

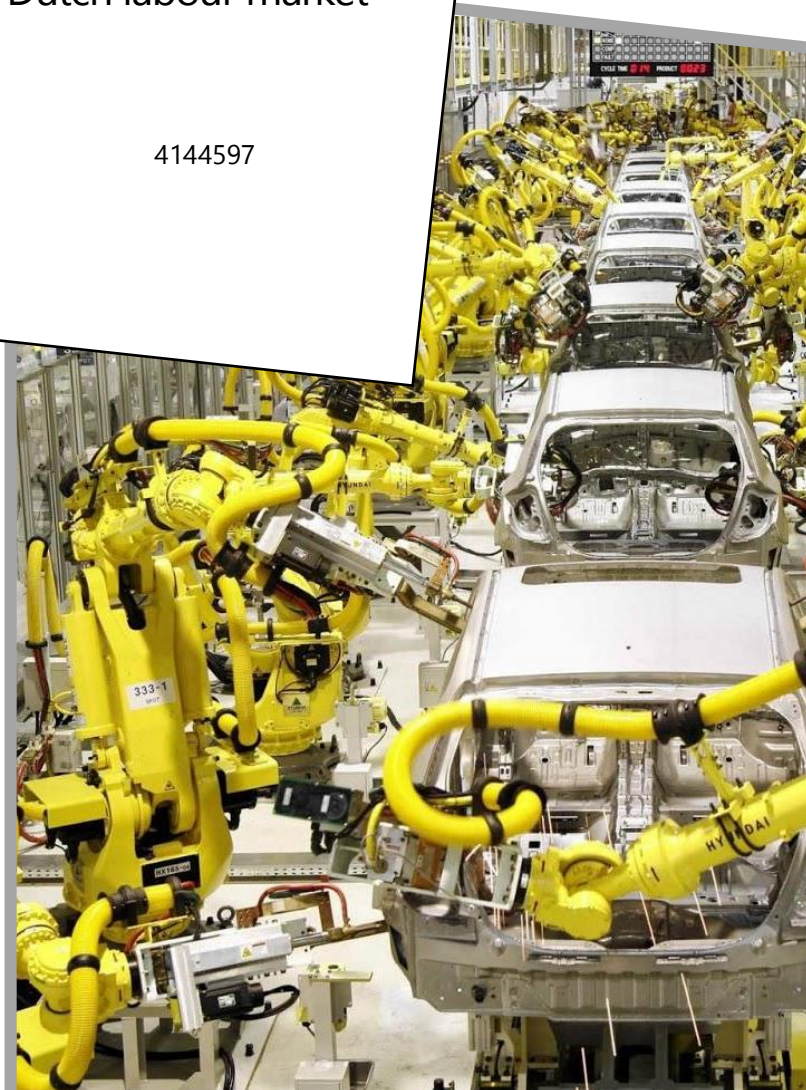


LOOKING  
FOR A  
JOB

Disappearing professions through  
technological development:  
Implications for the Dutch labour market

Jean Paul Schot

4144597



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Disappearing professions through technological development:

Implications for the Dutch labour market

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*in partial fulfilment of the requirements for the degree of*

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## PREFACE

One year ago, an informal talk about the master thesis was organized. During this meeting a recently graduated student said, 'Start your master thesis on time!' I took his words by heart started researching topics from that moment onwards. At some point, my curiosity was drawn towards an article of the Correspondent about implications of increasing unemployment through automation. When I met up with Martijn Warnier to talk about this topic my interest was sparked even more intensely and I decided to further investigate the implications of automation for the Dutch labour market by performing a Master Thesis project on the topic.

For the last 6 months, I spend lots of hours in libraries and put a lot of energy into this project. Performing the study has led me through many emotions, but I am proud of the result laying in front of you and happy with how it all unfolded.

Carrying out this master thesis project would not have been possible without the help of Martijn. Martijn always made time for me, made sure I was on the right track, gave feedback I could work with, but most importantly he guided me with honest interest and enthusiasm. I know, that without Martijn Warnier, this project would have been more of a struggle for me and I am grateful to have had you as my first supervisor.

I would also like to thank Niek Mouter for his work as my second supervisor. Niek always supplied a refreshing point of view which helped sharpen the focus of the research significantly.

I would like to thank my parents, Cor and Froukje, and my girlfriend, Madelon, for their continued support throughout my eight years of study. I have had hardships but your support always kept me going with a positive mindset.

Finally, I would like to thank the many friends and family whom I could exchange thoughts with and whom helped supplying constructive feedback on my work. It has been a hell of a ride and I am happy to have ridden it with all of you guys.

Yours sincerely,

Paul Schot

26 July 2019

## Executive summary

An unprecedented loss of jobs because of technological development has been a theme in every industrial evolution. In previous industrial revolutions occupations have disappeared, but the occupations always seemed to be replaced by new ones. There are signs that the effect of the fourth industrial revolutions with emerging technologies, such as developments in robotics and artificial intelligence will be different. Frey and Osborne (2018) have researched the potential effects on the occupations of this new revolution by assigning percentages of susceptibility to occupations. The report was focused on the American labour market and concluded 47 percent of all jobs in the US is at stake. The OECD acknowledges future labour market configurations will be impacted by technological changes and states it is a task of government bodies to facilitate changes in the labour market by providing policies (OECD, 2018). Countries have used the work of Osborne & Frey to determine the impact of technological development on their own country. They (Japan and Germany) either, recreated the machine learning algorithm to use the algorithm immediately on the country's occupation classification system (David, 2017; Dengler & Matthes, 2018) or they (Finland) used the susceptibility percentages determined by Osborne & Frey and matched them with national classification standards (Pajarinen & Rouvinen, 2014). Asscher, the previous Deputy Prime minister of the Netherlands, underlined the necessity of dealing with the possible changes of technological development in 2014 (Buddingh, 2014), but in the Netherlands, there has not yet been a study done like in Japan, Germany, and Finland. Furthermore, the literature shows other kinds of long-term labour forecasts are also lacking. This leads to a gap of knowledge in the research; The need for a long-term quantitative labour market forecast of the Netherlands, which accounts for technological developments. Additionally, there is no framework available yet that outlines how the Frey and Osborne research may be translated to other labour markets.

This research aims to enhance decision-making effort in the Netherlands. This aim is realized by determining the part of the workforce at stake of being replaced and by determining the policy space existent for making policy. The aim of this research leads to the following research question.

---

*“What are the quantitative effects of technological developments on job level for the Dutch labour market in 2030 and how can the defined policy space contribute to decision-making?”*

---

In the research the same kind of approach will be used as in the Finland research, meaning the susceptibility percentages of Osborne and Frey will be projected on the Dutch labour

market through translation of the classification standards. To gain knowledge on quantitative effects of technological developments on job level for the Dutch labour market in 2030, additional information is needed. First, the information on the Dutch labour market configuration is collected to determine the number of jobs per occupation. Secondly, there is a growth trend for each of the occupations. This trend needs to be incorporated to gain insight in the net change in jobs. Finally, the literature states on several occasions the fragile group of low-skilled workers will be impacted the most by disappearing jobs (Acemoglu & Restrepo, 2017; Berg, Buffie, & Zanna, 2016; Bonekamp & Sure, 2018; Duffy, Blustein, Diemer, & Autin, 2016; Grip et al., 2018). Consequently, there is a special focus in this research on the effects on this part of the workforce. Technological development is uncertain and although Osborne and Frey created percentages of susceptibility per job, it does not directly translate into a loss of jobs for an occupation. Scenarios are defined covering the bandwidth of technological development to address the uncertainty of technological development. To get towards the labour market forecast gathered data should be processed. This process requires data integration of the different sources. The general purpose data integration system (GPDIS) created by Doan, Halevy, and Ives (2012) is used as a framework to guide this process.

The susceptibility percentages and the labour market configuration are coupled by aligning the different classifications used in the US and the Netherlands. The result of this coupling proces is an outline of the spread of the workforce of the Netherlands over the percentages. The result is displayed in figure 1 specified for every sector.

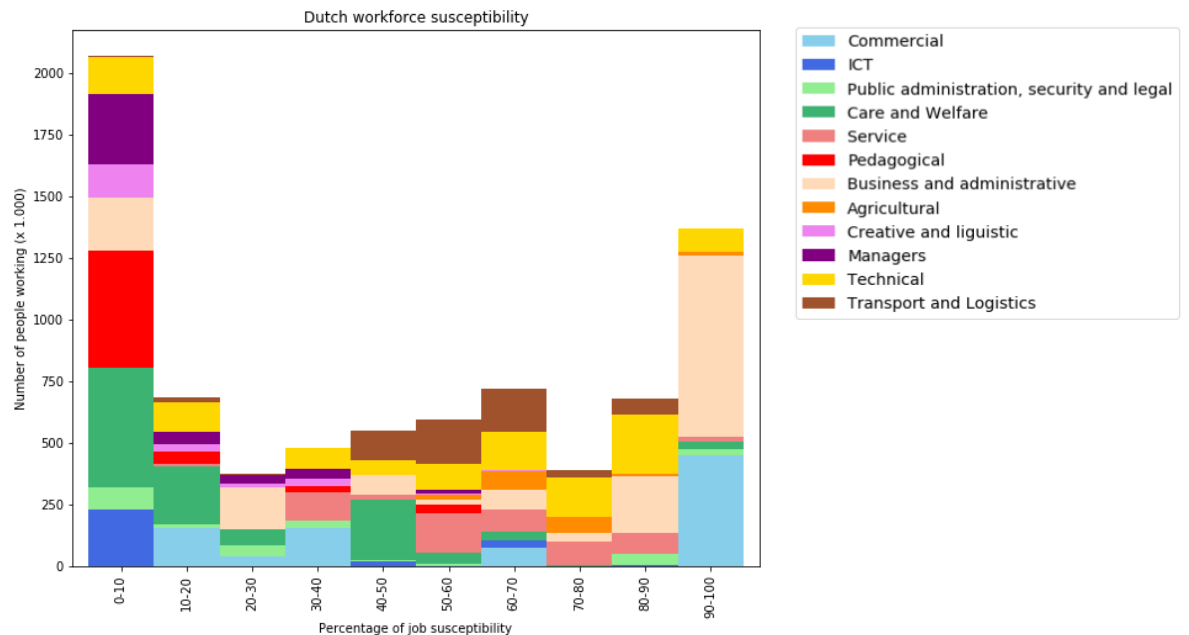


Figure 1: Workforce of the Netherlands spread over the susceptibility percentages of Osborne and Frey

Figure 1 shows the 'Commercial' and 'Business Administrative' are the sectors with the highest number of employments in the higher regions of the susceptibility percentages, and therefore, the sectors will probably be affected most by technological developments. It is also concluded roughly 2.5 million of in total 8.25 million workforce is, what Frey and Osborne call, 'highly susceptible'.

The data integration of the growth trend for every occupation shows a growth in the total number of jobs of 500.000. The data integration of the educational level of the current workforce results in an overall spread of 34.5 percent of the workforce with educational level low, 48.3 percent of the workforce with educational level medium, and 17.2 percent of the workforce with educational level high.

Integration of the loss of jobs, the growth trend and the educational level per occupation results in the final dataset. With this dataset and the creation of different technological development scenarios it is possible to answer the first part of the research question; "What are the quantitative effects of technological developments on job level for the Dutch labour market in 2030?". In table 1 the quantitative effects are stated per technological development scenario. The results show the number of jobs at stake for each of the scenarios plus the part of these jobs performed by workers with a low educational level.

*Table 1: The loss of jobs for the different technological development scenarios*

	Technological development scenario low	Technological development scenario average	Technological development scenario high
Total jobs at stake	750.000	2.600.000	4.700.000
Low educational level jobs at stake	475.000	975.000	1.575.000

In this research an important component is lacking. This component is the creation of new occupations. The total jobs at stake in table 1 represent the space to be filled with new jobs from the creation of new occupations. There are three scenarios possible after incorporation of new occupations. In the first scenario, the jobs of new occupations fill up the job market and the workforce successfully adjust with the current institutional arrangements. In the second scenario the jobs of new occupations also fill up the job market, but the workforce is not able to adapt properly to the new market configuration leading to a mismatch in labour supply and demand. In the third scenario the jobs of new occupations do not create enough work to suit labour supply. In this case, there is simply not enough work for the workforce. When regarding these future scenarios and the technological development scenarios the following is concluded. In the low technological development scenario, the first scenario may occur, but for the average and high technological development scenario, it is questionable if the current institutional arrangements will suffice. If either the mismatch scenario or the insufficient job creation scenario occurs the number of jobs at stake for the low educated workforce is significant



with roughly 1 million and 1.6 million for the medium and high technological development scenarios. Additionally, up to 2.6 million and 4.7 million for the medium and high technological development scenarios jobs are at stake for the total workforce. The jobs at stake form the policy space existing for policymakers to deal with these possible changes and protect the fragile group of low-skilled workers. It will be their task to create a resilient workforce and to create policies for the appearance of possibility two and three. The knowledge of the magnitude of the policy space may give guidance for this process and sets boundaries for the to be designed institutional arrangements.

It is recommended to the Ministry of Social Affairs and Employment to instate a committee to investigate how these different transitions of the labour market will affect the institutional arrangements and determine plans to mitigate the upcoming challenges.

Keywords: Industrial revolution, Emerging technologies, Job loss, Technological development

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# 1. Identifying the research problem

*"The rise of powerful AI will be either the best or the worst thing ever to happen to humanity. We do not yet know which."*  
Stephen Hawking

If you have visited a McDonald's restaurant over the last years, the sight may be familiar; several pillars with touchscreens that can be used to place an order. On these pillars, it is possible to place and specify your order and handle the payment completely autonomous. This development in technology is making the job of the cashier become obsolete and unnecessary. This is just an example. However, the changes are also noticed on a higher level. For example, when looking at the employment of newsrooms in the United States, a 45 percent loss of jobs is measured over the period of 2008 to 2017. Resembling a loss of 32.000 jobs (Grieco, 2018). Digitalization of newspapers seems to play a big role in this change. Another example is found in Asia, where a Japanese startup has set-up the first ever warehouse without human labour (Hornyak, 2018). Technological developments like this are putting warehouse employees out of work. This effect of robotization in warehouses is also regarded on a larger scale, for example in the US where revenues keep increasing but the employment numbers are dropping. A final example comes from the United Kingdom. The country has seen 85.000 jobs lost in the retailing business of the country's high streets (Burtler, 2018). Although there are probably more causes, online shopping certainly seems to be one of those. The examples show a trend and seem to stand for a broader societal change, namely a wave of digitalization and robotization across industries and a new industrial revolution seems to be on its way. With that, a question arises that has been famous in every industrial era; "Will unemployment rise as a consequence of technological development?".

## 1.1 Industrial revolutions & Economic views

In history, three different periods of industrial revolution can be distinguished. They were all triggered by emerging technologies (inventions of respectively the steam engine, electricity, and computing) and were all believed to destroy jobs (Mahdawi, 2017) at a faster rate than new jobs could be created (Keynes, 1933, p. 3). But when history is regarded, this proposition turned out to be untrue. Instead available jobs increased, because of the 'Luddite Fallacy'. The 'Luddite Fallacy' states production becomes more efficient through technological developments leading to lower prices for goods and leaving consumers with money they could spend on other commodities, leading to a rise in jobs ("Rethinking the Luddites," 2009). Furthermore, human labor has prevailed since humans had been able to



learn and adopt new skill sets through education, which were required for these new jobs (Goldin & Katz, 2009).

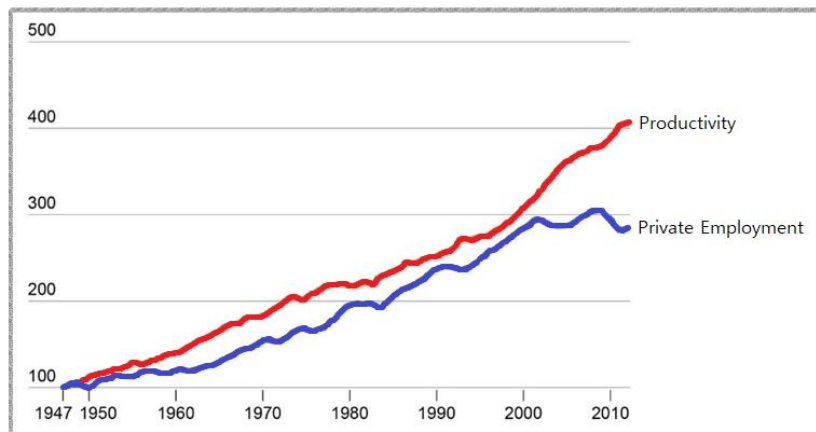
In the present technological era, the so-called fourth revolution (computerization and robotization of society (Marr, 2018)) looks to be on its way alongside emerging technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT). The examples about newsrooms, warehouses and retailers show changes are already happening in multiple businesses, but if changes like these will eventually lead to unprecedented unemployment is yet to be determined. Some say the 'Luddite Fallacy' will hold again, but others believe this revolution is different and believe it will bring significant unemployment.

According to Amazon CEO Bezos (Kucheriavy, 2018), 'It is hard to overstate how big of an impact AI is going to have.' If AI delivers on its promises, the technology will have a significant impact on societies. The introduction of such a technology will lead to creative destruction, as mentioned in the forties by Schumpeter. He states each innovation does not only create value, it also kills previous incumbents (creative destruction) (Schumpeter, 1942). Jobs can be one of these incumbents 'creatively destroyed' by technology. Looking at the earlier industrial revolutions it is concluded indeed some jobs were lost, but they were always replaced by new ones. This phenomenon is foreseen differently by Keynes (1930). In his belief, this creative destruction of jobs will lead to technological unemployment. Keynes idea is that the discovery of means of 'economizing the use of labor' will outrun the pace at which new jobs are created (Keynes, 1930). As stated earlier, so far this has not been the case in the past industrial revolutions, but technological changes of the present day, such as automation, robotization, and artificial intelligence, are having an arguably transformative effect on labor markets (Acemoglu & Restrepo, 2016), meaning Keynes may be right with his notion of technological unemployment after all.

## 1.2 Urgency for change

The urgency of dealing with technological developments is expressed by Brynjolfsson (2013). He states it starts with, what he and McAfee call; the decoupling of productivity and employment (productivity translates to the real gross domestic product (GDP) produced by an hour of labor) (Brynjolfsson & McAfee, 2011). The two factors have always shown a similar trend over time, but since the year 2000 productivity keeps on growing, while employment stays roughly the same (Rotman, 2013) (figure 3). Additionally, the current measurement of GDP is considered poor. There are two suggested reasons for the poor measurement. First, it struggles to measure the true value of the internet and tech-enabled services (*Technology and the Future of Work: The State of the Debate*, 2015). The reason for this struggle is the incapability of capturing the 'free services' (such as Facebook), which have price values of null and are therefore invisible in official statistics. Secondly, there is a lacking ability in the economic measurement of intangible assets, like intellectual property. This leads to more incomplete measurement of the GDP (Brynjolfsson & McAfee,

2016). Because of these two reasons the gap between productivity and employment is probably bigger than expected and therefore the situation is even more alarming.



*Figure 1 Productivity and employment in the US, 1947 - 2011 (Adjusted figure from US Department of Labour)*

Schwab is also a firm believer of the large impacts of the emerging technologies (Schwab, 2016). He states the fourth revolution is evolving at an exponential pace rather than a linear one and that humans are not capable of capturing such growth, because humans are hardwired to think linearly (Kroenke, Bunker, & Wilson, 2013). This makes it incredibly hard for a human to imagine and foresee the consequences of exponential development.

If Brynjolfsson and Schwab are right and the fourth industrial revolution leads to significant unemployment, jobs will disappear faster than new jobs can appear and at that point, the society will come to feel the impact of fewer employment opportunities (Aronowitz & DiFazio, 1994). The previous sections show the possibility for increasing unemployment is an urgent issue, which means researchers and policy makers should start thinking about the consequences of increasing loss of jobs.

### 1.3 Societal relevance

To face the challenge of possible unemployment there is a need to understand the problem and to regard possible policies to help coping with the challenge ahead. This challenge is also acknowledged by the Organisation for Economic Co-operation and Development (OECD) in their report “Transformative technologies and jobs of the future” (OECD, 2018). This report served as the background report for the G7 Innovation Ministers’ Meeting in March of 2018. It states technological changes create significant uncertainties and will impact in the near future. They see it as a task of government bodies to provide policies that facilitate changes in the labor market, such as “facilitating the redeployment of workers” (OECD, 2018).

As a developed country and member of the OECD, the Netherlands will also experience the fourth revolution and the reallocation and redefinition of its labor market. The previous deputy prime-minister of the Netherlands underlined this statement in 2014, by stating his concerns about technological unemployment (Buddingh, 2014). Since the possibility of

significant unemployment may have serious negative impacts, it is necessary to gain more insight into possible loss of jobs and consequences for the labor market to define policy measures to mitigate the negative consequences and utilize the positive consequences of a fourth revolution.

## 1.4 Research problem

In 'The future of employment', Frey and Osborne examine the susceptibility of this societal change amongst professions (Frey & Osborne, 2013). In their calculations of the percentage of professions disappearing until 2030, they calculated for example, a 97 percent chance for the profession "cashier" (as earlier described a profession already subjected to automation). In their research Osborne and Frey classify occupations with percentages above 70 percent as 'highly susceptible'. At the end of their report they conclude 47 percent of the current US jobs will fall in the category of 'highly susceptible'. The OECD also performed a study, which was based on the Frey and Osborne research. This research (Nedelkoska & Quintini, 2018) reports 10 percent of jobs will fall in the category of 'highly susceptible' in the US. The outcomes of the studies are totally different. If 10 percent of the US jobs are lost it may be considered manageable, but 47 percent loss of jobs will have huge consequence for the US labour market. The OECD study calculated their percentages for several countries. One of those countries is the Netherlands, where they calculated 6 percent of the total workforce to have highly susceptible jobs. The difference between the numbers for the US labour market results in a need for more research determine the differences in the studies and to conclude whether the another labour market forecast for the Netherlands based on Osborne and Frey would be valuable.

Literature on quantitative changes in the labour market because of technological developments is found for several countries. These countries either used the susceptibility percentages per occupation of Osborne and Frey and projected these percentages on their own labour market (for example Finland (Pajarinen & Rouvinen, 2014)), or they recreated the machine learning algorithm of Frey and Osborne and used the algorithm on their own occupation definitions (for example Japan and Germany (David, 2017; Dengler & Matthes, 2018)). Similar research has also been found in Russia (Zemtsov, 2017) and Turkey (Sümer, 2018), but for these countries it is unclear which approach they used. All the performed studies focus determining a labour market for a specific country, but they lack a mapping of their methodology.

The research problem for this research is: There is insufficient knowledge of long-term labour market forecasts for the Netherlands. The present scenario of the OECD for the Netherlands sketches a 6 percent loss of jobs, but the difference in outcomes for the US labour market between the OECD research and the Frey and Osborne research leads to a demand for more research on the topic. For the Netherlands more insights on possible future scenarios of the labour market can be vital for policy-making, in order to deal adequately with digitalization and automation. Altogether more literature research is

needed to gain insight in the discussion among scientists on the topic of the effects of technological developments on labour markets. Additionally, more research is needed on quantitative sources that look into the effects on the labour market (such as the research of Frey and Osborne and the OECD report). Finally it is important to regard the discussion in the Netherlands on the topic of technological unemployment. Which will lead to existing labour market forecasts for the country and sheds light on the specific case of the Dutch labour market.

## 2. A literature review on the effects of technology on the labour market

*“Love of wisdom”* – Philosophy

To get a better idea of the broad topic at hand, it is necessary to review what the state-of-the-art literature covers on the topic. The following chapter will cover the literature in four different subchapters. The first subchapter will cover all the different aspects found in literature with regards to technological developments. The second subchapter will cover literature on labour market forecasting with a specific focus on the effects of emerging technologies on this forecast. In the third subchapter views on the topic in the Netherlands are discussed. In subchapter four the concept of uncertainty is explained, and it is projected on this research. The insights of the first four subchapters will then conclude in a knowledge gap, after which the scientific relevance of this research becomes clear.

### 2.1 Aspects of the discussion on technological development

The research topic of the Frey and Osborne research is like the topic of this research. Both cover the impacts of technological developments on the labour market. The Frey and Osborne research is largely discussed and debated in the literature considering its citation numbers on several platforms ('Google Scholar', 'ScienceDirect', and 'Semantic Scholar'). It is assumed the articles citing Frey and Osborne cover one or more aspects of the discussions on technological unemployment. Therefore, the search is narrowed down to articles citing Frey and Osborne (in other words articles citing 'labour market forecasts' emphasized on technological developments). The citing articles on the three mentioned platforms show the number of articles is vast and further specification is needed. The citing articles are ordered on the number of their citations by other sources, since this gives an indication of how heavily they are discussed in the literature. Sources are selected from the top and their topic is subtracted and translated to a category. After the selection of first 100 sources on the platforms no new categories seem to emerge anymore. Therefore, the selection of new sources is stopped. The process results in 30 topic categories. The categories mentioned most in the analyzed literature are selected, since it means they are most discussed. 'Artificial Intelligence' is one of the categories that should be selected. It is not, since this research does not have a focus on the impact of specific technologies on labour markets. The selected categories are 'Industries affected by emerging technologies', 'Robots, humans and jobs (complementary or substitutes)', 'Education and Technology', 'Psychology/sociology/ethics of working', 'Industry 4.0', 'Economical theories', and

'Policies'. Each of these topics is analyzed by reviewing their literature. In appendix II the execution of this search plan is incorporated.

### 2.1.1 Industry 4.0 and the fourth industrial revolution

The new industry with all the emerging technologies in place is called the industry 4.0 and the process towards it the fourth industrial revolution. Different research states the fourth industrial revolution will have disruptive effects (Bonekamp & Sure, 2018; Kergroach, 2017; Strange & Zucchella, 2017). Bonekamp & Sure state a substantial decrease in standardized low-skilled work and an increase of work in planning and information technology (which can be categorized as high-skilled work). With that change the overall complexity of work will increase and therefore the average skill of the workforce needs to go up as well. Strange & Zucchella expect a change in the global value chain where the way the configurations are set between suppliers, firms and customers will change. Kergroach states solely addressing skill adaptation is not enough, also the resilience, adaptability and efficiency of the labour markets are important topics. It is not only people, but also markets that need change in order to get to the new Industry 4.0 with social stability and cohesion.

The literature describes the creation of disruption of the fourth industrial revolution in many ways. However, for different kind of occupational fields this could mean different things, since every occupational field is unique. In literature there are numerous cases of the effects on a specific field.

### 2.1.2 Industries affected by emerging technologies

The emerging technologies will cause disruption in many industries and fields. In the previously described approach to determine the aspects of the discussion on technological unemployment, several of the 300 analyzed sources focused on an implication for a specific industry. These studies were grouped in the category 'Industries affected by emerging technologies'. There are probably more industries being affected by technological development soon. However, no more are found in the literature. The cause of this incompleteness is attributed to the lack of developments in other industries so far and the skeptic views on technological developments within sectors. In this subchapter the affected industries identified from literature are reviewed.

#### *Manufacturing*

The amount of robotics in the world is growing vastly. Robotics are already introduced and used in the manufacturing industry, where numerous processes consequently are optimized (Freddi, 2018). Additive manufacturing, another word for 3D printing, is transforming manufacturing, while also creating a need for a new kind of technician that is able to handle this technology (Perez-Perez, Gomez, & Sebastian, 2018). Although they have been less studied, Augmented Reality (AR), Internet of Things (IoT), and Big Data Analytics (BDA) also create new opportunities for manufacturing as well (Freddi, 2018).

### *Transport*

Within the transport sector the biggest technology arising is automated driving. Which consists of several other technologies, such as sensor technology and AI (Milakis, Arem, & Wee, 2017). Although it is not yet adopted at this moment, several big companies are innovating and testing the technology. Moreover, by 2020 some Intelligent Transport Systems will be in play in the European Union. Part of which are connections between vehicles and also autonomous driving (Skeete, 2018). Although there are still a lot of policy challenges, once legislation is accepted and the technology is ready it may significantly disrupt different industries, such as the automotive industry, the trucking industry, and the taxi industry.

### *Supply chain management/Logistics*

BDA will have and already has a significant influence on Supply Chain Management (SCM) and as a consequence it is creating increasingly more automation in logistics (Rossmann, Canzaniello, Gracht, & Hartmann, 2017). Together with IoT and other technologies it is improving driver safety, lowering operating costs, and reducing the environmental impact (Hopkins & Hawking, 2018).

### *Accounting*

Accounting does traditionally have a lot of repetitive tasks, which makes automation easier. BDA is enabling this automation in accounting information systems (Esperanza & Jensen, 2017). Cognitive computing is another technology influencing automation in accounting (Marshall & Lambert, 2018). It is quantification of human thought processes into a self-learning algorithm. These innovations will replace some tasks for employees. However, the research done in this field does not state it will diminish the accountant's job, rather it will redefine them.

### *Medical field*

The research of the medical field covers a diverse application of emerging technologies. Clinical medical physicists will see their human labour be transitioned to be performed by robots with artificial intelligence (Tang, Wang, & Rong, 2018). Also the job of the nurse and the caregiver to the elderly will make a transition to suit a new technological environment (Booth, 2016; Pee, 2018; Tobis, Cylkowska-Nowak, Wieczorowska-Tobis, Pawlaczyk, & Suwalska, 2017). The technology may even be adopted earlier, since the aging problem in western societies and the shortage of nurses/caregivers is already creating a policy problem.

### *Journalism*

In journalism there is a kind of creativity of the journalist that is hard to automate. However in articles there is a certain structure and with the emerging technology of Natural Language

Generation (NLG) it is possible to generate articles without a journalist (Konstantin, 2016). The effects of this technology were already discussed in chapter one.

Changes in all these fields are dependent on their economic value. Therefore, employment is widely studied in economic theories.

### 2.1.3 Economic views on the labour market

There will not be an in-depth economic analysis of different economic theories on this research. It would however be valuable to shed light on the outcomes of this research regarding different macro-economic theories. This subchapter will however only consist of the economic notions found through the search plan.

Employment and productivity growth are long-established economic themes and are important when jobs are regarded. Research points to a decoupling of these two factors, whereas they used to be similar in behavior (as already touched upon in chapter 1) (Brynjolfsson & McAfee, 2011). Brynjolfsson and McAfee consider this to be sign of a transition in the labour market never seen.

Over the past century, technological innovation has always been in close relation with productivity gains at firm and country level. Moreover, competing firms have seen that in most cases the lesser productive firm will draw the shorter straw in the end (Leipziger & Dodev, 2016). With robots in play, productivity is rising (Graetz & Michaels, 2018). But, this will come with the destruction of jobs and will let the labor income share decline (Dauth, Findeisen, Sudekum, & Wossner, 2017).

In economic literature several measures have been written to deal with the transition, for example transformation of the tax system (Bonekamp & Sure, 2018), but no measure is undisputed and since the fourth industrial revolution has only just started the implications on a macroeconomic level are not completely clear yet.

From an economic standpoint, if a robot can outperform a human at an occupation and the costs are lower, companies will be sure to implement them, but it does not necessarily have to lead to a complete occupation being substituted. In some situations, people utilizing technology as a complement means even a higher productivity.

### 2.1.4 Robots, humans, jobs and skill-allocation

Many sources write about the influence of robots and the effect they are having on labour. A significant question is about the complementarity; 'Will the robot be a complement to human labour or a substitute?'

Robots have been around for a significant time. Manufacturing companies have so far been sequencing tasks and divided separate tasks in two kinds. Either to be performed by a robot or by human labour (Decker, Fischer, & Ott, 2017). With the emerging technologies robots can take over more tasks that used to be performed by humans. These robots either



take over the work, complement the worker, or make the work more efficient (and therefore less workers are necessary). Hamid, Smith & Barzanji (2017) vouch for the complementary work of robots. Their research gives some foundations for this claim. Namely, the economic mechanisms of automation and the difference in 'how something is experienced' versus algorithms build on artificial intelligence. Other research suggests in the US one robot reduces employment by seven jobs (Acemoglu & Restrepo, 2016) and in Germany a robot is replacing two jobs in manufacturing (Dauth et al., 2017). The jobs lost by this implementation were most of the time carried out by low-skilled workers (Acemoglu & Restrepo, 2016; Graetz & Michaels, 2018). Substitute or complement, the incorporation of robotics and automation in companies does also have social and ethical implications. The next section will elaborate further on this aspect.

### 2.1.5 Social implications and ethics of working

Robots may replace or complement workers, also the social and ethical implications need to be regarded by governments while mapping out policies. Working with or supervising robots is becoming more normal, but with this change ethical and social questions arise. For example, "Does society want robots to perform certain jobs?", and "How do we want interaction between complementary working robots and humans to be shaped?".

When history is regarded the adoption of technology is often highly debated. For example the smartphone shows how much technology and humans can become intertwined (Vincent, Taipale, Sapio, Lugano, & Fortunati, 2015). The arrival of new technologies will create new discussions about this kind of interaction between human and machine. Since artificial intelligence is still in its early years there is no sufficient empirical research available on these interactions and research (Moniz & Krings, 2016) states the importance of doing more of this kind of research is vital.

Swedish research (Liliequist, 2018) examined the perceptions of people on working with robots. The interviewees of this study did see the problems arising from cooperation between humans and machines. However, the interviewees did not see this as an obstacle.

There are also ethical issues emerging. For example, how should an autonomous driving car with passengers react when it faces the following situation; 'The car did not see a pedestrian in time. It can no longer come to a safe stop. It needs to choose whether it will hit a pedestrian or slam into a tree?' Such a situation needs to be decided by algorithms programmed into the autonomous car. How should such a situation be programmed? Or even, is this situation viable today?

Apart from working alongside robots and ethical implications there is also the meaning of work. People (by nature) 'want' to work and feel meaningful. In a more broad term this is regarded in literature as the psychology of working theory and research (Blustein, Kenny, Fabio, & Guichard, 2019) states that the loss of decent work could undermine the individual and societal well-being. Other research (Duffy et al., 2016) shows the decrease in low-

skilled jobs will increasingly force low-skilled workers into work they do not choose to do, but have to do, in order to make a living.

