Risk of automation and job satisfaction of Dutch workers

Kluitman, Gerardus

Master Thesis

‘Risk of automation & job satisfaction of Dutch workers’

Date: 6-01-’23

Name: G.J.B. Kluitman

Number: s2284146

Supervisor: dr. Van Lent

Master: Public Administration

Track: Economics & Governance

Word count: 13,593

Universiteit Leiden
The Netherlands

Abstract

With the rise in automation, inequality between low- and high-skilled workers has increased. Robotization allows for the substitution of human labor by capital, while artificial intelligence and machine learning can result in a complementary effect for high-skilled workers. With this risk of replacement due to automation existing for low-skilled manual workers, their job satisfaction may be negatively impacted, ultimately having a negative effect on their general well-being. This research has therefore looked at the effect of risk of automation on job satisfaction. Based on data from the LISS-panel, the routine task intensity-index as generated by Mihaylov and Tijdens (2019) and the risk of automation-index generated by Pouliakos (2018) a quantitative method was applied, consisting of descriptive statistics as well as the use of regressions, to provide an answer.

The descriptive statistics have shown that older workers tend to have a higher level of job satisfaction, while especially young low-skilled workers are subject to a low mean of job satisfaction. Furthermore, the research has found that tasks that differ from non-routine analytic tasks and thus are more subject to automation, negatively impact the level of job satisfaction for Dutch workers. When splitting the observations in to level of skill and age-group, the effect of the routine-task intensity index becomes inconsistent.

The research has also found that an increasing risk of automation-index negatively influences the level of job satisfaction, as it decreases the level of job satisfaction for Dutch workers by 0.026 for an increase in risk of automation by 1. When accounting for level of skill and age-group, an increasing risk of automation appeared to have a larger negative effect on the young low-skilled Dutch workers, supporting the thought of skill-biased technological change resulting in further inequality between low- and high-skilled workers.

The Dutch government should therefore aim at expanding the current training and education programs, offer further job placement services and other policies related to decreasing the negative effects of at risk of automation.

Table of Contents

1. Introduction

1.1 Introduction

Over the past decades automation has become more and more relevant within most sectors. Ever since the arrival of automation during the industrial age, with for example the invention of the steam machine, the world of industry has become ever more prevalent. Automation gives the possibility, in certain cases, to more efficiently and effectively perform specific tasks. These technological innovations can therefore complement workers in performing certain tasks. A modern example of such a complementary effect is the use of AI and algorithms by data scientists, in order to more efficiently and accurately look at and identify trends (De Bie et al., 2022). While the complementary effect of automation is very much positive, it can also result in the substitution of labor, ultimately resulting in workers becoming unemployed (Schwabe & Castellacci, 2020). While for some sectors automation heavily complements the workers and their tasks, other more labour-intensive jobs are subject to being substituted. These jobs are mostly predictable physical work, such as welding, soldering and working on the assembly line. Unpredictable physical work such as construction is less subject to automation (Chui et al., 2020).

According to recent literature, automation is able to influence wages and the demand for employment, particularly in a negative way for sectors and workers regularly performing routinized tasks (Autor & Dorn, 2013; Goos et al., 2014). Schwabe & Castellacci (2020) state, however, that while labor-demand and wages play major roles in determining a workers' well-being, one should also look at non-monetary effects of automation affecting this well-being. An example of this is the potential fear of a worker losing their job due to automation. This fear might result in a loss of job satisfaction. As Schwabe and Castellaci state, due to work playing a large role in the life of individuals, job satisfaction and other related attitudes towards a job influence the well-being. Furthermore, individuals that are not satisfied with their job are often less productive and have a lower level of motivation (Böckerman et al., 2011; Oswald et al., 2015). Ultimately, Ezzat & Ehab (2018) state that job satisfaction influences the labor force participation of both men and women. The general attitudes towards work therefore influence whether an individual decides to offer labor.

In the Netherlands, differing interesting trends regarding the well-being of individuals can be identified. First, the well-being of young individuals, aged 18-25 has decreased by 9 percentage points over the course of 2019 to 2021, while it has remained the same for the age group 25-55, but it has increased for the groups of 55-65 and 65-75 (CBS, 2022). Second, the well-being of lower-educated individuals has dropped over this period, while it has increased for higher-educated individuals. Lower-educated individuals often fill these lower-skilled jobs, which are more subject to automation. With the idea that the level of job satisfaction influences the well-being of individuals, it can be deemed interesting to look at the effect of automation on this level of job satisfaction.

Therefore, with the increase in automation, the trends in well-being and the influence of job satisfaction on the well-being of individuals, the following research question has been formed: *What is the effect of risk of automation on the job satisfaction of Dutch workers, and does it differ for high- versus low-skilled workers?*

To answer the research question, LISS panel-data and STATA will be used to complete the quantitative analysis. Besides the quantitative analysis, existing literature will be used to achieve a complete view on automation and job satisfaction.

1.2 Relevances

Scientific relevance

The scientific relevance can be found in the lack of current scientific research about the effect of automation on job satisfaction of Dutch individuals. A paper by Künn-Nelen & Smits (2022) did look at the effect of exposure to automation on the job security of Dutch workers, but did not look at job satisfaction, nor did it explicitly look at the differences between societal groups.

International literature regarding this mentioned relation does exist. A clear example of this is the research completed by Schwabe & Castellacci (2020), which directly looks at the effect of automation on job security and job satisfaction for Norwegian workers. Their findings state that automation in industrial firms has mainly a negative effect on low-skilled workers carrying out routine tasks. Besides this paper, two noteworthy papers can be identified. The first is by Abeliansky and Beulmann (2019), who brought forward the idea that automation has a negative effect on the mental health of workers. The second is by Schwabe (2019) who looked at the relationship between the fear of replacement and the well-being of an individual. According to his research, a fear of replacement has a negative effect on the well-being of younger workers, while it has a positive effect on the well-being of older workers.

As mentioned before, however, there appears to be no relevant literature regarding this effect in the Netherlands, which shows the need for research about this topic.

Relevance for public administration

The topics central in this research, ‘automation’ and ‘job satisfaction’, are highly relevant for public administration. In the world of public administration and public policy, looking at and analysing the trends regarding automation can be deemed as interesting as it regards a general societal trend which requires certain actions from policymakers.

An example of job satisfaction, and the related job security, being relevant is the subsidy ‘Nederland Leert Door’ created by the Dutch government. They have provided subsidies to allow workers whose jobs are at risk or which are uncertain, primarily due to the Covid-19 pandemic, to retrain themselves in order to acquire a better perspective on the labor market (Ministry of Social Affairs and Employment, 2022).

Finding whether automation influences job satisfaction and the desire to look for a new job, can contribute to generating knowledge regarding well-being and labor force participation of Dutch men and women. Policy regarding these topics can therefore be further optimized.

Societal relevance

The societal relevance can also be recognized. As stated in the introduction, job satisfaction is related to an individual’s well-being (Schwabe & Castellacci, 2020). It is therefore in the interest of both individuals as well as society as a whole, to identify whether automation has an influence on their well-being and choice to offer labor.

Furthermore, if the job satisfaction of a worker is low, it can be expected that their labor productivity is lower than desired. Oswald et al. (2015) have shown that the level of happiness is positively related to the level of productivity. In their research the individuals in the treatment group were made happier by being shown comedic clips. They appeared to be subjectively happier after watching the clips and showed a significant improvement in their productivity. Individuals that were viewed as unhappier showed a lower amount of productivity. With the importance of productivity for economic growth and therefore the economy as a whole, the relevance for society comes to light (Palle et al., 1995; Zulu & Banda, 2015).

2. Theory

2.1 Introduction theory

As mentioned in the scientific relevance, international research regarding automation and attitudes to work exist. Due to the broadness of automation as a concept, it will first be explained, after which job satisfaction and the related job security will be explained and linked to automation. The theory enables the research to be done and helps with the interpretation of the findings. It therefore contributes to understanding and improving policy regarding automation and job satisfaction, and ultimately the well-being of individuals.

