burke, Katie	2017		p. 2				p. 3	p. 2			3
Dau-Schmidt, Kenneth G.	2015									p. 1609	1
DeCanio, Stephen J.	2016			p. 38	p. 36-37		p. 39	p. 37-38		p. 39	5
Freeman, Richard	2015									p. 1	1
Frey and Osborne	2013	p. 45	p. 1	p. 15	p. 16	p. 18-19	p. 21-22	p.25	p. 24	p. 27	**9**
Goos, Manning, and Salomons	2014	p. 2524	p. 2520-2521								2
Grabner, Gall and Van Gool	2011					p. 8					1
Graetz and Michaels	2015	p. 21	p. 21								2
Hemous, David and Morten Olsen	2016						p. 44	p.44	p. 44	p. 44	4
Kaplan, Jerry	2016		p. 37-38	p. 38	p. 37	p. 37		p. 37	p. 37		**6**
LAU, MAK and NGAN	2002			p. 512							1
Nordhaus, William D	2015	p. 1	p. 41								2
OECD	2017			p.134-135							1
Pinney, Chris	2014		p.39								1
Pratt, G.A.	2015	p.52	p. 52	p. 53	p. 53-55	p. 59			p. 51	p. 58	**7**
Sachs, Benzell, and LaGarda	2015									p. 23	1
Scarpetta, Stefano	2016			p. 3						p. 3-4	2
Stringfield and Stone	2017									p. 177	1
Sundararajan, Arun	2017		p. 7			p. 7			p. 7	p. 11	4
Swanson, Jason	2017									p. 167-168	1
Thirgood and Johal	2017	p. 26	p. 26		p. 28	p. 31				p. 30	5
Yanagawa, Noriyuki	2016		p. 19	p. 18		p. 19	p. 19		p. 19	p. 19	**6**

Figure 5: Concept Matrix (Articles)

The second part of this chapter is the distribution of literature ordered by particular characteristics. First the distribution by year (release date) shall show the development of the research field. Second the research fields of the articles represent the broad or narrow scope of the field. Third the source will give more information about the foundation of the articles.

The used articles are distributed as shown in the following Figure 6.

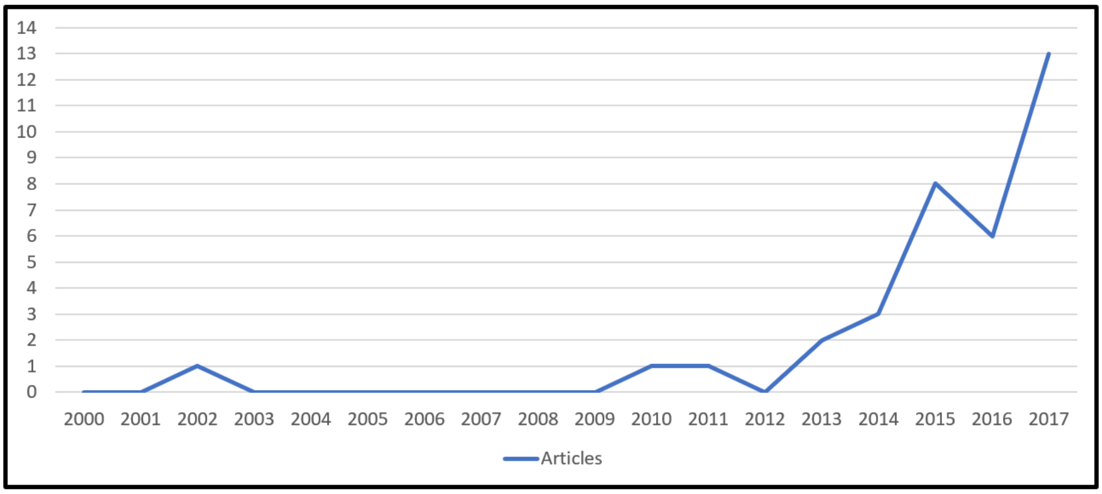

Figure 6: Articles, Distribution by Year

Although the field of work automation with IT already started before 1990, AI[3] was at that time "largely forsaken (...). It was widely thought that learning useful, multistage, feature extractors with little prior knowledge was infeasible" (LeCun, Bengio & Hinton, 2015, p. 438). Additionally the starting point for increased research was in 2009, when a neural network "achieved record-breaking results on a standard speech recognition benchmark" (LeCun et al., 2015, p. 438).

Therefore the used literature for this document is in the majority published after 2009. The distribution represents a living field of research with a fast development. This gives even more importance to this literature review as new articles arise every day and a published document becomes outworn after a short period of time. Additionally Moore's Law[4] is still valid (Holt, 2016, p. 10) and enables with its exponential acceleration the development of new/more powerful AI systems.

Research Field	Num
Economics	24
Education	1
Ethics	1
Information Technology	5
Politics	4
Sum	35

Table 2: Articles, Research Fields

[3] AI can be seen here as a generalization of neural networks or genetic algorithms (Lau, Mak & Ngan, 2002, p. 514)

[4] Back in 1965 Moore argued that engineers would be able to cram an ever-increasing number of electronic devices onto microchips. (Mann, 2000, p. 1) Indeed, he guessed that the number would roughly double every year—an exponential increase that has come to be known as Moore's Law (Mann, 2000, p. 1).

Therefore it is important to take a closer look at the current trend which is represented by the distribution of articles with its main focus on the last five years.

Next the articles are examined on their research field (Table 2). First this shall give an overview of the scope of the literature review. Now it is simple to distinguish whether the literature review focuses on a narrow or an interdisciplinary topic. Secondly it will provide the authors motivations and either tendency and potential bias of their research. It makes aware third of various techniques of research and providing information, as they occur in different research fields or as research can lack as it is context-relevant[5] (Rowley & Slack, 2004, p. 33). The exact linkage between articles and research fields can be accessed in the additional Excel-Sheet.

Before the found information will be presented, it is reasonable to give some insights on the recent technical development. This shall prepare and help the reader to understand the subsequent content more easily. It follows a classification of important terms.

1. Artificial Intelligence (AI)
   AI "can be defined as 'the capability of a machine to imitate intelligent human behavior' or 'an agent's ability to achieve goals in a wide range of environments' " (Aghion, Jones & Jones, 2017, p. 2).

2. Artificial Neural Networks (ANN)
   The biggest chance of creating an AI-System is currently seen in Artificial Neural Networks (ANN). ANNs consist "of many simple, connected processors called neurons" (Schmidhuber, 2017, p. 86) that imitate the basic structures of brains.

   To get a feeling for the broad impact of ANNs and the development of new applications, five examples (a-e) shall be delivered. They are devided by their environmental characteristics.
   In structured environments:
   (a) Instead of using well understood and mathmatically proofed structures, scientists used an ANN-System to speed up databases (Kraska, Beutel, Chi, Dean & Polyzotis, 2017). They could improve the performance by 28

[5] A panel research can be less reliable than a mathematically prooved research.

% (Kraska et al., 2017).
(b) In a Google Data Centre an ANN-System was used to reduce the energy needed for cooling. Before the process was driven by human knowledge and heuristics. The AI could reduce energy consumption by 40 %[6].
In fuzzy[7] environments:
(c) An ANN-System provides object detection for sorting plastic trash[8].
(d) A speech recognition ANN-System transcribes as well as a human[9].
In unstructured environments:
(e) The car manufacturer TESLA provides an autopilot that is using ANN techniques[10].