### 2.1.6 Education and technology

There is an important connection between education and the industrial revolutions throughout history. Every time a revolution diminished the number of jobs, new occupations have emerged. Training the workforce to fit the capabilities these new jobs require is important. Education towards these new capabilities is key. The question for this revolution is, "Can the transition of the workforce through education keep up with the fast-changing paced revolution?". In practice this means for example that a 45-year-old truck driver needs to be retrained to suit a job in ICT. Is this even a possibility?

With adaptation of robots to perform increasingly difficult skilled jobs, the future workforce needs to adapt as well. Research shows this adaptation is increasingly difficult for lower skilled workers (Grip et al., 2018). Other research indicates two thirds of the adults in Finland with a vocational education lack different skills such as problem solving, which can be seen as a 'high'-skill (Hämäläinen, Wever, Malin, & Cincinato, 2015). For these people, adaptation will be difficult. In the US the educational system in place is focused on standardization and didacticism. Research (Araya, 2015) states policies are needed to enhance the school system to suit a more extensive skillset.

Auon (2017) argues for three new literacies in order to create a creative mindset with mental elasticity, sufficient to suit future jobs. Data literacy and technological literacy to suit knowledge necessary to understand the emerging technologies, but also human literacy, to be able to function as a human being in this technological environment. Other research agrees with the literacies on data and technology but argues for a more specific skillset, namely "critical thinking, problem solving, collaboration across networks, agility and adaptability, initiative and entrepreneurialism, effective communication, accessing and analyzing, information, and curiosity and imagination" (Gravemeijer, Stephan, Julie, Lin, & Ohtani, 2017). Altogether the educational system in place is not designed to focus on the proposed skills. The ability for people to adapt to this changing environment lifelong continuous learning, training and education is necessary (Aoun, 2017; Bonekamp & Sure, 2018).

With the ongoing fast pace of change, some questions arise: "Will humans be able to adapt fast enough?", and "Is it possible to educate the workforce with a lower IQ towards higher skilled jobs?". These questions will remain unanswered, but already three scenarios can be distinguished. In the first scenario the fourth industrial revolution will not have a significant effect on the labour market and there is a smooth transition to a new labour market configuration. This scenario is regarded as the 'Null-scenario'. The second scenario stands for a mismatch in the jobs that are available and the workforce that needs to fill these jobs. In this scenario enough new jobs are created for the workforce, but the

workforce is not adapting fast enough to suit these jobs resulting in a mismatch in the labour supply and demand. This scenario is regarded as the 'Mismatch-scenario'. The third scenario is the scenario in which the growth of new jobs is not suiting the demand for jobs leading to increasing unemployment. This scenario is regarded as the 'Labour surplus-scenario'. If the effect of technological development is significant on the labour market, it is questionable if the people and the market will reconfigure by itself. If the second or third scenario occurs governments (and companies) need to play a role to help the workforce adapt to the new labour market or to configure the labour market.

### 2.1.7 Labour market policies

The scenarios described in previous section give an outline for the different futures of the labour market. If second or third scenario become true, the labour market changes and is reconfigured to a non-optimal equilibrium. In these scenarios' institutions are not in play for the workforce to cope with the changes. Therefore, policies need to be defined to handle problems and opportunities of the new emerging technologies.

Research shows different kinds of policies influencing the workforce. However, also the societal environment is important. The aging populations in most western countries will mean the grow of the workforce will be stagnant, whereas the elderly needy are increasing. Moreover, it is estimated low-wage workers are easier replaced than high-wage workers and that therefor inequality will rise (Berg et al., 2016).

There are enough ideas in the literature of possibilities to deal with the transition of the fourth industrial revolution. The basic income, a change in the educational system, and redefinition of taxes have already been proposed, but also slowing down innovation and change, sharing work, creating new work, redistribution of work, and fostering new social contracts are options (Marchant, Stevens, & Hennessy, 2014). On a higher level the policies are categorized as active labour market policies or passive labour market policies. Active labour market policies cover five different areas: public employment services, labour market training, youth measures, subsidized employment, and measures for the disabled (Martin, 1998). Passive labour market policies translate to spending on unemployment, social benefits, and early retirement benefits (Martin, 1998). Over the years different active and passive policies have been implemented to steer the labour market to an optimum. The fourth industrial revolution will have its effect on the labour market, and it has yet to be determined if the currently active labour market policies will suffice in the future.

## 2.2 Forecasting of the Labour market focusing on emerging technologies

Although there is a lot of research on labour market forecasting most of these resources do not comply with the focus of this research, since the focus is specifically on quantification of the effects on the labour market taking in regards the technological developments of the fourth industrial revolution. The covered studies so far are the research of 'Osborne and

Frey' and the OECD report on job susceptibility (Nedelkoska & Quintini, 2018). When further scanning through the research only one more relevant source is found suiting the focus of this research. Namely the paper 'Revisiting the risk of automation' performed by the Centre for European Economic Research (CEED) (Arntz, Gregory, & Zierahn, 2017). This research shows similarities to the OECD research and concludes in a classification of 9 percent jobs in the US are at high risk of being automated. It is necessary to compare these studies to understand the differences in outcomes.

As a drawback of their research, Osborne and Frey note they do not focus on within-occupation variation. They state, *"We emphasize that since our probability estimates describe the likelihood of an occupation being fully automated, we do not capture any within-occupation variation resulting from the computerization of tasks that simply free-up time for human labour to perform other tasks."* (Frey & Osborne, 2013, p. 43). Although Osborne and Frey seem to think this drawback will play a minor role, the research of the OECD and the CEED play into the drawback and incorporate within-occupation variation in their study by using data on individual level. This makes it possible for them to incorporate within-occupation variation on demographic variables.

Osborne and Frey react on this approach by OECD and CEED in a plea (Frey & Osborne, 2018). The first thing standing out from this plea is the following quote: *"Instead of relying primarily on tasks, the Mannheim study uses worker and firm characteristics, as well as demographic variables such as sex, education, age, and income. According to this approach, the more an accountant earns, the less automatable his job is. If he or she happens to have a PhD in sociology, the job is safer from automation. Similarly, a female taxi driver with a PhD is less likely to be displaced by a self-driving car than a man who has been driving a taxi for decades. Yet why should automation discriminate on the basis of worker characteristics?"* (Frey & Osborne, 2018). Hereby they show an important flaw in the CEED research (mentioned in the quote as the 'Mannheim study').

The OECD report does not contain this flaw. However, in the reaction piece, Frey and Osborne question this research as follows, *"The OECD uses individual level data from the PIAAC survey, which they argue explains why they find a lower percentage of jobs to be automatable, relative to our estimate. However, they do not provide any evidence to actually show that this is the case"* (Frey & Osborne, 2018). They do not claim that the OECD made a mistake, but in the opinion of Frey and Osborne the OECD lack to provide an explanation on making this new distinction.

The Osborne and Frey research neither is waterproof. Their percentages are first based on expert estimations, which means their basic assumptions are subjective. Additionally, in their research they use a classifier with an accuracy of 90 percent. In conclusion all the research on job susceptibility is in some way incomplete.

The three different sources estimating job susceptibility result into two different images about future susceptibility of jobs, namely a 9 or 10 percent of total US jobs being highly susceptible (Mannheim and OECD) versus 47 percent of total US jobs being highly susceptible (Frey and Osborne). The image the research of Osborne and Frey shows a significantly higher percentage. Such a percentage of jobs lost may have huge consequences for the American labour market. The quantification of these huge consequences is lacking for the US, but also for any other country. Therefore, the research of Osborne and Frey is selected to function as a foundation for this research and the eventual forecast. The outcomes of this research should also contain a reflection on the results for the Dutch labour market of the study by the OECD.

In the next paragraph the debate in the Netherlands on labour market transitions is addressed by comparing different kinds of literature.

### 2.3 Labour market forecasting in the Netherlands

When considering labour market forecasting in the Netherlands a search plan is followed to gain insight in the relevant organizations and scholars that are knowledgeable on the topic. The search is based on two steps. In the first step the relevant organizations and scholars are identified through desk research. When identification is complete the identified organization and scholars shall be analyzed in step two. Analyzing is done by looking into all relevant literature and other sources that focus on labour market forecasts and technological developments affecting these forecasts. The executed search plan is displayed in appendix III.

#### *Dutch labour research organizations*

Three research organizations in the Netherlands have been performing studies in the Netherlands on the topic. The first one is the "Rathenau institute". This institute delivered the report "Robot Society" (Est & Kool, 2015). In this report the institute chooses to follow the same line of reasoning as Frey & Osborne expressing their worries about the future. By following this line of reasoning, they also state it is no longer a fact that technological progress will lead to cheaper products, more purchasing power, and new & more jobs (figure 2). In the report they name "jobless growth" as one of the trends linked to possible technological unemployment affirming the scenario may lead to less employment. The trend is also used to point out the unfavorable scenario of high long-term unemployment rates, resulting in greater social inequality and more public unrest (Est & Kool, 2015). The second research organization is the CPB (Central Planning Bureau of the Netherlands). The prime job of this organization is to make economic forecasts and analyses. However, long term forecasts of the labour market are not found in their database. There is some research on the effect of digitalization of the labour market, but this research focusses on effects of empirical data and no usage of this data to make any forecast is discovered. The third organization is the WRR (scientific council for government policies).

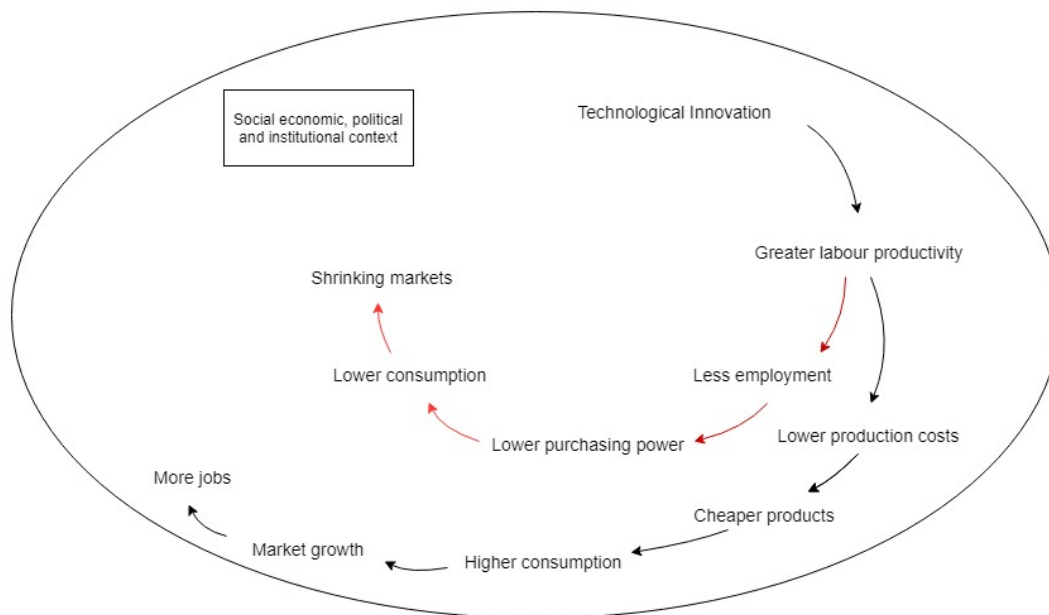


Figure 2: Visions on technology and labour: more or less jobs (Adjusted figure from Rathenau Institute)

This organization made the report 'Being the boss of the robots' (Went, Kremer, & Knottnerus, 2015), but the report is having an exploratory character based on historic data. It contains matters such as, "what changes can be seen in the market?" and "what is known about the consequences of these changes?". They state it is hard to foresee the future of the Dutch labour market and there is yet to be a study that tries to make such an estimation.

#### University organizations

There are also several organizations tied to universities performing research on the Dutch labour market. The first of which is the SER (Socio-Economic Council). This organization recognizes the two perspectives, with either people believing unemployment will rise or people believing new jobs will be created just as fast as old jobs are destroyed. In their research (*People and technology: working together*, 2016) they also see job polarization rise through hollowing out the middle class and pay attention to the fact that a transitional phase will be starting soon either way. They believe the workforce should be adaptable to suit new jobs. The second university organization is the RAO (Research Centre for Education and the Labour Market). The RAO developed a number of studies (for example 'Labour market forecasts by education and occupation up to 2022' (Bakens, Fouarge, & Peeters, 2018)) aimed at forecasting the labour market for the medium term, but no long term forecasts are found made by the organization. To forecast this development the Centre uses a forecasting model. They state it is not certain to which extend their model is accounting for automation of jobs. In comparison to this research, their research future scope is not similar, and they do not incorporate of digitalization. These conclusions make it impossible to use their estimations as a validation for this research. The last organization is the SEOR (independent consulting agency). In their research "Technology and Labour

market” (Koning & Rooij, 2017) they discuss the research that is mentioned in paragraph 2.1, but they do not produce any research themselves on the matter.

### *Scholars*

In the Netherlands there are several scholars researching the Dutch labour market. When analyzing the different universities and their researchers of the Netherlands two researchers are found who research the Dutch labour market and consider the influence of technological developments.

Wilthagen presented his view on the future of employment in a speech on 27 February 2018 (Wilthagen, 2018). His first point is technology equals power especially in the labour market. He does however not believe technological trends are separated from other parts of the labour markets such as globalization and demographics of the workforce. Wilthagen also makes a case for a debate on the topic, because he believes job redefinition is coming and a resilient workforce is required. After scanning his research, his speech and his research output, it is concluded no estimation on the vastness of this job redefinition is published by Wilthagen.

Salomons presented her vision on the future labour market in a speech for ‘Studium Generale Utrecht’ (Salomons, 2015). Salomons agrees with most economic scholars that an increase in total labour productivity is not leading to unemployment (historically seen). This belief is based on three premises. First, technology is rather a complement than a substitute. As her second premises she states the demand for goods and services contains elasticity resulting in an increase in the demand for labour. Finally, she states supply of the workforce contains elasticity in the long run. Salomons beliefs these premises will be true again, since she beliefs complementarity is more important than substitution. The speed of technology adaptation is most of the time overestimated, because of the ‘lump of labour fallacy’. The fallacy points to a thinking error by which people assume the amount of work is fixed, which is not the case considering there are always people losing and gaining jobs over time. Salomons does however acknowledge an increasing number of tasks can be performed through the usage of technology, but also points out lots of tasks remain uneasy to be caught in rules and are therefore hard for a computer to perform. Artificial intelligence may be able to increase this number of jobs, but according to Salomons there are still a lot of obstacles to overcome for this technology.

It is concluded none of the actors make a future estimation of the Dutch labour market in the long-term future. Some studies make estimations, but these forecasts are focused on a short-term. Of the performed research a lot is focused on the question “What will the impact of technology be?”, but they fail to carry out quantitative research on the matter and because of their top down focus the conclusions are broad.

## 2.4 Uncertainty on technological development trends

In the previous chapters no research on long-term labour markets forecast for the Netherlands is found. An important reason for the lack of such research is the uncertainty that must be dealt with for such a forecast, since there are a lot of factors influencing the labour market. Research shows consideration of uncertainty is essential for policy making (Walker, Marchau, & Kwakkel, 2006). This means the forecast can only be used if uncertainty about the forecast is addressed properly.

There are many definitions of the concept uncertainty. In this research the line of reasoning of Walker, Marchau, & Kwakkel (2006) is used to regard uncertainty. The concept of uncertainty is defined by them as “limited knowledge about future, past, or current events”. In their line of reasoning they use several other sources to envision uncertainty. Firstly, Funtowicz and Ravetz (1990) make clear uncertainty is divided in three groups, inexactness of information, unreliability of information, and the existence of borders of ignorance. Secondly, uncertainty is not per se solved by having proper information, even then uncertainty may stay an issue (Asselt & Rotmans, 2002). Finally, van der Sluijs (1997) underlines new information may also decrease uncertainty, since new knowledge can lead to broader a understanding of a situation. All the above make uncertainty a complex concept.

The OECD states labour market forecast have to be based on the economic growth climate in a specific country, the relationship with the economic growth climate in the world, and the creation of models (“Labour force forecast,” 2019). Rahman & Ulubasoglu (2015) describes the difficulty in regarding the economic growth climate by pointing out the multidimensional character; changes in public health, literacy, demography, and distribution of income. Acemoglu (Acemoglu, 2012) underlines this and states one of the underlying sources for economic growth is the development of technology. This multidimensional character creates uncertainty for a labour market forecast. The creation of models as a forecasting tool also creates uncertainty, since the creation of a model however means the simplification of reality (Box, 1976). The simplification means the full scope of the real situation can never be grasped by the model.

Forecasting the labour market brings multiple sources of uncertainty. Therefore, addressing this uncertainty should have a prominent place in the methodology of building the labour market forecast.



## 2.5 Knowledge gap & scientific relevance

Urgency and social relevance for insights of the future labour forecasts for the Netherlands have been elaborated extensively so far. In the previous subchapters the wide literature has been researched. This information will now be combined to discover where a gap of knowledge exists in the research.

Research on the literature shows changes in wide variety of sectors because of emerging technologies (manufacturing, logistics, accounting, transport, medicine and journalism). These changes may lead to people working as a complement of technology, the redefinition of occupations or the loss of jobs. An employee working alongside new technologies or an employee having a redefined occupation will need new skills plus education to perform the occupation.

The changes on job level cause changes in the labour market. What the influence will be is however unknown for the long term. Three different scenarios are drawn. These scenarios represent the spectrum of possibilities the changes may lead to. In the first scenario new jobs are created and the workforce can adapt to them without interference. Several sources (Aoun, 2017; Araya, 2015; Gravemeijer et al., 2017) state it is hard to believe the workforce will adapt by itself. They state for this reallocation to be successful; policies should steer towards the creation of an adaptable and resilient workforce. In the second scenario the labour market is also reconfigured and new jobs are created, but in this case the workforce is not sufficiently reallocated. When this reallocation does not happen appropriately, rising unemployment is a real scenario. In that case the consequences for the low-skilled workers seem to be the most rough (Acemoglu & Restrepo, 2017; Graetz & Michaels, 2018), which may result in increasing inequality. In the third scenario not enough, new jobs are created to replace the jobs susceptible by technology. In this case the labour supply is higher than the labour demand leading to a new kind of unemployment (since there is simply no space on the labour market for a part of the population). The debate on which of these scenarios will occur is ongoing. In this debate insights in the magnitude of the possible future labour market redefinition will help policymakers in the decision-making process.

As reviewed in the literature there are some studies trying to grasp the magnitude of technological development resulting in two directions of research. The research of the CEED & OECD state a small percentage of the jobs existing in the US nowadays is at risk of being automated, namely 9 & 10 percent. On the other side of the spectrum is the research of Frey and Osborne indicating 47 percent of total jobs are highly susceptible. These estimations however only give an indication of how many jobs may be susceptible, where there is also a demand for knowledge on the total labour market forecast. Determining insights in the loss of jobs in the Netherlands and the effects on the total labour market will be the major objective of this research.

Both stated directions (low percentage of 9 or 10 versus high percentage of 47) are suitable to serve as a foundation for this research. However, the OECD study already made a calculation of the job susceptibility in the Netherlands resulting in six percent of total jobs being at stake. For the high percentage of Frey and Osborne no translation is yet made to the Dutch labour market and if Frey and Osborne are right, the consequences will be huge for the Dutch society. Therefore, the estimations of Frey and Osborne will be used as a foundation to build upon to make the indication for the situation in the Netherlands.

When regarding the Netherlands specifically, the WRR mentions a study with this kind of research scope is yet to be carried out. Also, the SER states low-skilled workers probably have the biggest problem if rising unemployment does occur by stating the emerging technologies may lead to a hollowing out effect of the middle class. This event will push these middle-class employees to other lower skilled occupations. The risks for low-skilled workers is an important topic in the literature ((Acemoglu & Restrepo, 2017; Berg et al., 2016; Bonekamp & Sure, 2018; Duffy et al., 2016; Grip et al., 2018). Therefore, insights in the skill level of the workforce (that may lose their job as a result of developing technology) would be a valuable addition to this research.

Finally, Salomons makes an important contribution by pointing out the 'lump of labour fallacy'. This is a thinking error, where research does not incorporate the growth of new jobs into their estimation. This vision sharpens the focus of this research. First, the growth pattern of existing jobs should be incorporated. Second, the concluding outcomes on the number of jobs lost do not equal the number of people out of work, since there may be new jobs created for these people. For example, if the outcomes of the research will conclude in a thousand jobs lost, it does not mean a thousand people (performing these jobs) become unemployed, but it does mean this workforce will need to deal with some kind of retraining in order to fit those new jobs. Rather does the outcome of this research indicate a policy space available to use for policy makers.

Logically it would also be useful to incorporate the growth of the labour supply. But, when the forecast of the labour supply is regarded it is found that the supply of labour stays roughly constant at 9 million people until 2060 due to population demographics (Euwals, Graaf-Zijl, & Ouden, 2014). Therefore, this information is omitted.

In conclusion the knowledge gap is, "*The demand for quantitative occupational level insights in the Netherlands following the methods of Frey and Osborne and the consequences for the Dutch labour market and the workforce of these insights*". For these existing occupations the growth pattern should be incorporated to deal with the 'lump of labour fallacy'. The creation of new occupations and their growth pattern is unknown and not incorporated. Consequently, the supply of labour of these new occupations should be addressed in the conclusions. The concluding impacts on the low-skilled workers are most important, since this is the most fragile group of the workforce and they are expected to be impacted the most.

### 3. Research Design

The research gap identified in the previous chapter shows the need for quantitative occupational level insights in the Netherlands for the scenario of Frey and Osborne and the consequences for the Dutch labour market and the workforce of these insights. The aim of this research will be to explore these consequences. This chapter will explain how the research is designed to achieve that goal.

#### 3.1 Research question and sub-questions

As discussed in chapter one, the urgency to determine the consequences of robotization and digitalization on employment is right now. There is a strong common awareness for possible unemployment as one of the consequences. Chapter two shows there is a lack of research on labour market forecasts for the long-term future (2030 in this case), which considers an high technological development scenario. For the Netherlands insights in quantitative occupational level forecasts can be used as tool to design future policies. This demand for insights leads to the following research question:

*“What are the quantitative effects of technological developments on job level for the Dutch labour market in 2030 and how can the defined policy space contribute to decision-making?”*

The research is having a quantitative database-driven approach, which will use empirical occupational data of the Netherlands and the occupational susceptibility data of Frey and Osborne to construct and analyse future scenarios.

##### 3.1.1 Sub-questions

The research is split up into smaller objectives in order to eventually answer the main research question. These smaller objectives are translated into sub-questions. The sub-questions for this research are the following:

1. How can the labour market data and job susceptibility data be identified?
  - a. What data is selected for usage of this research and what are the characteristics?
  - b. Is there a need for additional data?
2. What effects on the Dutch labour market can be drawn by combining the occupational susceptibility percentages and workforce quantities per occupation?
  - a. How can the sources be merged together?
  - b. How many jobs are lost per sector?

3. What are the effects of empirical occupational growth trends on the labour market and what educational level is required per occupation?
4. What are the explorative scenarios to mitigate the uncertainty of technological development scenarios?
5. How may the methodology of labour market forecasting be generalized?

When the sub-questions are answered the answering of the main question can be addressed. The fifth sub-question is not needed to answer the research question but will contribute to the scientific contribution of this research, since there is not yet a generalized method to create a long-term labour market forecast.

### 3.2 Research Methods

Three types of data are needed to forecast the situation of the Dutch labour market in 2030. The types of data are; occupational percentages on job susceptibility, the labour market configuration of the Netherlands, and growth data about the Dutch labour market. Merging these types of data together will give a conclusive estimation of the future labour market configuration. Since the effects on low-skilled workers is important to regard (Bonekamp & Sure, 2018), there is a fourth data type added. The fourth dataset should cover a characteristic of the workforce representing the skill level of the workers. According to Wolff (1996) skill is a multi-dimensional concept, because most occupations require a variety of skills to perform the tasks belonging to the jobs. Research (Colecchia & Papaconstantinou, 1996) states in empirical studies most the time a proxy is made by basing skill on either educational level or occupation. This research will lead to a part of the workforce which have lost their job. This part of the workforce then needs to apply for another job. It is assumed the educational level is a better indicator to estimate if the worker will be qualified enough to perform the job. Therefore, in this research the educational level of the workforce is regarded as a level of their skill.

The first part of the research methods should incorporate the integration of the different datasets. The general purpose data integration system (GPDIS) created by Doan, Halevy and Ives (2012) is used as a framework to guide this process. The architecture for the integration data used in this framework is stated in figure 3. In the GPDIS multiple kinds of structured data sources are selected. This data is then parsed from the sources by wrappers into a data warehouse. The wrappers make sure the data loaded into the warehouse is readable for the warehouse operating system. The data warehouse then

functions as a repository for all the loaded sources. In this warehouse different sources can be coupled together. The coupled sources may be used for analysis.

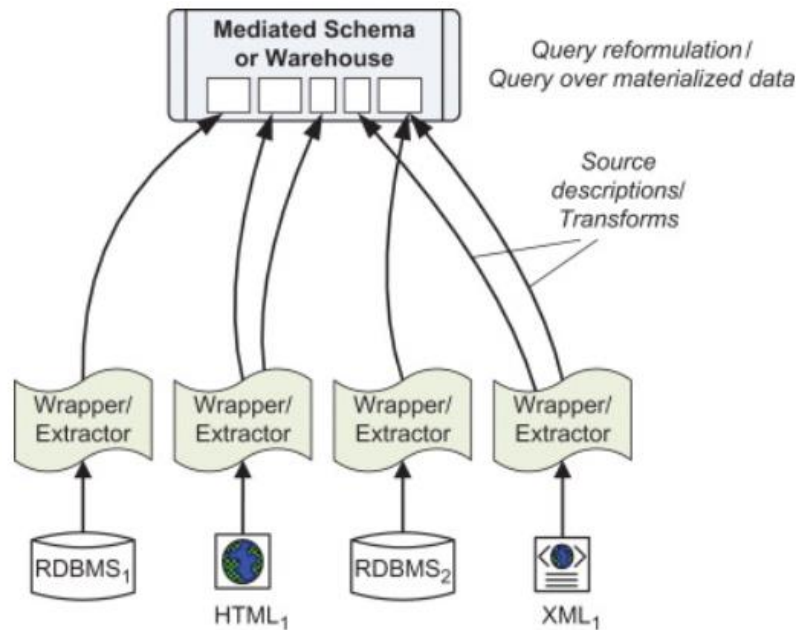


Figure 3: The basic architecture of a general-purpose data integration system (Doan et al., 2012)

The method of this research will be based on the framework of the GDPIS. The four specified data sets are the sources within the framework. The wrappers will prepare the sources to suit the characteristics of the data warehouse. This data warehouse will then be used to create a database. The program used to wrap the data and serve as warehouse for the data will be python. The research method for this research is stated in figure 4.

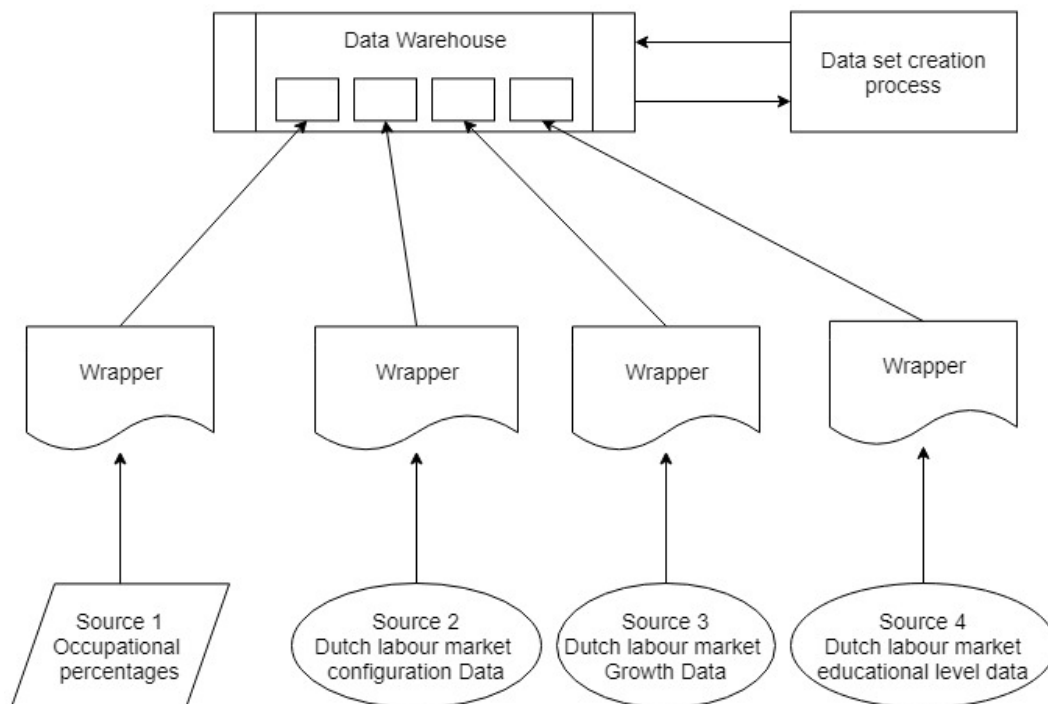


Figure 4: The research method for this research

The eventual database configured by usage of the data warehouse will function as a model to represent the Dutch labour market in 2030. This database should contain certain information per occupation. The required information of the database is stated in table 1. The data instances of the database will be the job occupations defined in the Netherlands. In the resulting dataset the characteristics shown in the table should be present for all of the instances. Finally this database is used for analysis to gain the required insights in the labour market situation of 2030.

*Table 1: Characteristics and corresponding datatypes of the final dataset*

Labour market database	
<i>Characteristic</i>	<i>Datatype</i>
Occupation Name	String
Number of workers	Integer
Susceptibility percentage	Float
Educational Level	Integer
Growth percentage	Float

### 3.3 Addressing uncertainty

In the literature review the necessity of addressing uncertainty is explained. With the usage of data, a new source of uncertainty is identified. The uncertainty of data is caused by data quality issues. There are three kinds of data quality issues defined according to Huang (2013); syntactic issues, semantic issues, and pragmatic issues. Syntactic issues are caused by the mismatch in database rules and stored data settings. Semantic issues happen when the purpose for which the data is stored is purpose it fulfills in the database. Pragmatic issues are caused by unsuitable data for a given. To guarantee data quality Huang defines 5 criteria which the data need to uphold; accuracy, completeness, consistency, timeliness, and presentation suitability. Accuracy problems can either be syntactic or semantic Syntactic accuracy problems are for example the entry of 'mle' as input for gender. Semantic accuracy problems are for example the entry of 'male' for 'Anne Brown'. Completeness problems arise when either the instances of input contain missing values or if complete records missing. Unbalanced data problems occur when there is a bias in the dataset and with timeliness problems the lack of representativity or outdated is meant. During the data identification phase the data quality issues need to be regarded to minimize and address the uncertainty in the data.

The second uncertainty is an uncertainty inherited from the Frey and Osborne research (appendix IV). In their research they are using a classifier method to appoint percentages to the occupations. This classifier is not 100 percent accurate. The accuracy percentage of this classifier is roughly 90 percent, meaning it will classify 90 percent of the occupations correct. The leftover 10 percent is what brings the uncertainty to this research. For this research it is assumed occupations are misclassified in both directions (some percentages are lower than they should be while others are higher than they should be). This assumption

means there are effects that are balancing each other. Therefore, the effect is assumed to be marginal and it will not be incorporated in this research.

The third uncertainty addressed in this research is due to the unknown development of technology, which is already addressed briefly in the literature review. The development of technology can be regarded as an external factor. Research (Börjeson, Höjer, Dreborg, Ekvall, & Finnveden, 2006) shows such uncertainty may be addressed with scenarios and for this case the research describes explorative scenarios to be the best suited. The aim of explorative scenarios is to regard all possible scenarios happening over a long timespan. The explorative scenarios are then designed to cover the wide scope of possible outcomes. Following this logic in this research three scenarios are defined. A low technological development scenario, average technological development, and high technological development. The low is the minimum boundary of the scope and the high is the maximum boundary of the scope. The average technological scenario helps to cover the scope but is not necessarily the middle point of the scope.

### 3.4 Research flow

The research flow of this research is translated into three phases. The first phase is data identification. In this phase the required data is identified, and their characteristics are regarded. The data quality issues, and the integration challenges are also addressed in this phase. The second phase is the data integration. In this phase the data in the data warehouse is regarded and the different datasets are set up to be integrated. The integration and formation of new datasets is also part of this phase. The database mentioned outlined by table 1 will be the final product of this phase. This database is used in the next phase; data analysis. In this phase the explorative scenarios are drawn, and the output product is subjected to these scenarios. The result of this process is analyzed and the insights of the Dutch labour market is concluded. The research flow is sketched in figure 5.

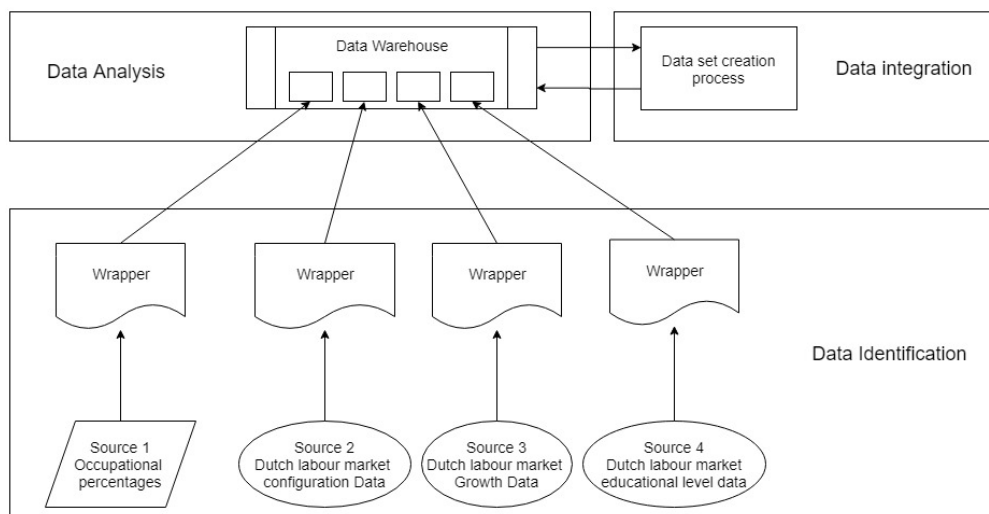


Figure 5: The research flow

In the next chapter the research will start by identification of sources and parsing these sources into the data warehouse. Additionally, the possible problems with the data quality will be addressed.