2.2. General theory

2.2.1 Introduction automation

In short, automation regards a variety of technologies/technological innovations that decrease the need for human intervention and thus labour in certain processes. With the ability to support or replace human labour, it is possible to more efficiently perform specific tasks. Automation has been present for quite some time, as the use of machinery to more efficiently perform manufacturing processes during the Industrial Revolution layed the beginning of automation as we know it (Groover, 2014, p.15). Logically, automation has evolved significantly. Where in the early days of automation the machines where relatively simple, such as steam engines that powered mills and locomotives, it has evolved into automation fully automating entire branches of a manufacturing process. An example of this is the automative industry, in which automation has replaced most human labour (Tool, 2020; IEEE, 2020). While robotization as seen in mostly industrial sectors is one form of automation, automation has taken on very complex forms aswell. It is therefore necessary to make a two-way between the classic perception of automation, robotization, and the newer form of automation, artificial intelligence. This is necessary as not all sectors are subject to robotization. For example, in the world of IT and data science, there is less room for robotization compared to industrial sectors. In these sectors Artificial Intelligence (AI) and machine learning have become more prevalent over the last decades. What is artificial intelligence, however? McCarthy (2007) states the following: “It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable.”. According to Goddard (2020), the main use of Artificial Intelligence is to replace the repetitive, difficult tasks of humans in the world of IT. AI therefore has no physical form which is, besides its function, one of the key differences between AI and robotics.

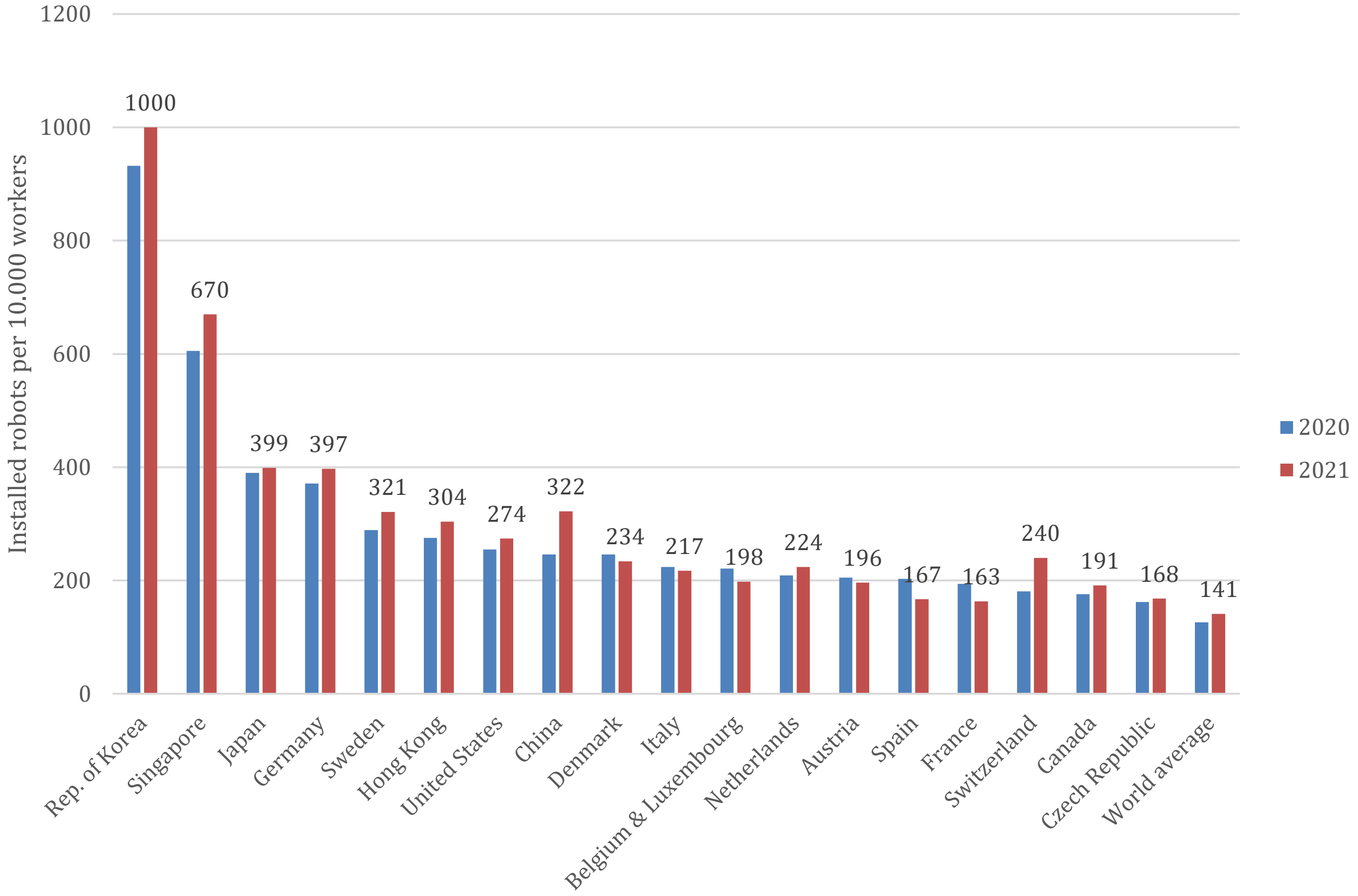
AI is, when compared to older forms of robotics, relatively new as it found its origins during the second world war with the creation of the Turing machine. During these early days, AI and robotization used to go hand in hand. According to Rajan & Saffiotti (2017) the early pioneers of AI thought of computers as a complement to make machines and robotics able to function by themselves. An example of this was ‘Shakey the robot’, created in 1966, who was able to reason and ultimately function by itself. While this example shows these two forms of automation being coherent, in reality as time passed robotics and AI drifted apart. AI started to focus less on solving real-world problems, while robotics continued working on physical obstacles (Rajan & Saffiotti, 2017). It is only since the beginning of this decade that more convergence between AI and robotics can be identified. An example of this convergence can be found in the world of autonomous cars, as they require both a certain level of artificial intelligence and robotics. The autonomous car makes use of a variety of sensors, generated by robotics, after which artificial intelligence is implemented to understand and learn the information gathered from the sensors. The car is then able to drive itself, which shows how artificial intelligence and robotics are able to work together (Lim & Taeihagh, 2019; Matzliach et al., 2022).

When looking at the future, it is thought that further robotics, artificial intelligence and similar technologies will be able to replace human labour even more.

To show the increase in implementation of automation, the following figure, figure 1, shows the robot density in the manufacturing industry for countries with advanced economies, for the year 2020 and 2021. The figure was produced by the International Federation of Robotics (2021; 2022) and their World Robotics 2021 and 2022 report. As can be seen by the increase in world average, from 126 to 141, the global trend to be identified is an increase in installed robots. This increase in robots shows further implementation of automation. For the Netherlands, an increase in installed robots per 10,000 workers can also be identified. For 2020, the number of robots per 10,000 workers was 209, while it has risen to 224 for 2021 (IFR, 2021; IFR, 2022). While the implementation of robots in The Netherlands is above the global average, similar European countries such as Denmark, Sweden and Switzerland have a higher robot density of 234, 321 and 240 respectively. Germany is the European country with the highest density of robots and has had an increase over the period of 2020-2021. This is logical, as Germany is the European country with the largest industry sector and therefore has more space for the implementation of robots (Eurostat, 2022).

Figure 1

'Robot density in the manufacturing industry, 2020-2021'



Source: World Robotics 2022

The growth in Artificial Intelligence is also noteworthy, as the global market size for AI was estimated at just $637.7 million for 2016, $87.04 billion dollars for 2021, and is expected to achieve a size of close to $1,600 billion by 2030 (Tractica, 2016; Presedence Research, 2021).

With this paper analysing the trend in the Netherlands, it should be mentioned that automation is also ever so prevalent in the Netherlands. Nearly half of the major companies in the Netherlands, 45%, makes use of AI, while in total 12% of Dutch companies uses some form of AI (CBS, 2021). As of yet, the Netherlands is relatively average when compared to similar countries in the EU which figure 1 also shows (CBS, 2019; Ploeger, 2022).

To further prove that automation in the Netherlands is taking place, the Netherlands paves the way for the development and testing of autonomous vehicles, including trucks, buses, and delivery vehicles. This can be identified by a statement of the Dutch Ministry of

Infrastructure and Water Management (2020) which states that the Dutch national government aims to take the lead in both the development and ultimately the implementation of these autonomous vehicles. Furthermore, in the Dutch healtcare sector automation is also becoming ever more prevalent. Robots are being used for dispensing medication, assisting with surgeries and assist or perform with other tasks. Where in 2009 just nine hospitals made use of a so-called 'Da Vinci Robot', which is a remote controlled robot for certain surgical procedures, this has grown to 22 in 2019 (CPB, 2017; Kregting, 2019).

In short, automation can be viewed as both an important as well as growing trend in the Netherlands. This can be identified by the increase in robots and the openness of the government for welcoming new technologies related to automation.