These examples will be later substantiated by the found articles.

3. Machine Learning (ML)
The ANN-structures become 'intelligent' due to ML algorithms (LeCun et al., 2015, p. 436). The current hype is especially based on Deep Learning (DL), which "has turned out to be very good at discovering intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government" (LeCun et al., 2015, p. 436).

4. Deep Learning & Data
"Deep Learning algorithms (...) learn and generalize their associations based on very large (...) 'training sets' that typically include millions of examples" (Pratt, 2015, p. 51). Usually the data needs to be prepared, but "human experts need many hours and days and weeks to annotate" (Schmidhuber, 2017, p. 86).

5. Artificial General Intelligence (AGI)
Some authors already mention AGI (Brynjolfsson & McAfee, 2017, p. 71, Nordhaus, 2017, p. 1), . It "can apply intelligence to a variety of unanticipated types of problems" (Brynjolfsson & McAfee, 2017, p. 71).
"It is 'merely an engineering problem', though certainly a very difficult

[6] https://deepmind.com/blog/deepmind-ai-reduces-google-data-centre-cooling-bill-40/
[7] "This means that the goals and/or the constraints constitute classes of alternatives whose boundaries are not sharply defined" (Bellman & Zadeh, 1970, p. B-141).
[8] https://iq.intel.com/dumpster-diving-robots-using-ai-for-smart-recycling/
[9] http://www.businessinsider.de/microsoft-research-beats-humans-at-speech-transcription-2017-8
[10] https://www.inc.com/kevin-j-ryan/how-tesla-is-using-ai-to-make-self-driving-cars-smarter.html

one." (Pennachin & Goertzel, 2011, p. 1). Nevertheless AGI is not in the scope of this literature review.

The found articles refer directly or indirectly to the technical developments of ANNs and DL. For not loosing importance in case of another technology which provides the same or even better results than ANNs, this literature review will keep in line with the general definition of AI (Aghion et al., 2017, p. 2).

2.4 Data Extraction

Now the sixth stage of the SLR scheme (Okoli & Schabram, 2010, pp. 6-7), the Data Extraction, is presented. The contents of the nine categories from the concept matrix will be illustrated one by one, expounding the units of analysis. This will show the importance of each article respective its quality. The content of each presented unit will be appropriate to the range of opinions in the articles. Hence the reader receives the including range between conservative and progressive attitudes regarding an unit and becomes enabled to benchmark opinions in the subsequent summary with discussion and in the final conclusion.

The units of analysis are all divided into eight topics, which are shown in the Figures (7-8 & 10-16). Articles that provide a topic are marked with 'X'. Please note, that firstly a single quote is mostly used for multiple units of analysis as they seldom cover only one aspect. Secondly, if an article is missing in the text, although it is marked in the figure, it was not forgotten. It is either a duplicate to another opinion, or will be mentioned in another section. This shall make it more comfortable for the reader and does not gloss over single opinions by general ones. If a topic is mentioned the first time, it is written in **bold**, afterwards it is written *italic.*

The first topic of the concept "Automation" represents the current status (Figure 7). The second topic represents the possible developments of Automation in the next five years (Figure 8).

As off **Today**, the AI struggles by interaction with the real world. There "are far more problems yet to be solved than ways presently known to solve them" (Pratt, 2015, p. 52). Still scientists question, whether an AGI system is reachable in the next years, as the "rapid growth in computation and artificial intelligence

Today	Agrawal, Gans and Goldfarb, 2017	Autor, David, 2014	Autor, David, 2015	Bessen, James, 2014	Brynjolfsson and McAfee, 2017	Frey and Osborne, 2016	Goos, Manning, and Salomons, 2016	Graetz and Michaels, 2015	Nordhaus, William D, 2017	Pratt, G.A., 2015	Thirgood and Johal, 2011
AI-Challenge: 'Real World'									X	X	
Decisions & Predictions	X										
Computing, Automation, AI & Robots		X	X	X	X	X		X	X	X	
Everyday (working life)		X			X		X				
Politics & Macroeconomics				X							
Education, Occupation & Skill							X	X			X
Productivity & Microeconomics		X	X	X		X		X			
Work acquisition & Wages		X	X			X	X				X

Figure 7: Automation: Today

will cross some boundary or Singularity" (Nordhaus, 2017, p. 1).

Today we speak about automation as replacing human labor by robotics and calculations. It increases "labor productivity and value" (Graetz & Michaels, 2015, p. 21). Although it is linked with the fear of reduction of labor, automation complements labor and "raises output in ways that lead to higher demand for labor" (Autor, 2014, p. 5). Additionally "labor saving inventions may only be adopted if the access to cheap labor is scarce or prices of capital are relatively high (Habakkuk, 1962)" (Frey & Osborne, 2013, p. 42). That way automation leads to "small increase in employment on average" (Bessen, 2016, p. 30) and does not lead to "major job losses" (Bessen, 2016, p. 30).

The previous facts influence the areas of automation, working life, occupations and wages, but there is a macroeconomic aspect, too. This automation driven process is called "Job Polarization" (Goos, Manning & Salomons, 2014, p. 2524). "The employment structure in Western Europe has been polarizing with rising employment shares for high-paid professionals and managers as well as low-paid personal service workers and falling employment shares of manufacturing and routine office workers." (Goos et al., 2014, p. 2524). Frey and Osborne refer to this as a "hollowing-out of middle-income jobs" (2013, p. 42).

Anyway, workers and machines are decoupled and "companies need to rethink the balance between minds and machines" (Brynjolfsson & McAfee, 2017, p. 15). Agrawal, Gans and Goldfarb (2017, p. 1) follow this call. They argue that AI transforms computer calculations into a "prediction technology".

That will lead in the **Near Future** (Figure 8) to broad "improved prediction in decision-making" (Agrawal et al., 2017, p. 1).

Near Future	Acemoglu and Restrepo, 2017a	Acemoglu and Restrepo, 2017b	Agrawal, Gans and Goldfarb, 2017	Arntz, Gregory and Zierahn, 2017	Autor, David, 2014	Autor, David, 2015	Bessen, James, 2014	Brynjolfsson and McAfee, 2015	Brynjolfsson and McAfee, 2017	Frey and Osborne, 2016	Goos, Manning, and Salomons, 2016	Graetz and Michaels, 2015	Kaplan, Jerry, 2017	Burke, Katie, 2015	Nordhaus, William D, 2017	Pinney, Chris, 2015	Pratt, G.A., 2015	Sundararajan, Arun, 2016	Thirgood and Johal, 2011	Yanagawa, Noriyuki , 2010
AI-Challenge: 'Real World'	X										X		X		X		X			
Decisions & Predictions			X																	
Computing, Automation, AI & Robots	X		X		X	X			X		X	X	X		X	X	X			X
Everyday (working life)	X	X			X		X				X			X				X		X
Politics & Macroeconomics	X			X			X	X			X									
Education, Occupation & Skill		X	X		X		X		X	X	X		X	X		X		X	X	X
Productivity & Microeconomics	X	X		X		X			X			X								
Work acquisition & Wages		X		X	X		X			X	X		X	X				X	X	