## 4. Data identification: What data is available and how is it structured?

Data identification suits many purposes. First, possible errors or problems with the data may be found. Secondly, the datasets are compared to set them up the data for further integration. Finally, also some additional data is identified, which is needed to make data integration possible. In this chapter the data used in this research will be identified.

### 4.1 Data identification

As already concluded in chapter two, for the occupational percentages of susceptibility the research of Osborne and Frey (2013) is used. The other three sources needed for this research are all based on labour market data of the Netherlands. In the Netherlands labour market data is gathered on a national level by the 'Centraal Bureau voor de Statistiek' (CBS). The CBS is a national agency of the Netherlands gathering all kinds of information, one of which is information about its labour market. CBS data on the labour market configuration is retrieved through a personal data request. The data on educational level and occupational growth are also retrieved from the CBS. This process is displayed in figure 6.

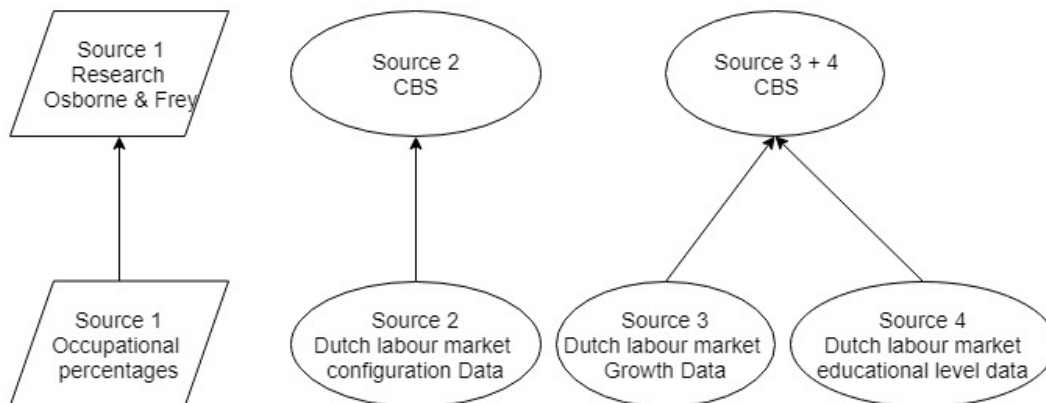


Figure 6: Retrieval of required sources

The occupational percentages of the Osborne and Frey are parsed through the wrapper first. Two data quality problems arise. The characteristic 'SOC-codes' sometimes contain an extra space for an instance of data ("29-1125 ") and the characteristic 'Occupation-name' does have a "\n" entry for every occupation name ("Recreational Therapist\n"). Both quality issues are semantic accuracy errors. They are resolved by performing python operations. The data that is loaded into the data warehouse has three characteristics. The corresponding characteristics and datatypes are stated in table 2.

*Table 2: Occupational percentages characteristics and corresponding datatypes*

Occupational Percentages	
<i>Characteristic</i>	<i>Datatype</i>
SOC-code	String
Occupation Name	String
Susceptibility percentage	Float

The second source parsed to the wrapper is the CBS data of the Dutch labour market configuration. Parsing this data does not seem to cause any problems. When analyzing the data occupations are found with 0 workers meaning there are less than 1000 people performing the specific occupation. It is an option to leave these occupations out of the research but leaving the occupations in the data will not cause problems and therefore these occupations are kept in the dataset. The characteristics and the corresponding datatypes of the Dutch labour market configuration are stated in table 3.

*Table 3: Dutch labour market configuration characteristics and corresponding datatypes*

Dutch labour market configuration	
<i>Characteristic</i>	<i>Datatype</i>
ISCO-code	Integer
BRC-code	Integer
ISCO Name	String
BRC Name	String
Number of workers	Integer

The data of the CBS on growth trends and educational level is packed in multiple datasets. The main dataset of these datasets is linking the number of workers to the occupations and educational levels. This main dataset is stated in table 4.

*Table 4: Characteristics of the main dataset for Occupational Growth trends and Educational level and their corresponding datatypes*

Dutch labour market Growth trends & Educational Level	
<i>Characteristic</i>	<i>Datatype</i>
ID	Integer
Educational_code	Integer
Occupational_code	String
Periods	String
Number of workers	Integer

The other two datasets are used as support to couple educational codes to educational levels and occupational codes to BRC-codes (BRC codes are the codes for classifying occupations in the Netherlands). These three datasets are all parsed through the wrapper to be placed into the data warehouse. This action does not give any issues. The characteristics and corresponding datatypes of the supporting datasets are stated in table 5 and 6.

Table 5: Characteristics and datatypes of supporting dataset 1

Dutch labour market Supporting dataset 1	
Characteristic	Datatype
Educational_code	Integer
Educational_level	Integer
Educational_description	String

Table 6: Characteristics and datatypes of supporting dataset 2

Dutch labour market Supporting dataset 2	
Characteristic	Datatype
Occupational_code	String
BRC-code	Integer
BRC-name	String

For explanatory purposes abbreviations for the datasets are used throughout the research. In table 7 the specified abbreviations are stated.

Table 7: Abbreviations of the datasets

Dataset	Abbreviation
Occupational percentages	OP
Dutch labour market configuration	WD
Growth trends & Educational Level	GE
Supporting dataset 1	SD1
Supporting dataset 2	SD2

## 4.2 Analyzing the identified sources

For data to be integrated there need to be keys corresponding between different data sources. In this research a key is regarded as the variable on which data coupling may take place. Data needs to be integrated in order to create the desired database. The hierarchy of how the datasets parsed into the data warehouse should be integrated is stated in figure 7.

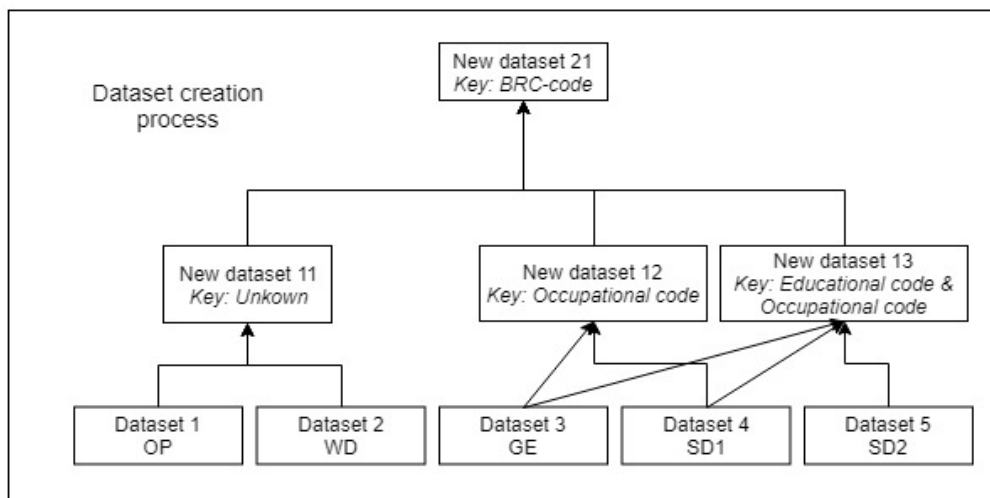
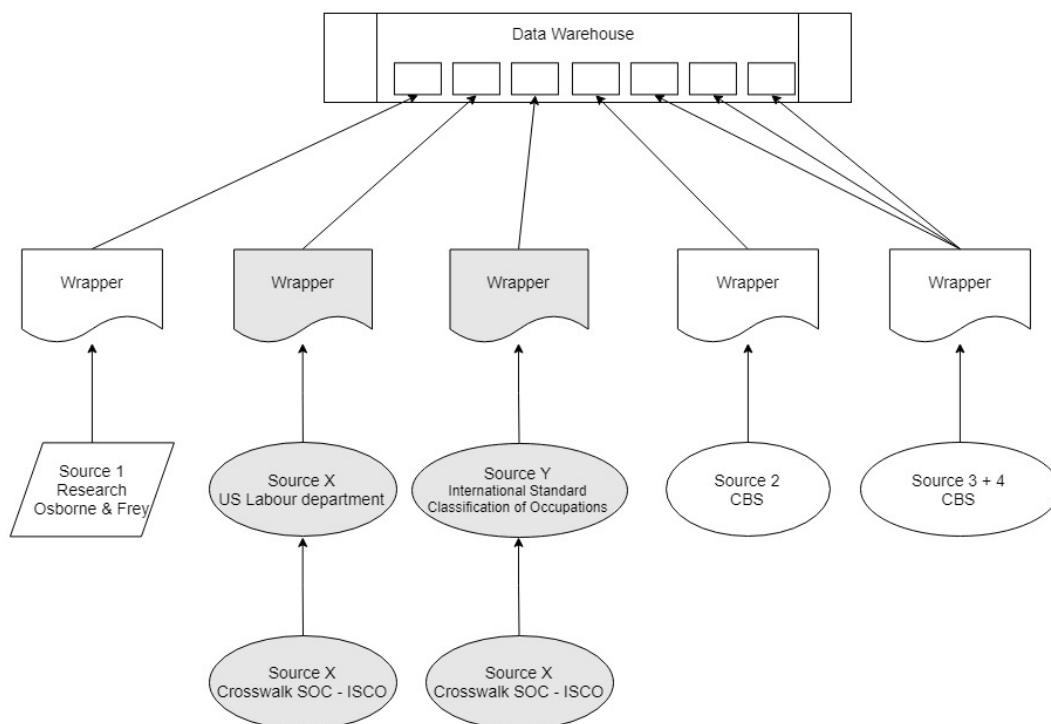


Figure 7: Flow of the dataset creation process

When regarding OD and WD (figure 7), more data quality problems are found, namely their classification of occupations is having different formats. OD follows the American classification of occupations (SOC), while the WD is following the international standard of classification of occupations (ISCO) (table 2 and table 3). To gain the ability to couple the databases a third data source is needed that is not yet available in the data warehouse. This data is found at the US labour department. The organization provides a source in their database that crosswalks between the SOC-codes and the ISCO-codes (addressed as crosswalk data (CD)). Incorporation of this source into the method is stated in figure 8.



*Figure 8: Incorporation of Crosswalk data*

The parsed data from the US labour department is also loaded into the data warehouse. The characteristics and datatypes of the crosswalk document are stated in table 8.

*Table 8: Characteristics and datatypes of the crosswalk data*

Crosswalk SOC – ISCO (CD)	
<i>Characteristic</i>	<i>Datatype</i>
ISCO-code	Integer
ISCO-name	String
SOC-code	Integer
SOC-name	String

When regarding the number of unique instances of ISCO and SOC codes in source 1, source 2 and source X discrepancies are discovered (figure 8). This finding should be

considered in the data integration part of this research. To be more certain about the right use of the ISCO codes one more source is added to the method. This source is extracted from the database of the 'International Standard Classification of Occupation' and contains the official existent ISCO-codes (figure 8). The characteristics and corresponding datatypes are stated in table 9.

*Table 9: Characteristics and corresponding datatypes official ISCO-codes*

Official ISCO (OI)	
<i>Characteristic</i>	<i>Datatype</i>
ISCO-code	Integer
ISCO-name	String

The new sources are also added to the flow of dataset creation. In appendix VI more information about the identified data is displayed plus images of what the actual data looks like.

In the following chapter, chapter 5, new datasets are created via data integration. This integration is split into two parts. In the first part new dataset 11 is created and in the second part dataset 12 and 13 are created (figure 7). At the end of the chapter these datasets shall be merged together to create the dataset containing all the required data for analysis.

## 5. Data integration: The creation of one database

Together the identified sources contain the information to build a labour market forecast. In this chapter the data is integrated. To goal of this integration step is to create the merged dataset stated in figure 9 as 'new dataset 21'.

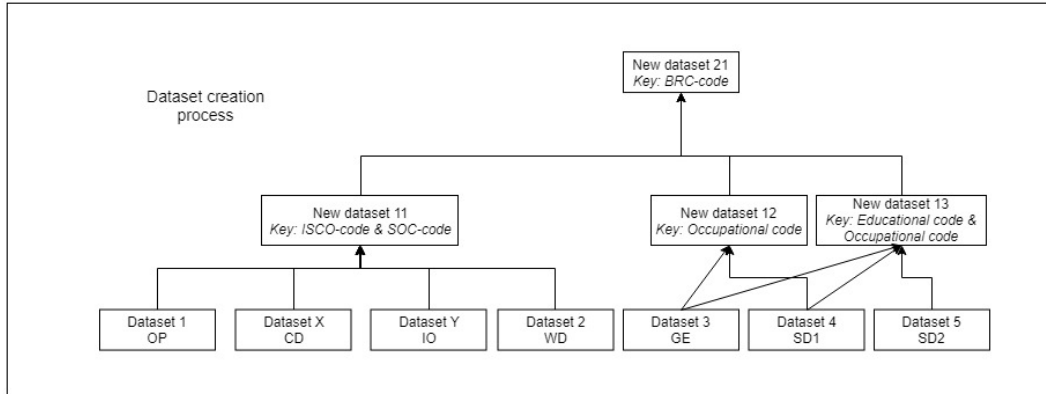


Figure 9: Dataset creation process

The integration is started by defining the job susceptibility for each of the occupations existing in the Dutch labour market. This definition results in the first result of this research, namely the spread of job susceptibility in the Netherlands and sectors. In this first step the occupational susceptibility data (OP) and the Dutch labour market configuration (WD) is merged. This process is stated in figure 9 and is regarded in this research as part 1 of the data integration. It should be noted, as described in the methods, the crosswalk SOC – ISCO (CD) and the Official ISCO (OI) are also needed, because of the difference in classification system used in the OP and WD. The result of this data integration step is 'new dataset 11' (figure 9).

Secondly, the Dutch labour market is also influenced by occupational growth trends. To determine the occupational growth trend per occupation the data needs to be unpacked from the CBS source and handled. This process will be covered in data integration part 2. As a result of this step dataset 12 is created (figure 9). Additionally, the low-skilled workers (in this research low-skilled equals a low level of education) are concluded to be a fragile group affected most by the loss of their job. Therefore, it is decided to determinate the educational level of the workers in each occupation. The educational level is defined by using the same source of data is the occupational growth trend. This process will also be covered in data integration 2 and the resulting dataset is 'new dataset 13'.

Finally, to forecast the Dutch labour market configuration the susceptibility data, the occupational growth trend data, and the educational level data need to be merged. This process is described by figure 9 with the creation of 'new dataset 21'. With this dataset and explorative technological development scenarios it is possible to estimate the future labour market configuration.

## 5.1 Data integration 1: Linking Osborne and Frey to the Dutch labour market

The datasets used to link the occupational susceptibility data are OP, WD, CD and IO. To create 'new dataset 11' the method in figure 10 is used. The data is handled, meaning it is configured to suit the research goal. Handling involves dealing with the data quality issues as well. The process will lead into some visualizations and conclusions. The outcomes will help answer the second research question, "What effects on the Dutch labour market can be drawn by combining the occupational susceptibility percentages and workforce quantities per occupation?".

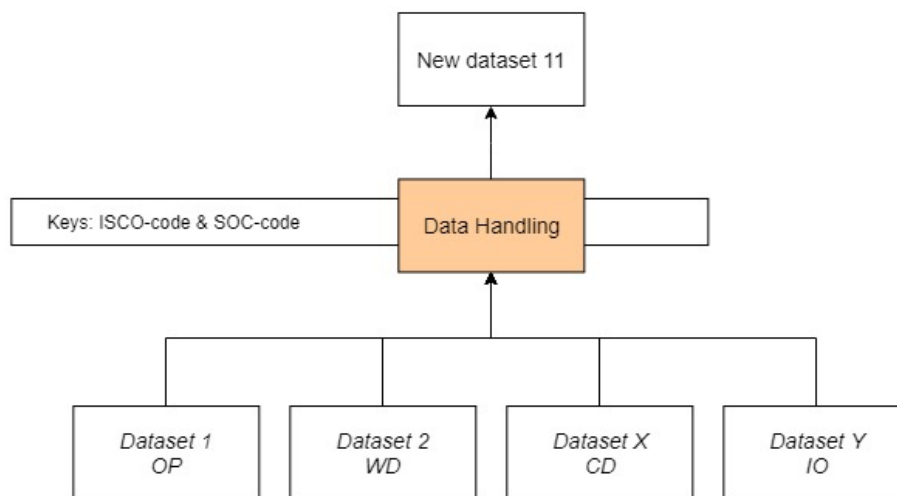


Figure 10: Method for data integration 1

### 5.1.1 Data handling

The process for data handling is displayed in figure 11. The process consists of four steps. The first step is coupling the data on ISCO and SOC codes. The second step is manually matching lost data of step one and finally in step three data duplicates are addressed. For a more detailed description of the data handling process appendix VII can be addressed.

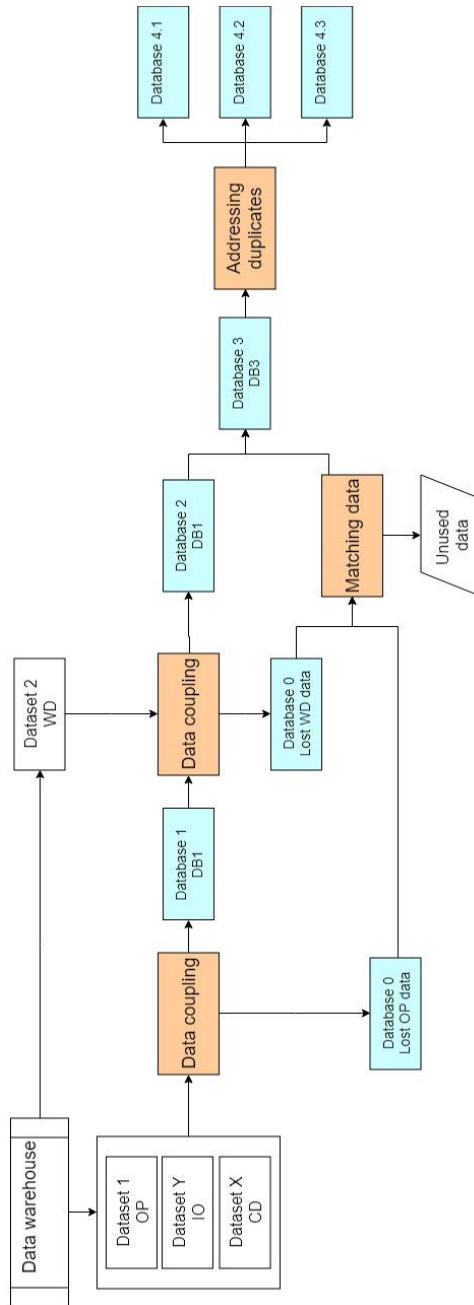


Figure 11: The data handling process

### Data coupling

When the data coupling process is started both the WD and the CD appear to have more unique ISCO-codes present within their data than present in the official ISCO dataset (IO). The IO dataset is used as a benchmark to couple the WD and the CD, since it contains the official ISCO-codes. The coupling process is started by linking the OP and the CD (the first data coupling process in figure 11). For this coupling only occupations present in the IO are selected. The coupling results in a loss 2 of the 702 occupations in the OD, because



Database 1 (DB1)

SOC 683 (Unique) - ISCO 402 (Unique)

*Figure 12: Database 1*

they are not in the IO. Another 17 unique SOC-codes are lost because their SOC-code is not present in the CD (appendix VII contains a more detailed outline of this process). It remains unclear why these 17 unique occupations are not aligned, but this loss results in a decrease in coverage. Data matching is needed to address this effect. The result after the loss of these types of data is a new data base (ND1)<sup>1</sup>. This database contains 683 unique SOC-codes all of which are linked to ISCO-codes (figure 12). Only 402 unique ISCO-codes are present in the ND1, which means there are duplicates (occupations in the ISCO classified as one occupation but having multiple assigned susceptibility percentages). The existence of these duplicates means that for several ISCO classified occupations it is unclear what their percentage is of the occupation to disappear. This uncertainty decreases the quality of the data and needs to be addressed. The characteristics and corresponding datatypes of the ND1 are stated in table 10.

*Table 10: Characteristics and datatypes of ND1*

New Database 1 (ND1)	
<i>Characteristic</i>	<i>Datatype</i>
SOC-code	String
Occupation Name	String
Susceptibility percentage	Float
ISCO-code	Integer

The DB1 is existing of occupations with a specified susceptibility percentage and a corresponding ISCO-code. The goal is to couple the percentage data to the workforce practicing these occupations. Therefore the ND1 needs to be coupled to the WD (the second data coupling in figure 11). The key used to realize this coupling is ISCO-code, resulting in a new database (ND2, figure 13). The characteristics and corresponding datatypes of the ND2 are stated in table 11.

Database 2    ISCO 395 (unique)  
Workforce 7.947.000

*Figure 13: New database 2*

<sup>1</sup> Datasets are in this research regarded as a datatype containing data stored into the warehouse. Databases contain the same kind of information, but are regarded as data still being processed.

Table 11: Characteristics and datatypes of ND2

New Database 2 (ND2)	
<i>Characteristic</i>	<i>Datatype</i>
ISCO-code	Integer
BRC-code	Integer
ISCO Name	String
BRC Name	String
Number of workers	Integer
Susceptibility percentage	Float

At the beginning of the second coupling the ND1 contained 402 unique ISCO codes. After the coupling process only 395 are matched which results in a loss of 7 unique ISCO codes with corresponding susceptibility percentage (these 7 ISCO-codes represent 9 SOC-codes, meaning there are some duplicates among them). On the other side of the coupling process 532 occupations are defined in the de WD with a corresponding ISCO-code. Since there was only a match for 395 ISCO codes a loss of 137 occupations from the WD are lost (a detailed description on how the data is lost is present in appendix VII). The discrepancies between the different sources must be the result of incorrect usage of the SOC and ISCO classifications. The usage of the official ISCO document gives guidance towards the proper use of the ISCO codes and as a result the matched results in ND2 are valid. The resulting DB2 (figure 13) contains the desired information, namely per ISCO-code defined occupation the number of people that are working in that occupation coupled to the estimated susceptibility of the job.

ND2 contains information on roughly 7.9 million people that are in the workforce. Since the overall workforce consists of roughly 8.5 million people it is concluded that a 6.9 percent loss of data occurred by coupling the data. To increase the coverage of the method the lost occupational susceptibility percentages should be manually matched to the workforce without a match. This will be the next step in this research.

### Data matching

In order to make a better coupling between the OD and the WD the residuals of the coupling process are manual matching. As shown in the previous section, on different occasions OP data loss is reported and on one occasion a part of the WD data is lost. The goal is to add as much matched occupations to the ND2 as possible, but since the residual of the WD consists of 137 instances these seem too many occupations to manually assess and match and therefore the amount of data should be decreased. To enhance the coverage the most, the manual selection should focus on the occupations in the WD with the largest workforce. Following this logic only the occupations with a workforce of at least 5.000 people are selected. This means that 22 of the 137 were selected to be matched (figure 14).

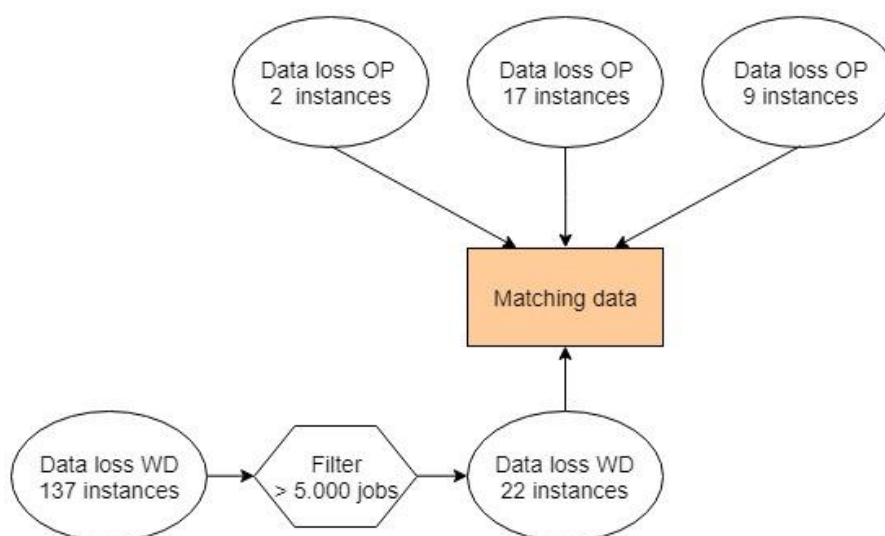


Figure 14: Process for manual matching of the uncoupled data

Manually matching of the 22 occupations from the WD data and 28 SOC occupations of the OD results in 6 matches for occupations (a detailed description of this process is available in appendix VIII). The 6 matched occupations are displayed in table 12.

Table 12: The six matched occupations

	SOC-code	ISCO-code	SOC name	ISCO name	Probability	Workforce (thousands)
1	29-1060	2212	Physicians and surgeons	Medical Specialist	0.0042	57
2	29-1111	2221	Registered Nurses	Nurses with higher education	0.0090	123
3	25-1000	2310	Postsecondary Teachers	Professors and other education practitioners of higher education	0.0320	55
4	15-1150	3512	Computer support specialists	Technicians for IT user support	0.6500	27
5	45-2090	9211	Miscellaneous Agricultural workers	Uneducated workers in agriculture	0.8700	9
6	11-1011	1000	Chief executives	Executive occupations	0.0150	14

These six occupations are added to the DB2. After the addition the workforce a new database (figure 11, New database 3 (ND3)) is configured and manual matching has led to a coverage in the database of 8.253.000 people (figure 15). When comparing the ND3 with ND2 a decrease in data loss is found. The loss of data for ND3 is only 3.3 percent. This means an improvement of 3.6 percent. ND3 is stored in the data warehouse.

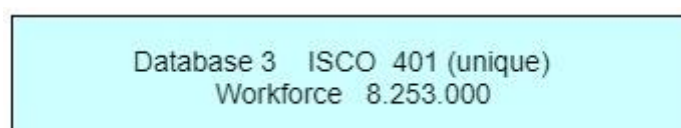


Figure 15: New database 3

Handling the data has led to a dataset with the number of workers for an occupation connected to a percentage of susceptibility of that job. However, after combining the data, for some occupations multiple susceptibility percentages are found.

### Addressing duplicates

Of the 401 ISCO unique occupations in the ND3, there are 163 occupations with only one probability (percentage of susceptibility). For the other 238 instances there are multiple of these probabilities.

#### *Additional explanation*

For some occupations the classification according to the ISCO is more general than the classification according to SOC. An explanatory example; In the ISCO classification a person working in a restaurant may be classified as 'Restaurant Employee', whereas in the SOC a distinction is made between a waiter and a barkeeper. Frey and Osborne used the SOC to build their percentages upon. Considering the example, they may have classified the waiter as 25 percent susceptible to technology and the barkeeper as 75 percent. In this research we are using the ISCO and by coupling of ISCO and SOC codes in this example 'Restaurant Employee' will have two different percentages.

#### Data example

Occupation: Executives on human resource  
 ISCO code: 1212  
 Percentages: 63%, 55%, and 96%

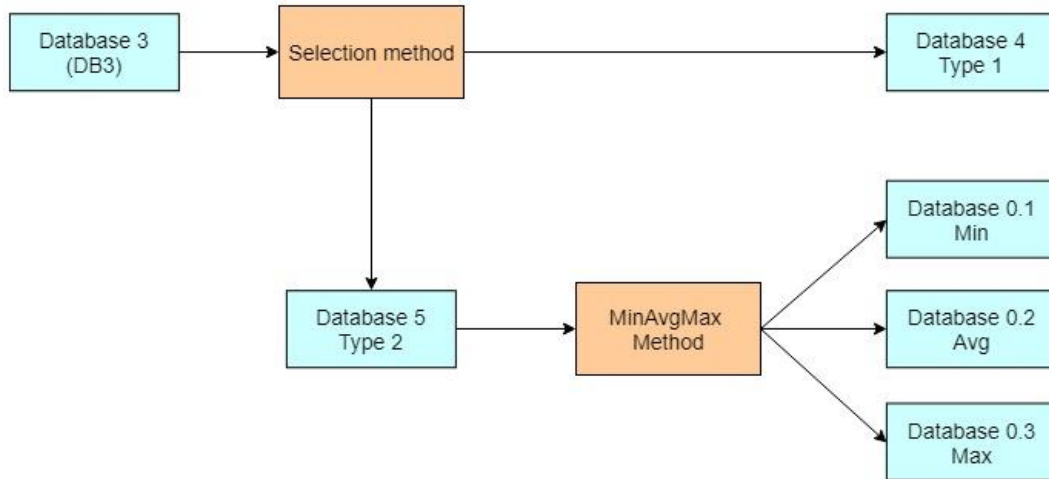
To specify these two types of probabilities the 163 occupations are labelled as type 1 occupations and the 238 occupations as type 2 occupations (figure 16). These types are specifically defined for this research and solely specified for clarification purposes. A more detailed description of this process can be found in appendix VIII.

Database 3 ISCO <b>401</b> (unique) Workforce 8.253.000	
Type 1 1 Value of Prob 163 instances	Type 2 2 or more Values of Prob 238

*Figure 16: Split in type 1 and type 2 occupations*

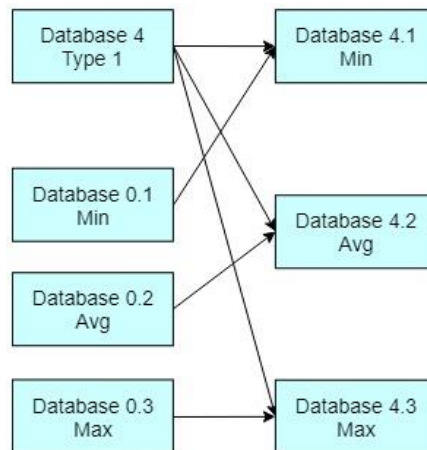
In order to deal with the multiple percentages ND3 is sliced into three separated databases. The process is drawn in figure 17. Per type 2 occupation the minimal percentage, the average percentage and the maximal percentage are determined. For these three

percentages three data bases are created containing all the minimal, average and maximal percentages. For the example the occupation, 'executive on human resource' translates into the usage of 55 percent in database 0.1, the usage of 71.3 percent in database 0.2, and the usage of 96 percent in database 0.3 for the occupational susceptibility percentage.



*Figure 17: Method of handling the uncertainty of percentages per occupation*

The three databases are merged again with the dataset of type 1 data for which there is only one percentage calculated (figure 18). The output of this method is three databases. 'Database 4.1 Min', containing the data configuration with the lowest percentages. 'Database 4.2 Avg', containing the data configuration with the average of the percentages.



*Figure 18: Merging of the type 1 and type 2 databases*

'Database 4.3 Max', containing the data configuration with the highest percentages. The wanted outcome specified at the beginning of this section as dataset 11 (figure 10) is found with the creation of the three selected databases (figure 19). The incorporation of the duplicate percentages result into three datasets and not one as in figure 13.

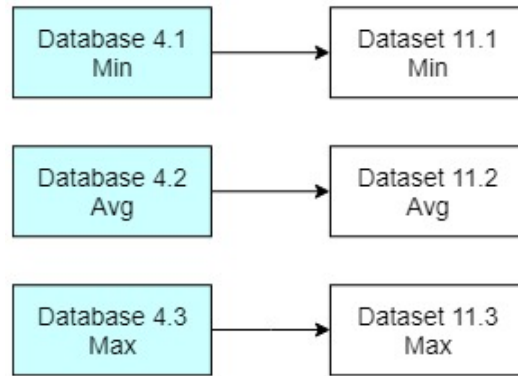


Figure 19: The three selected datasets

The result for the data creation process is displayed in figure 20. The datasets can be visualized making it possible to answer research question 2C. The next section covers this process.

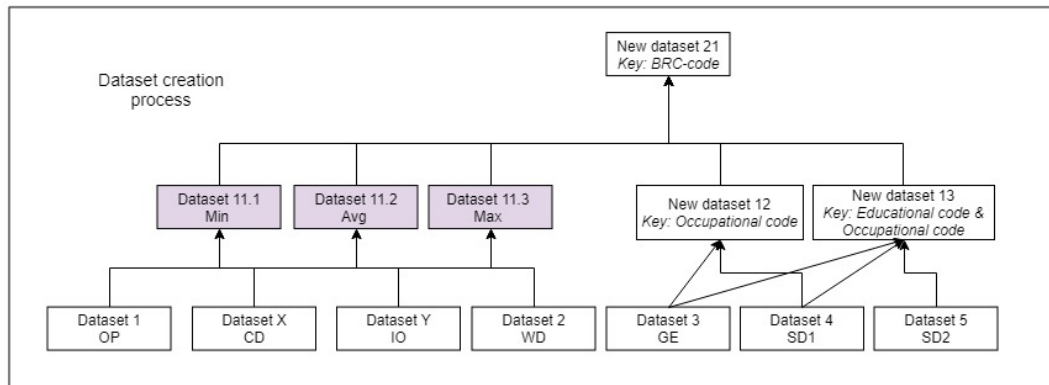


Figure 20: Dataset creation process after data integration part 1

### 5.1.2 Outcomes & Visualizations

Each of the datasets 11.1, 11.2, and 11.3 contain the susceptibility percentage of an occupation with a corresponding part of the workforce in the Netherlands. With the datasets the sub-question, 'What effects on the Dutch labour market can be drawn by combining the occupational susceptibility percentages and workforce quantities per occupation?' can be answered. The outcomes are specified per sector and in order to create a clearer image a graph is drawn of the distribution of the workforce over the scale of susceptibility percentages. This graph includes the susceptibility percentages of the 'average' dataset 11.2. In the graph (figure 21) the different sectors are specified.