Automation, the demand for labour, wages and productivity

As mentioned in the introduction, automation is able to influence the demand for labour, wages as well as productivity (Autor & Dorn, 2013; Goos et al., 2014).

Labour

One of the current identifiable theories regarding the effect of automation on the demand for labour is the theory of skilled bias. In short, it argues that skilled-bias technologies result in further polarization in the demand for specific labour and the related wages between high- and low-skilled workers. Furthermore, Sachs and Kotlikoff (2012) present a dire message after generating a model, which states that so called 'smart machines' are able to directly substitute young low-skilled labour, while older workers with higher skills are mainly complemented. Following Sachs and Kotlikoff's statements, they argue that it would lead to lower wages for the younger generation, resulting in a further difference between the young low-skilled and older high-skilled workers. Schwabe and Castellacci (2020) state, however, that this negative perception of automation to be identifable as the further polarization, can not be recognized in research related to this topic.

Schwabe and Castellacci (2020) also put forward the job polarization hypothesis. This hypothesis states that automation and technological innovations complement high-skilled labour, resulting in higher wages and a higher demand. Furthermore, low-skilled workers are not impacted due to their jobs regarding manual and personal tasks which are deemed hard to automate. This hypothesis argues that middle-skilled workers are negatively impacted, simply due to their tasks being more subject to automation. Autor (2015) states, however, that only some of the tasks of middle-skill jobs are subject to automation, with many of the middle-skilled jobs demanding a combination of tasks at both a higher and lower level of skill, making it harder for the job to be automated.

A paper by Kromann, Skaksen and Sørensen (2011) looked at the impact of automation on labour productivity and employment. By making use of the implementation of industrial robots to measure the level of automation, their empiral study found that automation decreases employment in the short run, while in the long run it resulted in either an increase in employment or it returning to the level before the implementation of industrial robots. With their paper looking at cross-country differences, they also mention that, as a result of specialization, it is harder for industries within certain countries to implement automation. These industries may gain less in employment as a result of this automation.

It appears multiple theories exist for the effect of automation on primarily the demand for labour. Ramaswamy (2018) has reviewed and summarized the available theory and evidence regarding technological change, automation and employment. In short, he makes three main statements. The first states that increasing automation and the adoption of robots does not result in a loss of aggregate employment, the second states that low-skilled workers in routine jobs are more subject to job loss due to automation, the third states that a demand for new types of skilled workers will occur. The third statement argues that a demand for jobs related to applying and inventing automation will take place, for which the new rise in global demand for software engineers can be seen as an example (California Business Journal Newswire, 2022; U.S. Bureau of Labor Statistics, 2022).

Based on these statements, a clear difference in effect of automation on the demand for high- and low-skilled workers can be identified. Jobs that can be deemed as routine are more subject to automation, and these are often filled by young, low-skilled workers.

Wages

Besides the effect on demand, the effect on automation on wages, mainly as a result from the mentioned effect on demand, is also recognizable from the available literature. A study completed by Acemoglu and Restrepo (2016) identified that low-skill automation takes over low-skill labour by capital. Interestingly enough, they also mention that the new rise in artificial intelligence might replace certain tasks that currently high-skilled workers perform, ultimately resulting in these high-skilled workers being replaced by automation aswell. Acemoglu and Restrepo (2016) developed a task-based model, where low-and high-skilled workers were put against machines (automation) for performing certain tasks. The automation replaces the labour, indifferent of the related level of skill. With the potential replacement of labour by capital, the wages related to the labour are suppressed and are subject to decrease. This effect on wages is fairly simple. With automation being able to potentially more efficiently and effectively replace a worker, the worker will have to accept lower wages in order to maintain their job. Their final statement is that low-skill automation will always result in an increase in wage inequality between lower- and higher-skilled workers, while automation affecting high-skilled workers will reduce it. This is due to automation negatively impacting both type of workers, depending on the skill level of automation.

While Acemoglu and Restrepo (2016) clearly identify a negative effect of automation on the wages of individuals based on their model, other literature argues that, once again, high-skilled workers who experience a complementary effect are subject to higher wages. Lower-skilled workers who perform routinized jobs and are thus more subject to substitution are more at risk of a decrease in their wage (Holzer, 2022). Holzer also states that workers who are able to gain education and/or training that are complementary to automation will be able to benefit.

A paper by the Dutch Bureau for Economic Policy Analysis (2019) identified a different trend. First, they recognize that firms that implement automation are likely to induce workers leaving the firm and decrease the total days worked, which ultimately results in a wage income loss near 8% of one year of earnings for the workers. The wage rates within the measured firms show no change however, which indicates that primarily the loss of a job results in income loss. Automation within the firm itself appears to not heavily affect the wages.

In short, automation can result in job displacement, where workers that were previously performing tasks that have been automated may lose their jobs. This can ultimately lead to a decrease in wages for the affected workers, as they potentially have to find new employment at a lower pay rate.

Productivity

The literature indicates that automation also has a predominantly positive effect on the labor productivity of individuals. Automation is able to positively influence the productivity by allowing the machines and certain technologies to more accurately and efficiently perform tasks. The idea of a complementary effect argues that these technologies positively performing tasks at a faster and more accurate level, result in the worker's workload decreasing making it possible for them to focus on more complex tasks. The general thought is that this would positively influence the productivity, which is backed by multiple papers:

The earlier mentioned paper by Kromann et al. (2011) also looked at the effect of automation on labor productivity, and found that both in the short- as well as the long-run the labor productivity of the sector increased. It should be noted that this paper did not look at differing levels of skill, so the differences between workers who had routine-tasks subject to replacement by automation and high-skilled workers performing analytical tasks were not accounted for.

Research by Autor (2015) also indicates that automation has a positive effect on productivity, stating that in the long run the labor productivity would increase.

Furthermore, a paper by Gao (2021) analyzed the impact of automation on the employee productivity in the banking sector. This sector has mostly high-educated workers and Gao found that automation, to be identified in the forms of ATM's, mobile- and internet banking, have had a positive impact on the labor participation of workers. The research also mentions, however, that bad implementation of automated technology, such as system failure taking place, resulted in an increasing workload, ultimately negatively impacting the productivity of the workers.

The substitutionary effect, however, argues that the implementation of for example robotics results in a decrease in the necessary tasks of a worker, as these robots may take over these tasks (Bughin et al., 2021). If the implementation of automation results in the substitution of labor and the workers are not provided with retraining or resources necessary for transforming their roles, the productivity of workers will decline as a result of struggling to adapt or finding a new job.

Overall, the effect of automation on the productivity of workers depends of whether the effect is complementary or substitutionary. A complementary effect, predominantly on workers with a high level of education and skill, is likely to result in a positive effect on the productivity. For this positive effect to take place, the quality of implementation should be at a sufficient level. In general, the literature indicates that the productivity increases over time. A substitutionary effect can take place if workers are not able to adapt well to the implementation of automation, or when they are to be substituted for capital.

2.2.2 Automation and job satisfaction

This research will analyse the relation between risk of automation and job satisfaction for Dutch workers. It is necessary to explain the definition of job satisfaction, mention the influences on job satisfaction, to then ultimately mention the available research regarding the effect of automation on job satisfaction.

Job satisfaction

The definition of job satisfaction can simply be interpreted as to which amount an individual likes their job. To be more precise, Locke (1976, p. 1304) stated that job satisfaction is “a pleasurable or positive emotional state resulting from the appraisal of one’s job or job experiences.”. While the definition in itself is fairly logical, it is mostly interesting to look at the differing factors that influence the level of job satisfaction of a worker. Before looking at these factors, it should be mentioned that in some literature job satisfaction is viewed as one-dimensional, contrary to the multidimensional approach used in this research. The one-dimensional view states that it solely entails the attitude of a worker towards their job, which can not be split into multiple or individual aspects (Lawler, 2005; Vujičić et al., 2014)

Sharma and Jyoti (2009) have looked at the large amount of studies that have been conducted on job satisfaction. According to them, the majority of research argues that influences on job satisfaction vary and should be seen as multidimensional. The following literature has looked at factors that influence job satisfaction:

O’Brien and Dowling (1981) have found that age is positively correlated with job satisfaction.

Stone (2000) recognized a relation between job satisfaction and salary satisfaction.

Chiok Foong Loke (2001) found that positive leadership behaviours, such as ‘inspiring a shared vision’ and ‘enabling others to act’ have a significant positive relationship with job satisfaction.

Joseph and Richard (2002) found a strong correlation between perceived job security and job satisfaction. They also stated that the environment of the work place is strongly related to job satisfaction.