Figure 8: Automation: Near Future

The learning process of this technology "has actually become simpler as performance has improved" (Pratt, 2015, p. 52). In the opinion of Acemoglu and Restrepo this will lead to industrial robots which will "spread rapidly in the next several decades and assume tasks previously performed by labor" (2017a, p. 32). Autor calls the development a "possibility of replacing labor on a scale not previously observed" (2015, p. 4).
But still, not only the (unstructured) real world stays an obstacle for AI, social abilities are challenging, too. Although it "is not to say that machines will never sense or express emotions; indeed, work on affective computing is proceeding rapidly. The question is how these capabilities will be perceived by users. If they are understood simply as aids to communication, they are likely to be broadly accepted. But if they are seen as attempts to fake sympathy or allay legitimate concerns, they are likely to foster mistrust and rejection" (Kaplan, 2017, p. 37). This is accentuated by Nordhaus's final statement, that AGI "is not near" (2017, p. 42).
Hence the focus of this thesis is driven by Routine-Biased Technological Change (RBTC), which is described by Goos, Manning and Salomons as follows:

"RBTC will typically cause less routine employment to be used in the production of a given level of output, so differences in routineness across industries will cause industry employment shares to change even if industry output shares do not" (2014, pp. 2520-2521). Thus not every occupation is tackled the same, the majority persists of "a mixture of tasks from across the skill spectrum" (Autor, 2014, p. 39). As robot density increases, workers "will be freed from the drudgery of performing dangerous or boring jobs, allowing them to pursue or create more personally rewarding forms of work while the relative cost of many essential goods become cheaper" (Pinney, 2014, p. 39). Brynjolfsson and McAfee state that "the successful companies (...) will be those that bring together minds and machines (...) very differently than most do today" (2017, p. 24).

Yanagawa (2016, p. 19) delivers (in Figure 9) an example how working life might look like. He estimates human tasks as a controlling entity as well as an instance adding value to a standard procedure and communication which requires social skills.
As "computers can process information many times faster than humans" (Burke, 2017, p. 2), AI does the high frequent work. But humans are needed to fix wrong outputs. The results are still dependent on the fed data and "learning is still gradual and can be thrown off by incorrect or inaccurate information" (Burke, 2017, p. 2).

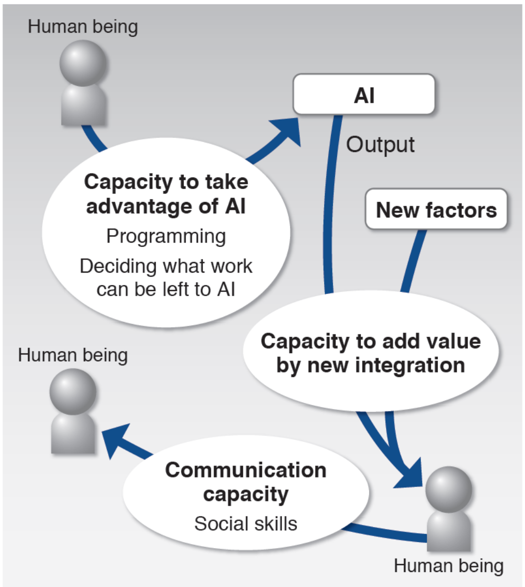

Figure 9: Humans working next to AI (Yanagawa, 2016, p. 19)

But the possibility of unemployment due to the use of AI raises the question how strong the impact might be. Frey and Osborne found that "around 47 percent of total US employment is in the high risk category." (2013, p. 44). In turn Arntz, Gregory and Zierahn relate to Frey and Osborne's research (Arntz, Gregory & Zierahn, 2017, p. 0). They did not put their focus on whole occupations, but on single tasks within occupations. If occupations are only partially

automated by AI, "automation risk of US jobs drops (...) to 9 %" (Arntz et al., 2017, p. 0).
Anyway, "computer automation is linked to job losses for low-wage jobs and job gains for high-wage occupations. That is, computer automation is implicated in a major reallocation of labor across occupations" (Bessen, 2016, p. 30). Some will state that the work is gone forever (Brynjolfsson and McAfee (2015, p. 9), but Brynjolfsson and McAfee argue that "there is no static ?lump of labor,? since the amount of work available to be done can increase without bound"[11] (2015, p. 9)[12].
But what will happen to those who loose their job? Sundararajan estimates "short-term freelance relationships rather than (...) full-time employment" (2017, p. 7). Digital Disruption transforms the well known career to short term contracts (Thirgood & Johal 2017, p. 27). "For all its benefits, however, technology has begun to reshape the labour market and accelerate a shift away from the traditional standard employment relationship." (Thirgood & Johal 2017, p. 27).

The second category, Artificial Intelligence, follows. AI's role is split into the **New Influence Factor** (Figure 10) , the **Range of Influence** (Figure 11) and **Border of Influence** (Figure 12). This category is driven by the question: "What does AI provide?".

[11] Brynjolfsson and McAfee consolidate this statement by quoting Alfred Marshall's (1890) book, Principles of Economics, "Human wants and desires are countless in number and very various in kind." (2015, p. 9)

[12] The questionmarks belong to the original quote.

New Influence Factor	Acemoglu and Restrepo, 2017b	Aghion, Jones and Jones, 2017	Agrawal, Gans and Goldfarb, 2017	Akst, Daniel, 2013	Andreopoulos and Tsotsos, 2013	Autor, David, 2015	Borenstein, Jason, 2015	Brynjolfsson and McAfee, 2017	DeCanio, Stephen J. , 2014	Frey and Osborne, 2016	Kaplan, Jerry, 2017	LAU, MAK and NGAN, 2016	OECD, 2017	Pratt, G.A., 2015	Scarpetta, Stefano, 2017	Yanagawa, Noriyuki , 2010
AI-Challenge: 'Real World'			X		X		X		X	X		X		X		
Decisions & Predictions			X		X			X								
Computing, Automation, AI & Robots			X		X		X		X	X		X		X		X
Everyday (working life)						X	X			X			X		X	X
Politics & Macroeconomics	X	X		X												
Education, Occupation & Skill	X	X			X						X	X	X			X
Productivity & Microeconomics		X					X	X		X					X	X
Work acquisition & Wages	X	X		X	X		X			X			X		X	X

Figure 10: Artificial Intelligence: New Influence Factor

In regard to Moore's law and calculation speed "there have been no signs of a slowdown (...) and there is every reason to expect that this kind of growth will continue." (DeCanio, 2014, p. 38).
As a *New Influence Factor* Andreopoulos and Tsotsos "demonstrate that the performance of such systems in strictly controlled environments often vastly outperforms the capabilities of the human visual system" (2013, p. 827).
Due to its ability of "improved prediction" (Agrawal et al., 2017, p. 1) and improved decisions (Brynjolfsson & McAfee, 2017, p. 58), AI "is now spreading to domains commonly defined as non-routine", turning "non-routine tasks into well-defined problems" (Frey & Osborne, 2016, p. 15). Then AI systems can do more then just "dull, dirty and dangerous tasks" (Borenstein, 2016, p. 31). Yanagawa describes this as follows: "it is impossible for computers or robots to be perfectly independent from human beings and work at their own will and consequently take human beings' jobs. So it should be noted, first of all, that AI or robots will not take human beings' jobs but the people using them will take other people's jobs" (2010, p.18). Additionally Kaplan says, "Good products, including increasingly autonomous machines and applications, don't go haywire unless we design them poorly." (2017, p. 38), but still "we need to develop engineering standards for increasingly autonomous systems, perhaps by borrowing concepts from other potentially hazardous fields such as civil engineering" (Kaplan, 2017, p. 38).
Still AI is far more complex than systems that are designed by humans and "the creditability of automated systems is not easily measurable" (Lau et al., 2016, p.