The first conclusion drawn from the graph is the relatively large portion of the workforce working in either 'Commercial' or 'Business and Administrative' containing a high susceptibility percentage (between 90 and 100 percent). This part of the workforce is therefore expected to be replaced the easiest.

It is concluded there are also sectors where the susceptibility percentages are not in the highest regions, but still are around and above 50 percent for the most part of the workforce of the sector. These sectors are the 'Transport and logistics professions', 'Technical professions', and 'Service professions'.

The distribution of the workforce over these susceptibility percentages also shows sectors with a lot of people working in professions relatively safe for emerging technologies. Among these sectors are the 'ICT professions', 'Managers', 'Creative and Linguistic professions', and 'Pedagogical professions'.

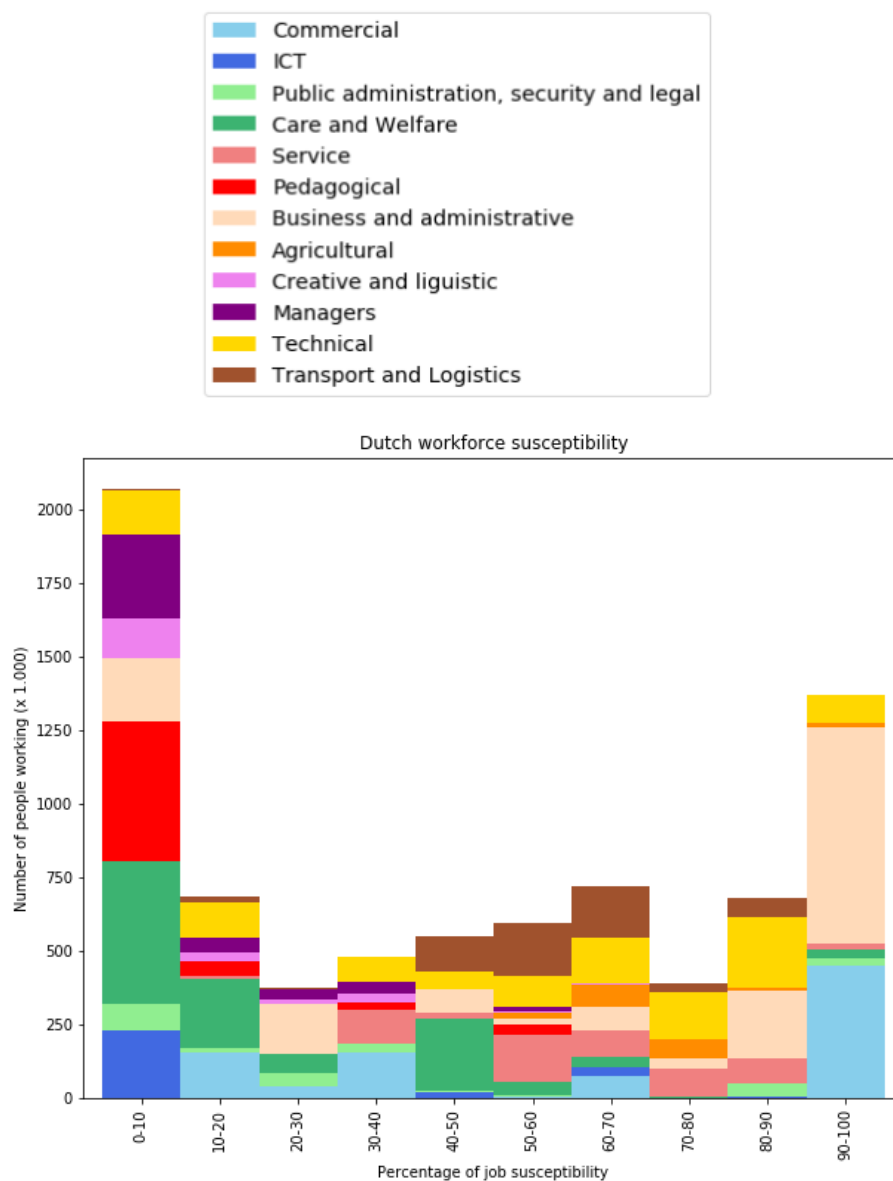


Figure 21: the workforce of the Netherlands grouped in susceptibility percentages

The three specified datasets contain the information of the probability an occupation is suscepled by 2030. These probabilities need to be put through technological development scenarios to forecast the real jobs lost, but first the occupational growth trend per occupation is defined as well as the educational level per occupation. This process is described in the next section.

## 5.2 Data Integration 2: Incorporation of occupational growth trends and educational level of the workforce

The datasets used to retrieve information about the occupational growth trends on existing jobs and the educational level are GE, SD1, and SD2 (for specification regard section 'data identification'). The process to create the datasets needed for this research is described by figure 22. The goal is to determine the occupational growth trend per occupation and to determine a corresponding educational level needed to perform the occupation.

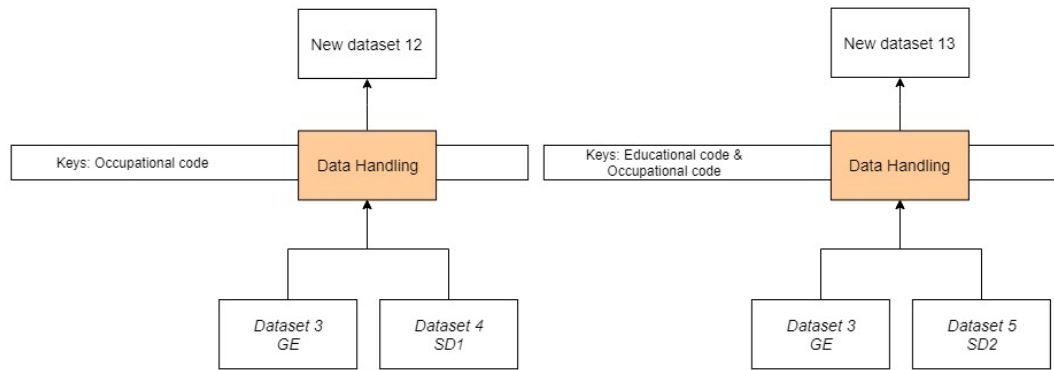


Figure 22: The processes to create the datasets for occupational growth (left) and educational level per occupation (right)

### 5.2.1 Occupational growth trends

The datasets needed in the process to determine the occupational growth trends are GE and SD1. These datasets are both retrieved from a particular source of the CBS and are complements of each other. The GE dataset contains all the relevant data needed to determine the occupational growth trend, but some of the data is encrypted.

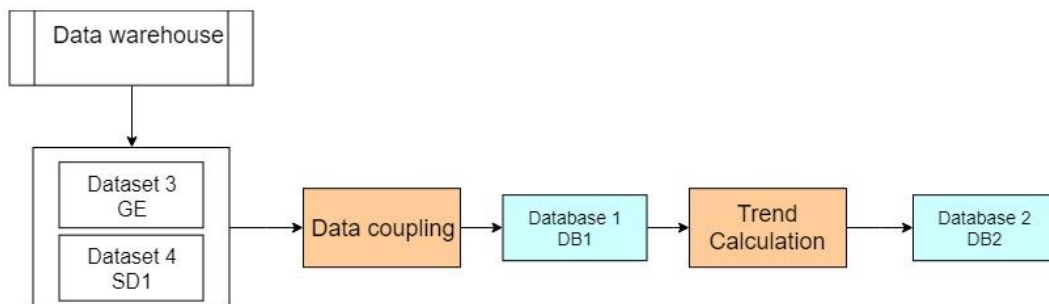


Figure 23: Process of determining occupational growth trend



To unencrypt the data (necessary to determine occupational growth trends) dataset SD1 is necessary. After the dataset is unencrypted into a new database the trend are calculated. The process of determining the occupational growth trend is described by figure 23.

### Data coupling

The dataset GE is containing the data. The occupational code is still encrypted therefore SD1 is needed. In table 13 and table 14 two examples for the datasets are displayed. The data is coupled by using the 'occupational code' as key. The coupling of this data does not give any data quality issues, which can be explained by the fact that these two datasets are complements of each other.

*Table 13: Example of dataset GE*

<i>ID</i>	<i>Occupational Code</i>	<i>Periods</i>	<i>Number of workers</i>
209444	A000163	2003JJ00	29

*Table 14: Example of dataset SD1*

<i>Occupational Code</i>	<i>BRC Code</i>	<i>Occupation Name</i>
A000163	111	Teachers of higher education

After the coupling of the datasets database 1 is created (DB1). An example of one occupation in the data is displayed in table 15. The dataset contains the number of workers per occupation for the years 2003 until 2018. This output is used to calculate the growth trend.

*Table 15: Example of coupled database 1*

<i>BRC Code</i>	<i>Periods</i>	<i>Number of workers</i>
111	2003	29
111	2004	23
.....	.....	.....
111	2018	56

### Trend calculation

For this research the assumption is made that a linear growth trend between 2003 and 2018. The growth trend can either be an increase or a decrease. The linear growth trend is determined by using the number of workers for the last year of the data (2018) and the beginning year (2003). For 'BRC code 111' this selection is stated in table 16. The growth trend is calculated according to formula 1. In this formula the number 15 stands for the years between the first trend point (2003) and the last trend point (2018).

Table 16: Data used for trend calculation BRC code 111

BRC Code	Periods	Number of workers
111	2003	29
111	2018	56

$$\text{Growth trend} = \frac{\text{Number of workers 2018} - \text{Number of workers 2013}}{15}$$

Formula 1: calculation growth trend

The calculation for the growth trend of 'BRC code 111' results in 1.8 growth per year ((56 – 29) = 27 -> 27 / 15 = 1.8). Since the growth trend is needed for the period until 2030 this number is multiplied by 12 to determine the growth over the whole period. The growth trend resulting from this calculation is an increase of 21.600 jobs for 'BRC code 111' (a multiplication is used of times thousand since in the original data the amounts were in thousands). This trend is calculated for each occupation.

### 5.2.2 Educational level per occupation

The datasets needed to determine the educational level of a particular occupation are the GE and the SD2, but also the SD1 will be used to connect the occupation code. The occupation code is needed to connect the educational level to the other created datasets. The occupational code is coupled as was shown in the previous section. The educational level is extracted from the same source as the growth trend and therefore a similar procedure is carried out. The data for educational level is encrypted in the GE and therefore the SD2 is necessary to unencrypt the data. After the dataset is unencrypted into a new database (DB3), the educational level 0 is adjusted and finally the educational level per occupation is defined. The process of determining the educational level is described by figure 24.

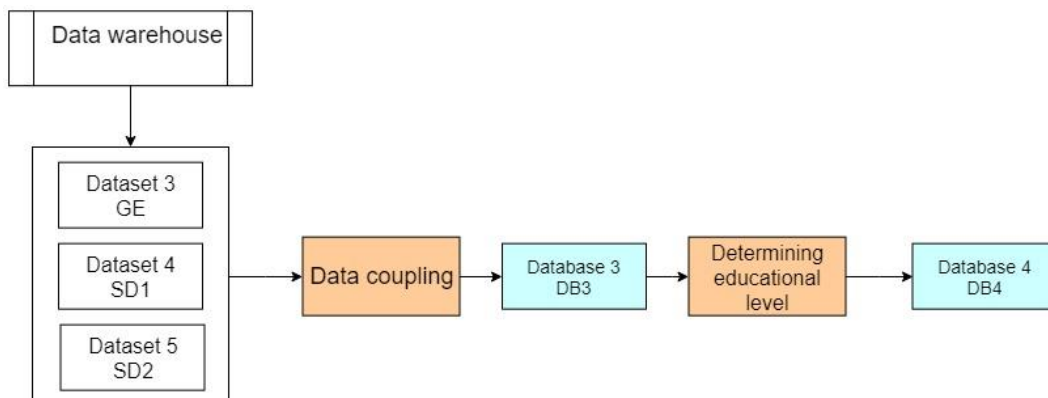


Figure 24: Process of determining the educational level

#### Data coupling

The dataset GE is containing the data needed for coupling of educational level. This data is encrypted that is why SD1 and SD2 are needed. In table 17 and 18 examples of datasets

GE and SD2 are displayed. The data coupling of SD1 is performed just as in the previous section. The 'educational code' is used as key for SD2. The coupling of the data does not give any data quality issues, which can be explained by the fact that these two datasets are complements each other.

*Table 17: Example of data from the GE*

<i>ID</i>	<i>Occupational Code</i>	<i>Educational Code</i>	<i>Periods</i>	<i>Number of workers</i>
209444	A000163	20188700	2003JJ00	0

*Table 18: Description of how educational level 1 is encrypted*

<i>Educational Code</i>	<i>Educational level</i>	<i>Education description</i>
20188700	1	Low

The coupling of the different datasets results in information about the number of workers per occupation per educational level for the years 2003 until 2018 (DB3). In table 19 an example of coupled data is showed for BRC-code 111 and the year 2003.

*Table 19: Coupled data for BRC code 111 and year 2003*

<i>BRC code</i>	<i>Educational Level</i>	<i>Periods</i>	<i>Number of workers</i>
111	1	2003JJ00	0
111	2	2003JJ00	27
111	3	2003JJ00	2
111	0	2003JJ00	0

### *Determining Educational level*

With the creation of DB3 the educational level per occupation can be determined, but first the meaning of the different educational levels is regarded. The definition of the different educational levels is stated in table 20.

*Table 20: Specification of the educational levels (SOURCE CBS)*

<i>Educational level</i>	<i>Level</i>	<i>Description</i>
0	Unknown	For these workers their educational level is unknown
1	Low	The highest achieved educational level is low education. This includes basic education, the VMBO, the first three years of HAVO or VWO, and/or MBO1.
2	Medium	The highest achieved educational level is medium education. This includes the last 2/3 years of HAVO/VWO, MBO2, MBO3, and/or MBO4
3	High	The highest achieved educational level is high education. This includes education on the educational level of HBO or WO (University).

Educational level 0 workers have an unknown status of what their education has been. It is assumed unknown workers at least had a minor form of education (since these people are occupying a job in the dataset), because of this assumption it follows level 0 workers can be merged with level 1 workers. Before the merger the weight of the workers of educational level 0 is assessed to determine the effect of the merger. The cumulative number of workers (all occupations for the years 2003 until 2018 in the dataset) is calculated as a measure of the weight of the workers. Table 21 shows the level 0 workers account for only 0.9 percent. This means the level 0 workers can be merged with the level 1 workers without the assumption significantly impacting the outcomes.

*Table 21: cumulative number of workers and their weight towards each other*

	Cumulative number of workers (2003 until 2018)	Distribution percentage
Number of level 0 workers	1.219	0,9%
Number of level 1 workers	31.636	24,1%
Number of level 2 workers	56.039	42,6%
Number of level 3 workers	42.599	32,4%

After this merger the dataset contains information on the number of workers. These are specified for educational level 1,2, and 3 and for each of the years 2003 until 2018. An example of the data is displayed in table 22. This example contains the data for the occupation with BRC code 111.

*Table 22: Data outline for BRC code 111*

Example BRC 111	Educational Level 1	Educational level 2	Educational level 3
2003	0	2	27
2004	0	0	23
2005	0	1	24
2006	0	1	24
2007	0	2	24
2008	0	2	25
2009	0	2	29
2010	0	2	32
2011	0	3	28
2012	0	4	32
2013	1	4	40
2014	0	4	44
2015	0	4	44
2016	0	4	43
2017	0	6	47
2018	0	5	51

To take different economical climates throughout the years into account all the years of the data will be regarded when determining the educational level of an occupation. All the workers are added up per educational level for all the years. The result of this process will be a cumulative number of workers per occupation, which translates to an occupational distribution percentage for each of the educational levels per occupation. In table 23 this process is drawn out for occupation BRC 111.

*Table 23: Determining the occupational distribution percentages for BRC 111*

Example BRC 111	Educational Level 1	Educational level 2	Educational level 3
Total number of Workers (2003 – 2018)	1	46	537
Occupational distribution percentages	0,2%	7,8%	92,0%

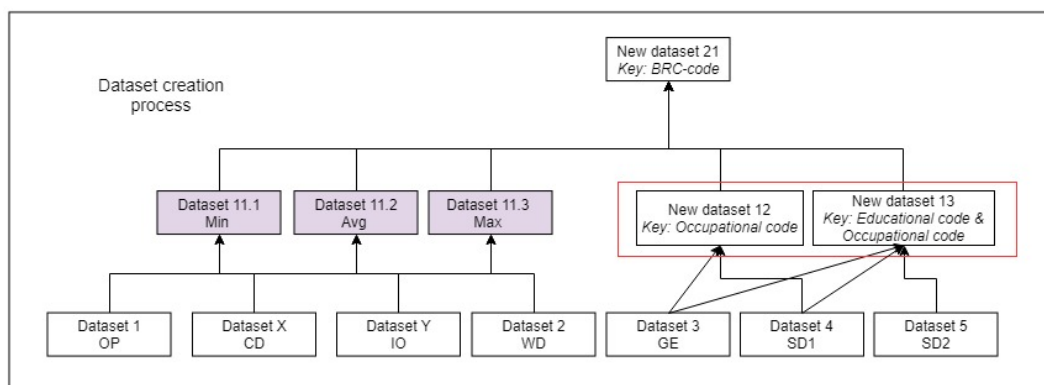
The idea is to determine for each occupation a corresponding educational level needed to perform the occupation. For BRC code 111 this educational code would then probably be level 3, since most of the workforce performing this occupation has educational level 3. However, when examining the data there are also occupations found where there is no majority of the workforce for one of the educational levels. Therefore, it is decided to keep the occupational distribution percentages as guideline.

#### Additional explanation

If the research concludes in a loss of 1000 jobs for the occupations with BRC code 111, it will translate to a loss of 2 educational level 1 jobs, 28 educational level 2 jobs, and 920 educational level 3 jobs.

### 5.2.3 Outcomes & visualization

Data integration 2 results in two new datasets, dataset 12 and dataset 13 (figure 25). Dataset 12 contains information for occupational growth trends and dataset 13 contains information on the educational level required to perform an occupation.



*Figure 25: Data creation process for dataset 12 & dataset 13*

The overall occupational growth trend is regarded in table 24. The occupational growth trends found through data handling were either a growth in the number of jobs or a decrease in the number of jobs. The overall net difference is a growth of 785.000 jobs. This means without the incorporation of technological development trends there would be an increase in the number of jobs and since the labour supply is expected stay on the same level it would translate to a surplus of jobs.

*Table 24: Overall occupational growth trend*

	Number of jobs
Job growth	1.526.000
Job decrease	741.000
Net difference	785.000

The spread of the educational level per occupation is determined in the previous section. The overall educational level of the Dutch population is a result of considering all these percentages. This result is displayed in table 24. In the Netherlands the population is highly educated with the highest percentages in educational level 2 and 3 (table 25).

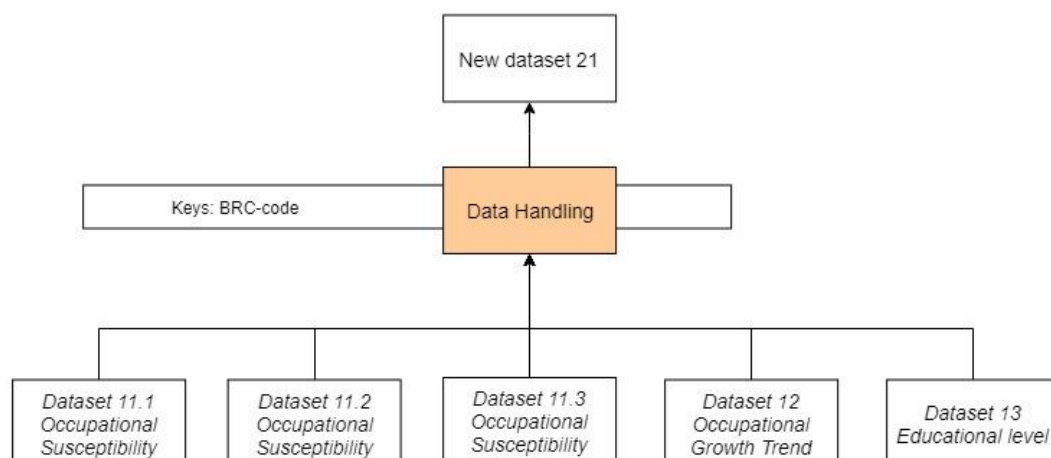
*Table 25: Spread of educational level*

	Percentage Educational level 1	Percentage Educational level 2	Percentage Educational level 3
Overall	22.0 %	41.2 %	36.8 %

In the next section the occupational susceptibility percentages, the occupational growth trend and the educational level will be integrated into one dataset.

### 5.3 The integrated database

The information on occupational susceptibility, occupational growth trends, and the educational level have resulted in dataset 11 (spread over three datasets), dataset 12, and dataset 13 (figure 26).



*Figure 26: Process for dataset integration*

The different occupational susceptibility percentages all need to be handled with the occupational growth trend and the educational level resulting in three different integrated datasets (21.1, 21.2, & 21.3). This process is displayed in figure 27.

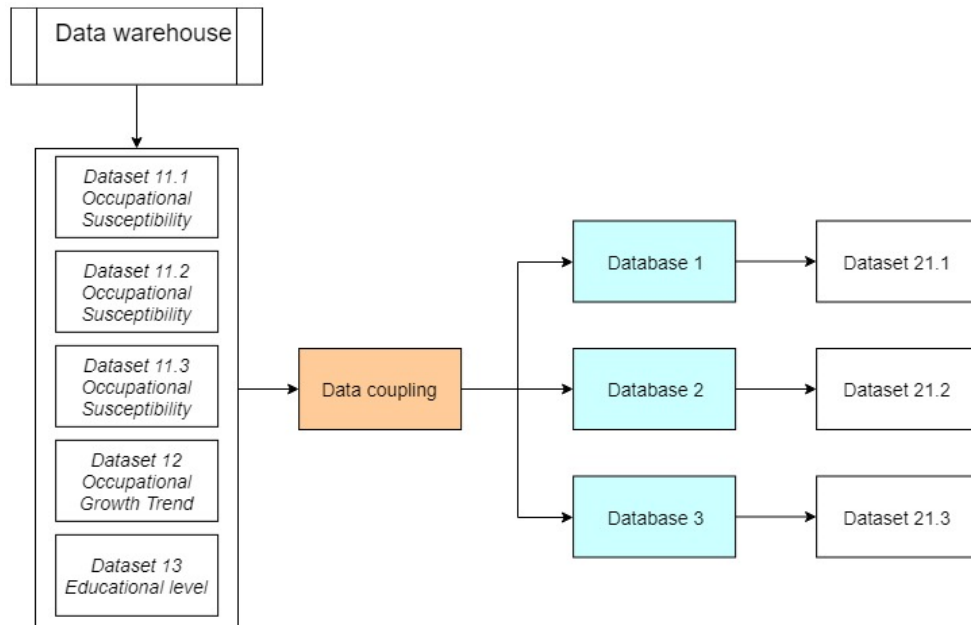


Figure 27: Integration process

In the data coupling process one problem is encountered, namely the estimations of occupational susceptibility are defined for ISCO codes whereas the occupational growth trends and the educational level are defined for BRC codes. This problem needs to be regarded in the next chapter when the explorative scenarios are drawn.

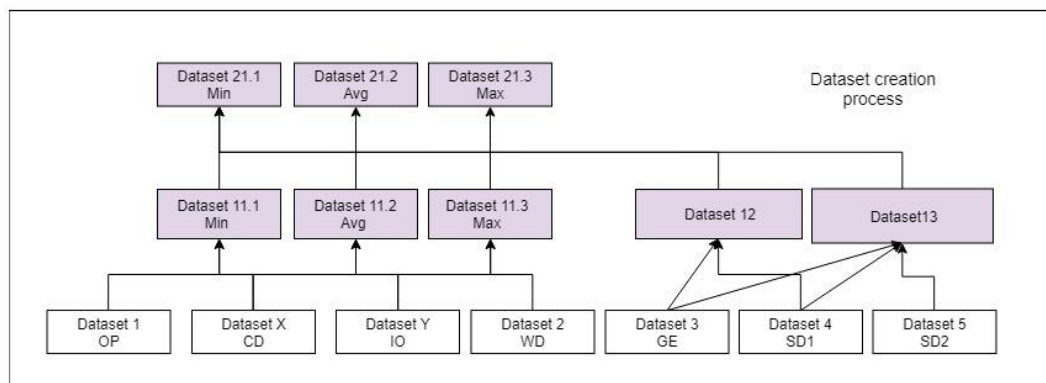


Figure 28: Definition of final datasets

With the definition of dataset 21.1, 21.2, and 21.3 the data integration phase has been completed. In the next section the datasets will be subjected to the different technological development scenarios. After this process the dataset is analyzed and sub-question three and four, 'What are the effects of empirical occupational growth trends on the labour market and what educational level is required per occupation?' and 'What are the

explorative scenarios to mitigate the uncertainty of technological development scenarios?' are answered and the main research question can be addressed.



## 6. Data analysis: Determining the space for policy

The output of the data integration contains the occupational susceptibility percentages. The percentages do not yet translate to a loss of jobs, in other words there is still an uncertainty on how these percentages translate to a loss of jobs. This uncertainty is already specified in the methodology chapter as the uncertainty of technological development. In this chapter the resulting datasets of the previous section will be subjected to explorative technological development scenarios. The result of this process will be used for analysis to answer the third and fourth sub-question of this research and eventually address the main question.

### 6.1 Explorative technological development scenarios

The outcomes of the analysis so far have provided a percentage of susceptibility per occupation (for example there is a 1.5 percent change the occupation of 'chief executive' (ISCO-code 1000) has disappeared by 2030 as a result of technological development and the 14.000 people who work at this occupation lose their jobs). The percentages do not yet give an estimation on the real loss of jobs. In order to make this estimation the 'amount' of technological development occurring in the period until 2030 should be regarded, but it is not possible to gain clear insights in the 'amount' of technological development. This is because the future of technological development is uncertain. To mitigate this uncertainty and still make the estimation for the loss of jobs, different scenarios are drawn up. The defined scenarios are a low-tech scenario ("What if technological development will be low?"), a medium-tech scenario, and a high-tech scenario. The scenarios are defined as follows. In the research of Osborne and Frey (2013) there are three categories defined; low susceptible occupations, medium susceptible occupations, and highly susceptible occupations. Osborne and Frey set the boundaries of these categories as follows. Low susceptible are the occupations with probabilities defined between 0 and 30 percent, medium susceptible are the occupations with probabilities defined between 30 and 70 percent, and highly susceptible are the occupations with probabilities defined between 70 and 100 percent. The same boundaries are used in this research. For these categories several the loss of jobs needs to be defined per technological development scenario. The percentage of jobs lost in occupations are defined per category in table 26. The values of the low-tech, medium-tech and high-tech percentages are set to result in the coverage of the full scope of the uncertainty on technological development.

*Table 26: Percentages of occupational job loss per category*

Technological development scenario	Percentage range 0% - 30%	Percentage range 30% - 70%	Percentage range 70% - 100%
Low-Tech	0%	0%	60%
Medium-Tech	0%	25%	80%
High-Tech	0%	50%	100%

#### Additional explanation

The job truck driver has a susceptibility of 79 percent, according to the research of Osborne and Frey. The occupation truck driver is in the 'highly susceptible range (70% - 100%)'. If there are 100.000 truckdrivers in the Netherlands, the effect of the technological scenario is as follows.

Low tech	-	60 percent of jobs are lost	-	60.000 jobs lost
Medium tech	-	80 percent of jobs are lost	-	80.000 jobs lost
High Tech	-	100 percent of jobs are lost	-	100.000 jobs lost

The three datasets resulting from the data integration (21.1, 21.2, and 21.3) are subjected to the drawn scenarios (figure 29).

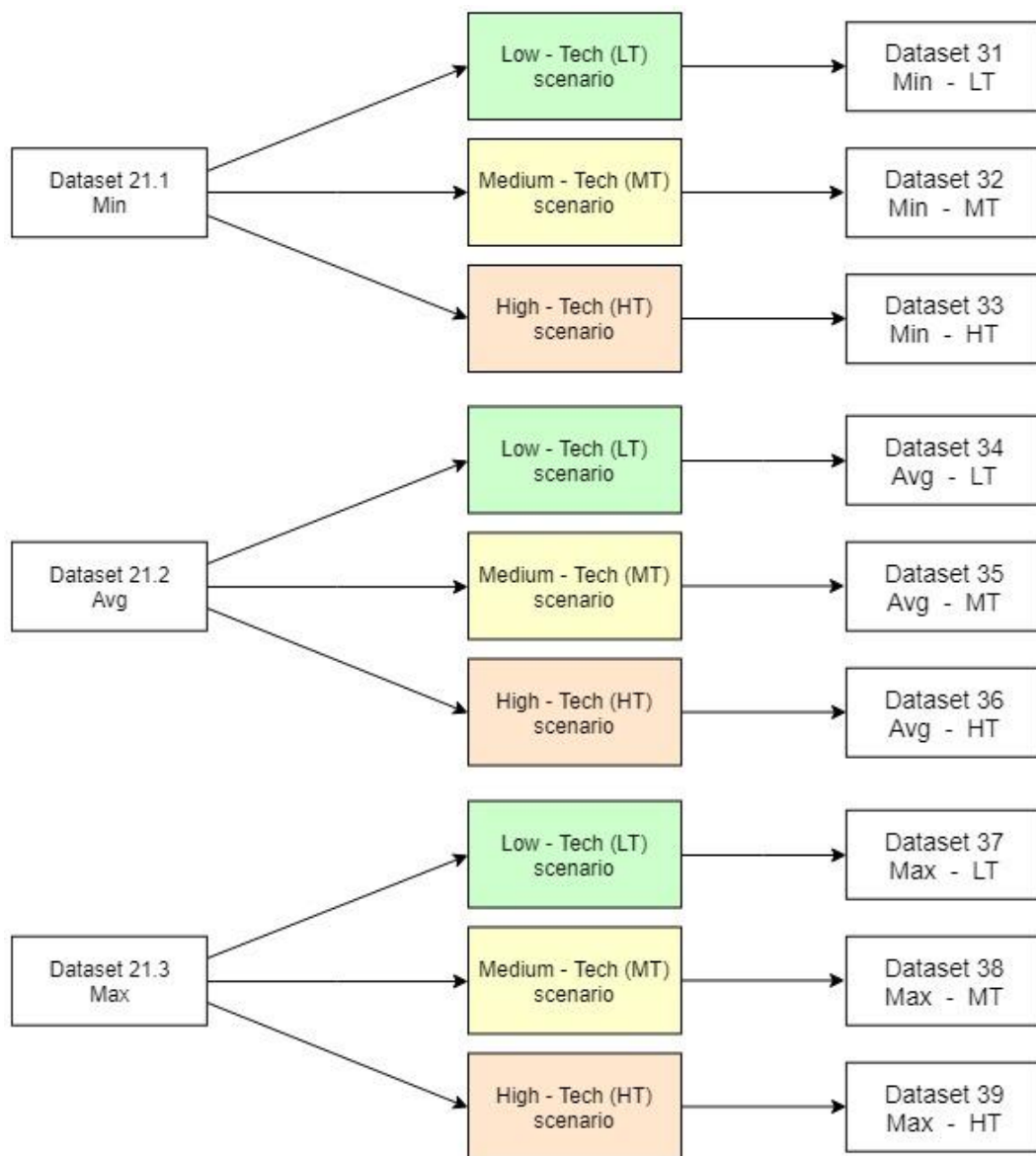


Figure 29: The different datasets subjected to the technological scenarios

The process leads to nine different databases. The databases contain the same kind of information for 9 different scenarios. The purpose is to include the full scope of the technological development scenarios. To cover the full scope, it is assumed only three datasets are needed. The dataset with the least number of expected job loss is selected as one of the boundaries for the scope. This is the dataset with the information for the minimal occupational percentages and the lowest technological scenario, because the occupational susceptibility percentages are scaled down in dataset 31 and the low technological scenario focusses only on the highest percentages to be affected by technological development. The opposite is true to for the dataset with highest expected loss of jobs and consequently it results in the other boundary of the scope. The dataset selected for this purpose is dataset 39 containing the highest occupational percentages in combination with the high technological development scenario. Since the full scope needs to be regarded also a dataset in between the boundaries is regarded. The dataset selected for this purpose is dataset 35 with the average occupational susceptibility percentages and this dataset is subjected to the medium technological development scenario. With these three datasets (31, 35, 39 (figure 29)) the bandwidth is covered; therefore, the other six datasets are not incorporated in the continuation of this research. The analysis of the loss of jobs for each of the selected datasets leads to the visualization in figure 30.