Hague (2004) identified a linear connection between job satisfaction and age, as well as a relationship between job security and the gender of an individual.

As this literature shows, many factors can be recognized that influence the level of job satisfaction either in a positive or negative manner. Sharma and Jyoti (2009) saw this large sum of factors and tried to conduct a research that ranked the influence of the factors. After conducting their research on a sample of teachers, and asking their preferences, their findings showed that the largest influence was the working environment, followed by wage.

Automation and job satisfaction

While a lot of research has been performed on varying factors that may or may not influence the level of job satisfaction of individuals, the research specificially focussed on the effect of automation is limited. There have been multiple researches completed with a theme quite similar to this research.

First, a paper by Abeliansky and Beulmann (2019) has brought forward the idea that automation has a negative effect on the mental health of workers. According to their research, major factors that explain this negative effect on mental health are the fear of decreased wages, as well as a potential decrease in expected economic conditions.

Second, Schwabe (2020) mentions that he looked at the relationship between the fear of replacement and the well-being of an individual. According to his research, automation has a negative effect on the well-being of younger workers, while it has a predominantly positive effect on the well-being of older workers. This difference can be explained by the earlier mentioned skill-biased technologies hypothesis as well as the polarization hypothesis. This is due to younger workers perceiving automation as a threat, in contrary to the older workers who believe that it will have a complementary effect, improving the general societal well-being of these older workers (Schwabe, 2020).

The effect of automation on job satisfaction has yet to be measured in the Netherlands, but the research completed by Schwabe & Castellacci (2020) did research this effect for a sample of workers in Norway. They combined microdata for a few thousand workers over the period 2016-2019, with information regarding the use and adoption of industrial robots in Norway. Their main findings state that the implementation of automation has induced about 40% of employed workers to have an increase in fear of potential replacement by such innovative technologies. This fear appears to also negatively influence the job satisfaction of employed workers in the present. Furthermore, they find that the negative effect is mainly induced by workers with a lower level of skill, usually with routinized tasks and ultimately more at risk of automation.

Another interesting thought was put forward by Frey and Osborne (2017), who stated that technological change and innovation would result in a decrease in the amount of low quality jobs, due to these low quality jobs being substituted by labour. This would therefore result in the average job quality increasing over time, potentially positively influencing the level of job satisfaction. It should be noted that this does not account for the employment shift to other sectors with a similar low level of job quality (Eurofound, 2018).

Job (in)security

As mentioned in the previous literature, job security influences the level of job satisfaction. It should therefore also be mentioned. Job security regards the chance that an individual will be able to maintain their job. As such, a job with high security provides the individual with a smaller chance of losing their job. If the job security is low, the likeliness of the individual to lose their job is therefore higher. Multiple papers define job security in a relatively simple manner, namely as the type of employment contract a worker has (Maurin & Postel-Vinay, 2005; Künn-Nelen & Smits, 2022). A permanent employment contract can be seen as more secure when compared to a fixed-term contract.

The concept of job security can also be identified in a different manner, namely the security that having a job offers to an individual regarding their income, safety and other social aspects that a job offer. This paper will not use this more social definition given to job security however, but it will use the definition mentioned in the previous paragraph. Furthermore, a twoway should be made between job security and job insecurity as in the literature job insecurity is also often used, contrary to job security. The meaning of these two concepts is ultimately the same, but the definition differs. Job insecurity namely regards the level or state of uncertainty regarding the continual of a worker and their employment. It therefore appears to be the opposite of job security.

Job security is influenced by many different factors. While examples such as recession and downsizing are logical, automation does appear to also have an influence (Reinardy, 2012; Künn-Nelen & Smits, 2022). In 2022, Künn-Nelen & Smits researched the effect of tasks, very similar to automation, on job security in the Netherlands. They made multiple interesting observations. To analyse the variable tasks, they looked at the level of routinization, aswell as the risk of automation. The level of routinization was determined based on older literature which made a dichotomy between routine and non-routine tasks. Within these routine tasks they made a difference between manual and cognitive tasks, while for non-routine tasks they made a difference between manual, analytic and interactive tasks. To determine to what classification a task should be assigned to, they made use of the work done by Mihaylov & Tijdens (2019), who managed to classify over three thousand tasks to one of the mentioned five categories of routinization. To then assign a job to a category, they estimate what tasks are regularly performed in each job. For the risk of automation, they used the automationindex of the OESO, created by Nedelkoska & Quintini (2018). Nedelkoska & Quintini made use of the work done by Frey & Osbourne (2013), who looked at 70 different jobs and the tasks a job comprised of. They followed this by modelling the chance of automation. Nedelkoska and

Quintini looked at tasks on an individual level, instead of looking at a job as a whole. This therefore results in a more accurate estimate of the automationrisk. For the Netherlands, Nedelkoska and Quintini estimate the risk of automation to be near 44%. For jobsecurity, they looked at the type of employment. They argue that a permanent contract offers a higher level of security, in comparison to a temporary or more flexible contract.

This also corresponds with a paper of Chui et al. (2020), which stated that unpredictable physical work has a severely lower chance of being automated in comparison to predictable physical work. Jobs such as working on the assembly line have a significantly higher chance of being automated, thus potentially resulting in the loss of an individuals job. If the job corresponds to predictable physical work, it is logical to derive a lower sense of job security. Unpredictable physical work which has more variation in its tasks, such as construction work, is less likely to be subject to automation. This difference can mainly be found in the technical feasibility to implement automation into a job. Chui et al. (2020) gives percentages, for which they state the percentage of technical feasibiliy of automation for predictable physical work at 78%, in comparison to a mere 25% for unpredictable physical work.

According to Künn-Nelen and Smits (2022) and related research, exposure to automation and routinization has little to no effect on the job security of individuals performing non-routine, high skilled tasks, while predictable low-skilled physical work is negatively impacted. With job security being linked to job satisfaction, this further complements the idea that automation has a stronger negative effect on the low-skilled workers.

2.3 Hypotheses

The earlier mentioned theory has shown that it is expected that exposure to automation has a negative effect on the level of job satisfaction. In specific, individuals with low-skilled, routine jobs appear to be negatively impacted, while high-skilled, non-routine workers appear to either not be influenced, or be complemented. Following this theory of either a substitutionary or complementary effect taking place, depending on the level of skill and level of routinization, multiple hypotheses can be generated.

As the paper of Schwabe & Castellacci (2020) and similar papers have shown, automation and the risk of automation have a generally negative effect on the job satisfaction of low-skilled workers. High-skilled workers are more subject to a positive effect, however. Following these findings and applying it to Dutch workers, it is expected that an increasing risk of automation has either a positive or negative effect on the job satisfaction of Dutch workers in general.

Hypothesis 1:
H0: Exposure to potential automation has no effect on the job satisfaction of Dutch workers.
H1: Exposure to potential automation has a positive or negative effect on the job satisfaction of Dutch workers.

Chui et al. (2020) have shown that certain types of work are more effected, and at risk for substitution of labor to capital, than others. Certain sectors that are male-dominated fall into this category of high risk of being substituted. Combined with the ideas of Sachs and Kotlikoff (2012), the findings of Schwabe & Castellacci (2020) and the skill biased technologies hypothesis, which state that young low-skilled workers will be negatively impacted in comparison to older high-skilled workers, further driving inequality between the groups, hypothesis 2 has been generated.

Hypothesis 2:
H0: Risk of automation has no stronger effect on young low-skilled workers, in comparison to other groups in society.
H2: Risk of automation has a stronger negative effect on the job satisfaction of young low-skilled workers, in comparison to other groups of workers in society.

It should be mentioned that if H0 cannot be rejected for the first hypothesis, this is paired with the assumption that H0 for hypothesis 2 can neither be rejected.

3. Data*

The data that will be used to complete the quantitative analysis will be gathered from multiple components of the LISS-panel, over the period 2008-2022. It consists of data of close to 7500 individuals. The LISS-panel gathered data by asking respondents on a monthly basis, against payment, to fill out an online questionnaire (LISS, 2022). It should be mentioned that certain components of the LISS-panel are only asked on a yearly basis. Furthermore, due to the LISS-panel only including certain variables crucial to this research since 2020, the descriptive statistics will make use of the entire period of 2008-2022, while the actual regressions used to generate the results consists of just the period 2020-2022.

Regarding the LISS-panel, the components ‘Work and Schooling’ and ‘Background Characteristics’ will be used. Within these components, a large scale of observations and thus data regarding automation and job satisfaction can be recognized.