512). In case of failure, humans need to fix the AI (Yanagawa, 2016, p. 19). Complementary to Figure 9 this case illustrates Autors observation that "journalists and expert commentators overstate the extent of machine substitution for human labor and ignore the strong complementarities" (2014, p. 1). And still the "vast amounts of data" (Carey, 2017, p. 135) for AI training need to be generated.
Firms will recognize different forces. Aghion, Jones and Jones mention three ways. First the "wage gap between skilled and unskilled labor" (Aghion et al., 2017, p.34) will increase, second "the introduction of A.I. allows firms to automate and dispense with middle-men performing monitoring tasks (in other words, firms should become flatter, i.e. with higher spans of control)" (Aghion et al., 2017, p.34) and third AI "should encourage self-employment by making it easier for individuals to build up reputation" (Aghion et al., 2017, p.34). The last idea is also described by Scarpetta, too, as the "flourishing of the 'gig', 'on-demand', 'sharing', 'peer-to-peer' or 'platform' economy" (2017, p. 3). "Though still small in scale, the platform economy raises probing questions about wages, labour rights and access to social protection for workers, as well as employers and consumers" (Scarpetta, 2017, p. 3).
Hence the job polarization, "makes us better off collectively by making some of us worse off" (Akst, 2013). Acemoglu and Restrepo describe this as follows: Even "though automation expands productivity—a force which always raises welfare—it also reduces employment." (2017b, p. 34)

The *Range of Influence* (Figure 11) is expanded as follows: There are "Eight Technical Drivers" (Pratt, 2015, p. 53) that push robots and AI forwards in huge steps. These "drivers" (Pratt, 2015, p. 53) are "1) Exponential growth in computing performance (...) 2) Improvements in electromechanical design tools and numerically controlled manufacturing tools (...) 3) Improvements in electrical energy storage (...) 4) Improvements in electronics power efficiency (...) 5) Exponential expansion of the availability and performance of local wireless digital communications (...) 6) Exponential growth in the scale and performance of the Internet (...) 7) Exponential growth of worldwide data storage (...) 8) Exponential growth in global computation power" (Pratt, 2015, pp.53-55). "The use of big data is afforded by one of the chief comparative advantages of computers relative to human labor: scalability" (Frey & Osborne, 2016, p.16). Agrawal, Gans and Goldfarb state "that as AI improves, tasks in more complex environment can be handled by machines" (2017, p. 21). The only pitfall is that the input data must

Range of Influence	Agrawal, Gans and Goldfarb, 2017	Akst, Daniel, 2013	Andreopoulos and Tsotsos, 2013	Autor, David, 2015	Bessen, James, 2014	DeCanio, Stephen J. , 2014	Frey and Osborne, 2016	Kaplan, Jerry, 2017	Pratt, G.A., 2015	Thirgood and Johal, 2011
AI-Challenge: 'Real World'	X		X				X		X	
Decisions & Predictions	X								X	
Computing, Automation, AI & Robots	X		X				X	X	X	
Everyday (working life)					X	X		X		X
Politics & Macroeconomics		X		X						
Education, Occupation & Skill			X	X	X	X		X		X
Productivity & Microeconomics	X						X		X	X
Work acquisition & Wages		X		X	X	X				X

Figure 11: Artificial Intelligence: Range of Influence

be good. "An example of this problem arose in early research on neural networks, where the task was to train a neural network to determine the presence or absence of a certain vehicle type in images. The neural network was initially capable of reliably detecting the objects of interest from the images of the original dataset. However, on a new validation dataset of images, the performance dropped drastically." (Andreopoulos & Tsotsos, 2013, 873). Anyway, "as of 2016, AIs are able to drive cars and trucks, defeat human champions in chess, checkers, Jeopardy!, Scrabble, and Go, take orders and serve food in restaurants, teach exercise classes in a retirement home, advise doctors on symptoms and treatments of particular diseases, deliver packages, take the place of welders, inspect dangerous offshore oil rigs, and write political speeches" (DeCanio, 2014, pp. 35-36). "In other words, automation and AI have reached a level at which cognitive human functions can be easily replicated and replaced, even in traditionally white-collar cognitively based careers" (Thirgood & Johal, 2011, p. 28).
Considering this, even "if automation does not reduce the quantity of jobs, it may greatly affect the qualities of jobs available" (Autor, 2014, p. 9). At least, "its useful to observe that we don't actually automate jobs, we automate tasks" (Kaplan, 2017, p.37). But still this will lead to the requirement of "new skills that are difficult to acquire" (Bessen, 2014, p. 31).

The *Border of Influence* (Figure 12) is the last part about AIs capabilities and shall sketch out AI's limits.
Although there are many examples which make believe that AI and "robots of

Border of Influence	Acemoglu and Restrepo, 2017b	Agrawal, Gans and Goldfarb, 2017	Andreopoulos and Tsotsos, 2013	Autor, David, 2014	Autor, David, 2015	Brynjolfsson and McAfee, 2017	DeCanio, Stephen J. , 2014	Frey and Osborne, 2016	Grabner, Gall and Van Gool, 2017	Kaplan, Jerry, 2017	Pratt, G.A., 2015	Sundararajan, Arun, 2016	Thirgood and Johal, 2011	Yanagawa, Noriyuki , 2010
AI-Challenge: 'Real World'			X	X	X		X		X					
Decisions & Predictions	X		X											
Computing, Automation, AI & Robots	X	X		X	X		X		X					
Everyday (working life)	X					X		X		X		X	X	X
Politics & Macroeconomics		X									X			
Education, Occupation & Skill	X		X	X	X	X		X	X	X		X	X	X
Productivity & Microeconomics							X				X			
Work acquisition & Wages	X					X		X		X		X	X	X

Figure 12: Artificial Intelligence: Border of Influence

various types are likely to become ubiquitous (...) by mid-century" (DeCanio, 2014, p. 36), there are some abilities which still face great hurdles.
Autor says that AI does not detect "purposiveness" (2014, p. 26) and refers to Grabner, Gall and Van Gool who explain: "Objects are usually made for some purpose. Hence, the functionality often is the most obvious common denominator for the members of an object class. We have proposed an affordance detector where functionality is handled as a cue complementary to appearance, rather than being a consideration after appearance-based detection" (2017, p. 8). This means, that humans can detect an objects purpose out of its delivered value, rather than out of its shape (Grabner et al. 2017, p. 8).
Brynjolfsson and McAfee describe the situation as follows "Machine learning systems (and all other forms of AI) still lack common sense" (2017, p. 86). Agrawal, Gans and Goldfarb argue "that it is for more complex tasks that humans have a comparative advantage relative to machines" (2017, p. 22), as long as there is no particular default or heuristic used (2017, p. 22). Autor adds: "I expect that a significant stratum of middle skill, non-college jobs combining specific vocational skills with foundational middle skills—literacy, numeracy, adaptability, problem-solving and common sense—will persist in coming decades" (2014, p. 41). This is why Acemoglu and Restrepo "assume that skilled labor has a comparative advantage in new tasks" (2017b, p. 4). Especially for projects, where "site and environmental conditions, safety, interested third parties, and other factors that are likely to influence" (Ballard, Tommelein & Whelton, 2002, p. 4) the work,

interrupt a limited AI perception, these human advantages will turn up to be predominant. In this regard, Sundararajan expects "a labor market in which full-time jobs may be broken up into tasks and projects" (2016, p. 7). Additionally Yanagawa says "that social skills such as communication or team work are much less likely to be replaced by AI, and that in fact jobs requiring such social skills are increasing" (2010, p. 19). Next to team work and projects, an "unstructured work environment can make jobs less susceptible to computerisation" (Frey & Osborne, 2016, p. 25). Furthermore, "except as a novelty, who wants to watch a selfdriving racecar, or have a mechanical bartender ask about your day while it tops up your drink? Lots of professions require these more social skills, and the demand for them is only going to grow as our disposable income increases" (Kaplan, 2017, p. 37).
Reaching the end of the concept *Border of Influence*, there is one more opinion to be quoted. "Social and emotional intelligence are skills that have not yet been mastered by AI; adaptability, creativity, and a desire for constant learning will be beneficial in a rapidly changing environment; and computational and analytical thinking will be necessary to design and complement new technologies." (Thirgood & Johal, 2011, p. 31).