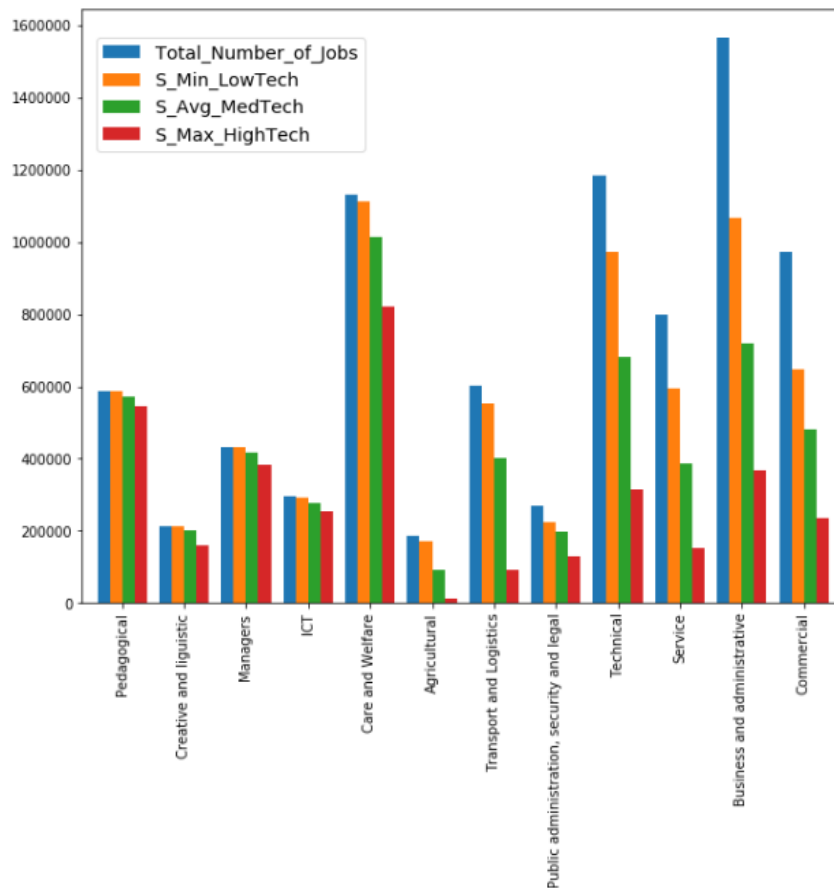


Figure 30: The number of jobs lost per sector for each of the selected datasets

The difference between the scenario's is also captured by regarding the overall jobs lost for each of the scenario's. In table 2 the overall jobs lost are displayed.

*Table 27: Jobs lost per scenario*

Scenario	Jobs lost
Minimum - Low Tech	1.363.795
Average – Medium Tech	2.792.350
Maximum – High Tech	4.769.000

To get a better insight into the sectors affected most by the technological developments the data for these sectors is regarded. This process will be performed on the data for the 'Average – Medium Technology' scenario. The 'Commercial' and 'Business and Administrative' sectors are the most affected. In the 'Commercial' sector the loss of jobs can be ascribed for 84,4 percent to cashiers and sales assistants. These kind of jobs seem to be jobs requiring low-skilled labour. In the 'Business and Administrative' sector there is a larger spread across different occupations that causes the loss of jobs in the sector. However, a 32,9 percent is ascribed to different administrative occupations, but also different kinds of accountancy related occupations seem be a proportional part of the workforce (14 percent).

The sectors 'Service', 'Technical', and 'Transport and Logistics' are also addressed. The 'Service' sector has the most loss of jobs for the catering business, distributed over waiters (37 percent), sous-chef (12,4 percent), and chef (10,9 percent), but also cleaning occupations account for a part of the loss of jobs (13,7 percent). In the 'Technical' sector a lot of craft specialists are concluded to have high losses in jobs. The kind of occupations require a low education, but a lot of practise is needed to master the craft. Examples of such occupations are carpenters, painters, welders, bakers, and car mechanics. These examples together account for a loss in jobs of 28,9 percent for the sector 'Technical'. The final sector is 'Transport and Logistics'. Shelf fillers and loaders account together for 243.000 of the 602.000 people who are working in this sector. In the regarded average scenario only 25 percent of the workers in these occupations lose their job since their susceptibility percentages are 64 and 51 percent (and therefore the fall in the region of 'medium susceptible' (between 30 and 70 percent)). However, if technological development goes faster than anticipated more jobs might be at stake. In this technological development scenario the majority of loss of jobs in the sector 'Transport and Logistics' is mostly ascribable to vehicle operators of all sorts (truckers, cab drivers, crane operators).

The effects on different sectors are compared to the sectors found in the literature review for validation purposes. The literature review validates the commercial sector being impacted by stating jobs will be lost in the accounting sector, because in accounting a lot of repetitive tasks are performed on (Esperanza & Jensen, 2017). In the literature review, transport (Milakis et al., 2017), logistics (Rossmann et al., 2017), and manufacturing (Freddi, 2018), were also stated to be sectors affected by the emerging technologies. This

research validates these statements as well, since the data output of jobs in 'transport & logistics' also shows a lot of high susceptibility percentages (figure 30). In the literature review the medical field was also mentioned as one of the sectors affected by emerging technologies (Booth, 2016; Pee, 2018; Tobis et al., 2017). The research output contradicts this statement, almost no job loss is found in the three scenarios for the sector 'care and welfare'. A possible explanation for this difference may be the requirement interactions with patients for these occupations. The tasks in the medical field may be susceptible however the social part of patient contact is not so easily replaced. Overall the findings seem to be in line with the research.

The number of jobs lost is high for each of the scenarios. Especially for the Avg-MT and the Max-HT scenarios, where respectively 33 percent and 56 percent of the jobs are lost. But, even in the Min-LT scenario 17 percent of the jobs in occupations that exist today will be lost. When the most affected sectors are regarded a high number of jobs seems to be at stake for the low-skilled part of the workforce. As proposed for this research also the incorporation of the growth trends of existing jobs shall be realized. Combining the growth trend of current jobs and the loss of jobs due to technological development creates a labour market forecast.

## 6.2 Occupational growth trends and occupational susceptibility

To determine the growth per occupation the information of the occupational growth trend and the occupational loss of jobs needs to be combined. The occupational percentages define per scenario which and how many jobs are lost per occupation. It is assumed, if an occupation is affected by technological development, the affection is the growth trend. Therefore, the occupational growth trend on historical data is not incorporated for these occupations. For the remainder of occupations, the occupational growth trend is used. As concluded in the data integration chapter the loss of jobs per occupation due to technological development is calculated for ISCO-codes. In the Netherlands the classification system BRC is used. This classification system is based on the ISCO system and therefore also corresponding BRC-codes are defined for each ISCO-code (figure 31).

	isco_code	isco_name	brc_code	num_working	brc_sector	Probability	jobs_lost_ET
211	9112	Schoonmakers in hotels, kantoren e.d.	1121	163	11	0.37	0.0
354	9111	Huishoudelijke hulpen en schoonmakers in huis...	1121	63	11	0.69	0.0
355	9121	Personeel voor het wassen en strijken met de ...	1121	4	11	0.81	2.4
356	9122	Autowassers	1121	7	11	0.37	0.0
357	9123	Glazenwassers	1121	6	11	0.66	0.0
358	9129	Andere schoonmakers	1121	5	11	0.83	3.0

Figure 31: Example of the data for BRC occupation 1121

For each of the BRC-codes the loss of jobs for the corresponding ISCO-codes are added up and are used as the occupational growth trend of this BRC occupation. In the example of BRC code 1121 (figure 31) the number of jobs lost would be 5.4 (to retrieve the real loss of jobs this number needs to be multiplied by 1000). An additional explanation of why this method was chosen is stated in appendix IX. The result of this method is a dataset with incorporated effect of technological development per BRC classified occupation. Table 28 shows the data for the first seven entries of the data of the medium technological development scenario.

*Table 28: BRC defined occupational growth trends (technological development)*

BRC-code	Labour force	Occupational growth trend (Technological development)
111	55.000	0
112	33.000	0
113	108.000	0
114	144.000	0
115	69.000	0
121	43.000	- 6.250
131	135.000	- 8.750

Now also the occupational growth trend based on the historical data is added. Table 29 shows the data for the first seven entries of the dataset.

*Table 29: BRC defined occupational growth trends (technological development & historical)*

BRC-code	Labour force	Occupational growth trend (Technological development)	Occupational growth trend (Historical)
111	55.000	0	21.600
112	33.000	0	- 23.200
113	108.000	0	21.600
114	144.000	0	- 800
115	69.000	0	28.800
121	43.000	- 6.250	19.200
131	135.000	- 8.750	36.000

The technological development occupational growth is leading, since it is the basis of this research. Consequently, for the BRC occupations with a technological development growth trend, it is assumed this is the growth trend for the occupation. If there the occupation is

not affected by technological development the historical growth trend is used as the growth trend. The result for the first seven BRC occupations is stated in table 30.

Table 30: The effect on the number of jobs per BRC occupation

BRC-code	Labour force	Increase in the number of jobs	Decrease in the number of jobs
111	55.000	21.600	
112	33.000		- 23.200
113	108.000	21.600	
114	144.000		- 800
115	69.000	28.800	
121	43.000		- 6.250
131	135.000		- 8.750

In the next section the results for each of the technological development scenarios are analyzed and visualized.

### 6.3 Outcomes for each technological development scenario

The three defined datasets (Min-LT, Avg-MT, and Max-HT) forecast the growth of the Dutch occupations for a low, medium, and high technological development scenario. The scenarios lead to three different outputs. The educational level specified per occupation is used to assess the consequences for the low-skilled workers.

#### 6.3.1 Outcomes low technological development scenario

In figure 32 the jobs lost and job growth trend per sector is stated for the low technological scenario. There are several sectors (1,2,10 and 13) for which the job growth trend is bigger than the number of jobs lost, but the overall effect on the labour market seems to be negative.

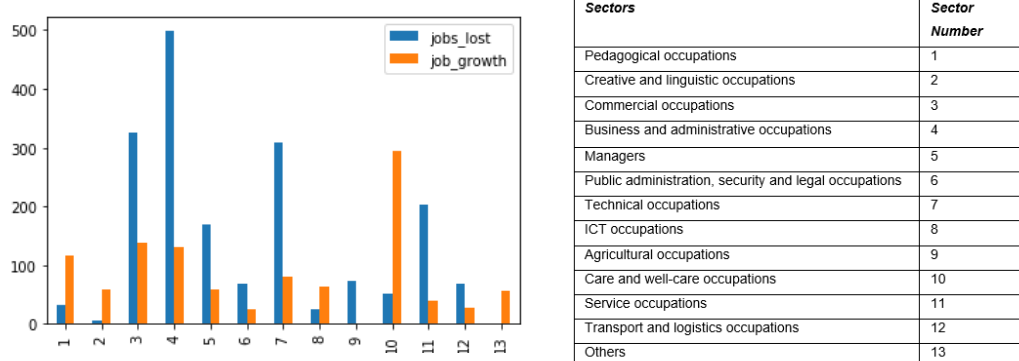


Figure 32: jobs lost and job growth per sector (Min-LT)

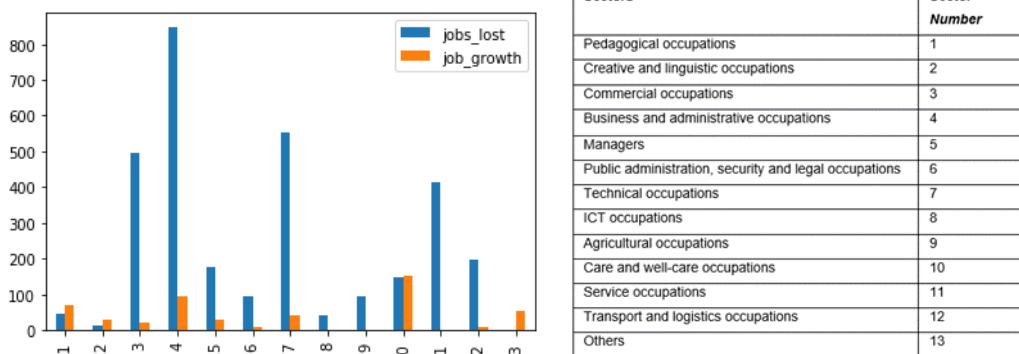
Table 31 shows the exact number of jobs lost in the labour market. The labour market forecast is a loss of roughly 750 thousand jobs for the low technological scenario. In this scenario there is a growth in jobs where educational level 3 is required and jobs with educational 1 or 2 required show a loss of jobs of roughly 500 thousand each. This conclusion support the findings of other research, where it stated lower skilled workers are earlier affected by the loss of jobs (Acemoglu & Restrepo, 2017; Berg et al., 2016; Bonekamp & Sure, 2018; Duffy et al., 2016; Grip et al., 2018).

*Table 31: job growth and jobs lost per educational level (Min-LT)*

	<i>Job growth</i>	<i>Jobs lost</i>	<i>Difference</i>
<i>Educational level 1</i>	100.056	573.069	-473.013
<i>Educational level 2</i>	347.302	879.766	-532.464
<i>Educational level 3</i>	630.926	373.822	257.104
<i>Total</i>	<b>1.078.284</b>	<b>1.826.657</b>	<b>-748.373</b>

### 6.3.2 Outcomes medium technological development scenario

The visualizations for the Avg-MT dataset are stated in figure 33. The first conclusion to be drawn is job growth for the medium technological scenario stays roughly the same, when comparing it to the low technological visualizations<sup>2</sup>. The loss of jobs seems however higher for this scenario, especially the jobs lost in the sectors commercial, business & administrative, technical and service.



*Figure 33: jobs lost and job growth per sector (Avg-MT)*

The overall difference in the effect on jobs is stated in table 32. The dissimilarity in overall difference of jobs lost between the low technological development scenario and this scenario is roughly 1.85 million. In this scenario the difference between the growth and loss is namely 2.6 million. This 2.6 million is a significant loss when it is compared to the overall workforce of the dataset, which is 8.25 million people translating to a 32 percent loss of jobs. Additionally, losses for every educational level are concluded, but the comparison between the educational level losses result in bigger losses for the workforce with an

<sup>2</sup> Take notice; A different range is used on the Y-axis for figure 34, 35, and 36



educational level of 1 or 2. The same conclusion as in the low technological development scenario.

Table 32: job growth and jobs lost per educational level (Avg-MT)

	<i>Job growth</i>	<i>Jobs lost</i>	<i>Difference</i>
<i>Educational level 1</i>	34.636	1.010.934	-976.298
<i>Educational level 2</i>	113.639	1.501.544	-1.387.905
<i>Educational level 3</i>	364.297	602.157	-237.860
<i>Total</i>	<b>512.572</b>	<b>3.114.635</b>	<b>-2.602.063</b>

### 6.3.3 Outcomes high technological development scenario

The most extreme scenario is represented by the high technological development scenario. Figure 34 shows the loss of jobs is even more vast for this scenario. With high losses in sector 3,4,7,11, and 12. Significantly higher than the losses in the medium technological development scenario.

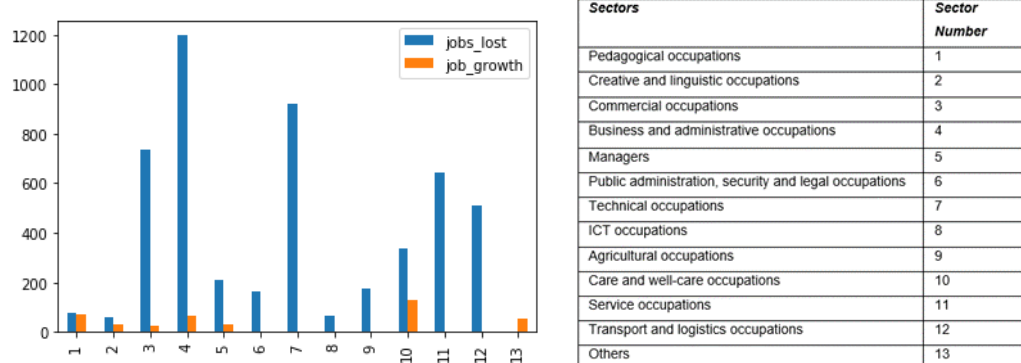


Figure 34: jobs lost and job growth per sector (Max-HT)

In table 33 the overall job growth and loss of jobs is stated leading to a labour market forecast for the high technological scenario. The scenario results in a loss of their job for 4.7 million people in the workforce translating into a 57 percent of all jobs in the Netherlands.

Table 33: job growth and jobs lost per educational level (Max-HT)

	<i>Job growth</i>	<i>Jobs lost</i>	<i>Difference</i>
<i>Educational level 1</i>	29.459	1.612.049	-1.582.590
<i>Educational level 2</i>	86.414	2.448.518	-2.362.104
<i>Educational level 3</i>	280.983	1.030.719	-749.736
<i>Total</i>	<b>396.856</b>	<b>5.091.286</b>	<b>-4.694.430</b>

In the low technological development scenario, the loss of jobs is calculated to be around 750.000. This loss of jobs is already significant, but with the current policy mechanism in play and the creation of newly defined jobs this loss may be overcome. The medium and high technological development scenarios show a loss of jobs of 2.6 and 4.7 million. Although job creation of new jobs is not incorporated yet these numbers of unemployed people or having the need to be retrained will have huge consequences and it is doubtful if current policy mechanism will still be enough.

## 7. Discussion & Limitations

With all the panic about AI, people forget its stupendous promise. One example: "Artificial intelligence can spot Alzheimer's way earlier than doctors." - Steven Pinker

The future labour market estimation of the previous chapter and the methods leading up to the estimations are reflected upon in this chapter. In the chapter, the assumptions and limitations of the research will be assessed, and the research outcomes will be discussed.

### 7.1 Limitations of the labour market estimations

Throughout the research, several flaws have arisen. These flaws create limitations for the labour market estimations. The lack of incorporation of newly defined occupations creates the biggest limitation. If there was information on this variable it would have been possible to determine a more inclusive labour market estimation.

In the Netherlands, the classification used is the BRC. This classification is based on the ISCO classification. Determination of the occupational growth trend via data integration results in a decrease in coverage of the original data because the occupational growth trend of some occupations is not incorporated (see appendix IX for details). Therefore, the estimation of occupational growth trends is less accurate than it should be.

The methodology is built upon the research of Frey and Osborne, which is based on expert estimations, therefore, the methodology will never lead to a completely objective future estimation. It is however inherent for a forecast on the labour market to have such uncertainty incorporated, but it makes validation of the methodology and outcomes an important topic to minimize the uncertainty as much as possible.

Additionally, as mentioned in the literature review, there have been other studies such as the OECD & CEED research that took another approach on providing a labour market forecast. These studies divert from the Osborne and Frey research by redefining the susceptibility percentages. The results of these studies sketch a very different future estimation than proposed in this research and in the research of Osborne and Frey, namely their estimates for the US labour market are 10 percent of jobs being highly susceptible versus 47 percent in the Osborne and Frey research. The approaches differ in their main assumption hence the difference in estimation making it hard to determine which approach is the best. Throughout the research more assumptions have been made, these assumptions are summed up in appendix I.

Due to limit resources of time and the comprehensive character of validation, for this research, a thorough validation of the labour market forecast is not achievable. However, some validation strategies are defined as how the validation process should be approached. Several validation methods are viable to use to determine the robustness of

some of the assumptions of the forecast. Structural validation is the first one. In this methodology, the assumptions are manually adjusted to determine the rigidity of the current setting. Exploratory modeling (Kwakkel & Haasnoot, 2019) is the second one and can be used for the same purpose, this methodology is more elaborate and investigates a broad spectrum of the settings for the assumptions. Another kind of validation method is to perform expert interviews with Wiltshagen and Salomons (scholars in the Netherlands). The goal of such interviews should be to determine the credibility of the used methodology in this research.

On a final note it needs to be said future estimations like the ones in this research will always contain uncertainty, therefore important not to use the outcomes of this research as facts, but rather as guidelines for future policymaking.

## 7.2 Practical use of the labour market estimations

The first way to use this research is through its outcomes. In chapter six the loss of jobs is defined for three scenarios with regards to occupational susceptibility through technological developments and historical growth trends. The labour market estimation for a low technological development landscape shows an increase in the number of jobs lost by 0.8 million. For the medium technological development scenario, the data shows a job loss of 2.6 million people and for the dataset, with a high technological development scenario, even 4.7 million people will lose their current job (figure 35).

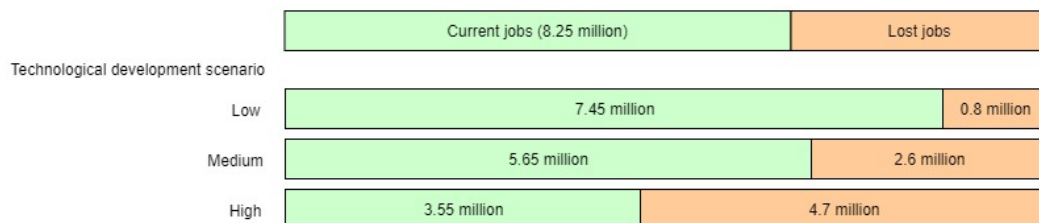


Figure 35: Outcomes of the three different technological development scenarios

Determination of the knowledge gap in chapter two leads to the 'lump of labour fallacy', which says research like this one is often forgetting to account for new occupations. Consequently, the number of jobs lost does not lead directly to unemployment but it creates a policy space. In this policy space, there is space for new occupations to fill in the gap the loss of jobs leaves and space for decision-makers to provide policy. This approach of the policy space leads to the earlier defined possible future scenarios of what might happen to the labour market of the Netherlands (figure 35). These are the null-scenario (no occurring problems, the labour market will reconfigure itself), the mismatch-scenario (there are enough jobs to suit the workforce, but the labour supply is not suiting the particular jobs), and the labour surplus-scenario (there are not enough jobs to suit the workforce).



Figure 36: Future scenarios for the Dutch labour market

#### Regarding the policy space

If the loss of jobs of the lower estimation is regarded (0.8 million jobs lost figure 35), it is imaginable to believe the null-scenario may happen (figure 36). In this case, part of the workforce will transition to newly created jobs in the next ten years. The loss of jobs will, however, have an impact on the system and for the lower estimation problems may occur. A problem may occur when a low-skilled occupation disappears, and the workers of this occupation get back on the labour market. They might not be equipped with the right skills to fit into a new job.

#### Example

'Truck platooning' (autonomous driving of a sequence of trucks in a 'platoon', with only an actual driver in the first truck), will decrease need for truck drivers. A small portion is still needed to drive the first truck of a platoon, so a small portion of the original truck drivers will keep their jobs.

There will also be new jobs created through this development. There will be an increase in engineers, who will have to fix trucks which broke down. These engineers do not only need to have mechanical knowledge, but also know-how of the platooning software. IT companies will arise to create the IT infrastructure and software to make the platooning of trucks possible.

According to this research, the average truck driver had a low-skilled education. Following the example, the newly created jobs seem to require a higher level of skill, which indicates a possible mismatch in labour supply and demand. Research by the RAO (Künn, Poulissen, Eldert, & Fouarge, 2018) underlines this by stating low-skilled workers overall take almost zero additional training during their career, which makes finding new employment for this group of people especially hard. This development may increase unemployment rates.

Regarding the higher estimations, an increasingly higher portion of the workforce is at stake of losing their job (figure 35). Hamid, Smith & Barzanji (2017) believe the emerging technology will be a compliment to workers and therefore the loss of jobs would mean new jobs would arise. This implicates the workers would be able to work in the same industry.

Retraining could, in that case, be carried out through the employer and new skills needed would be minor. Other research (Acemoglu & Restrepo, 2016; Dauth et al., 2017) suggests the technologies will be substitutes for work. Following this reasoning, the people who lost their job would have to be retrained to suit a significantly other job and retraining would not be carried out by the employer. Substitution or complementation will differ per job, but the higher estimations will put more pressure on the current institutional arrangements and the chances of the mismatch-scenario, the labour surplus-scenario, or a combination of both scenarios happening will increase.

#### Mismatch scenario

A mismatch in the available work and the labour supply means there is enough work and there are also enough unemployed people to fill these jobs, but this part of the workforce needs either assistance or retraining (figure 36). Without this assistance, they are simply not able to get the job. As mentioned before this retraining of workers may be realized by companies themselves when they see another position fit for the worker. In another scenario, the worker would just be fired in favor of the application of technology. In that case another job might arise for this worker but in another field of work requiring retraining of the worker. In that case, the UWV is the designated agency to (if applicable) take care of social benefits in a period of unemployment and help in retraining the worker towards a new job. The question is, 'Will the UWV be able to handle a significant increase in workers who need help?' The changes in the labour market and an increase in the amount of work will put more pressure on the UWV. Over the years the organization has had numerous problems, such as wrongful payments of social benefits ("Minister Koolmees: problemen UWV nog groter dan gedacht," 2019) and waiting lists for medical exams (Weel, 2019). Two consequences of the mismatch scenario are the increase in workers who need social benefits and the increase in workers who need guidance towards their new job. Of course, there will also be people who take care of themselves and do not need help but following this research, it is not likely the labour market is configuring itself with the possibility of up to 4.7 million people transitioning towards a new job.

#### Unemployment scenario

In the unemployment scenario, another kind of problem arises (figure 36). This scenario implicates there is an insufficient number of jobs to cover the workforce. If the government does not act these people will have to address the social benefits of the UWV. In the previous section, this matter is already addressed.

The part of the workforce without a job will keep looking for a job, in other words, the demand for labour is high and if the jobs do disappear and not enough jobs comes back a significant part of the population may be out of a job. Since there is a need of humans to perform meaningful work (Blustein et al., 2019), these people will probably keep on looking for work and in the worst scenario end up performing unregistered jobs. Or even jobs return

that had become obsolete in the past but return because of the labour supply. There are lots of different ways to deal with this high surplus of labour. Some examples are given.

### Actor analysis

To determine the actors in the Netherlands responsible for dealing with the possible

#### Example 1

Research agreed (Aoun, 2017; Bonekamp & Sure, 2018; Gravemeijer et al., 2017) a new educational system is needed to suit the future labour market's needs. The government can create this new educational system and put more emphasize on personal assistance. This change probably requires more teachers/teaching assistants and helps relieve unemployment.

#### Example 2

Research performed on the meaning of work state that by nature people want to work (Blustein, Kenny, Fabio, & Guichard, 2019). Living off social benefits will not give people meaning in life; therefore, the government may hire people to perform so-called 'bull-shit jobs' to keep them working. An example of a bull-shit job is the job of elevator operator.

problems in the labour market an actor analysis is performed (appendix X). The analysis concludes in the definition of the most important actors. The Ministry Social Affairs and Employment (SAE) is defined as the main actor. This ministry focusses on making participation in the society available to anyone. In other words, it is their responsibility to make sure everyone with the appropriate age and want/need to work is working. Moreover, this ministry also has the responsibility to help those without a job and help them to get back into society and to support them while being unemployed. Social benefits, such as state pensions and benefits to the unemployed, are also under the governance of the ministry of SAE. The second actor of importance is the UWV. The UWV is an executing agency working under the authority of the ministry of SAE. The organization has the responsibility to judge and pay the social benefits to people who qualify for them. The final actor of importance is the "Social Economic Council" (SEC). Together the trade unions and the employer's organizations are seated in the SEC. Together with "Crown members", which are government selected researchers, professors or civil servants, form the SEC. The SEC focusses on negotiation between the different parties and is responsible for writing the collective labour agreement (CLA), which is a written contract between the different parties. The possible susceptibility of jobs and the policy space created consequently should be used by the ministry of SAE. The policy space provides clarification of the possible future labour market configurations and can be used as a tool for policymaking on matters of employment. It can be used to design the policies for the UWV and supports the SEC negotiations.

For a lot of people, an epic scenario of 4.7 million people losing their current job seems impossible but remember the farmers in the first industrial revolution. In that time a large

portion of the workforce was working in agriculture. At the time machinery decreased the need for workers. The norm became for children to go to school and be educated. At the time it must have felt like a rigorous change, but in hindsight, it now seems normal. The future is unknown; therefore, it is better to be prepared for the most impacting scenario and to determine its implications.

### 7.3 Generalizing the methodology

The second way to use the research is through the generalization of the methodology used. The generalized methodology can support other countries estimating their future labour markets. The generalized methodology is stated in figure 37.

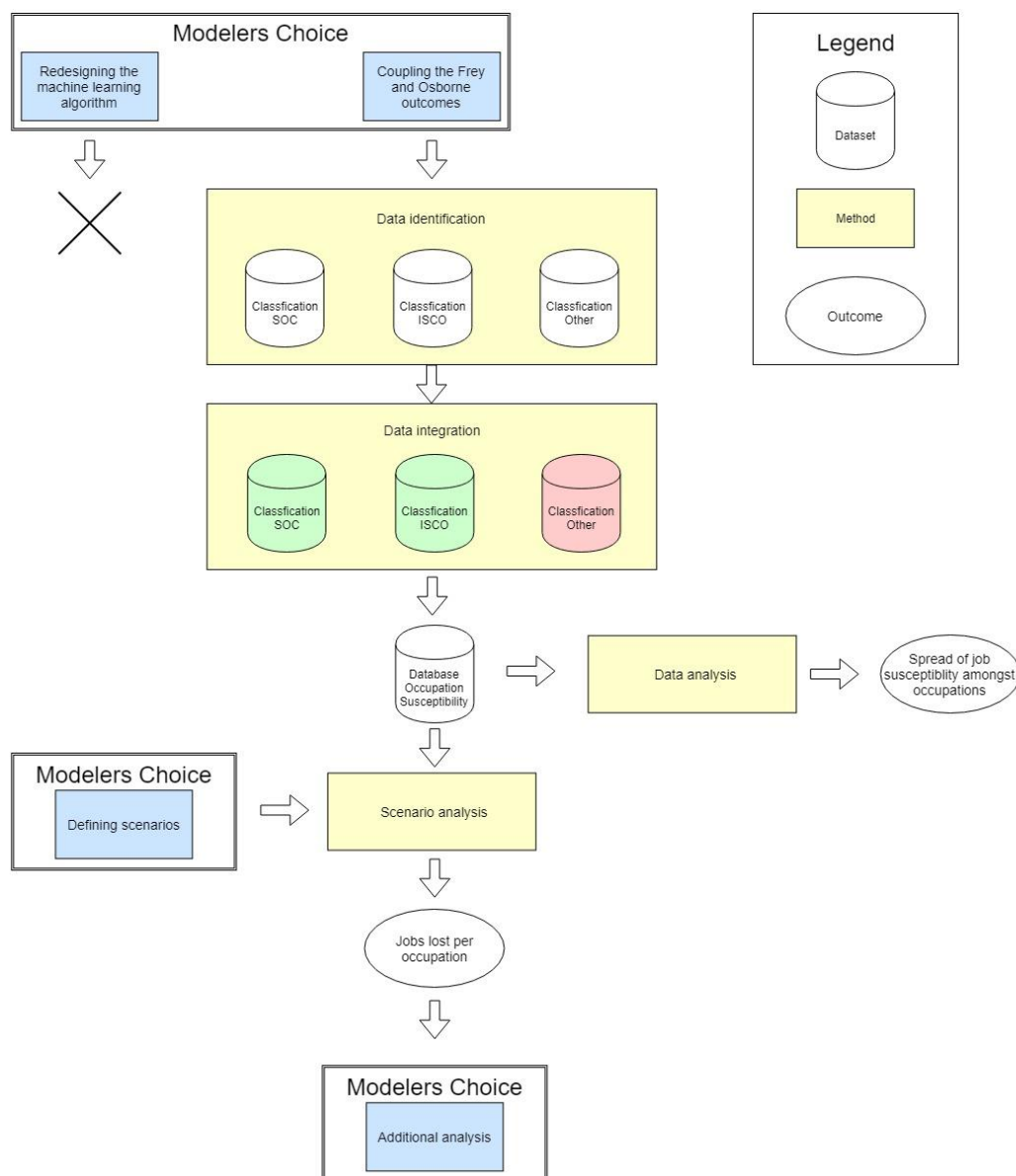


Figure 37: The generalized method of this research



In the literature, two ways of determining the labour market forecast for a country have been described. The first way is redesigning the machine learning algorithm (used in the Frey and Osborne research) like the research for Japan, Germany, the CEED and the OECD (David, 2017; Dengler & Matthes, 2018). The second way is coupling the susceptibility percentages of Osborne and Frey to the occupations in a particular country like the case in Finland (Pajarinen & Rouvinen, 2014). It is the choice of the modeler which starting point he chooses because there is no evidence in the literature on which method is better. This research followed the second way; therefore, the generalization of the method is performed on this assumption.

The first step in the process is data identification (figure 37). In this step, the classification method of the country is determined and the labour market sources are identified. Possible data quality issues are identified as well. If the country is using the SOC classification the only data needed is a labour market configuration document that contains quantitative information per occupation with accompanying SOC-code. If the country is using another kind of classification system, a crosswalk document is needed to link the different classifications of the countries to each other. When no such crosswalk document is available clustering may also be a valid option. The second step is data integration. In this step, the data of different sources is coupled and matched. The outcome of this process is used to analyze the spread of the workforce over the susceptibility percentages, which is the first outcome of the method. The spread of the workforce gives a global indication of whether a lot of jobs are highly susceptible in the country or if the country is relatively unaffected by possible upcoming technological developments. The outcome is also used as a basis for the labour market forecast. To determine the actual jobs lost for a country the modeler needs to decide on (a) technological development scenario(s). After defining the scenarios, the loss of jobs per occupation for a specific country can be determined. This is the second outcome. The loss of jobs is not the only factor in forecasting the labour market. The modeler may choose to use the loss of jobs for further analysis and as a basis for the labour market forecast.

For this research, the susceptibility of jobs in the Netherlands is researched. Programming was used to carry out the process steps. The coding used in the research may be used as a foundation for future research (the code is published on online platform 'GitHub' and may be assessed through [https://github.com/PaulSchot/Master\\_Thesis](https://github.com/PaulSchot/Master_Thesis)). The classification used in the Netherlands was the ISCO. The coding of the research may, therefore, be best used if the research country is either using the SOC classification (in alignment with the Osborne and Frey research) or the ISCO classification. If another classification system is used, the coding will only be helpful to some extent. Additionally, in this research, the loss of jobs is used as a basis for the labour market forecast together with the occupational growth trends.