Within the first, major component, ‘Work and Schooling’ a detailed depiction of the labor characteristics of an individual can be found. These characteristics include the type of labor contract such as permanent or temporary, the level of job satisfaction, which is measured from 1 to 10 and whether an individual is looking for a new job and why. Furthermore, the sectors and general area of expertise of individuals can also be found. For this research, the main used variables are level of education, level of job satisfaction and the sector/job individuals work in/have. Within this component, a large sum of subjective questions can be identified. An example of such a question is the following: ‘How satisfied are you with your current work?’, which is on a scale of 0 to 10, with 0 being not at all satisfied, and 10 being fully satisfied. This question is fundamental for this research, as it gives a nominal value to the dependent variable ‘job satisfaction’. A second question/variable relevant for performing the research is the ISCO-08 code assigned to a profession. The profession is given by asking: “What is your current profession? / What profession did you exercise in your last job?’, but due to privacy legislation the exact profession is not given in the dataset. A final question, relevant as it will be used as a control variable for job security, is ‘What is the chance that you lose your main job in the next 12 months?’.

The second component ‘Background Characteristics’ depicts general information of individuals within the panel data. Examples are data regarding age and gender, both variables relevant for this research. The component mainly consists of objective, neutral information which therefore leaves no clear space for subjective input. The questions asked within this component do not focus on opinions, feelings or similar subjective input. Examples of these questions are ‘Year of birth’, ‘Primary occupation’, ‘Personal gross monthly income in Euros’ and so on. The question ‘What is the highest level of education you have achieved a degree in?’ will be used to split the observations into different levels of skill, as will be explained chapter 4.

To complement the LISS-panel, the list of Mihaylov and Tijdens (2019) regarding the routine-task intensity-index of the ISCO-08 job classifications will be used. ISCO-08 is short for the International Standard Classification of Occupations, and is a system used by major international organizations such as the United Nations to both classify and describe occupations. It first divides the occupations into 10 groups, after which the occupations are further divided and ultimately become individual occupations. The values of the index do not vary per year, but are cross-sectional based on their observations on the year (2019).

Third, to measure the risk of automation, figure 2 of the skill-based approach as used by Pouliakas (2018) will be used. Pouliakas managed to create a figure which consists of the mean probability of automation by 2-digit ISCO-08 occupation. Once again, the values for this index do not vary for each year, but are consistent for the regarding occupations. Furthermore, the values for each 2-digit occupation are ranged between 0 and 1. 0 meaning no risk of automation for the occupation, while 1 indicates a certainty that the occupation will experience automation.

*Künn-Nelen & Smits (2022) made use of the Dutch 'Nationale Enquête Arbeidsomstandigheden'. While I inquired about and contacted TNO regarding making use of the data of the survey, they stated that only researchers working together with TNO can have access to the data. Therefore this research will make use of the LISS-panel.

4. Research method

4.1 Base of research

The independent x-variable in this research is 'risk of automation', which will be split into multiple independent variables. The dependent y-variable is 'job satisfaction'. The research will follow a quantitative method. Based on a large sum of data, gathered from the LISS-panel, a deductive statement will be made. By making use of descriptive statistics and making use of regression analyses certain patterns are subject to identification. A simple multiple linear regression, based on the idea of Ordinary Least Squares, will be used to analyze the effect of automation on job satisfaction.

4.2 Operationalization

With automation and job satisfaction being two relatively broad concepts, this section will analyze how these variables will be researched. With the research topic looking at the effect of the risk of automation on job satisfaction, first the operationalization of risk of automation will be made clear, followed by the operationalization of job satisfaction. The measurement of automation is based on two independent variables, with the first being and the routine-task intensity-index, the second being the risk of automation-index for ISCO-08 jobs.

Independent variable 'Routine-task intensity-index'

The research topic aims to examine the effect of the risk of automation on job satisfaction. To analyze this risk of automation, the first independent variable will be the task based-index as presented by Mihaylov and Tijdens (2019) in which they rank jobs as listed by the ISCO-08 categories to a distribution in tasks. This independent variable is equal to the variable used by Künn-Nelen and Smits (2022), which will be further explained.

In table 1, the different categories/classification of tasks, along with some examples of tasks for every category, can be found. Antonczyck et al. (2009) generated this table, which first assigns a task to whether it can be viewed as non-routine or routine. Second, for the non-routine category, whether it can be viewed as an analytic, interactive or manual task, while for the routine category, it is distributed in cognitive and manual tasks. The tasks assigned to the non-routine analytic category regard primarily high-skilled tasks, such as developing, researching, investigating and similar tasks. Non-routine interactive regards a combination of high- and middle-skilled tasks, such as teaching and marketing. Non-routine manual regards tasks that have a low level of repetitiveness and are ultimately less subject to automation in the form of robotization. The tasks do require manual labor however. Repairing and patching and nursing often require physical work. This category regards jobs that require a middle- to low-level of skill.

Routine cognitive regards routine tasks which have a repetitive manner but require a level of cognitive action. The routine manual tasks are the tasks most subject to automation in the form of robotization. As can be seen in table 1, tasks such as fabricating, transporting and the production of goods fall into this category. Routine manual tasks have a high level of repetition to them. When performed by humans, they also require physical activity of the workers. This combination of being repetitive and requiring physical activity results in a higher level of potential automation.

Table 1

'Classification of tasks'

Category	Tasks
Non-routine analytic	developing, researching, designing and gathering information, investigating, documenting
Non-routine interactive	informing, advising and training, teaching, tutoring, educating and organizing, planning/preparing working processes and promoting, marketing, public relations and buying, providing, selling and to be supervisor
Routine cognitive	measuring, controlling, quality checks
Routine manual	fabricating, producing goods and supervising, controlling machines and transporting, stocking, posting
Non-routine manual	repairing, patching and nursing, serving, healing

Source: Antonczyck et al. (2009)

As mentioned, this research makes use of the task based-index as generated by Mihaylov and Tijdens (2019). The ISCO-08 job classification, as explained in chapter 3, divides occupations into groups and subgroups, allowing for a clear overview and assignment of an occupation to a group. To generate the index, Mihaylov and Tijdens assigned over 3.000 tasks, part of ISCO-08, to one of the mentioned categories found in table 1. Following assigning these tasks, they estimate the share of tasks every job/occupation consists of.

After assigning and estimating the tasks of every job, the index was generated. For every ISCO-08 job, a score for each category as mentioned in table 1 was assigned, based on the researchers interpretation. In total, the five categories for each job add up to 1. Ultimately, this results in the variable named routine task-intensity, ranging from a value of -1 to 1. If the value is -1, the level of repetitive tasks is low, while if it equals 1, it is high.

For this to make more sense, the distribution for the following two ISCO-jobs will be shown as examples in table 2. For the ISCO-08 job 'Construction managers', the non-routine analytic category of tasks has a value of 0.6363636 and the non-routine interactive has a value of 0.3636364. The values for the other categories are 0. This shows that the job of construction managers has a low level of routine-tasks, and requires mostly analytic and interactive tasks. These tasks are linked to a higher level of skill.

The second column shows the values for each category for 'heavy truck and lorry drivrs', a job quite different from construction managers. As can be identified from the table, the values for the non-routine analytic and interactive categories are 0, while the value for the routine cognitive is identified as 0.5714286 and for non-routine manual at 0.4285714. With a category of routine tasks being larger in share than of the non-routine categories, the routine task-intensity is put as 0.1428572. As it is larger than 0, it consists of an above average value for repetitive, routine-tasks.

Table 2

'Example of routine-task intensity-index'

Code	ISCO	NRA	NRI	RC	RM	NRM	RTI
1323	Construction managers	0.6363636	0.3636364	0	0	0	-1
8332	Heavy truck and lorry drivers	0	0	0.5714286	0	0.4285714	0.1428572

Source: Mihaylov and Tijdens (2019)

In short, in this research the ISCO-08 jobs for each individual as identified in the dataset over the period of 2020-2022, will be linked to the scores assigned by Mihaylov and Tijdens (2019). The mentioned categories will then be used as independent variables, in order to explain to which extent tasks being repetitive/routine influence the level of job satisfaction.

Independent variable 'Risk of automation-index'

The second major independent variable, which will be used in a separate model, is the risk of automation-index. Künn-Nelen and Smits (2022) also made use of such an independent variable, which proved to have a significant influence on the level of job security. The variable risk of automation in this research is based on the table generated by Pouliakas (2018). In his research, Pouliakas aimed at identifying the determinants of 'automatability risk'. By making use of available data, tasks and the needed skills within certain jobs, he bundled jobs based on their two-digit ISCO-08 code together to establish a mean estimated risk of automation. Poulikas' risk of automation is measured in a similar manner as the task based-index, with the risk of automation having a value between 0 and 1. For the risk of automation-index, a 0 means no risk of automation, while 1 indicates a high level of risk.