As the influence factors of AI are expounded, the effects on the labor market will be shown in the categories **Shrinking Market**, **Equilibrium** and **Growing Market**.

The first category regarding the labor market, *Shrinking Market* (Figure 13) represents the downsides of AI and automation including mass unemployment (Acemoglu and Restrepo, 2017a, pp. 36-37).

There will be more automation than only where "the work is dull, dirty, dangerous, and dear" (Brynjolfsson & McAfee, 2017, p. 99). Agrawal, Gans and Goldfarb order tasks "in terms of diminished likelihood" of automation by AI (2017, p. 22). "The lowest index states might be ones that, because they arrive frequently, there is knowledge of what the optimal action is in each and so they can be programmed to be handled by a machine. The highest index states similarly, because the optimal action cannot be determined can also be programmed. It is the intermediate states that arise less frequently but not infrequently where, if a reliable prediction existed, could be handled by humans applying judgment when those states arose" (Agrawal et. al., 2017, p. 22).

Shrinking Market	Acemoglu and Restrepo, 2017a	Agrawal, Gans and Goldfarb, 2017	Akst, Daniel, 2013	Autor, David, 2014	Borenstein, Jason, 2015	Brynjolfsson and McAfee, 2015	Brynjolfsson and McAfee, 2017	DeCanio, Stephen J. , 2014	Frey and Osborne, 2016	Hemous, David and Morten Olsen, 2002	Burke, Katie, 2015	Yanagawa, Noriyuki , 2010
AI-Challenge: 'Real World'		X									X	
Decisions & Predictions		X										
Computing, Automation, AI & Robots	X	X	X	X	X	X	X		X	X	X	
Everyday (working life)	X			X			X	X				
Politics & Macroeconomics	X		X							X		
Education, Occupation & Skill			X	X			X	X		X		X
Productivity & Microeconomics	X				X	X			X		X	
Work acquisition & Wages	X			X				X	X	X		

Figure 13: Labor Market: Shrinking Market

Hence, "tasks to be handled by machines (...) might create the economic conditions" (Agrawal et. al., 2017, p. 23) that the "drive for efficiency" (Borenstein, 2015, p. 31) will not only complement "middle and low-skilled blue-collar occupations" (Autor, 2014, p. 13). "Instead of automating repetitive tasks, technology today is climbing the cognitive ladder, using artificial intelligence and brute processing power to automate (however imperfectly) the functions of travel agents, secretaries, tax preparers, even teachers—while threatening the jobs of some lawyers, university professors, and other professionals who once thought their sheepskins were a bulwark against this sort of thing" (Akst, 2013, p. 11).
But what about the "detailed data annotation" (Burke, 2015, p. 1)? "Experts envision an even more efficient future, in which" (Burke, 2015, p. 3) AI "can learn and adapt to new situations on their own, cutting humans out of the loop" (Burke, 2015, p. 3). Brynjolfsson and McAfee state that there "is a real possibility that (...) labor will, in aggregate, decline in relevance because of technological progress" (2015, p. 11).
Regarding AI and robots: "Most likely, there will be even faster growth ahead as low-priced general-purpose models (...) are adopted in simple manufacturing and service work" (Frey & Osborne, 2016, p. 22). "With expanding computational capabilities, resulting from technological advances, and a falling market price of computing, workers in susceptible tasks will thus reallocate to nonsusceptible tasks" (Frey & Osborne, 2013, p. 23). "According to our estimates, about 47

percent of total US employment is at risk" (Frey & Osborne, 2013, p. 1). Therefore the expansion "of AIs' skill sets (...) is likely to depress wages over time" (DeCanio , 2014, p. 38).
Thirgood and Johal see a shift in the human career though the rising importance of AI (2017, p. 27). Traditional full-time and part-time jobs will transform to short term contracts or projects (Thirgood & Johal, 2017, p. 27). Further they forecast the disruption to even break up projects into tasks and micro-tasks until the hybrid tasking (with AI) will terminate with fully automated work (Thirgood & Johal, 2017, p. 27). Especially if the "speed of the changes" (Yanagawa, 2010, p. 19) is significantly fast, the negative impact will be "the direct displacement of workers by robots" (Acemoglu & Restrepo, 2017a, p. 33).

Following, those opinions that state an *Equlibrium* regarding the amount of available human labor (Figure 14) are presented.

Equilibrium	Acemoglu and Restrepo, 2017b	Aghion, Jones and Jones, 2017	Autor, David, 2014	Borenstein, Jason, 2015	Brynjolfsson and McAfee, 2017	DeCanio, Stephen J. , 2014	Frey and Osborne, 2016	Hemous, David and Morten Olsen, 2002	Kaplan, Jerry, 2017	Burke, Katie, 2015
AI-Challenge: 'Real World'				X	X		X			X
Decisions & Predictions							X			
Computing, Automation, AI & Robots	X			X	X		X	X		X
Everyday (working life)		X			X	X			X	X
Politics & Macroeconomics	X		X			X			X	
Education, Occupation & Skill		X				X			X	X
Productivity & Microeconomics	X	X	X		X					X
Work acquisition & Wages	X	X	X			X		X	X	

Figure 14: Labor Market: Equilibrium

Borenstein says that "financial considerations, the drive for efficiency, and overconfidence in technology are strong driving forces that can push humans 'out of the loop.' " (2015, p. 31). To put this in perspective, he adds: "Placing too much confidence in technology, often at the expense of other sources of information, seems to be a growing problem" (Borenstein, 2015, p. 31). Frey and Osborne also see a big hurdle for AI, too: "The difficulty of perception has ramifications