## 7.4 Relevance for EPA program

This research has been carried out as part of the master program 'Engineering & Policy Analysis (EPA)' at TU Delft University. The relevance of this research for the program is based on the positioning of the research, the complication of the problem, the research question, the approach used to address the issue, and the resulting policy advice. The positioning of the research should contain an international grand challenge. By regarding the sustainable development goals of the United Nations as existing 'the' grand challenges, it is concluded this research is focusing on 'decent work and economic growth' ("TheGlobalGoals for Sustainable Development," 2017). The research contributes towards decent work for the workforce of the Netherlands by determining possible effects in the future. There is practically no labour market forecast research performed for the Dutch labour market, that provides a quantitative result and gives proper credit to possible technological development scenarios. Therefore, policymakers have inadequate information to make future policy. Additionally, the UWV, who takes care of the redeployment of the workforce and social benefits, is already having problems. More insights are needed to create adequate policy arrangements and make sure the welfare state of the Netherlands is not at stake. The accompanied research question to address the issue was; *What are the quantitative effects of technological developments on job level for the Dutch labour market in 2030 and how can the defined policy space contribute to decision-making?* The approach to address this research question focusses on the development of a labour market forecast by utilizing desk research, data analytics, python coding skills, and modeling. The resulting policy advice is to determine the consequences of current institutions of different outcomes of the policy space and to design possible strategies to deal with these consequences.

## 8. Conclusions

In the previous chapters, a long-term labour forecast was set up with a specific emphasis on the implications of technological development. In this chapter, the original purpose of this research will be linked to the outcomes of the analysis. A brief recap is drawn to restate the original purpose of the research. This recap is followed up by the answering of the research question. The research question will be answered by walking through the sub-questions and answering them. After answering the main research question the scientific relevance and the societal relevance of the performed research is addressed. This research paves the way for new research but could also use support to validate the research. Therefore, recommendations for future research are drawn up that may enhance the research, validate the methodology of the research, and may follow up on this research.

### 8.1 A brief recap

The fourth industrial revolution is on its way alongside emerging technologies, such as Artificial Intelligence and Advanced robotics. In every industrial revolution so far the fear exists jobs would disappear at a faster rate than new jobs are created (Mahdawi, 2017), but so far this has never been the case. Brynjolffsen & McAfee (2016) state this industrial revolution will be different than other industrial revolutions and believe the fear of the loss of jobs is justified. Osborne and Frey (2013) tried to quantify these allegations by determining the susceptibility of occupations in the US. For the US they concluded 47 percent of the existing jobs to be highly affected by the technological developments of this industrial revolution. Several studies used the report of Frey and Osborne to determine the number of highly susceptible jobs in other countries. In the Netherlands, no such estimation is made yet resulting in a lack of knowledge about long-term labour market forecasts for the country.

A labour market forecast was made to fill this gap in the literature and to determine the effects of this labour market forecast the main research question is answered.

### 8.2 Answering the research question

In the third chapter of this research, the main research question is stated. The main research question of this research is;

*“What are the quantitative effects of technological developments on job level for the Dutch labour market in 2030 and how can the defined policy space contribute to decision-making?”*

Five research questions are formed to split the research into parts. First, these five research questions need answering before the main research question is addressed.

### 8.2.1 How can the necessary labour market data and job susceptibility data be identified?

To look for answers to the first research question of this research chapter four includes a data identification process. The identified data are the occupational percentage data of the Osborne and Frey research, the labour market configuration data of the CBS, and another source of the CBS containing information on occupational growth trends and occupational levels per occupation. By analyzing these sources, it becomes clear that two additional sources are necessary. The first source is a crosswalk document of the US labour department and the second source is a document containing the ISCO codes per occupation defined by the ISCO. Moreover, some data quality issues are found that needed to be addressed, if the data was to be integrated. With the identified sources data could be integrated and analyzed.

### 8.2.2 What effects on the Dutch labour market can be drawn by combining the occupational susceptibility percentages and workforce quantities per occupation?

The integration of the occupational percentage data and the labour market configuration data leads to three datasets. The datasets were used to analyze the current susceptibility of employment in the Netherlands and lead to the answer to the second research question. For the 'average' scenario the spread of susceptibility percentages over the jobs of the Netherlands is stated in figure 38. The sectors 'Commercial' and 'Business and Administrative' will be the most affected by the developments, but also the sectors 'Service', 'Technical', and 'Transport and Logistics' are affected. Also concluded is a relatively large number of people working in so-called low-skilled occupations in the Netherlands, examples of such occupations are waiters and truck drivers. This is in line with the expectations drawn in the literature review (Acemoglu & Restrepo, 2017; Berg et al., 2016; Bonekamp & Sure, 2018; Duffy et al., 2016; Grip et al., 2018).

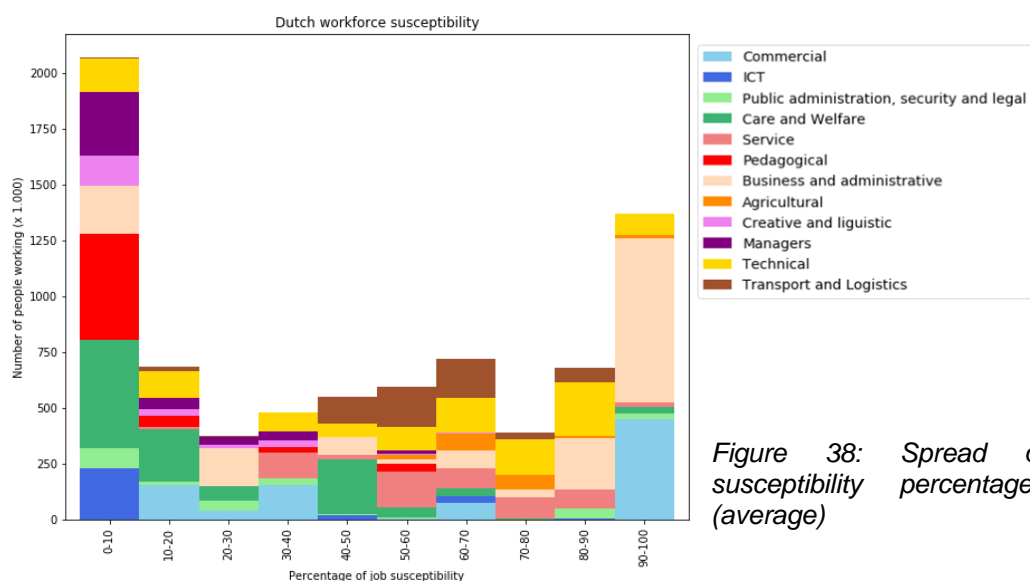


Figure 38: Spread of susceptibility percentages (average)

### 8.2.3 What are the effects of empirical occupational growth trends on the labour market and what educational level is required per occupation?

The labour market forecast also needed growth projections for the occupations not affected by technological development. The empirical growth trend is determined for each of the occupations. The overall occupational growth trend effect is displayed in table 34. This means if the occupations existing nowadays would show the same growth trend as they did of the last 15 years there would be a growth in the number of jobs of 785.000.

*Table 34: Overall occupational growth trend*

	Number of jobs
Job growth	1.526.000
Job decrease	741.000
Net difference	785.000

The educational level per occupation was determined by specifying the spread of educational level for each occupation. The overall educational level of the Dutch population is a result of considering all these percentages. This result is displayed in table 35. In the Netherlands, the population seems high educated with the highest percentages in educational level 2 and 3.

*Table 35: Overall spread of educational percentages*

	Percentage Educational level 1	Percentage Educational level 2	Percentage Educational level 3
Overall	22.0 %	41.2 %	36.8 %

### 8.2.4 What are the explorative scenarios to mitigate the uncertainty of technological development scenarios?

The susceptibility probabilities defined per occupation do not give any enclosure on how many jobs may be susceped. This means there is still uncertainty about the effect of the probabilities. This uncertainty was mitigated using explorative scenarios. The scenarios were defined as displayed in table 36. An example is given to explain how the scenarios were used. If the occupation 'truck driver' has a probability of being susceped of 79 Percent, it is in the range of 70 – 100 percent. If the number of truck drivers is 1.000, it means in the low-technology scenario 600 of these jobs are lost, 800 in the medium-technology scenario are lost, and 1.000 of these jobs are lost in the high-technology scenario are lost.

Table 36: The explorative scenarios

Technological development scenario	Percentage range 0% - 30%	Percentage range 30% - 70%	Percentage range 70% - 100%
Low-Technology	0%	0%	60%
Medium-Technology	0%	25%	80%
High-Technology	0%	50%	100%

### 8.2.5 How may the methodology of labour market forecasting be generalized?

In the previous section 'discussion', the methodology of this research is generalized and an accompanying explanation is given. In figure 39 the generalized methodology is stated.

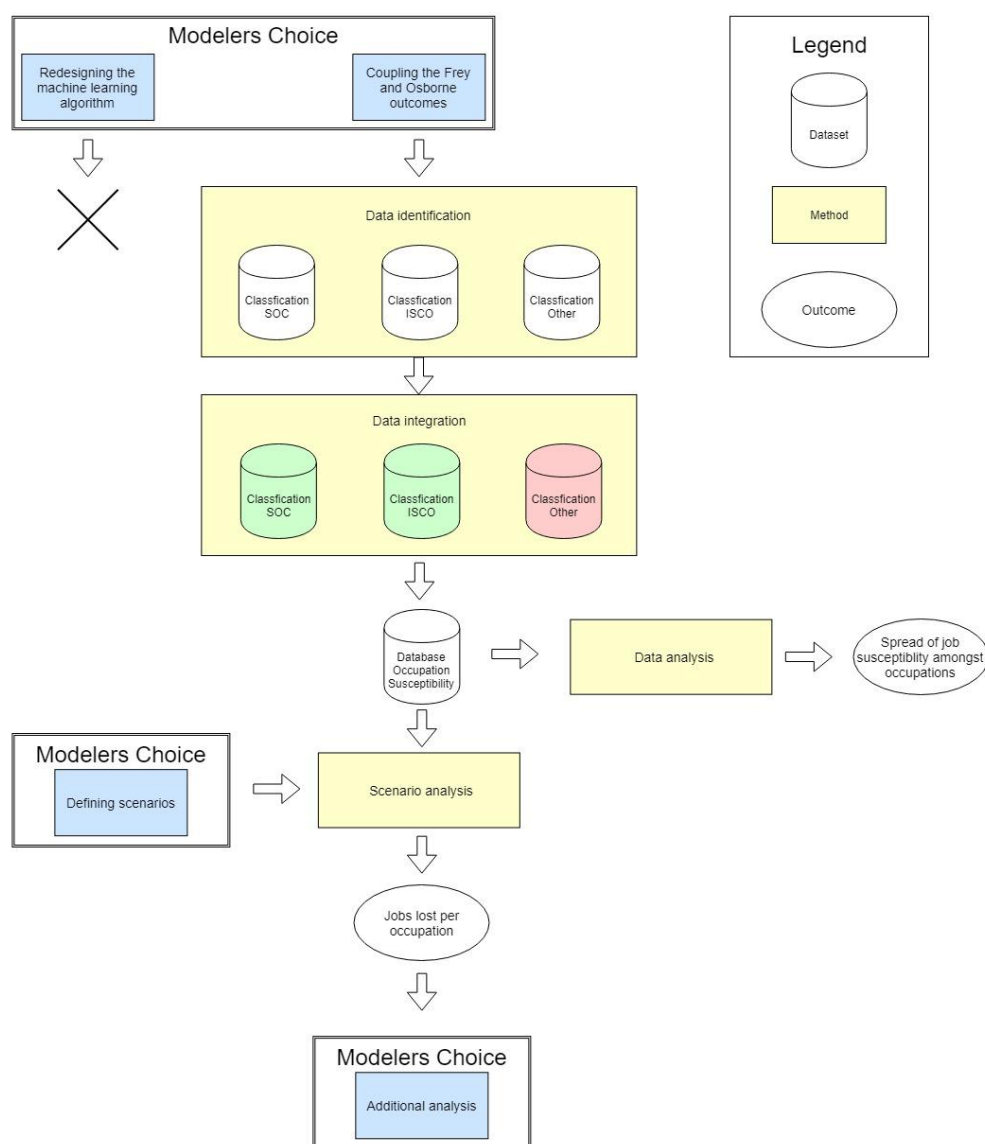


Figure 39: The generalized methodology

### 8.2.6 The main research question

The main research question of this research is as follows *“What are the quantitative effects of technological developments on job level for the Dutch labour market in 2030 and how can the defined policy space contribute to decision-making?”* The question is twofold and can be separated into;

1. The quantitative effects of technological developments on job level for the Dutch labour market in 2030
2. Contribution of the defined policy space for decision making

The first part of the research question is answered first. The quantitative effects of technological developments on job level result in a loss of 0.8 million for the low technological development scenario, a 2.6 million loss of jobs for the medium technological development scenario, and a loss of 4.7 million jobs for the high technological development scenarios.

The consequences of the loss of jobs for the technological development scenarios for the policy space are shaped by the determination that the losses will not directly mean unemployment for this part of the workforce. There are three scenarios can unfold (figure 36). The first scenario accounts for the creation of new jobs at the same pace as old jobs are destroyed and that the workforce can fill them appropriately. In the second scenario, the creation of new jobs is making up for the loss of jobs but lead to unemployment, because the workforce is not flexible to fill the newly created jobs. In the third scenario, the creation of jobs is lacking and therefore unemployment is rising because the workforce simply has no jobs to fill. In the next section, the second part of the main research question is answered.

### 8.3 The social contribution & policy advice

The OECD stated future labour market configurations will be impacted by technological changes and states it to be a task of government bodies to make policies facilitating changes in the labour market (OECD, 2018). The previous Deputy Prime minister of the Netherlands underlined the necessity of dealing with the possible changes in technological development as well (Buddingh, 2014). The Frey and Osborne research showed which occupations are at stake of being suscepted by technological developments, but for the Netherlands no quantitative data on its workforce was available. The loss of jobs occurring for the different technological development scenarios determines the space for policy. Additionally, the analysis showed 1 million of all the jobs lost for the medium technological scenario and 1.6 million of all jobs lost for the high technological scenario are jobs performed by workers with educational level 1. This part of the workforce was already concluded to be the most vulnerable in the literature review of this research (Acemoglu & Restrepo, 2017; Berg et al., 2016; Bonekamp & Sure, 2018; Duffy et al., 2016; Grip et al.,

2018). The outcomes for the labour market and the effect on low skilled workers can be used by policymakers as a tool for policymaking.

The current institutional arrangements may fail, because of insufficient funds for social benefits, insufficient resources for retraining, and because the executing agency UWV is already having problems. Following the scenarios, it is advised towards policymakers to design new institutional arrangements. These institutional arrangements should include a plan to scale up social benefits ('What to do if demand for social benefits increases?'), a plan to scale up support for labour market guidance ('What if the number of unemployed people increases and need to be retrained into a significantly different job?'), and a plan to create resilience within the future workforce by adjustment of educational curriculums.

It is recommended to the ministry of SAE to instate a committee to investigate how different transitions of the labour market, sketched research, will affect the institutional arrangements. The committee should address the proposed questions and determine plans to mitigate the upcoming challenges.

#### 8.4 The scientific contribution

The literature describes the research of Frey and Osborne (Frey & Osborne, 2013) to be the first research estimating job susceptibility as a consequence of the fourth industrial revolution. Several studies (Arntz et al., 2017; David, 2017; Dengler & Matthes, 2018; Nedelkoska & Quintini, 2018) took the research as a starting point but redesigned the way occupations were given their susceptibility percentage. Other research (Pajarinen & Rouvinen, 2014) did not redesign the susceptibility percentages but coupled the susceptibility percentages to a specific national classification system. In this research, the second approach was used, but there was no methodology found in the literature to determine how the different data should be coupled and integrated. This indicates a gap in the literature as mentioned in chapter 2.5. The scientific contribution of this research is to fill this gap by creation of a generalized methodology from this research. The methodology of this research guides other researchers and helps them to make estimations for labour markets in other countries. The methodology was generalized to create the ability for other countries to create an estimation for their future labour markets. The generalized methodology is stated in figure 39.

The generalized methodology needs to be regarded as a first version and validation plus enhancement can help increase its value. After usage of the methodology to determine the susceptibility of jobs for other countries, it can be concluded if the methodology is enough. Considering it is the first version, there are probably some 'rough edges' of the methodology and these studies will probably have some recommendations to enhance the methodology.

The methodology is built upon the research of Frey and Osborne, which is based on expert estimations, therefore, the methodology will never lead to a completely objective future estimation. It is, however, inherent for research like this to have such uncertainty



incorporated. Due to uncertainty about the future making a labour market forecast always be a challenge but having an idea of possible future scenarios based on quantitative research will help to determine the spectrum of possible scenarios. As already mentioned before the result of using the methodology should be regarded as a policy space for decision-makers, where an overview is created of what scenarios might happen.

## 8.5 Recommendations for future research

There are several recommendations for future research. The first of which is validation. The approach of this research is explorative, because of this explorative character a lot of assumptions had to be made. These assumptions affected the validity of the research. Several validation methods are viable to use to determine the robustness of some of the assumptions of the forecast. Structural validation is the first one. In this methodology, the assumptions are manually adjusted to determine the rigidity of the current setting. Exploratory modeling (Kwakkel & Haasnoot, 2019) is the second one and can be used for the same purpose, this methodology is more elaborate and investigates a broad spectrum of the settings for the assumptions. Another kind of validation method is to perform expert interviews with Wilthagen and Salomons (scholars in the Netherlands). The goal of such interviews should be to determine the credibility of the used methodology in this research.

As stated in the previous section the generalized methodology is the first version of this methodology. Future research should focus on utilizing this methodology for other labour markets to determine the transitions for other countries. Through this utilization, the methodology may be sharpened and increase the validity. Gaining insight in other countries may also have another value. It would be beneficial to gather all the data for all European countries. With this data, a more inclusive picture can be drawn for the whole European labour market since a lack of jobs in southern European countries is already resulting in migration for labour purposes.

Employment and the supply of work is naturally an economic theme. In this research, the field of economics was briefly addressed, but it would be beneficial for this research to regard its methodology and the outcomes through a macroeconomic lens.

Finally, as proposed in the social contribution section, the outcomes of this research should be used by policymakers. The policymakers should use the outcomes as guidelines and should make plans to mitigate possible problems resulting from changing labour market configurations.

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## Appendices

## Appendix I: Assumptions

### Assumption 1

It is assumed the articles citing Frey and Osborne cover one or more aspects of the discussions on technological unemployment. Therefore, the literature search is narrowed down to articles citing Frey and Osborne (in other words articles citing 'labour market forecasts' emphasized on technological developments).

### Assumption 2

The current unemployed workforce is not regarded. The reasoning for this assumption is that there will always be a percentage of the workforce that is unemployed at a certain point in time. In other words, either going from in conversion towards new job or unemployed for the rest of their lives. The current unemployed workforce is assumed to always at least be roughly at this level.

### Assumption 3

It is assumed the percentages of susceptibility created by Osborne and Frey for American occupations are the same for the corresponding occupations defined by the Netherlands. For example, for the job of truck driver it is assumed the same capabilities are needed to perform the occupation in the US and the Netherlands.

### Assumption 4

The values to determine the number of jobs lost for the low, medium, and high technological development scenarios are manually drawn. These boundaries could be set differently resulting in other results for job loss.

### Assumption 5

For this research the assumption is made that there was a linear growth trend between 2003 and 2018. It is assumed occupations are showing trend behavior, not random. Therefore, smooth linear movement is assumed.

### Assumption 6

It is assumed the educational level is the best indicator in this situation to estimate if an employee will be qualified enough to perform an occupation. Therefore, in this research the educational level of the workforce is regarded as a level of their skill.

### Assumption 7

It is assumed workers with educational level 0 at least had some education, since these people are occupying a job in the dataset. These workers are transformed to having educational level 1.

#### Assumption 8

The loss of jobs for an occupation is equal to the spread of educational level. Therefore, it is not the case that low skilled workers in an occupation may be earlier fired.

#### Assumption 9

The choice for low-tech, medium-tech and high-tech percentages are assumed to cover the full scope of the uncertainty on technological development.

#### Assumption 10

The occupational percentages define per scenario which and how many jobs are lost per occupation. It is assumed, if an occupation is affected by technological development, the affection is the growth trend.

## Appendix II: Literature review research, aspects of technological unemployment

Search plan

### Step 1

Select the first 100 sources that seem somewhat relevant

- 100 results scholar
- 100 results science direct
- 100 results semantic scholar

Select results based on most cited/influential

### Step 2

Note down all the key words and select the ones that are applicable to this research

### Step 3

Define the major topic in literature

### Step 4

Search by using the keywords in cited material/ write down keywords

For every major topic select relevant papers

### Step 5

Read abstracts/introductions/conclusions

Step 1 Select the first 100 sources that seem relevant

- 100 results scholar
- 100 results science direct
- 100 results semantic scholar

Select results based on most cited/influential

*“Search words (within future of employment)” that have been used*

- Robots
- Skill
- Industry 4.0
- Economic/economics
- Education
- Psychology/Social



Step 2 Note down all the key words and select the ones that are applicable to this research

Descriptions	Google Scholar	Scopus / ScienceDirect	Semantic Scholar	Total
Meaning of emerging tech for a specific business	4	20	13	37
Robots, humans and jobs (complementary or substitutes	11	6	11	28
Artificial Intelligence	4	9	10	23
Education and Technology/ educational transformation	8	8	4	20
Psychology/sociology/ethics of working	6	2	8	16
Industry 4.0	7	5	3	15
Macroeconomics/economy	8	4	3	15
Policies (imposing limits/how to handle revolution)	4	3	3	10
Skill-based/skill-allocation/routine based/ task based	1	2	6	9
(Risk of) automation	1	6	1	8
Future	3	3	2	8
Automation	2	2	3	7
Consequences of technology	3	1	3	7
Workplace automation	4	1	1	6
Digitization	4	1	1	6
Inequality	2	1	3	6
Other Countries (finland, germany, japan, uruguay/argentina, turkey	2	0	4	6
Technology unemployment	3	2	1	6
Employment	1	2	3	6
Jobs lost in America	3	1	1	5
Politics (employment as a strategy)	2	1	0	3
(Governance of) algorithms	1	2	0	3
Basic income	1	1	1	3
Innovations	0	2	1	3
Similar research as Osborne and Frey	1	0	1	2
Small cities	0	1	1	2
Aging population	1	1	0	2
Market opportunities for women in digital era	0	0	2	2
Transform work of human experts	1	0	0	1
Occupational mobility	0	0	1	1

### Step 3 Define the major topic in literature

Meaning of emerging technology for a specific topic

The emerging technologies will cause disruption in many industries. There has been done a large amount of research on the influence on smaller parts of the industries. For example, meaning for manufacturing or meaning for clinical medical physicists.

Robots, humans and jobs

Many sources write about the influence of robots and the change that they have on labour. A significant question in these sources is about the complementarity or the substitution of robots to human labour.

Artificial intelligence and Skill-allocation (Skill-based, routine-based, task-based)

Of course, artificial intelligence is a major topic in the literature since this technology makes new kinds of substitutions of labour possible. In this way routine-based work is more susceptible for robots that use artificial intelligence.

Industry 4.0 and the fourth industrial revolution

The new industry with all the emerging technologies in place is called the industry 4.0 and the process towards it the fourth industrial revolution.

Education and technology

There is an important connection between education and the revolutions that have appeared in history. Every time a revolution diminished the number of jobs, new jobs were created. To train people to fit the new jobs education is key. The question for this revolution is, "Can the transition of the workforce through education keep up with the fast-changing paced revolution?". Moreover, is it for example possible that a 45-year-old truck driver is retrained to suit a job in ICT?

Psychology/sociology/ethics of working & Algorithms

Working with or supervising robots is a becoming more normal, but with it do also come ethical and social questions. Does society want that robots perform certain jobs? For example, a nursing robot or a waiter robot.

Macroeconomics/Economics

Employment and productivity growth are long-established economic themes. Research point to a decoupling of these two factors, whereas they used to show similar behavior.

Policies & Basic income & Aging population & inequality

Policies need to be defined to handle problems and opportunities of the new emerging technologies. Research shows policies that are viable such as the use as a basic income.

But also, the societal environment is important, for example the aging populations in most western countries will let need for labour go up. Moreover, the estimation is that low-wage workers are way easier replaced than high- wage and that therefor inequality will rise.

#### Other Countries

Different countries have used the research of Frey and Osborne to project the research on their society. They use different approach to make this projection, but all use a top-down approach.

#### Similar research as Osborne and Frey

Some research tries to put the research of Osborne and Frey under a microscope and try to determine the validity of their work or come up with an enhanced conclusion.

Step 4 Search by using the keywords in cited material/ write down keywords

For every major topic select relevant papers & Step 5 Read abstracts/Extract information

Eventual used sources are numbered and the sources that were not are marked as 'XX'.

#### **Meaning of emerging technology for a specific topic**

1.1 Delphi propection on additive manufacturing in 2030: Implications for education and employment in Spain (Perez-Perez et al., 2018)

- Additive manufacturing is made possible by the fourth revolution
- Need for new kind of technicians
- Implications on employment market and jobs (SPAIN)

1..2 Digitalisation and employment in manufacturing (Freddi, 2018)

- Technology, mainly robots studied. 3D printing, IoT, Augmented reality, BDA less studied
- New type of skills demanded in manufacturing
  - o Service provision and software development

2.1 Policy and society related implications of automated driving: A review of literature and directions for future research (Milakis et al., 2017)

- The vast change of automated driving
- The effect of automation
- A transport and logistic focus
  - o What are the plus and minus of automated driving?

2.2 Level 5 autonomy: The new face of disruption in road transport (Skeete, 2018)

- Acceptance by EU of advanced Intelligent Transport systems

- Disruption of automotive sector
- Policy challenges

### 3.1 The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study (Rossmann et al., 2017)

- Role of big data analytics
- Increasingly more automation
- Increased importance for human intuition, trust and strategic decision-making

### 3.1 Big Data Analytics and IoT in logistics: a case study (Hopkins & Hawking, 2018)

- Role and impact of big data analytics and IoT
- Economic advantages

### 4.1 An accounting information systems perspective on data analytics and big data (Esperanza & Jensen, 2017)

- Big data and data analytics in the accounting information system
- Does not immediately say something about employment

### 4.2 Cloud-based intelligent accounting applications: Accounting task automation using IBM Watson cognitive computing (Marshall & Lambert, 2018)

- AI in accounting
- Task automation in accounting

### 5.1 Artificial intelligence will reduce the need for clinical medical physicists (Tang et al., 2018)

- AI in the medical field
- Combining robotics with machine learning

### 5.2 Artificial intelligence in healthcare robots: A social informatics study of knowledge embodiment (Pee, 2018)

### 5.3 Informatics and Nursing in a Post-Nursing Informatics World: Future Directions for Nurses in an Automated, Artificially Intelligent, Social-Networked Healthcare Environment. (Booth, 2016)

- Transition of the nursing job to suit the new technologies
- How will it transition

### 5.4 Occupational therapy students' perceptions of the role of robots in the care for older people living in the community (Tobis et al., 2017)

- Robotics in taking care of the elderly
- Exploration about the possibilities

### 6. Mapping the field of algorithmic journalism (Konstantin, 2016)

- Economic possibilities

- Natural language generation can perform tasks of professional journalism at a technical level

7. Predictive maintenance for a wood chipper using supervised machine learning (Lindstrom, 2018)

- Predictive modelling
- Reduce downtime and avoid accidents
  - Can lead to less work

### ***Robots, humans and jobs & Skill-allocation (Skill-based, routine-based, task-based)***

8.1 Automation, per se, is not job elimination: How artificial intelligence forwards cooperative human-machine coexistence (Hamid et al., 2017)

- we argue humans and machines can cross-fertilise in a way that forwards a cooperative coexistence
  - economic mechanisms of automation
  - Dichotomy of experience that separates the first-person perspective of humans from artificial learning algorithms
  - The interdependent relationship between humans and machines
- Policy makers must implement alternative educational approaches that support lifelong training and flexible job transitions

8.2 Service Robotics and Human Labor: A first technology assessment of substitution and cooperation (Decker et al., 2017)

- Service robotics
- Early days of robotics, task sequencing - > automate the tasks that are viable
- Robots increasingly take over non-standardized tasks
- robots do not necessarily substitute human labor, but complement it and, in specific areas, make it even more productive.
- Take over work, complement worker, or makes work more efficient

8.3 Robots at Work, G Graetz, G Michaels (Graetz & Michaels, 2018)

- economic impact of industrial robots, using new data on a panel of industries in 17 countries from 1993-2007
- While robots had no significant effect on total hours worked, there is some evidence that they reduced the hours of both low-skilled and middle-skilled workers.

8.4 Robots and jobs: evidence from US labor markets D Acemoglu, P Restrepo (Acemoglu & Restrepo, 2017)

- Negative and significant impact on employment and wages
- Most affected: low-skilled men, routine-manual jobs, and manufacturing
- One robot reduces employment by 7 jobs

8.5 German robots-the impact of industrial robots on workers W Dauth, S Findeisen, J Südekum, N Woessner (Dauth et al., 2017)

- Every robot destroys two manufacturing jobs.
- robots raise labor productivity but not wages. Thereby they contribute to the decline of the labor income share.

### ***Industry 4.0 and the fourth industrial revolution***

9.1 Consequences of Industry 4.0 on human labour and work organization L  
Bonekamp, M Sure (Bonekamp & Sure, 2018)

- Compromised article of different research
- The main findings indicate that Industry 4.0 would lead to a substantial decrease in standardized low skill
- and an increase in high-skill activities, embracing planning, control and IT-related tasks.
- Most researchers expect a growing complexity in many job profiles, along with an increasing need for cross-functional work organization and cross-company partner networks.
- They also project a growing importance of continuous learning, training and education
- As a result of those developments, a transformation of the tax system is suggested, away from the current focus on labour taxes.

9.2 Industry 4.0, global value chains and international business (Strange & Zucchella, 2017)

- affect the location and organization of activities within global value chains
- potential adoption and impact of the new digital technologies (commonly known collectively as Industry 4.0), to contrast these technologies with existing technologies, and to consider how the new technologies might lead to new configurations involving suppliers, firms and customers.
- the new digital technologies have considerable potential to disrupt how and where activities are located
- draw attention to the potential cyber-risks and implications for the privacy of individuals, and hence, the need for regulation.

9.3 Industry 4.0: new challenges and opportunities for the labour market (Kergroach, 2017)

- overall picture of the latest technological trends altogether referred to as the Fourth Industrial Revolution (Industry 4.0),
- their impact on the changing structure of the labour market,
- the demand for prospective skills,
- as well as emerging policy challenges.
- The author concludes that ensuring the resilience, adaptability and efficiency of labour markets are therefore not only a matter of addressing the skills needs of the Next Production Revolution

- but also, a prerequisite to social stability and cohesion.

### ***Education and technology***

#### 10.1 Robot-proof: higher education in the age of artificial intelligence (Aoun, 2017)

MIT-press book

- In the past, automation was considered a threat to low-skilled labor. Now, many high-skilled functions, including interpreting medical images, doing legal research, and analyzing data, are within the skill sets of machines.
- calibrates them with a creative mindset and the mental elasticity to invent, discover, or create something valuable to society—a scientific proof, a hip-hop recording, a web comic, a cure for cancer.
- The new literacies of Aoun are data literacy, technological literacy, and human literacy.
- need data literacy to manage the flow of big data, and technological literacy to know how their machines work, but human literacy—the humanities, communication, and design—to function as a human being. Life-long learning opportunities will support their ability to adapt to change.

#### 10.2 What mathematics education may prepare students for the society of the future? (Gravemeijer et al., 2017)

- critical thinking and problem solving, collaboration across networks, agility and adaptability, initiative and entrepreneurialism, effective communication, accessing and analyzing information, and curiosity and imagination (Wagner, 2014).
  - o Wagner, T. (2014). The global achievement gap: Updated edition. New York, NY: Perseus Books Group.
- Many others add Information and Communication Technology literacy.
- General education must lay the foundation for a wide variety of levels and types of work.
- We would argue that the focus must be on foundational education.
- emphasize the importance of one of the key 21st century skills: critical thinking.

#### 10.3 Education and working life: VET adults' problem-solving skills in technology-rich environments (Hämäläinen et al., 2015)

- The results indicate the critical issue that more than two thirds of adults with vocational education and training have weak skills or lack the skills in solving problems in technology-rich environments and that more than one fifth of these adults are at risk.

#### 10.4 Rethinking US Education Policy (Araya, 2015)

- Author: American education system is based on an outdated factory model of schooling dominated by standardization and didacticism
- Fails to prepare students adequately for the entrepreneurial knowledge economy

#### 9.1 Consequences of Industry 4.0 on human labour and work organization (Bonekamp & Sure, 2018)

They also project a growing importance of continuous learning, training and education

### ***Psychology/sociology/ethics of working & Algorithms***

11.1 Artificial Intelligence: Are there any social obstacles? An empirical study of social obstacles (Liliequist, 2018)

- asking the question what we should do once we do not need to work more?
- Or from an existential perspective, raising issues of what responsibilities we have as humans and what it means to be human?
- This research not for these questions
- Swedish interviews
- was an agreement that we need to address these as soon as possible, but they did not view this as an obstacle.

11.2 Social robots from a human perspective (Vincent et al., 2015)

- Lessons learned from previous widely adopted technologies, such as smartphones, indicate that robot technologies could potentially be absorbed into the everyday lives of humans in such a way that it is the human that determines the human-machine interaction.

11.3 The psychology of working theory. (Duffy et al., 2016)

- Over the last 60 years, several overarching theories have been proposed attempting to explain how individuals make career decisions and are ultimately satisfied with work,
- With more low-skilled work disappearing the lower class is forced into positions that they do not pick, but they must do that. They have no other option

11.4 Expanding the impact of the psychology of working: Engaging psychology in the struggle for decent work and human rights (Blustein et al., 2019)

- Psychology of working theory
- the loss of decent work undermines individual and societal well-being, particularly for marginalized groups and those without highly marketable skills.
- we offer exemplary research agendas that focus on examining the psychological meaning and impact of economic and social protections, balancing caregiving work and market work, making work more just, and enhancing individual capacities for coping and adapting to changes in the world of work.

11.5 Robots working with humans or humans working with robots? Searching for social dimensions in new human-robot interaction in industry (Moniz & Krings, 2016)

- robotic systems in different systems of work organization at the manufacturing shop-floor level.
- The integration of such complex socio-technical systems needs further empirical and conceptual research about “social” aspects of the technical dimension.