One problem of the independent variable should be noted, however, as the variable risk of automation-index solely looks at the mean of the two-digit ISCO-08 code, and not at the differences between the level of skill of workers within the subgroups. It is therefore less accurate than if it was based on a four-digit ISCO-08 code.

The dependent variable:

The dependent variable *job satisfaction* is directly measurable. In the questionnaire of LISS-panel, the main question regarding job satisfaction is ‘‘How satisfied are you with your current work?’. This is on a scale of 0 to 10 with 0 being not at all satisfied and 10 being fully satisfied (LISS-panel, 2022).

Control variables

To be able to get the most accurate results, and ultimately the best depiction of the effect of the risk of automation on the job satisfaction of Dutch workers, multiple control variables should be taken into account. As mentioned in chapter 2, multiple factors that influence job satisfaction can be found.

First, age and gender will be accounted for. Age is measured as an integer value, with the simple question ‘Age of the household member’. The gender is measured as ‘Male’ or ‘Female’.

Second wage should be accounted for. In the LISS-panel, the variable brutoink_f gives an integer value for the personal gross monthly income in Euros.

Third, level of education will be accounted for, as the literature has shown that a higher level of education is often related with a higher job satisfaction. The level of education will be measured by looking at a ranking of 1 to 7, with 1 being no achieved diploma/certificate and 7 having a post-tertiary diploma/certificate.

Fourth, as mentioned in the literature, job security appears to have an influence on the level of job satisfaction. It will be measured by the question ‘What is the chance that you will lose your main job in the next 12 months?’. This question gives an integer value of 0 to 100%.

Formulas

Following this operationalization, the following formula’s lay the foundations for the regression:

The first, simple/short regression formula for a multiple regression analysis is as follows:

$$(1)\ JS_{cg} = \alpha + \beta 1NRA1 + \beta 2NRI2 + \beta 3NRM3 + \beta 4RC4 + \beta 5RM5 + \varepsilon$$

The second, long regression, which will be used in producing the results, will take the varying control variables into account:

$$(2)\ JS_{cg} = \alpha + \beta1NRA1 + \beta2NRI2 + \beta3NRM3 + \beta4RC4 + \beta5RM5 + \beta6a6 + b7gender7 + \beta8gw8 + \beta9LoE9 + \beta10jsec10 + \varepsilon$$

In regression 2, JS regards the job satisfaction per category with JS being 0 < JS < 100. Age, gender, gross wage, level of education and job security are the main control-variables. As can be seen, the five mentioned categories for the task based-index are all measured as individual independent variables. Age, gender, gross wage and job security are the variables that, based on the available literature, have a significant effect on the dependent variable, but as they are not the main purpose of this research, will be used to control for a potential omitted variable bias.

Model 2, the third regression, regards the effect of the risk of automation-index as generated by Pouliakos (2018) on the level of job satisfaction:

$$(3)\ JS_{cg} = \alpha + \beta2a2 + b3gender3 + \beta4gw4 + \beta5LoE5 + \beta6jsec6 + \varepsilon$$

Besides the main independent variable, the risk of automation-index, there is no difference in the dependent variable nor the control variables.

Notable omitted variable bias

As mentioned in the theoretic framework of this research, many variables appear to have an influence on the dependent variable job satisfaction. It is due to the lack of available data not possible to take all the factors that the literature have shown to have an effect on job satisfaction into account. Therefore, an omitted variable bias will exist. To belittle the effect of this OMV on the dependent variable, the variables that can be deemed as most important will be taken into account as control variables.

Skill and age-groups

To analyze the second hypothesis and be able to answer the research question, a difference should be made between the observations based on skill and age. In this research, the level of skill is split into low-, middle- and high-skilled as mentioned by the CBS (2021). Low-skilled individuals have no education, or have only achieved a degree in primary school, middle school, lower levels of high-school or the lowest level of a vocational education. Middle-skilled individuals have a degree in the higher levels of high school or a degree in one of the middle to higher levels of vocational education. High-skilled workers have a degree at either an university of applied sciences or university (CBS, 2021). In this research, no further differentiation has been made between a bachelor, masters or further degree.

Second, the age-groups are also split into three different groups. First are the group of young workers, aged 16-30. Second are the group of middle-skilled workers, aged 31-49. Third are the older workers, aged 50+. While young workers are often viewed as the age-group of 16-25, due to a lack of data the group of 26-30 has been added to the category ‘young’ (CBS, 2022).

Control group

A control group is a group that is used as a baseline to compare the results of the treatment group. In this research, the group of old high-skilled workers will be used as a control group. While the literature does show that they are subject to automation, the type of automation is complementary and thus does not result in an increased risk of replacement due to automation. Furthermore, this research is not able to account for a complementary type of automation, such as artificial intelligence, taking place.

The purpose of including this group is to compare and ensure that the potential changes in the treatment group, low-skilled workers, are due to automation.

Reference variable

A reference variable is a variable that is used as a baseline or point of comparison in research or statistical analysis. It is a standard against which other variables can be compared or measured. Reference variables are often used in research and statistical analysis to help better understand the relationships between different variables and to identify patterns or trends that may not be apparent when examining individual variables in isolation (Reynolds et al., 2013).

With this negative effect of automation replacing certain jobs not being relevant for the non-routine analytic category, as these tasks require a high level of skill, it will be used as the reference in order to analyze a potential negative effect of automation on job satisfaction. With the different categories in total adding up to a value of 1, and these therefore being dependent on each other, making use of the reference variable helps with countering the collinearity between the different categories for the independent variable of the task based-index.

5. Descriptive statistics

Several concepts lay at the center of this research. Regarding these concepts, several trends can be identified. This section of the paper will therefore make use of descriptive statistics to identify trends regarding these concepts.

5.1 The descriptive statistics for automation

In table 3 the frequencies for the risk of automation, by level of skill as well as by age-group, can be found. It shows the distribution in percentages, with each individual graph adding up to a total of 100%. Varying interesting observations can be made based on the differences between the groups. First, the differences between the different age categories for the high-skilled group appears to be little. The dominant frequencies appear to be for 0.45, 0.50 and 0.51 for all age categories. This can be due to the type of work performed by these high-skilled workers falling into occupations allocated to these numbers. It does show that the high-skilled workers, independent of their age, fall mostly into the same level of risk of automation.