for manipulation tasks, and, in particular, the handling of irregular objects, for which robots are yet to reach human levels of aptitude. This has been evidenced in the development of robots that interact with human objects and environments. While advances have been made, solutions tend to be unreliable over the myriad small variations on a single task, repeated thousands of times a day, that many applications require" (2013, p. 25). This problem leads to the thought: "Perhaps we are inventing new tasks just as quickly as we are automating old tasks. The fraction of tasks that are automated could be constant, leading to a stable capital share and a stable growth rate" (Aghion et al., 2017, p. 6).
In this case it does not matter whether humans will work (...) side by side with" (Brynjolfsson & McAfee, 2017, p. 102) robots or provide "detailed data annotation" (Burke, 2015, p. 1). Kaplans idea is that humans can operate in "professions that rely (...) on building trust or rapport with other people" (2017, p. 37).
In the big picture "the elasticity of final demand can either dampen or amplify the gains from automation. Conceivably, productivity growth in construction could outstrip demand so that the value of further construction would fall even faster than output rose. But this hypothetical response cannot capture the general case. Because household consumption has at least kept pace with household incomes over the very long run, we know that most technological improvements have ultimately translated into increased consumption rather than greater savings" (Autor, 2014, p. 10). "Perhaps more importantly, proliferation of AI might shift workers' preferences in the direction of offering less labor to the market for any given wage, because robots could take over some of the tasks that are now frequently purchased. Availability of low-cost household robots could reduce the need to earn money income to hire house cleaning or elder care services" (DeCanio, 2014, pp. 37-38).
Arntz, Gregory and Zierahn researched on the impact of AI on employment and choose an approach on tasks, showing that, comparatively, only 9 % of occupations are at risk (2017, p. 0). This lowers the estmation of "47 percent" (Frey & Osborne, 2013, p. 1) significantly.
Even if the amount of automation is higher, Acemoglu and Restrepo argue that the "stability of the balanced growth path implies that periods in which automation runs ahead of the creation of new tasks tend to trigger self-correcting forces, and as a result, the labor share and employment stabilize and may even return to their initial levels. Whether or not this is the case depends on the reason why

automation paced ahead in the first place” (2017b, p. 3).

Although there have been some opinions that predict mass unemployment, *Growing Market* (Figure 15) provides such views that imply a growing human labor market.

Growing Market	Aghion, Jones and Jones, 2017	Agrawal, Gans and Goldfarb, 2017	Andreopoulos and Tsotsos, 2013	Arntz, Gregory and Zierahn, 2017	Autor, David, 2014	Autor, David, 2015	Bessen, James, 2014	Brynjolfsson and McAfee, 2015	Brynjolfsson and McAfee, 2017	Frey and Osborne, 2016	Hemous, David and Morten Olsen, 2002	Kaplan, Jerry, 2017	Pratt, G.A., 2015	Sundararajan, Arun, 2016	Yanagawa, Noriyuki , 2010
AI-Challenge: 'Real World'			X			X			X		X		X		
Decisions & Predictions		X													
Computing, Automation, AI & Robots					X		X		X						
Everyday (working life)	X	X	X	X	X	X		X		X	X	X	X	X	X
Politics & Macroeconomics				X			X			X					
Education, Occupation & Skill	X	X	X	X	X	X		X		X	X	X	X	X	X
Productivity & Microeconomics	X								X		X	X			
Work acquisition & Wages	X	X	X			X		X		X	X	X		X	X

Figure 15: Labor Market: Growing Market

At first Bessen states that ”computer use is associated with about a 1.7 % increase in employment per year. This association is true in general and also for occupations that perform more routine tasks and for mid-wage occupations” (2016, p. 2). Further Andreopoulos and Tsotsos research ”led to the realization that more control over the data acquisition process is needed” (2013, p. 884), which can employ many people as the training sets ”typically include millions of examples.” (Pratt, 2015, p. 51). In his article from 2015, Autor determines that there are two job categories: ”One category includes tasks that require problem-solving capabilities, intuition, creativity, and persuasion. These tasks, which we term ’abstract,’ are characteristic of professional, technical, and managerial occupations. They employ workers with high levels of education and analytical capability, and they place a premium on inductive reasoning, communications ability, and expert mastery. The second broad category includes tasks requiring situational adaptability, visual and language recognition, and in-person interactions—which we call ’manual’ tasks” (p. 12). In his article from 2014 he stresses that ”workers benefit from automation if they supply tasks that are complemented by automation" (p. 10). Brynjolfsson and McAfee find even more possibilities for employment. "There are impressive examples of digital creativity and innovation, including machine-generated music and scientific hypotheses, humans are still better at coming up with useful new ideas in most domains." (2015, p. 10) Additionally they argue in their book that "computers still don't really understand the human condition, since they don't experience the world" (2017, p. 125). Hence the "approach is to have the machine take the 'busywork' "(Brynjolfsson & McAfee, 2017, p. 125). Agrawal, Gans and Goldfarb argue "that AI is a prediction technology" (2017, p. 26), but "predictions cannot be valued in the absence of knowing how payoffs arise" (Agrawal et al., 2017, p. 26). Hence the knowledge of payoffs and the adjustments to the AI are up to humans. Additionally, "judgment can delay a decision (and that is costly) and it can improve that decision (which is its value) but it cannot generate experience that can be applied to other decisions (including future ones)" (Agrawal et al., 2017, p. 10). Therefore human labor will stay important.

Yanagawa links a high adaptable skill set with human workers (2016, p. 19). "We are experiencing very rapid changes in addition to longer life spans than ever, and so we need to acquire new skills whenever they are necessary, no matter how old we may be" (Yanagawa, 2016, p. 19). In Aghion, Jones and Jones opinion this skill set and AI favor "the development of self-employment" (Aghion et al., 2017, p. 41).

Hemous and Olsen operate in a broader scope. They "introduced automation in a horizontal innovation growth model" (Hemous & Olsen, 2002, p. 44), which consists of three phases: "After an initial phase with stable income inequality and stable factor shares, automation picks up. During this second phase, the skill premium increases, low-skill wages stagnate and possibly decline, the labor share drops—all consistent with the US experience in the past 50 years—and growth starts relying increasingly on automation. In a third phase, the share of automated products stabilizes, but the economy still features a constant shift of low-skill employment from recently automated firms to as of yet non-automated firms. With a constant and finite aggregate elasticity of substitution between low-skill workers and machines, low-skill wages grow in the long-run. Wage polarization can be accounted for once the model is extended to include middle-skill workers." (Hemous & Olsen, 2002, p. 44). Sachs, Benzell, and LaGarda describe this as follows: As workers "produce outputs that are imperfect substitutes of the outputs of robots, workers will experience a rise in demand for their products, and this can result in a virtuous circle of rising wages, savings, and production, producing the openended constant growth" (Sachs, Benzell, & LaGarda, 2015, p.23). Hence, the "extent of computerisation in the twenty-first century will thus partly depend on innovative approaches to task restructuring" (Frey & Osborne, 2016, p.24) and enables human "to perform ever more ambitious tasks" (Kaplan, 2016, p.37).

Subsequently the last category **Skill Set & Education** (Figure 16) will be presented. It will show opinions regarding the human role.

Skill set & Education	Agrawal, Gans and Goldfarb, 2017	Akst, Daniel, 2013	Arntz, Gregory and Zierahn, 2017	Autor, David, 2014	Autor, David, 2015	Brynjolfsson and McAfee, 2015	Brynjolfsson and McAfee, 2017	Dau-Schmidt, Kenneth G. , 2017	DeCanio, Stephen J. , 2014	Freeman, Richard , 2015	Frey and Osborne, 2016	Hemous, David and Morten Olsen, 2002	Pratt, G.A., 2015	Sachs, Benzell, and LaGarda, 2015	Scarpetta, Stefano, 2017	Stringfield and Stone, 2016	Sundararajan, Arun, 2016	Swanson, Jason, 2017	Thirgood and Johal, 2011	Yanagawa, Noriyuki , 2010
AI-Challenge: 'Real World'				X																
Decisions & Predictions																				
Computing, Automation, AI & Robots				X						X			X			X				
Everyday (working life)			X	X			X				X						X	X	X	
Politics & Macroeconomics		X			X	X		X	X					X	X				X	X
Education, Occupation & Skill	X	X	X	X	X	X	X			X	X		X			X	X	X		X
Productivity & Microeconomics	X							X	X	X	X	X					X			
Work acquisition & Wages		X					X			X	X	X	X	X	X	X	X		X	