## ***Macroeconomics/Economics***

12.1 Disruptive technologies and their implications for economic policy: Some preliminary observations (Leipziger & Dodev, 2016)

Technological innovation has been at the core of firm level productivity gains and the economic growth of countries

- notion that more productive firms will displace less productive ones in a Schumpeterian fashion.
- Disruptive technologies can certainly benefit the consumer by providing cheaper, more accessible goods or services.

8.5 German robots-the impact of industrial robots on workers (Dauth et al., 2017)

- Every robot destroys two manufacturing jobs.
- robots raise labor productivity but not wages. Thereby they contribute to the decline of the labor income share.

8.3 Robots at Work (Graetz & Michaels, 2018)

- We find that industrial robots increased both labor productivity and value added.
- Our panel identification is robust to numerous controls, and we find similar results instrumenting increased robot use with a measure of workers' replaceability by robots, which is based on the tasks prevalent in industries before robots were widely employed.
- We calculate that the increased use of robots raised countries' average growth rates by about 0.37 percentage points.
- We also find that robots increased both wages and total factor productivity.

9.1 Consequences of Industry 4.0 on human labour and work organization (Bonekamp & Sure, 2018)

- As a result of those developments, a transformation of the tax system is suggested, away from the current focus on labour taxes.
- of the tax system is suggested, away from the current focus on labour taxes.

## ***Policies & Basic income & Aging population & Inequality***

13.1 Robots, growth, and inequality (Berg et al., 2016)

- The bad news is that inequality worsens, for several reasons. First, robots increase the supply of total effective (workers plus robots) labor, which drives down wages in a market-driven economy. Second, because it is now profitable to invest in robots, there is a shift away from investment in traditional capital, such as buildings and conventional machinery. This further lowers the demand for those who work with that traditional capital.

13.2 Technology, unemployment & policy options: Navigating the transition to a better world (Marchant et al., 2014)

- This article offers an economic and social framework for addressing this problem, and then provides an inventory of possible policy options organized into the following six categories:  
(a) slowing innovation and change; (b) sharing work; (c) making new work; (d) redistribution; (e) education; and (f) fostering a new social contract.

13.3 What happens if robots take the jobs? The impact of emerging technologies on employment and public policy (West, 2015)

- but we need to determine how emerging technologies are affecting employment and public policy.

## Appendix III: Literature review labour market forecasting in the Netherlands

Search plan

### Step 1

Desk research: Identification of relevant organizations and researchers

### Step 2

Analyze their point of view and research output

### Step 1 Identification of relevant organizations and researchers

In this step an online search was performed to identify relevant actors that are forecasting labour market transition. The following relevant actors were found.

Dutch labour research organizations

1. Rathenau institute
2. CPB
3. WRR

Univerisity organizations

4. SER
5. ROA
6. SEOR

University Professors

7. Anna Solomons, University Utrecht
8. Ton Wilthagen, University Tilburg

Interest group

9. Denkwerk

### Step 2 Analyze their points of view and research output

Often the written text of this appendix is directly copied or translated from the original source and are notes of the original text. The original sources are in every case stated before or after the text and are highlighted.

#### 1. Rathenau institute

The Rathenau wrote a report about the fourth industrial revolution named '**Robot society**' (Est & Kool, 2015).

- Also follow the line of reasoning of Brynjolffsen & McAfee and Frey & Osborne  
Focus on short term
- Rethenau in this source: Analyzing the Dutch situation nowadays, mostly on the background of other companies. Based on OECD data
- multi factor productivity (MFP) the OECD raises the issue of their sustainability. MFP growth in the Netherlands has namely been one of the lowest among selected OECD countries in the last 25 years. In this regard, the call for innovation is becoming more and more urgent.

Demographic changes – as one of the challenges

How worrisome is this prospect, considering that the unemployment rate is already so high (in the Netherlands currently 8.7 per cent)?

- More recently, a new phenomenon has arisen jobless growth.
- Linking this trend to the idea that robots and computers can quickly take over many jobs gives rise, at least at first glance, to a politically thorny scenario: a high long-term unemployment rate, greater social inequality, and more public unrest.
- The biggest problem now is that we do not have an informed picture of the dynamics of innovation and its influence on labour (and the division of labour) in the Internet era.
- On October 9, 2014, the government has asked the Social and Economic Council of the Netherlands (SER) to come up with an advice on how technology will influence the labour market and what kind of skills people will need in the future. The SER is an advisory and consultative body of employers' representatives, union representatives and independent experts, that aims to help create social consensus on national and international socioeconomic issues. Moreover, the Scientific Council for Government Policy (WRR) has started a project on the future of work.

On the one hand, there are concerns about technological unemployment and job polarization (erosion of employment in middle class jobs which require midlevel skills). Others see chiefly opportunities and argue that in the past, innovation has always sparked more economic growth, prosperity, and welfare; and smart machines will do so again

This occurs via 'second-order effects' in which savings achieved by productivity growth flow back into the economy. This consensus has started crumbling since 2010, among not only critics such as Brynjolfsson & McAfee but also well-known economists such as Krugman and Summers. This crumbling consensus is based not only on facts – scientific observations concerning employment creation in the short, medium and longer term – but also on changing perspectives on the underlying economic dynamics (see for example various 'diagnoses' of current economic problems by Gordon, Brynjolfsson & McAfee, Cowan, Krugman, Summers, and Rifkin).

This debate has been stoked by the investigators Frey & Osborne, who predict that in the next twenty years nearly half the current number of jobs in the US may be taken over by computers or robots. To ensure a good debate, it is important also to consider, alongside IT as a means of automating jobs, the role of IT in the creation of new jobs. Attention also needs to be paid to the economic, social, ethical and legal aspects involved in how IT influences work, how IT changes the organization of work, and finally the influence of IT on prosperity or, more accurately, the influence of IT on our capabilities for acquiring income and assets. These four issues still come up very little in public debate.

#### Policy options

- The robot society as a positive prospect
- Socially responsible innovation
- Education and Training
- Prosperity

## 2. CPB

The CPB is the Dutch planning agency. It is expected of such an institute to perform research in long term labour market growth. However, by scanning their website and database there is no such source found. Additionally, after directly contacting the CPB they did not supply such a source.

However, there are signs in other research that the CPB does research on the matter (**Went et al., 2015**). Quote from this research:

*“Wel hebben Bas ter Weel en Wiljan van den Berge van het cpb onderzocht wat de betekenis is geweest van digitalisering voor de Nederlandse arbeidsmarkt. Zij komen in hoofdstuk 5 van deze verkenning tot de conclusie dat digitalisering de afgelopen vijftien jaar vooral de banen voor middelbaar opgeleiden – en dan vooral aan de onderkant daarvan – onder druk hebben gezet, al blijkt dat in Nederland wel minder het geval te zijn dan in andere landen zoals de vs. Belangrijk is evenwel dat digitalisering de meeste impact heeft op taken binnen banen. Secretaresses die voorheen vooral met typen, het aannemen van de telefoon en het verdelen van de faxberichten bezig waren, doen nu andere taken, zoals planning en projectmanagement.”*

### 3. WRR

The WRR investigated the future of work. They have written the report ‘Being the boss of the robots’. **(Went et al., 2015)**

Quotes in this research:

*“Wat precies de effecten van robotisering op de arbeidsmarkt van de toekomst zijn, is lastig te voorzien. Voor zover bekend, is daarnaar in Nederland nog geen onderzoek gedaan.”*

*“In deze wrr-verkenning presenteren we geen utopieën of dystopieën over de toekomst van werk. Ook publiceren we geen beroepenlijstjes of de nieuwste hightech-snufjes. De vraag die centraal staat is meer verkennend van aard, namelijk wat de betekenis van digitalisering en robotisering is en kan zijn voor de toekomst van werk. Een drietal thema's wordt uitgediept. Het eerste is: welke robotisering (en digitalisering) zien we vanuit het perspectief van de arbeidsmarkt nu en in de toekomst op ons afkomen, en welke factoren spelen daarbij een rol? Het tweede: wat is bekend over de gevolgen van digitalisering en robotisering voor werk? 17 En ten derde stellen we de vraag welke vraagstukken een plek moeten krijgen op de beleidsagenda van de overheid, en wat de handelingsmogelijkheden zijn voor wetenschappers, werkgevers en werknemers en hun organisaties, en anderen.”*

### 4. SER

In the report ‘Human and Technology’ the SER expressed their vision on the future of work **(People and technology: working together, 2016)**

Two perspectives in the discussion Fierce discussion is taking place worldwide about the potential consequences of digitization. Some commentators are optimistic about the new opportunities that digitization offers, while others fear it will lead to massive job losses, in part because robots are in fact already taking over jobs.

On balance, then, there is less work about for those in the middle segment, and more for both low-skill and high-skill workers. Job polarization has therefore increased in the Netherlands, but not as much as in other countries.

It is difficult to predict which products or services will do the same in the years ahead.

The unemployment rate may increase (temporarily) during the transitional phase because certain groups will not be able to make the switch (immediately) to new jobs, new tasks and the new, required competences. To get through the transitional phase, working people must be adaptable, i.e. able to respond quickly to changes

How to go about the uncertainty that the fourth industrial revolution brings. The sketched scenario's by research suggest changes. How do we deal with those changes?

The more we can maintain our leading position in innovation, the greater our chance of profiting from new technologies

- Support innovativeness
- Make the organization of work forward-looking
- Utilize opportunities for new employment
- Equip people through learning and professional development

## 5. ROA

As part of the Education and Labour Market Project (POA)<sup>1</sup>, the Research Centre for Education and the Labour Market (ROA) develops a number of research activities aimed at a better understanding of the medium-term developments in supply and demand on the Dutch labour market (**Bakens et al., 2018**).

The question is then to what extent the forecasting model adequately picks up this process. While the risk of automation of occupations is not explicitly part of the ROA forecasting model, we do find a negative correlation between the expansion demand in occupations and the automation risk in those occupations.

- No long term research

## 6. SEOR

*“Verklaring andere focus van Frey en Osborne Hoe kan men tot zulke verschillende conclusies komen? Een reden hiervoor zou kunnen zijn dat Frey en Osborne naar beroepen kijken en per beroep kijken of dit een hoog risico heeft om te verdwijnen. Arntz, Gregory en Zierahn beweren echter dat bij veel beroepen die bij Frey en Osborne het label*

*‘verhoogd risico op verdwijnen’ hebben een belangrijk deel van de werkzaamheden (‘task’) niet of maar gedeeltelijk automatiseerbaar is. De vertaling van taken naar werkgelegenheid door Arntz, Gregory en Zierahn lijkt echter enigszins arbitrair, omdat er geen goede data zijn over het aantal uren per taak. Daarom is de negen procent banenverlies waarop zij uitkomen niet hard. Het lijkt eerder een ondergrens. Het artikel van Arntz, Gregory en Zierahn sluit aan bij het artikel van Chui, Manyika en Miremadi (2015) waarin ook wordt benoemd dat de focus moet liggen op de mogelijkheid van het automatiseren van taken in plaats van banen. Zij benoemen dat slecht vijf procent van de beroepen volledig geautomatiseerd kan worden en dat voor zestig procent van de beroepen geldt dat deze voor ten minste dertig procent geautomatiseerd kunnen worden. Dit leidt tot een ondergrens van ten minste 45 procent van de werktaken die geautomatiseerd kunnen worden. In het artikel wordt geen vertaling gemaakt naar de impact hiervan op de werkgelegenheid”. (Koning & Rooij, 2017)*

Moreover, they express their doubts about the long term forecast of the future labour market.

#### 7. Anna Solomons, University Utrecht

Paper 1: “Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share,” **(D. Autor & Salomons, 2018)**

- We find that automation displaces employment and reduces labor's share of value-added in the industries in which it originates (a direct effect). In the case of employment, these own-industry losses are reversed by indirect gains in customer industries and induced increases in aggregate demand. By contrast, own-industry labor share losses are not recouped elsewhere.

Paper 2: "Robocalypse Now: Does Productivity Growth Threaten Employment?," **(D. H. Autor & Salomons, 2017)**

- Is productivity growth inimical to employment? Canonical economic theory says no, but much recent economic theory says ‘maybe’—that is, rapid advances in machine capabilities may curtail aggregate labor demand as technology increasingly encroaches on human job tasks, ultimately immiserating labor. We refer to this immiseration scenario as the “robocalypse,” and explore empirically whether it is coming to pass by analyzing the relationship between productivity growth and employment using country- and industry-level data for 19 countries over 35+ years. Consistent with both the popular (‘robocalypse’) narrative and the canonical Baumol hypothesis, we find that industry-level employment robustly falls as industry productivity rises, implying that technically progressive sectors tend to shrink. Simultaneously, we show that country-level employment generally grows



as aggregate productivity rises. Because sectoral productivity growth raises incomes, consumption, and hence aggregate employment, a plausible reconciliation of these results—confirmed by our analysis—is that the negative own-industry employment effect of rising productivity is more than offset by positive spillovers to the rest of the economy. Rapid productivity growth in primary and secondary industries has, however, generated a substantial reallocation of workers into tertiary services, which employs a disproportionate share of high-skill labor. In net, the sectoral bias of rising productivity has not diminished aggregate labor demand but has yielded skill-biased demand shifts.

- It has not happened, yet but a shift has happened

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Notes Anne Salomons 'Banen bedreigd? Arbeidsmarkten in de digitale revoluties' (Salomons, 2015)

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Economist

- Introduction about the fourth revolution
- Mentions the Frey and Osborne research, but does not come about if she believes in it
- Technology is seen as a very important factor
  - o Especially economics
- Nobel prize economics for Solow -> productivity increases mainly because of new technologies
- Quote Paul Krugman "productivity isn't everything but in the long run it is almost everything"
- Economic framework: supply and demand of labour
- Is the supply of labour holds elasticity? If there are new jobs, can they be filled by the workforce
- Total labour productivity has not historically lead to unemployment
- Three reasons why economists believe this
  - o Technology is more a complement than a substitute
  - o The demand for goods and services has elasticity which makes the demand for labour increase
  - o The supply of the workforce has elasticity in the long run
- Plus, new technologies take on average 15 to 30 years to be adopted
- This is the first insight

Distribution of labour and wages

- Skill-biased technological change hypothesis
- New hypothesis
  - o Think from the computer perspective
  - o David Autor, Frank Levy, Richard Murnane
- Routine based
- Change in hypothesis
  - o Middle educated workforce susceptible
  - o Least susceptible high and low
- Job polarization

#### Personal view of dr. Salomons

- Complementarity more important than substitution: collaboration between human and machine
- Reaction on O&F = lump of labour fallacy
  - o Famous thinking error
  - o There is a set number of jobs in the market, which is never the case
    - This misses the fact that jobs that are susceptible lead to a bigger pie and therefore new labour
- Estimation that the speed of which technology is adapted is most of the time overestimated

#### This is explainable by using two paradoxes

- Paradox of Polanyi (1966): Tacit knowledge
- Paradox of Moravec (1988): "The hard problems are easy, and the easy problems are hard"
- There are a lot of things that are not able to make explicit and therefore not codable

#### Machine learning is new kind of technology, that makes new things possible

- But there are still a lot of obstacles

#### After questions in the rooms

- America is not dealing in the same way as the European countries with wages. European countries such as the Netherlands are a lot better at keeping the minimum wage at a level that's fairer. This is a policy choice.
-

8. Ton Wilthagen, University Tilburg

- Focus is on design of the labour market and concrete solution. Policy based
- No research found that he considers these long-term ideologies
- Sociological influenced

Notes Ton Wilthagen 'Toekomst zonder werk?' (Wilthagen, 2018)

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- Technology is power
  - o That also goes for the labour market
- It is not separable of other parts of the labour market
  - o Globalization
  - o Demographics
  - o Cultural changes
  - o Politics
- The debate is necessary
- We see the changes in banking, but it is not to be seen separable from the economic crisis
- New jobs are also the result of technology
  - o But whom is going to be employed on these jobs?
- Reshoring
- Technology does not have a random effect but an effect on certain competencies of humans
- We need to have a resilient workforce
- Human update of required knowledge should be a thing
- We are fascinated by contracts, but we should be talking about the shape of education
- There is no TomTom to know what kind of new education one need
- Technology can be a curse or a blessing
  - o Technology can also help the people who need it by finding a new job
  - o Example of the exoskeleton to help people to work again

Ton does elaborate on a future with jobs loss because of technology. However, he does not seem to have an indication on how many jobs this can be. He focusses more on the part of how it should be dealt with in order to keep people employed.

---

## Appendix IV: Research Osborne & Frey

Frey and Osborne tried to grasp the susceptibility of all existing jobs. Their research is the first research that quantifies the meaning for the future of employment (Frey & Osborne, 2013). Their result is an estimation of the susceptibility of 702 occupations. For example, for the occupation heavy truck driver they calculated a 79 percent chance that the occupation is susceptible by the year 2030 because of technological developments. In their research they state no claim is made on total susceptibility of occupations. They are simply assigning susceptibility chances to occupations.

In this appendix a short overview of their work is presented. They came to their results through the following method. The database of O\*NET, which is an official organization working for the US labour department collecting occupational data, was used to extract data. The data contained information on all occupations in the US. For all these occupations the data is containing different kinds of information, such as what kind of education is needed to perform the job and indications to what extend different 'variables' are needed to perform the job. As an example, the variable finger dexterity is shown in figure 40.

Computerisation bottleneck	O*NET Variable	O*NET Description
Perception and Manipulation	Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.

Figure 40: Variable finger dexterity of ONET

As a starting point for their research sat together with a group of experts. With whom a workshop was held to manually classify 70 different occupations. Together they estimated and then classified the jobs either as 0 (not susceptible in 2030) or a 1 (susceptible in 2030) (table 37).

Table 37: Rating through expert workshop (Osborne and Frey)

Expert workshop	Estimate susceptibility
occupation 1	0
occupation 2	1
occupation 3	1
...	....
occupation 70	0

After this classification they used the output and the O\*NET data on the different variables as training dataset. An exemplary situation for the training dataset is stated in table 38 (this is not the real data; the data is simplified example). The training set was then used

together with an AI algorithm to design a classifier method that would be able to make estimations for the full dataset.

*Table 38: Exemplary situation of training dataset*

<b>Combining</b>	Estimate susceptibility	Finger dexterity	Originality
occupation 1	0	10	80
occupation 2	1	70	25
occupation 3	1	80	15
...			
occupation 70	1	60	30

The designed classifier takes the variables of O\*NET as input and then puts out a percentage of susceptibility. A simplified version of such a classifier is stated in equation 2. Osborne and Frey concluded their classifier has a 90 percent accuracy meaning 90 percent of the occupations classified by the experts as susceptible are also classified as such by the classifier.

$$\text{Susceptibility of jobs} = \text{Finger dexterity} * 0.8 + \text{Originality} * 0.2$$

*Formula 2: Susceptibility of jobs*

Following the simplified classifier and the training set example a final situation after classification of the whole data set would look like the situation in table 39.

*Table 39: Data after usage of the classifier*

<b>Final classification</b>	Estimate susceptibility (Experts)	Finger dexterity	Originality	Estimate susceptibility (Classifier)
occupation 1	0	10	80	0,24
occupation 2	1	70	25	0,61
occupation 3	1	80	15	0,67
occupation ...	...	...	...	...
occupation 70	1	60	30	0,54
occupation 71	-	95	33	0,83
Occupation ....	-	...	...	...
occupation 702	-	33	20	0,30

As their most important findings they concluded 47 percent of total US jobs is in the category highly susceptible (above 0.7) and that wages and educational attainment show a negative correlation with the probability of susceptibility of that occupation (Frey & Osborne, 2013).

## Appendix V: Labour market policies research

### *Search plan*

#### Step 1 Search of sources

Search 1: Policies AND Unemployment (20 results)

Search 2: Labour market policies (20 results)

#### Step 2 identification of policies

- Active / passive policies
  - Insider/outsider
  - Active labour market policies (ALMP)
- 

#### Step 1

Search query: Policies AND Unemployment	Number of sources
Country specific	7
labour market policies	6
supply side	3
Monetary policy	2
Macroeconomics	2
Quantitative	1
Wages	1
Insiders outsiders	1
Insurance work-search	1

Search query: Labour market policies	Number of sources
evaluation	3
OECD	3
working policies	2
effectiveness	2
activating	2
lessons	1
institutional setting	1
Informal sector	1
microeconomic	1
globalization	1
real-wage determination	1
living and equal wages	1
macroeconomic	1
deregulation	1

## Step 2

### Source 1; **What Works Among Active Labour Market Policies**

*Evidence From OECD Countries' Experiences* (Martin, 1998)

- Difference between active and passive policies
  - o Active measures comprise a wide range of policies aiming at improving the access of the unemployed to the labour market and jobs, job-related skills and the functioning of the labour market.
    - Spending on active measures is, in turn, split into five program areas: public employment services; labour market training; youth measures; subsidized employment; and measures for the disabled.
  - o Passive measures cover spending on unemployment and related social benefits and early retirement benefits.
- Using the OECD data set on active measures, it is possible to compute three different measures of the 'spending effort' of countries: (i) the share of public spending on active measures as a percentage of GDP; (ii) spending on active measures per person unemployed; and (iii) the number of participants on active programs relative to the size of the labour force.

#### Ways to stimulate employment

- \*\*\*\*\*Public training programs
  - o They usually account for the largest share of spending on active measures: on average, OECD countries devoted 27 per cent of their total public spending on active measures to training programs in 1996, up from 23 per cent in 1985
- Job-search assistance
- Subsidies to private-sector employment
- Direct job creation in the public sector

### Source 2; **Evaluating Unemployment Policies: What Do the Underlying Theories Tell Us?** (Snower, 1995)

- Laissez-fair policy
  - Do nothing
- Demand management policies
  - 1. hiring for public sector
  - 2. raise aggregate product demand
- Supply side policies
  - Raise productivity of workers
- Institutional policies
  - Change labor market institutions, such as wage-bargaining systems, job search support

Source 3; **Technology, Unemployment & Policy Options:**

*Navigating the Transition to a Better World* (Marchant et al., 2014)

More focused on unprecedented unemployment

- (a) slowing innovation and change; (b) sharing work; (c) making new work; (d) redistribution; (e) education; and (f) fostering a new social contract.



## Appendix VI: Data identification

There are three types of main datasets used in this research. The first one is the occupational data source defined by Osborne and Frey. This source contains probabilities per occupation. The occupations are classified by SOC-code, which is the American classification standard to classify occupations (figure 41).

	Rank	Probability	soc_code	Occupation
0	1.	0.0028	29-1125	Recreational Therapists
1	2.	0.003	49-1011	First-Line Supervisors of Mechanics, Installer...
2	3.	0.003	11-9161	Emergency Management Directors
3	4.	0.0031	21-1023	Mental Health and Substance Abuse Social Workers
4	5.	0.0033	29-1181	Audiologists

Figure 41: The first five instances of the table that is used

The second data source used in this research is the quantitative data on Dutch occupation. This data was obtained through a personal request to the Dutch bureau of statistics. This source contains numerical data on the number of employees working in a specific job ordered by the international standard (figure 42).

	isco_code	isco_name	brc_beroeop	brc_name	num_working
0	110	Officieren	634	Militaire beroepen	6
1	210	Onderofficieren	634	Militaire beroepen	6
2	310	Andere rangen	634	Militaire beroepen	10
3	1000	Leidinggevende functies	551	Managers z.n.d.	14
4	1100	Directeuren van grote ondernemingen, beleidvo...	551	Managers z.n.d.	0

Figure 42: The first five instances of the table that is used

The third data is Labour market data containing job quantities over the years. This information is used to determine the occupational growth and the educational level of an occupation. The data is packed in multiple datasets. The main dataset of these datasets is linking the number of workers to the occupations and educational levels. Figure 43 shows the data of the main dataset. Educational code and occupational code are encrypted. The additional datasets are used to unencrypt this data.

	ID	ed_code	occ_code	periods	num_working
0	209284	2018700	A000161	2003JJ00	30
1	223204	2018740	A000161	2003JJ00	118
2	237124	2018790	A000161	2003JJ00	337
3	251044	2018820	A000161	2003JJ00	3
4	209289	2018700	A000161	2004JJ00	28

Figure 43: Data outline of main dataset

The three described datasets contain the main information needed to carry out the research. Some additional sources are used as described in 'data identification'. The first of these is the crosswalk document of the US labour department. This content contains information about the connection between the US classification standard (SOC) and the international classification standard (ISCO). This document can be used to link the probabilities of occupational data to the numerical data of the Netherlands (figure 44).

	isco_code	isco_08_title	soc_code	soc_10_title
0	110	Commissioned armed forces officers	55-1011	Air Crew Officers
1	110	Commissioned armed forces officers	55-1012	Aircraft Launch and Recovery Officers
2	110	Commissioned armed forces officers	55-1013	Armored Assault Vehicle Officers
3	110	Commissioned armed forces officers	55-1014	Artillery and Missile Officers
4	110	Commissioned armed forces officers	55-1015	Command and Control Center Officers

Figure 44 The first five instances of the table that is used

The second additional source is the official data of the ISCO is addressed. This source contains all the unique ISCO-codes (figure 45). This document can be used for verification purposes.

	isco_code	ISCO-88	English title
0	110	110	Admiral
1	110	110	Brigadier, army
2	110	110	Cadet, officer: armed forces
3	110	110	Captain, air force
4	110	110	Captain, army

Figure 45: The first five instances of the table that is used

# Appendix VII: Data coupling occupational percentages & labour market configuration

(Side note, in this part of the analysis the colors can be used as a legend. It will give guidance on which data is used where)

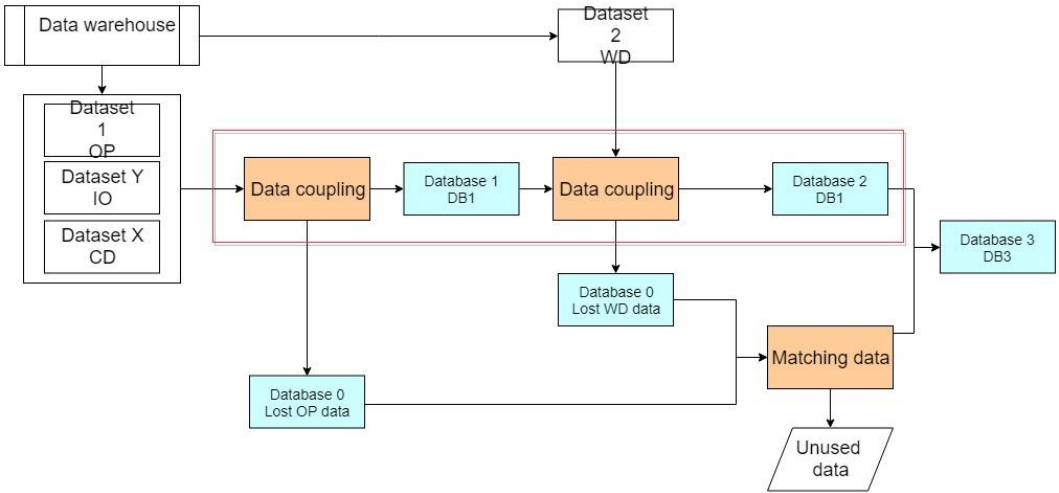


Figure 46: The coupling process

In figure 47 the datasets needed for data integration part 1 are stated. Osborne and Frey’s research contains the susceptibility percentages. The CBS data contains quantitative occupational data on the Dutch labour market. In between is the crosswalk data that will merge them together and the ISCO official is used for assessing the official existent ISCO codes.

Osborne & Frey (OP)	SOC 702
Crosswalk Occupations (CD)	SOC 878 - ISCO 438
ISCO Official (IO)	ISCO 436
CBS configuration (WD)	ISCO 532

Figure 47: The databases for data integration 1

The official data of the ISCO-standard exists of 436 unique ISCO codes. When comparing this number to the crosswalk data and the CBS data 2 more unique ISCO codes are discovered in the crosswalk data and the CBS data even contains 96 more unique ISCO codes (figure 48). For now, the focus will be on the crosswalk document. The mismatch with the CBS data will be handled later.

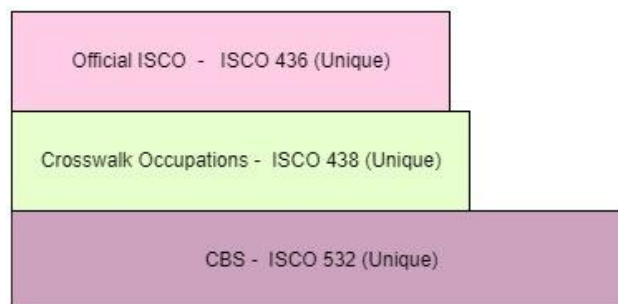


Figure 48: Difference in instances of different datasets

The two ISCO codes in the crosswalk data but not in the official data can be seen in figure 49. The two jobs do not seem to be important occupations for this research, since they are very specific occupations. The assumption is not many people in the Netherlands are performing these jobs. The classification of the SOC naming the one an 'All other' category and the other a 'specialist' category underlines this statement. After these considerations it is decided that the two occupations will be removed from the data.

	isco_code	isco_08_title	soc_code	soc_10_title
0	211	Physical and earth science professionals	19-2099	Physical Scientists, All Other
1	315	Ship and aircraft controllers and technicians	53-2022	Airfield Operations Specialists

Figure 49: Two left out data instances

The removal of this data has consequences for the crosswalk and occupational data. The removal process is graphically projected in figure 50 and figure 52.

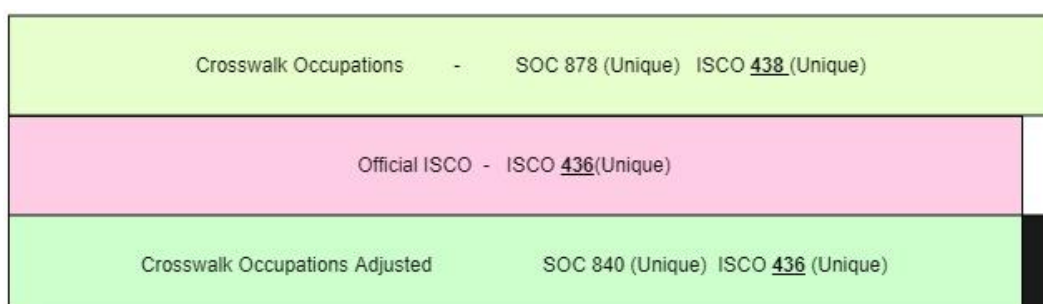


Figure 50: Difference with removal of two instances



Figure 52: Difference with removal of two instances

After the removal of this data the coupling of the data may be realized. This step includes the coupling of the occupational data and the crosswalk data to be coupled to new data. When analyzing the two sources difference in SOC-code, there are mismatches for both data sources.

```

The length of unique SOC-codes in ODC
700
The length of unique SOC-codes in CRS
838
Difference in unique SOC-codes between ODC and CRS
138
Number of SOC-codes    in ODC    &&    Not in CRS
17
Number of SOC-codes    in CRS    &&    Not in ODC
155

```

Figure 51: Mismatches in new dataset

The mismatch is displayed in figure 51. The missed 155 SOC-codes can be simply explained by the fact that Osborne and Frey did not include all the occupations defined by the SOC. The 17 missed SOC-codes from the occupational data can however not be directly explained.

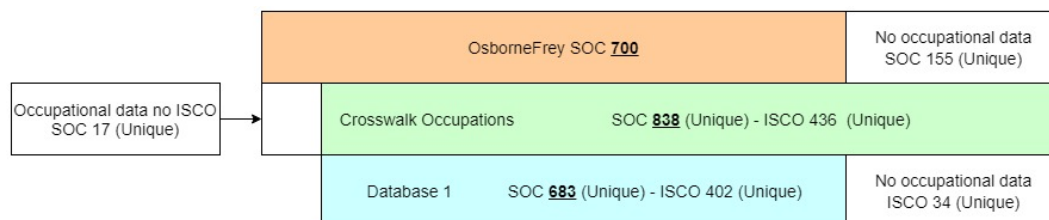


Figure 53: Outline of mismatch

When zooming in on the data (figure 53) 9 of the missed 17 occupations are found to be in the 'all other' category, which might explain the mismatch. For the other missed occupations there seems to be some among them, such as 'Registered nurses' and 'Postsecondary teacher', for which it is not clear why they were not matched.

When considering the spread of probabilities there seem to be percentages across the whole spectrum (0 to 1). It may have been a problem to leave out the 17 occupations if all the percentages were around the same susceptibility percentages, since it may have affected the outcomes. It is however still important to create a better coverage and to manually match occupational susceptibility percentages with occupational labour numbers.

The missed probabilities will be matched to professions in the CBS data in the data matching phase.

	Rank	Probability	soc_code	Occupation
0	15.	0.0042	29-1060	Physicians and Surgeons
1	46.	0.009	29-1111	Registered Nurses
2	48.	0.0095	25-3999	Teachers and Instructors, All Other
3	112.	0.032	25-1000	Postsecondary Teachers
4	142.	0.055	29-9799	Healthcare Practitioners and Technical Workers, All Other
5	207.	0.2	39-4831	Funeral Service Managers, Directors, Morticians, and Undertakers
6	208.	0.21	15-1179	Information Security Analysts, Web Developers, and Computer Network Architects
7	212.	0.22	15-1799	Computer Occupations, All Other
8	218.	0.23	29-2037	Radiologic Technologists and Technicians
9	242.	0.31	13-1078	Human Resources, Training, and Labor Relations Specialists, All Other
10	273.	0.4	29-2799	Health Technologists and Technicians, All Other
11	300.	0.5	49-9799	Installation, Maintenance, and Repair Workers, All Other
12	348.	0.63	31-9799	Healthcare Support Workers, All Other
13	359.	0.65	15-1150	Computer Support Specialists
14	390.	0.71	47-4799	Construction and Related Workers, All Other
15	501.	0.87	45-2090	Miscellaneous Agricultural Workers
16	572.	0.92	51-9399	Production Workers, All Other

Figure 55: 17 missed occupations

After the coupling of the first data integration step the second step in the process starts (figure 54). In this step the newly created data is coupled to the CBS data. The 'puzzle' of this coupling step is displayed in figure 53.