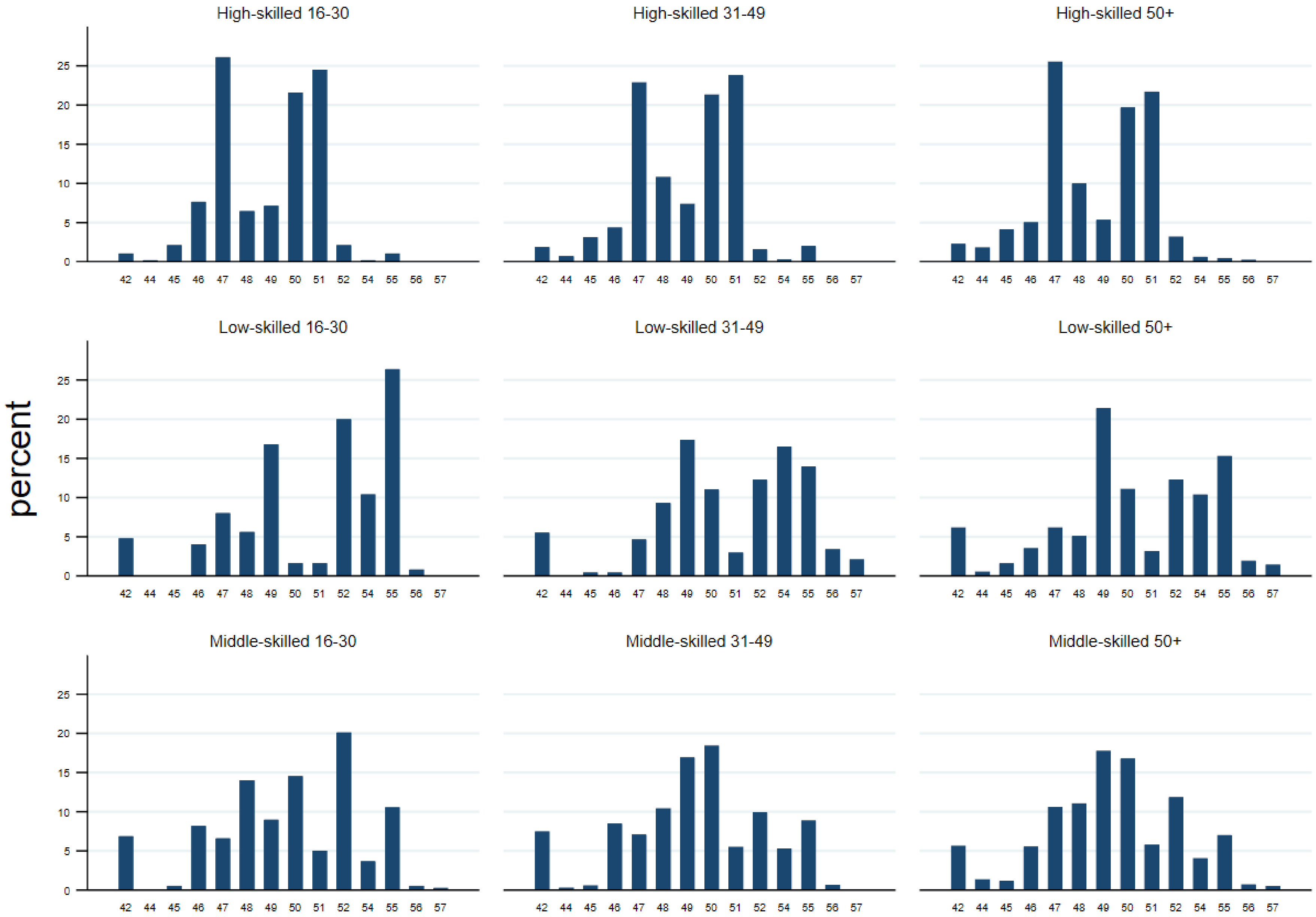
When looking at the low-skilled group, it appears that the younger low-skilled workers have a distribution more skewed towards the right, and thus a greater risk of automation. This can be seen as for the values of 0.52 and 0.55 the percentual frequency are the highest. For the middle-aged group of low-skilled workers the distribution is also predominantly to the right, but it is less skewed and more evenly distributed. This also seems to be the case for the older group of low-skilled workers, who actually have a peak in the distribution at a value of 0.49.

Finally, the group of middle-skilled workers is fairly evenly distributed in regards to the risk of automation. The younger middle-skilled workers do appear to be skewed somewhat to the right, showing a higher risk of automation, while the other age categories are more evenly spread with peaks in the middle.

In short, the frequencies of a higher risk of automation are higher for the low-skilled group, while within this group the younger workers are also more skewed towards a higher risk.

Table 3

'Table of frequencies for risk of automation by skill and age group, in percentages



Routine-task based-index and descriptive statistics

Generating descriptive statistics and frequencies for the varying categories regarding routinization and the related index results in a large sum of tables. These are therefore added to the appendix.

The frequency tables for the routine-task intensity index have shown multiple trends corresponding to the literature. Non-routine analytic tasks, the first category, require the use of a higher level of cognitive skills and problem-solving abilities. These are therefore more prevalent for high-skilled workers. Their tasks often involve interpretation and analyzing complex data. The high-skilled workers are often involved in these tasks, as they have the necessary skills and expertise to perform them effectively. Table 10, found in the appendix, also shows this idea. The tables shows the frequency distribution of non-routine analytic tasks in percentages for every skill and age-group. With the bar furthest to the left indicating a value of 0 for the task, furthest to the right a value of 1, it becomes clear that high-skilled workers, indifferent of age, have the highest share of non-routine analytic tasks.

For non-routine interactive tasks the trend as mentioned for non-routine analytic tasks is similar. High-skilled workers, indifferent of age, appear to have a higher level of non-routine interactive tasks. The share of these tasks for low-skilled workers is, to no surprise, lower than that of the middle-skilled workers.

Routine cognitive tasks, which regard the use basic cognitive skills and often repetition, are most prevalent for low-skilled workers, especially the younger group. The group of middle-skilled may also be involved in routine cognitive tasks, although to lesser extent than the low-skilled group. Logically, the group of high-skilled workers are unlikely to be involved in these tasks, as they by definition do not require a high-level of skill.

The category of routine manual tasks show that low-skilled workers have the largest share. The prevalence of these type of tasks is not as high as expected however, with the share of routine cognitive tasks being larger for this group.

Finally, non-routine manual tasks are highly frequent for the low-skilled workers. Middle-skilled workers also appear to perform this type of tasks regularly, albeit less often than the low-workers. The results for high-skilled workers show barely any share of this task, with a large majority having a value of 0.

In short, the descriptive statistics show no real unexpected trends regarding the share of the five categories and level of skill/age-group. Noteworthy is the large share of routine cognitive and non-routine manual tasks for low-skilled workers.

5.2 Job satisfaction

According to the earlier mentioned research, the level of job satisfaction is often found to be higher for high-skilled workers.

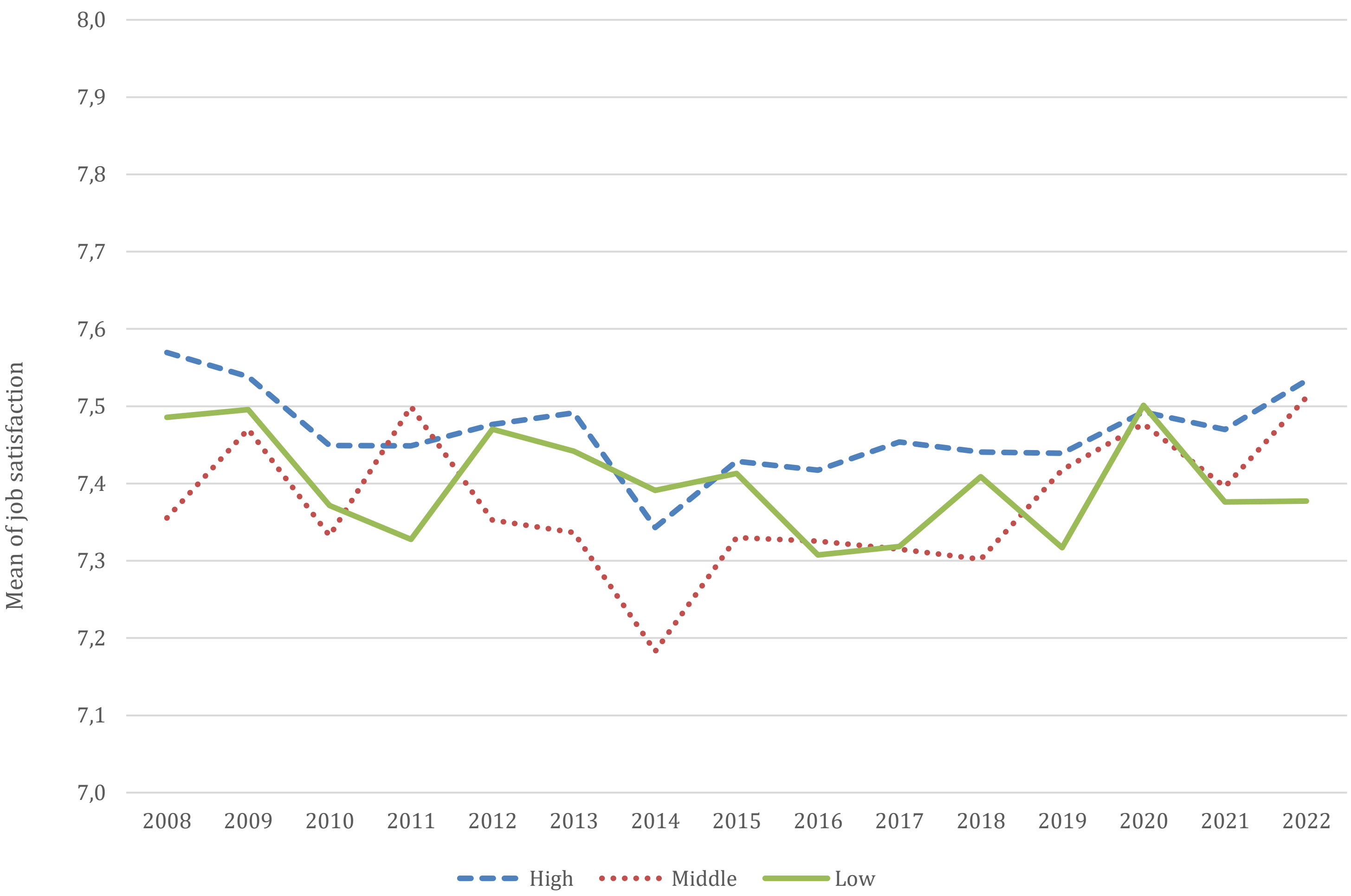
In graph 1, the mean job satisfaction of the different levels of skills over the period 2008-2022 can be found. The graph is based on the available data from the LISS-panel. It appears that over the period of 2008 to 2014 the general level of job satisfaction has decreased for all the different levels of skill. Over the last few years the level of job satisfaction has been increasing however.