Figure 16: Human Role: Skill Set & Education

Although there is an economic force to automate, "workers increasingly focus on a diverse set of tasks" (Arntz et al., 2017, p. 6). "In this and other ways, the issue is not that middle-class workers are doomed by automation and technology, but instead that human capital investment must be at the heart of any long-term strategy for producing skills that are complemented by rather than substituted for by technological change." (Autor, 2014, p. 27). Therefore it is not necessarily an overall hard cut towards unemployment as the employment sector can ensure "that its offerings develop workplace skills and (...) create meaningful workplace learning opportunities" (Swanson, 2017, pp. 167-168). "Importantly, when machines are produced with a technology similar to the consumption good, automation can only reduce wages temporarily: a prolonged drop in wages would end the incentives to automate in the first place" (Hemous & Olsen, 2002, p. 44). For Stringfield and Stone "two priorities of preparing for future work seem clear. The first is an increase in the need for specific technical skills. (...) The second is the increasing importance of social skills" (Stringfield & Stone, 2016, p. 177). Additionally, Pratt estimates that "some human services will probably continue to command a premium compared to robotically produced ones" (2015, p. 58). Nevertheless "as the cognitive capabilities of digital machines expand, students may need less education in science, technology, engineering, and math and may benefit from a greater emphasis on design thinking, entrepreneurship, and creativity to prepare them for a microentrepreneurial career" (Sundararajan, 2016, p. 11). The most important phrase regarding these careers will be: " 'who-owns-the-robots-rules-the-world' (...) Regardless of whether technological advance is labor-saving or capital-saving, skill-biased or not, and regardless of the speed with which robots or other machines approach or exceed human skill sets, the key to the effect of the new technologies on the well-being of people around the world is who owns the technologies" (Freeman, 2015, p. 6). Especially the distribution of AI in the form of capital is discussed extensively. First, the "issue, in other words, isn't technological but distributional—which is to say political. Automation presents some of us with a kind of windfall. It would be not just churlish but short-sighted if we didn't share this windfall with those who haven't been so lucky" (Akst, 2013, pp. 12-13). Second, if "the adoption of new information technology continues to undermine the bargaining power of employees and unions in the workplace, employees will have to rely more on legislation to address their needs" (Dau-Schmidt, 2017, p. 1609). Third, tax "and benefits schemes must also evolve to protect those who lose out from change, while social protection schemes need to reflect new work arrangements, such as consulting, freelance and other contracts that no longer fit into traditional employee-firm relationships" (Scarpetta, 2017, pp. 3-4). Fourth, "government redistribution can ensure that a pure productivity improvement raises well-being of all generations" (Sachs et al., 2015, p. 23). Fifth, "we will need institutional reforms – for example, public policy support to encourage new capacity building and provide learning opportunities" (Yanagawa, 2010, p. 19). Last, governments "can also support workers in a more indirect manner by investing in public programs that provide stability amidst an uncertain employment landscape" (Thirgood & Johal, 2011, p. 30). As he does not want the innovation to slow down, DeCanio is against broad legislation: "Large-scale taxation and redistribution schemes have adverse effects on effort and innovation, and would entail expansion of government power to the point where economic outcomes would essentially be determined by the political process" (2014, p. 38). But in the case that AI brings mass unemployment and spreads social inequality, humans still have the ability to revolt (Brynjolfsson & McAfee, 2015, p. 12)[13].

3 Summary

Now the seventh stage of the SLR scheme (Okoli & Schabram, 2010, pp. 6-7), Synthesis of Studies, is presented. Here the contents of the eight units of analysis are brought together and discussed. This shall prepare for the final answer of the research questions in the conclusion (section 4).
First, the summary will start with the technical empowering that will arise though AI ("Computing, Automation, AI & Robots", "AI-Challenge: 'Real World' " and "Decisions & Predictions").
Second, the changes in the labor market will be covered ("Everyday (working life)", "Education, Occupation & Skill" and "Work acquisition & Wages").
Third, the influences on microeconomics and macroeconomics ("Productivity & Microeconomics" and "Politics & Macroeconomics") are reviewed.

Throughout the articles none of the authors contradicted Moore's law for the next few years. ANN calculations "can be broken into parallel operations—because no communication of intermediate results are needed" (Pratt, 2015, p. 55). Until now impressing AIs are only released by big IT companies (Google, Amazon, Apple, Microsoft etc.). Hence the mass of calculations is a hurdle, but might be solved by means of the eight drivers (Pratt, 2015, pp. 53-55). Nevertheless, none of those drivers is allowed to slow down or to stop evolving for a "Cambrian Explosion in robotics" (Pratt, 2015, p. 52).

The biggest leap, which is enabled by ANN, is that now problems can be solved that were not computable before (Agrawal et al., 2017, p. 26). This leap is explained by Autor as "POLANYI'S PARADOX". He quotes "Michael Polanyi's (1966) observation that 'We know more than we can tell.' " (Autor,

[13] Revolution does not necessarily mean a broad shift. It can already start by putting barbecue sauce on sensors, so the robot is not able to perform in an appropriate manner (https://www.bizjournals.com/sanfrancisco/news/2017/12/08/security-robot-homeless-spca-mission-san-francisco.html).

2014, p. 8) to explain that there are tasks that we perform, but cannot implement for a computer. This occurs as the rules (even for a simple task) can be not quite obvious or require generalization or knowledge about the shape of the world (Autor, 2014, p. 8). Therefore teaching a computer/AI how to manage a task seams infeasible (Autor, 2014, p. 8).

Due to this, the authors are of the opinion that tasks, which require routine will decrease due to RBTC (Goos et al., 2014, pp. 2520-2521). Therefore tasks that are performed repeatedly will decrease because much data can be collected to train AIs. The same procedure happens by automating non-routine tasks (Frey & Osborne, 2016, p. 15), just that the collection of data for the training sets takes more time.
This holds true for unstructured environments (Andreopoulos & Tsotsos, 2013, p. 827), but as environments become unstructured or fuzzy, AIs performance drops drastically (Andreopoulos & Tsotsos, 2013, p. 873). Hence in the beginning there will be two major fields in which AI will be used: First, environments that are transformed by reengineering, so that they become structured enough for an AI to operate in them. Second, threr will be approaches to handle tasks that are "dull, dirty and dangerous" (Borenstein, 2016, p. 31). The completion of the fundamentals of this second field will enable even more tasks to become automated. Until then scientists will wonder whether AI is able to detect "purposiveness" (Autor 2014, p. 26 and Grabner, Gall and Van Gool, 2017, p. 8), learn social behavior (Kaplan, 2017, p. 37) or understand humans and the world (Brynjolfsson & McAfee, 2017, p. 125). For today we can determine, "that AI is a prediction technology" (Agrawal et al., 2017, p. 26) that creates value by "knowing how payoffs arise" (Agrawal et al., 2017, p. 26) as it finds patterns in huge datasets, so it has "the capability (...) to imitate intelligent human behavior" (Aghion et al., 2017, p. 2).

The everyday working life will change dramatically - if the tasks that are involved in the occupation can be automated by AI. Those obviously involve the routine occupations, no matter if they are in an assembly line mostly carried out by "middle and low-skilled blue-collar workers" (Autor, 2014, p. 13) or in any other process chain without contact to the front office like "traditionally white-collar based careers" (Thirgood & Johal, 2011, p. 28).