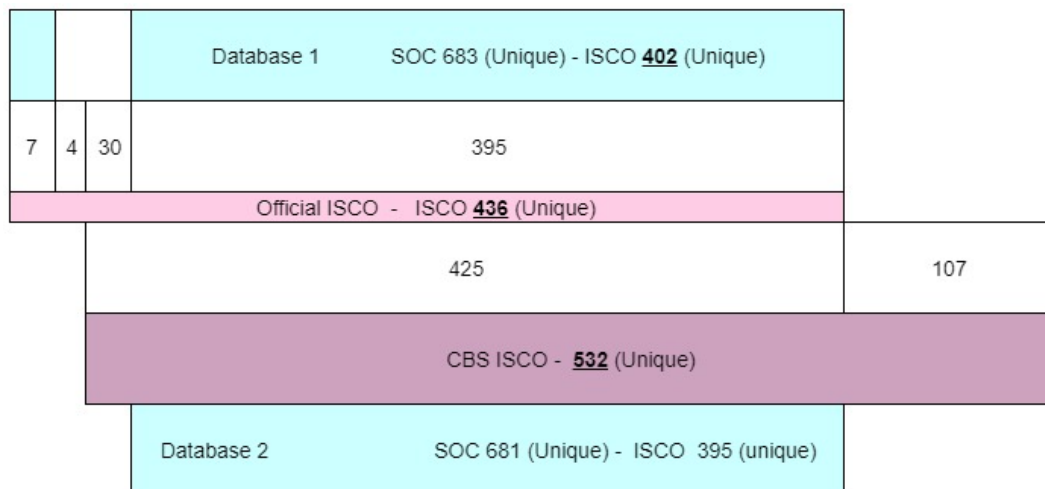


Figure 54: The coupling process and the mismatch in instances

The process shows 7 instances of unique ISCO-codes from the database 1 are lost in the coupling process, but when examining the new database 2 the lost ISCO-code are only accounting for a loss of two more SOC-codes lost (figure 56 from 683 to 681).

```
len(new_df2['soc_code'].unique())
```

681

Figure 56: Evidence of result of the coupling process

On the other side of the spectrum also 107 ISCO-codes in the CBS data are lost. There may be matches between the lost ISCO-codes and the lost SOC-codes in the data matching process this will be examined and additional links between ISCO and SOC will be made.

An overview of the situation is displayed in figure 57. On the one side CBS data with an ISCO-code, but without matching occupational data are displayed. On the other side CBS data with ISCO-codes per occupation, but these ISCO codes are not represented in the official source of the ISCO.

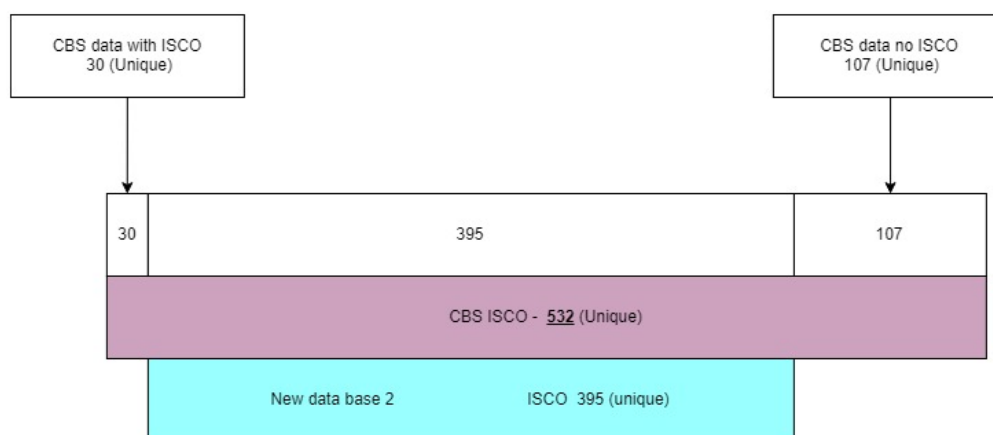


Figure 57: Overview of the second coupling

After the coupling process it is possible to determine how many occupational data is lost in the coupling process and for many employees the lost data is accounting. Figure 57 shows coupled data contains almost eight million people of the original just over eight and a half million.

ISCO <u>30</u> (unique) Workforce 408.000	New data base 2    ISCO <u>395</u> (unique) Workforce 7.947.000	ISCO <u>107</u> (Non existant) Workforce 182.000
----------------------------------------------	--------------------------------------------------------------------	--------------------------------------------------------

Figure 58: Coverage of the dataset

The coverage of the total workforce is enough with a coverage of roughly 93 percent, but through data matching of the unmatched data it may be possible to even increase this number.





## Appendix VIII: Matching data

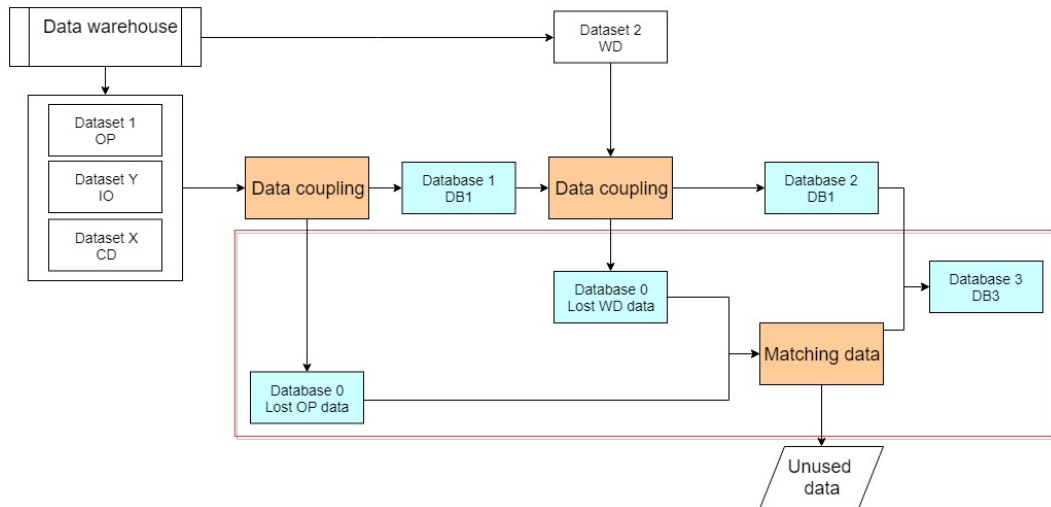


Figure 59: Data matching process

The data matching is the second part of the data integration 1. In figure 59 the steps data and process are displayed with the red box. The goal of the data matching is to create a better coverage of the data. Figure 60 shows the coverage of the data before data matching. The coverage is roughly 93 percent before data matching.

```
Number of people working in newly created dataframe
7947000
Number of people working occupations 30X professions
408000
Number of people working occupations 107X professions
182000

Number of people working in the Netherlands
8537000

Percentage of people lost in combining datasets: 6.9%
```

Figure 60: Coverage before matching

The first uncoupled data used is the Lost OP data. In figure 61 these SOC defined occupations are stated. There are 26 occupations for data matching present.

	Rank	Probability	soc_code	Occupation	isco_code
0	15.	0.0042	29-1060	Physicians and Surgeons	0
1	46.	0.009	29-1111	Registered Nurses	0
2	48.	0.0095	25-3999	Teachers and Instructors, All Other	0
3	112.	0.032	25-1000	Postsecondary Teachers	0
4	142.	0.055	29-9799	Healthcare Practitioners and Technical Workers, All Other	0
5	207.	0.2	39-4831	Funeral Service Managers, Directors, Morticians, and Undertakers	0
6	208.	0.21	15-1179	Information Security Analysts, Web Developers, and Computer Network Architects	0
7	212.	0.22	15-1799	Computer Occupations, All Other	0
8	218.	0.23	29-2037	Radiologic Technologists and Technicians	0
9	242.	0.31	13-1078	Human Resources, Training, and Labor Relations Specialists, All Other	0
10	273.	0.4	29-2799	Health Technologists and Technicians, All Other	0
11	300.	0.5	49-9799	Installation, Maintenance, and Repair Workers, All Other	0
12	348.	0.63	31-9799	Healthcare Support Workers, All Other	0
13	359.	0.65	15-1150	Computer Support Specialists	0
14	390.	0.71	47-4799	Construction and Related Workers, All Other	0
15	501.	0.87	45-2090	Miscellaneous Agricultural Workers	0
16	572.	0.92	51-9399	Production Workers, All Other	0
0	70.	0.015	11-1011	Chief Executives	0
1	137.	0.047	11-9013	Farmers, Ranchers, and Other Agricultural Managers	0
2	157.	0.076	39-1021	First-Line Supervisors of Personal Service Workers	0
3	406.	0.74	39-9021	Personal Care Aides	0
4	258.	0.37	47-5081	Helpers—Extraction Workers	0
5	292.	0.48	47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters	0
6	425.	0.77	45-3021	Hunters and Trappers	0
7	456.	0.83	45-3011	Fishers and Related Fishing Workers	0
8	483.	0.85	53-7062	Laborers and Freight, Stock, and Material Movers, Hand	0

Figure 61: Occupations for data matching of SOC

The second data is the lost WD data. In figure 612 the ISCO defined occupations are stated. Originally this were 107 occupations, but, as proposed in chapter 5, only the occupations with 5.000 or more employees are selected for selection.

isco_code	isco_name		brc_beroep	brc_name	num_working
6	2221	Verpleegkundigen met hogere opleiding	1012	Gespecialiseerd verpleegkundigen	123
5	2212	Medisch specialisten	1011	Artsen	57
8	2310	Professoren en andere onderwijsgevenden in het hoger onderwijs	111	Docenten hoger onderwijs en hoogleraren	55
4	2211	Huisartsen	1011	Artsen	35
18	3512	Technici voor informatie- en communicatietechnologie: gebruikersondersteuning	821	Gebruikersondersteuning ICT	27
71	7000	Ambachtslieden	1311	Overig	27
96	8300	Bestuurders van voertuigen en bedieningspersoneel van mobiele installaties	1214	Vrachtwagenchauffeurs	21
88	8100	Bedieningspersoneel van stationaire machines en installaties	771	Productiemachinebedieners	20
52	4100	Administratieve medewerkers	431	Administratief medewerkers	19
12	2000	Intellectuele, wetenschappelijke en artistieke beroepen	712	Ingenieurs (geen elektrotechniek)	16
10	2519	Software- en applicatieontwikkelaars en -analisten, niet elders geclassificeerd	811	Software- en applicatieontwikkelaars	15
0	1000	Leidinggevende functies	551	Managers z.n.d.	14
9	2513	Web- en multimediaontwikkelaars	811	Software- en applicatieontwikkelaars	14
20	2300	Onderrwijsgevenden	114	Leerkrachten basisonderwijs	13
66	5320	Verzorgend personeel in de gezondheidszorg	1051	Verzorgenden	12
11	2523	Netwerkspecialisten	812	Databank- en netwerkspecialisten	11
2	310	Andere rangen	634	Militaire beroepen	10
102	9110	Huishoudelijke hulpen en schoonmakers in huishoudens, hotels en kantoren	1121	Schoonmakers	10
24	9211	Ongeschoolde arbeiders in de akkerbouw	921	Hulpkrachten landbouw	9
51	4000	Administratief personeel	431	Administratief medewerkers	8
0	110	Officieren	634	Militaire beroepen	6
1	210	Onderofficieren	634	Militaire beroepen	6

Figure 62: Occupations for data matching ISCO

By manually assessing the two datasets in figure 61 and figure 62 for six occupations a match is found. In figure 63 the manually coupled occupations are the ones with an identified ISCO code.

	Rank	Probability	soc_code	Occupation	isco_code
0	15.	0.0042	29-1060	Physicians and Surgeons	2212
1	46.	0.009	29-1111	Registered Nurses	2221
2	48.	0.0095	25-3999	Teachers and Instructors, All Other	0
3	112.	0.032	25-1000	Postsecondary Teachers	2310
4	142.	0.055	29-9799	Healthcare Practitioners and Technical Workers, All Other	0
5	207.	0.2	39-4831	Funeral Service Managers, Directors, Morticians, and Undertakers	0
6	208.	0.21	15-1179	Information Security Analysts, Web Developers, and Computer Network Architects	0
7	212.	0.22	15-1799	Computer Occupations, All Other	0
8	218.	0.23	29-2037	Radiologic Technologists and Technicians	0
9	242.	0.31	13-1078	Human Resources, Training, and Labor Relations Specialists, All Other	0
10	273.	0.4	29-2799	Health Technologists and Technicians, All Other	0
11	300.	0.5	49-9799	Installation, Maintenance, and Repair Workers, All Other	0
12	348.	0.63	31-9799	Healthcare Support Workers, All Other	0
13	359.	0.65	15-1150	Computer Support Specialists	3512
14	390.	0.71	47-4799	Construction and Related Workers, All Other	0
15	501.	0.87	45-2090	Miscellaneous Agricultural Workers	9211
16	572.	0.92	51-9399	Production Workers, All Other	0
17	70.	0.015	11-1011	Chief Executives	1000
18	137.	0.047	11-9013	Farmers, Ranchers, and Other Agricultural Managers	0
19	157.	0.076	39-1021	First-Line Supervisors of Personal Service Workers	0
20	406.	0.74	39-9021	Personal Care Aides	0
21	258.	0.37	47-5081	Helpers—Extraction Workers	0
22	292.	0.48	47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters	0
23	425.	0.77	45-3021	Hunters and Trappers	0
24	456.	0.83	45-3011	Fishers and Related Fishing Workers	0
25	483.	0.85	53-7062	Laborers and Freight, Stock, and Material Movers, Hand	0

Figure 63: Data after matching

The six occupations are added to database 2 (defined in the data coupling process) and together they form database 3 (figure 64).

Database 3	ISCO 401 (unique)
Workforce	8.253.000

Figure 64: Database 3

Figure 65 shows the part of the workforce in the lost occupations and in the database 3. The coverage of the dataset has increased by manually matching the data. The new coverage is almost 97 percent.

```

Number of people working in newly created dataframe
8253000
Number of people working occupations 24X professions
102000
Number of people working occupations 107X professions
182000

Number of people working in the Netherlands
8537000

Percentage of people lost in combining datasets: 3.3%

```

Figure 65: Coverage after matching

## Appendix IX: Coupling occupational growth data

In this appendix the coupling process for the occupational change is described. The appendix will cover all the steps that are taken to couple the CBS occupational change data.

In data integration 1 the loss of jobs is calculated per occupation for three scenarios. A exemplary outcome for three occupations in one scenario is drawn in table 40 (numbers are non-real). In the table ISCO-code 1111 does have a loss of jobs of 0 estimated by the analysis of Osborne and Frey. To sketch the situation more complete it is necessary to determine the growth pattern of these occupations.

*Table 40: Exemplary outcome for three occupations*

ISCO code	Loss of jobs
1011	20.000
1111	0
1112	5.000

To gain insight in either the increase or decrease of the remainder of jobs occupational data of the CBS is used. This source contains information on the yearly number of jobs per occupation for the period 2003-2018. The outcomes of analysis 1 contained per occupation an ISCO code, but also a BRC code. This BRC code is used in data analysis 2 to determine for which jobs the change needs to be calculated. While first examining the data, it is found three unique BRC codes are lost (figure 66).

Dutch labour market data (DLMD)		BRC 114 (unique)
Output data DA1	ISCO 365 (unique)	- BRC 111 (unique)

*Figure 66: Difference in BRC*

The lost occupations are managers, military occupations, and occupations others (table 41). These occupations account for roughly 180.000 people that are left out of the dataset. When compared to the leftover dataset it is found that it only accounts for around 2 percent of extra data. The effect of these occupations is marginal and therefore leaving out these occupations is valid

*Table 41: The three lost occupations*

	Number of employees
Managers	9.000
Military occupations	26.000
Occupations Other	144.000

There are two ways of coupling the data to define the change per occupation. The occupations of the data integration outcome show on the one side ISCO occupations and on the other side accompanying BRC codes. An example of BRC code 711 is stated in figure 67.

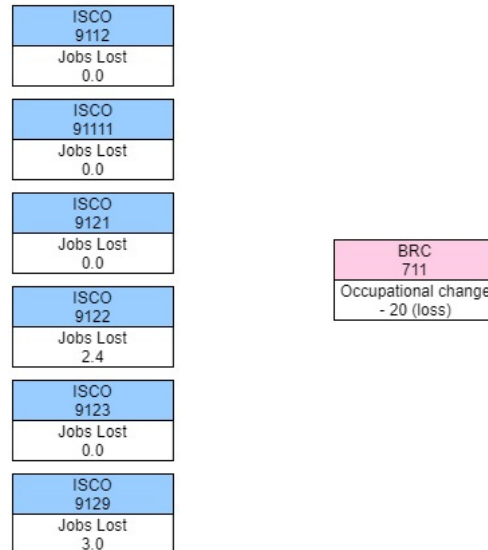


Figure 67: Example of BRC code 711

The first way is to define the occupational growth trend for all the ISCO codes. In figure 68 this process is displayed for BRC 711. For this BRC code there are six corresponding ISCO codes. Of these codes there are two ISCO codes already containing information from the Osborne and Frey research (9122 and 9129). For the leftover occupations the occupational change can be defined by distributing the information of the new CBS source. The problem with this method is that there is not information on this distribution. Therefore, using this method will cause invalidity.

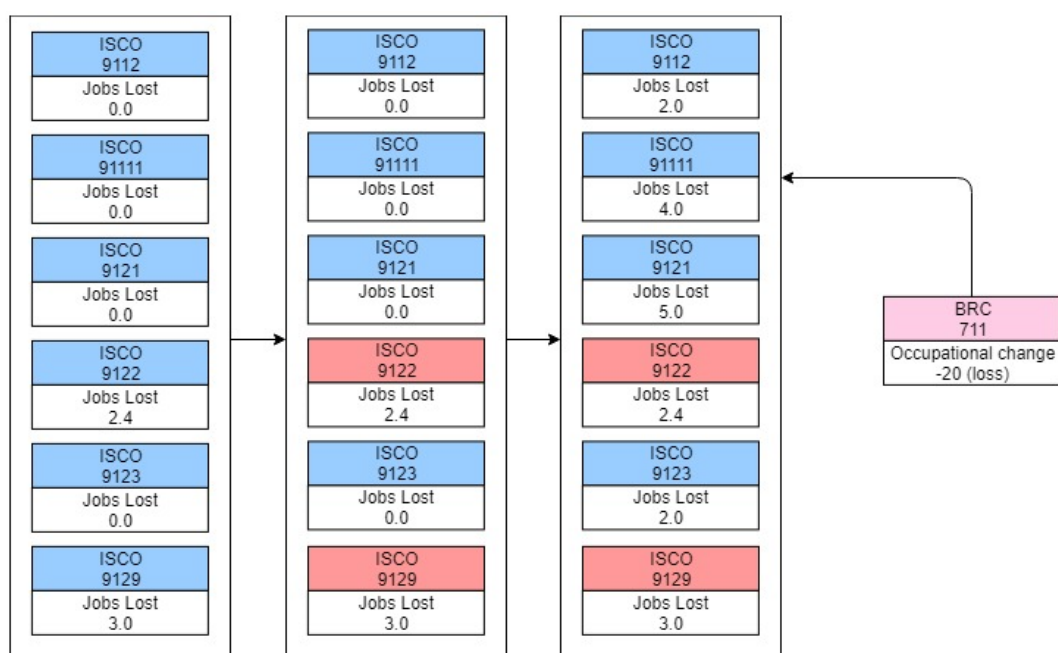


Figure 68: Defining the growth trend for all of the ISCO codes

The second way is to group the ISCO codes to the corresponding BRC code (figure 68 displays an exemplary situation). For this method the overall jobs lost are summed up and grouped. If the combined loss of jobs for the grouped occupation is still 0, the occupational growth trend is used and if the grouped occupation is higher than 0 the grouped ISCO occupations will account for the growth trend. However, when the grouped occupation a loss of jobs higher than 0 according to the Osborne and Frey research, it does not necessarily mean that all the separate ISCO defined occupations (in this grouped occupation) are above 0 (which is the case in the example of figure 69). This means the occupational growth trend of some ISCO defined occupations are not incorporated when using this method. However, this method will not discredit the validity of the data.

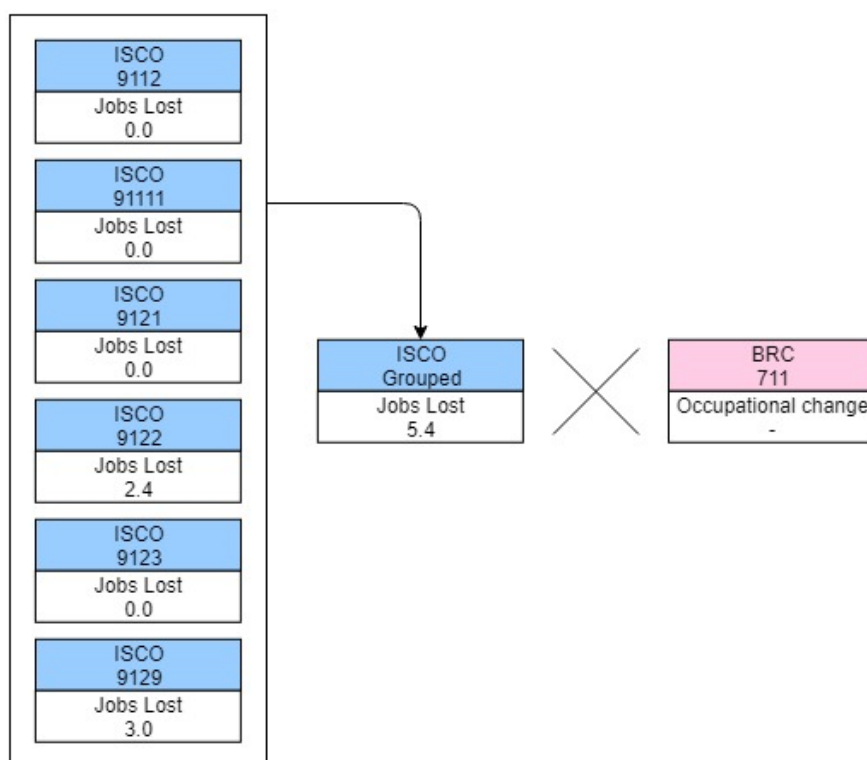


Figure 69: Group ISCO codes to corresponding BRC codes

The exploratory nature of this research results already in several uncertainties. To minimize the extra uncertainties the second method of the two explained methods selected as the most suitable to work with. It is however important to account for the incompleteness of this method. After further examination coverage percentages of 79, 67, and 61 percent are found for different input databases (table 42). The loss of data for this method shall be covered in the conclusions.

Table 42: Coverage percentages

	Min	Avg	Max
Num working original	5.980	3.105	2.829
Num working final	4.577	2.077	1.734
Percentage in dataset	79 %	67%	61%

## Appendix X: Actor analysis

It is important to have an idea of the actor arena in which the outcomes of this research can be used, therefore an actor analysis is performed. The methodology that will be used to perform the actor analysis was described in the book “Policy Analysis of Multi-Actor Systems” (Enserink et al., 2010). Since only a rough sketch of the situation will be made only step two and three of their method will be used.

2. Inventory of the actors involved

3. Exhibiting the formal chart

Step one is about problem formulation. The research problem for this research was addressed in chapter one and two, therefore it need not to be done. Step four and five include determining the interests and perception of different actor, as well as mapping out interdependencies. These steps can be useful, but since this research is exploratory the research will not lead to a policy advice and therefore underlying perceptions, interests and interdependencies do not matter. Step six is about the consequences of all the steps. Since not all the steps are included some conclusions will be drawn, but only on step two and three. The goal of the use of this methodology in this way is to gain a raw image of the actor arena.

### Inventory of actors involved

In table 43 all the actors involved are listed.

*Table 43: Involved actors*

<b>Governmental actors</b>	<b>Employers</b>
Ministry of Social Affairs & Employment (SAE)	Private companies
Ministry of Economic Affairs & Climate policy (EAC)	Governmental organizations
Ministry of Finance (Fin)	Self-employed (ZZP)
Ministry of Infrastructure and Water (I&W)	<b>Representative parties</b>
European Parliament	Trade Unions
<b>Labour Market actors</b>	Employers organizations
Employees working in the Transport and Logistics sector	Government Unions
Unemployed workers	<b>Support parties for unemployed workers</b>
	Uitvoeringsinstituut WerknemersVerzekeringen (UWV)
	Non-profit organizations

The most important governmental party is the ministry of Social Affairs & Employment, since are responsible for policymaking about unemployment. This ministry may be interesting to interview in order to make better scenarios.

#### Mapping formal relations

Based on the specified actors in table 41 the formal relations between them can be mapped. The result of this formal mapping is displayed in figure 70.

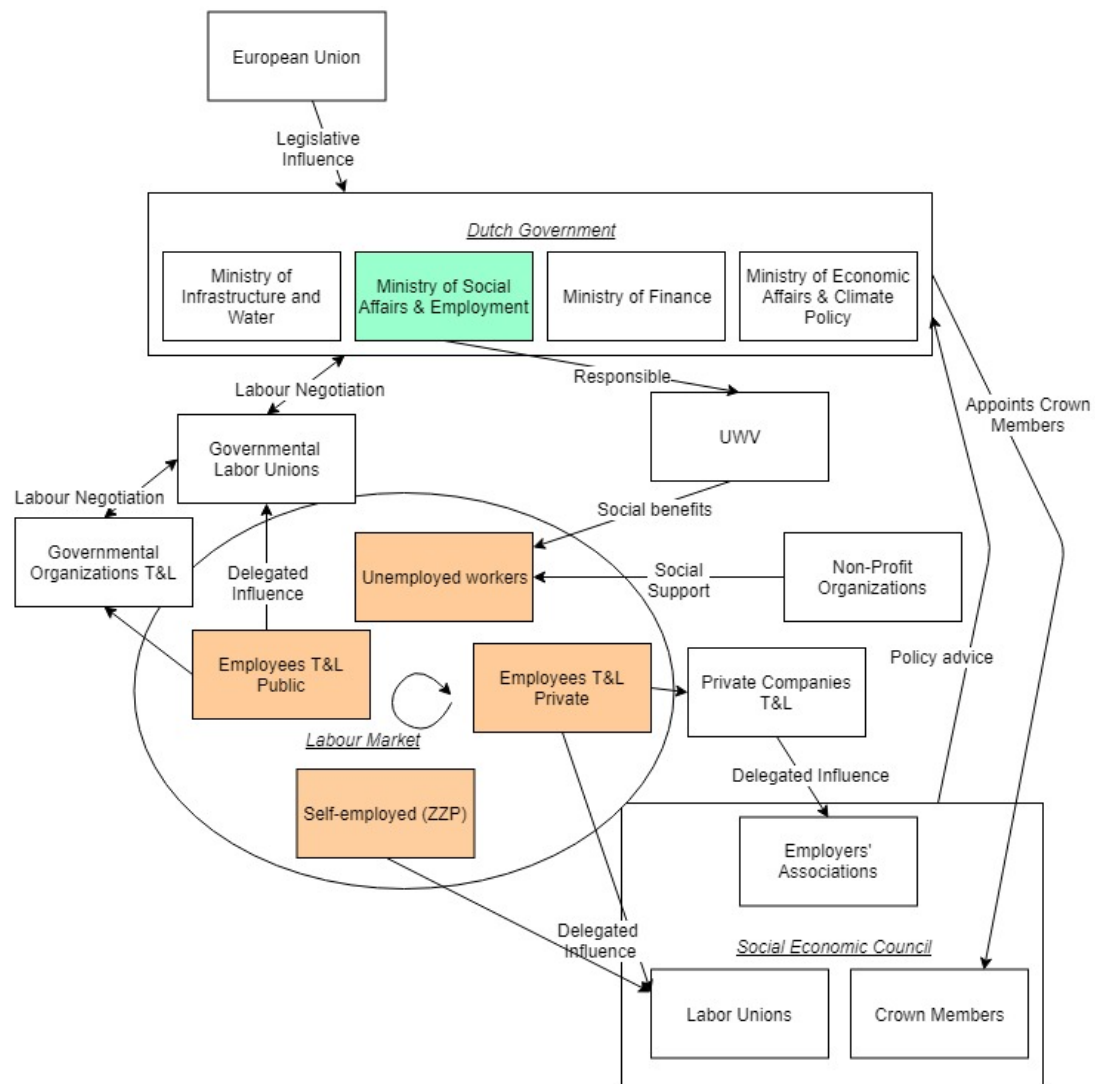


Figure 70: Formal chart for this research problem

This research will essentially focus on the orange blocks in the figure. The goal will be to determine per occupation what the number of employees is. The ministry of SAE will probably have a classification model for all the occupations that exist in the Netherlands. This classification model is probably what the main policies are based on therefor if this classification model can be acquired it will be enough to be matched with the O\*NET occupation database. For the eventual scenarios that are needed to answer sub-question six of this research more information is needed to determine these scenarios. Doing research on the Social Economic Council may be helpful in determining these scenarios.



## Actors of interest

This appendix contains all the relevant actors, grouped by their formal status. Some more background information on the identified actors will be supplied and for some their relations will be specified.

### *Governmental actors*

- Ministry of Social Affairs & Employment

The ministry of social affairs & employment (SZW) is the main actor. This ministry focusses on making participation in the society doable to everyone. In other words, it is their responsibility to make sure that everyone that has the right age and wants/needs to work is working. Moreover, this ministry is also responsible to help those who have times of hardship in order to help them back in society. Social benefits, such as state pensions and benefits to unemployed people, are also under the governance of the ministry of SZW.

- Ministry of Economic Affairs & Climate policy

The ministry of economic affairs & climate policy (EKZ) is the government actor that is responsible for the overall policies for economic affairs, such as trade, industry and innovation. The government has an overall agenda and the policies of the ministry of SZW need to be in alignment with the ministry of economic affairs.

- Ministry of Finance

The ministry of finance (Fin) is responsible for the government budget. More unemployment means that more people need financial state support. The ministry of SZW can decide how to handle such situations but needs the approval of the ministry of finance in the end. If the digitization and robotization cause higher unemployment the pressure on the state finance will also rise.

- Ministry of Infrastructure and Water

The ministry of infrastructure and water (I&W) is responsible for the public part of the transport and logistics sector. This part employs people working at for example ports, road maintenance, and bridges. As employer the ministry of I&W can choose his own strategy to handle robotization and digitization. In other words, they can choose for alternatives with more employment of people instead of machines.

- European Parliament

Robotization and digitization is a widespread phenomenon, therefore all the countries in the European Union (EU) will see a similar impact. The European parliament can use its legislative power to form overall policies or legislation to countermeasure unemployment.

#### *Labour Market actors*

- Employees working in the Transport and Logistics sector

The workforce that is employed in the Transport & Logistics sector are eventually the center of the scope. It is questionable if they are a real actor since it is debatable if they hold any power. Although one might say they can strike, and they can start working as a self-employed entity. The employees are working either for the government or a private company, if not self-employed

- Unemployed workers

The unemployed workers are also part of the center of the scope. In total the workforce and the unemployed people resemble the total labor market. When to more and more people are unemployed the pressure will build on the helping actors, such as the UWV and the Non-profit organizations.

#### *Employers*

- Private companies

The private companies are the largest employers for the transport and logistics sector. If new technologies emerge that are more efficient and/or cheaper than workers, they will probably implement the new technology meaning a decrease for that job.

- Governmental organizations

Many organizations in the transport & logistics sector are either totally governed by the government or owned by the government. Governed organizations are for example "Rijkswaterstaat", which is a large organization with around 9.000 jobs. Government owned organizations are for example "Schiphol" (2.000 jobs) or the "Port of Rotterdam" (1.200 jobs). There are more governmental organizations and together they will account for a significant number of the total jobs in the T&L Sector. Since the government is owner of these kind of companies, it is easier for the government to influence these kinds of companies than it is to influence private companies.

- Self-employed (ZZP)

Next to the private companies and the governmental organizations the last way to be employed in the transport and logistics sector is to be a self-employed worker. As a self-employed worker you will probably not fire yourself, but it may be that the craft or knowledge that you have becomes obsolete and that the companies you work for automate or digitalize the work. The number of self-employed workers in the Netherlands is rising and since their rights and obligations are different from the private and governmental organizations it is valid to take them into account as a separate group.

#### *Representative parties*

- Trade Unions

Trade unions are created as a representative party for employees. In the Netherlands there are different kinds of trade unions, such as FNV, CNV, and VCP. Of these three the FNV is the most relevant one since they have a separate part for employees in Transport and Logistics. The self-employed workers are also represented by a part of the FNV.

- Employers organizations

On the other side of trade unions there are employers' organizations. They are the representative party for employers. In the Netherlands the three biggest employers' organizations are VNO-NCW, MKB-Nederland, and LTO Nederland.

- Government Unions

Employees of the government have their own government unions ("Rijksvakbonden"). These government unions negotiate with the government for their CLA.

#### *Support parties for unemployed workers*

- Uitvoeringsinstituut WerknemersVerzekeringen (UWV)

The UWV is an executing organization that works under the authority of the ministry of SZW. The organization has the responsibility to judge and pay the social benefits to people who qualify for them.

- Non-profit organizations

Non-profit organizations are in this case the organizations that help people in poverty, which is in most cases of them being without work. Examples of these organizations are the "Voedselbank" and the "Armoedefonds". With increasing unemployment, the pressure

on these kinds of organizations will increase and their help at some point does not suffice anymore

#### **Additional information Formal Chart**

- SER

Together the trade unions and the employer's organizations are seated in the "Social Economic Council" (SER). Together with "Crown members", which are government selected researcher, professors or civil servant, form the SER. The SER focusses on negotiation between the different parties and to write the collective labour agreement (CLA), which is a written contract between the different parties.

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