In the case of unemployment, there are six major possibilities for "job reallocation" (Bessen, 2016, p. 30):

First, climbing up the ladder of education to gain a job for high-paid professionals and managers (Goos et al., 2014, p. 2524) - without governmental help may become economically out of reach for most of the workforce. Additionally this path does not ensure a new employment, as technology races on during the reallocation.
Second, finding a job in a sector which requires tasks that are not (yet) seen to become automated soon, like "Social and emotional intelligence, (...) adaptability, creativity, (...) and computational and analytical thinking" (Thirgood & Johal, 2011, p. 31).
Third, becoming a part of the so called " 'gig', 'on-demand', 'sharing', 'peer-to-peer' or 'platform' economy" (Scarpetta , 2017, p. 3). "Some of these jobs may allow for greater flexibility for the workers but they often lack full coverage of social protection, have lower access to training opportunities and provide weaker career progression than those in more traditional, open-ended jobs." (Scarpetta , 2017, p. 3)
Fourth, working in project-oriented occupations. As projects occur only 'one time' due to several inluencing factors (Ballard et al., 2002, p. 4), they are likely not to create enough data to become automated. Additionally "humans are still better at coming up with useful new ideas in most domains." (Brynjolfsson & McAfee, 2015, p. 10)
Fifth, as there is no static "lump of labor" (Brynjolfsson & McAfee, 2015, p. 9), the unemployed will have a better chance for a new job, when the third phase of Hemous's and Olsen's "horizontal innovation growth model" (2002, p. 44) picks them up.
Sixth, in the lucky case of not needing much money as goods become cheaper could occur (Pinney, 2014, p. 39). Alternatively a governmental welfare program, financed by taxed, could free unemployed form seeking labor - for at least a while (Thirgood & Johal, 2011, p. 30).

Productivity will rise as algorithms can operate all day long, because AI does not need to sleep. Brynjolfsson and McAfee describe the situation as follows: "Fill in the blank: If our competitors implemented a successful machine learning system for ________ , we'd be in serious trouble" (2015, p. 9). Hence companies are forced to collect data and try to build up AI systems as fast as possible. As goods become cheaper (Pinney, 2014, p. 39), margins tend to reduce, too. New innovative products need to be invented or unemployment rises as wages cannot be paid.

In the model used by Pratt, 2015 the pressure for a single company rose at first (Pratt, 2015, pp. 57-58). But overall demands "for the goods produced" rose, directly after (Pratt, 2015, pp. 57-58). Regarding goods, people were "at least somewhat satiated, but people were not satiated in their wants and instead soon discovered new areas of demand. Some human labor was displaced as technology expanded, but supply and demand in the labor market drove a series of transitions so that labor shifted to meet the new demand in other areas, and there was no sustained trend to greater unemployment over time. Instead, average wages increased because technology lifted the productivity of labor." (Pratt, 2015, pp. 57-58). If Pratt's opinion is applicable to the future, "labor saving inventions may only be adopted if the access to cheap labor is scarce or prices of capital are relatively high (Habakkuk, 1962)" (Frey & Osborne, 2013, p. 42). Otherwise, if "the future of work is characterized by longer spells of unemployment, we can expect that many will require financial support for longer periods of time as they attempt to transition back into the labour market." (Thirgood & Johal, 2011, p. 30). In this case, even if they get orders from the platform economy, "workers are more likely to hold jobs and multiple income sources challenges the role of statutory working hours, minimum wages, unemployment insurance and other pillars of our traditional labour market institutions and policies." (Scarpetta , 2017, p. 3). Regarding policies, many authors are of the opinion that governmental regulations and legislations will be needed to be revised and supplemented (Akst, 2013, pp. 12-13, Scarpetta, 2017, pp. 3-4, Sachs et al., 2015, p. 23, Yanagawa, 2010, p. 19, Thirgood & Johal, 2011, p. 30).

4 Conclusion

After the initial literature search with search queries, forward and backward searches, the filtering of duplicates and the screening process, the data extraction and the summary demonstrate the found information. Therefore the three research questions are are seen to have been answered and the findings will be finally illustrated before an outlook will be presented.

1. "Which kind of tasks can now be automated that were not computable without ANN?"
   The easiest way to answer this question is to categorize tasks into "routine", "non-routine" and "unstructured". Routine tasks become obsolete for human labor day by day as they are automated by traditional comput-

ing. Non-routine tasks are likely to be complemented by AI. The speed of automation will be determined by the possibility of collecting data and the amount of unforeseen influence factors. Last the unstructured tasks will stay for human employment and become "more ambitious" (Kaplan, 2016, p.37) as the "lumb of labor" (Brynjolfsson & McAfee, 2015, p. 9) increases.

2. "Where is the boundary of actual AI executing tasks or how can human labor stay ahead of the automation wave?"
The first thing to note here is that humans own capital (= AI and robots) and are generally enabled to vote for legislatioin and regulation. Nevertheless not all occupations can be given the possibility of solving more and "more ambitious" (Kaplan, 2016, p.37) tasks. Therefore, social "and emotional intelligence (...) adaptability, creativity, (...) and computational and analytical thinking" (Thirgood & Johal, 2011, p. 31) might be the key factor for human success in the future. Additionally "humans are still better at coming up with useful new ideas in most domains." (Brynjolfsson & McAfee, 2015, p. 10) In this regard, the "extent of computerisation in the twenty-first century will thus partly depend on innovative approaches to task restructuring" (Frey & Osborne, 2016, p.24). In other words, humans will be forced to keep thinking and shall not trap themselves in comfortable routine.

3. "Does AI influence the way job acquisition will be done?"
For high-skilled workers, job aquesition will not change significantly. Maybe some companies will try to filter candidates not only by job interviews, but additionally with AI evaluated tests. This will not reshape the process significantly. As most wages will rise and fall regarding the current status of the country in the horizontal innovation growth model (Hemous & Olsen, 2002, p. 44). On the other side low to middle skilled occupations are likely to recieve a more disrupted form of job acquisition (Thirgood & Johal, 2011, p. 27). "As the relationship between employee and employer has changed over time, the responsibilities of each party have become less clear. This uncertainty can often leave workers vulnerable to mistreatment, particularly given the rising popularity of alternative classifications that do not address workers as employees" (Thirgood & Johal, 2011, p. 27). Additionally the traditional career might be broken up into little projects, micro-tasks (Thirgood & Johal, 2011, p. 27), which will lead into the " 'gig', 'on-demand', 'sharing', 'peer-to-peer' or 'platform' economy" (Scarpetta , 2017,

p. 3).

With these final statements the research questions were answered. Hence the research problem has been solved.

5 Outlook

The findings of the literature search leave some further questions, which shall be mentioned for future research:

1. Is there a way to enable AI to learn social behaviour like creativity, purposiveness, flexibility or common sense?
   If yes, what is the hurdle to gain these advantages?

2. Pratt (2015, pp. 55-56) mentions four possible ideas to empower AI:
   (1) Memory-Based Autonomy
   (2) High-Speed Sharing of Experiences
   (3) Learning from Imagination
   (4) Learning from People

3. Can an AI be reverse engineered so that it can adequately tell humans how it reached a specific answer? In case the reverse of Autor's "POLANYI'S PARADOX" (2014).

4. Finally nongovernmental organizations (like the WTO) shall be requested to publish guidelines for companies/countries regarding wealth distribution should the case arise that they reach monopoly market shares due to the first mover advantage with an appropriate AI system.

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