Furthermore, the graph shows that high-skilled workers, to be identified as the blue line, generally have a higher level of job satisfaction in comparison to both middle- and low-skilled workers. While for some years the mean job satisfaction is higher for middle- and low-skilled workers, visible in the years 2011, 2014 and 2021, the high-skilled workers have a higher level of job satisfaction.

While the main idea from the literature appeared to be a decrease in the job satisfaction of lower-skilled workers in comparison to primarily the high-skilled workers, such a trend is only to a small extent visible in graph 1.

Figure 2

Mean of job satisfaction for different skill-groups, 2008-2022



In table 4, the job satisfaction by skill level and age-group can be found. The table shows varying interesting results. First, the level of job satisfaction for high-skilled workers appears to be generally higher than for the other skill-groups. For example, for all ages, the job satisfaction is higher for high-skilled workers. Especially for the group of high-skilled young workers, aged 16-30, the job satisfaction of 7.284 is fairly higher than 7.092 and 6.990 for middle- and low-skilled workers respectively. For the age group of 31-49, the level of skill appears to have little influence on the level of job satisfaction. The job satisfaction for this group lies between 7.3 and 7.4 for all skill levels.

While for the middle-aged group there seems to be little difference in levels of job satisfaction, the difference in job satisfaction for the young group appears to vary by a larger margin. While for young high-skilled workers the job satisfaction has a mean of 7.284, for low-skilled workers it has a value of just 6.990.

Furthermore, the table shows that the level of job satisfaction for the different age groups varies by a relatively large amount. For the group of low-skilled workers, the difference between the job satisfaction of old workers in comparison to young workers is 0.624. As the level of job satisfaction is measured from 0 to 10, this appears to be a large gap. For the other skill levels, older workers also have a higher mean job satisfaction. The results identifiable in table 4 also correspond with literature, with a paper by O'Brien and Dowling (1981) mentioning a small positive correlation between age and job satisfaction. This may be because of several advantages/benefits that older workers gain, such as higher salaries and potential achieved success (Burks, 2016).

Table 4

'Job satisfaction by level of education'

		High skilled		
Age	16-30	31-49	50+	Difference Young-old
Job satisfaction	7.284	7.362	7.702	-0.418
		Middle-skilled		
Age	16-30	31-49	50+	Difference young-old
Job satisfaction	7.092	7.337	7.547	-0.455
		Low-skilled		

Age	16-30	31-49	50+	Difference Young-old
Job satisfaction	6.990	7.334	7.614	-0.624

6. Empirical results

In this section of the paper, the varying results gathered by performing the earlier mentioned statistical analyses through the use of Stata will be presented. First, the results for the combined dataset of Dutch workers, indifferent of skill- and education level, will be presented. Following these results, the measured effect of automation on job satisfaction of varying groups, based on level of skill and age, will be presented and analyzed.

6.1 Risk of automation and job satisfaction of Dutch workers

$$(1)\ JS_{cg} = \alpha + \beta 1NRA1 + \beta 2NRI2 + \beta 3NRM3 + \beta 4RC4 + \beta 5RM5 + \beta 6a6 + b7gender7 + \beta 8gw8 + \beta 9LoE9 + \beta 10jsec10 + \varepsilon$$

$$(2)\ JS_{cg} = \alpha + \beta 2a2 + b3gender3 + \beta 4gw4 + \beta 5LoE5 + \beta 6jsec6 + \varepsilon$$

The formulas, as can be identified above, lay at the basis for generating the results. The independent variable in the formula is the level of job satisfaction, while the independent variables are the varying categories for the routine-task intensity-index' and the risk of automation-index respectively. With both the tasks and the risk of automation-index being measured at a range from 0 to 1, with values lying in between, the following tables will show the effect of an increase in the value of a task by 1 and the related change in the level of job satisfaction, which is on a scale from 0 to 10.

Table 5 shows the effect of the independent variables on the level of job satisfaction of Dutch workers. In table 5, the whole group of Dutch workers is taken into account.

Table 5

'Effect of task based-index and risk of automation-index on job satisfaction' n: 4261

	Category	
Model 1	Non-routine analytic	Reference
	Non-routine interactive	-0.295*
	Non-routine manual	-0,370***
	Routine cognitive	-1.121***
	Routine manual	-0.370***
Model 2	Risk of automation	-0.026**

Note: controlled for age, gross wage, gender, perceived job security and education
*p<0.05 **p<0.01 ***p<0.001

With the non-routine analytic type of tasks being put as a reference in order to counter collinearity, non-routine interactive, non-routine manual, routine cognitive and routine manual all appear to have a significant, negative effect on the level of job satisfaction.

Especially noteworthy is how an increase of the value for routine cognitive tasks by 1 results in a decrease in the level of job satisfaction by -1.121, with a highly significant statistical effect being visible. Furthermore, an increase in the score of the routine manual category by 1 results in a decrease in the level of job satisfaction by 0.370. The tasks with a higher chance of being automated thus appear to negatively influence the level of job satisfaction.

Interestingly enough, the non-routine categories also negatively influence the level of job satisfaction. An increase in the value for non-routine interactive and non-routine manual tasks results in a decrease in job satisfaction by 0.295 and 0.370 respectively.

Model 2 shows the effect of risk of automation on the level of job satisfaction. The effect appears to be significant, with an increase in the risk of automation by 1 resulting in a decrease of the level of job satisfaction by 0.026.

Table 5 shows, in short, that for the collective of Dutch workers, an increase in the value for any of the categories besides non-routine analytic, results in a decrease in job satisfaction for Dutch workers. An increase in the value for the routine cognitive category appears to have the largest negative effect, while non-routine interactive appears to have the smallest negative effect. Furthermore, an increase in the risk of automation-index as generated by Pouliakas (2018) also negatively influences the job satisfaction, albeit in a smaller manner. An increase in the risk of automation-index results in a decrease of job satisfaction by 0.026.

6.2 Automation and job satisfaction by skill and age-group

In order to analyze hypothesis 2, regarding the influence of automation on differing levels of skill and age-groups, it is necessary to generate multiple empirical results for these categories.

As can be seen in table 6, the effect of the varying tasks on job satisfaction when making a division in both skill and age group, is inconsistent and mostly insignificant. For all different age groups regarding the low-skilled workers, the effect of the tasks have no significant influence. This counters the initial thought that the job satisfaction would be lowered by an increasing margin of a task being at a larger risk of automation. As seen in the table, however, no such effect can be noted.

The effect of the risk of automation-index on the job satisfaction of young low-skilled does appear to be significant. The value shows that an increase in the risk of automation-index by 1 would result in a decrease in job satisfaction of 0.377. A decrease of 0.377 can be seen as quite large, due to the job satisfaction being measured on a range of 0-10. While there appears to be a significant effect of risk on automation on the younger low-skilled group, middle and older low-skilled workers appear to not be influenced by the risk of automation. No significant effects can be identified for these age groups.

Table 6

Task based-index and risk of automation-index on job satisfaction of low skilled workers

		Low-skilled		
Age		16-30	31-49	50+
Model 1	Non-routine analytic	Ref.		
	Non-routine interactive	-6.094	2.661	0.267
	Non-routine manual	-4.287	-0.439	-3.30

	Routine manual	-5.271	0.917	-0.604
	Routine cognitive	-3.224	0.768	-0.621
Model 2	Risk of automation	-0.377**	-0.027	-0.030

Note: controlled for age, gross wage, gender, perceived job security and education
*p<0.05 **p<0.01 ***p<0.001

Table 7 shows the effect of the independent variables on the job satisfaction of high skilled workers, for all three age groups. Contrary to the results identified for the low-skilled group, multiple significant effects can be found. For the young high-skilled group, a significant effect can be found for the effect of non-routine manual tasks on job satisfaction. An increase in the value for non-routine manual tasks by 1 would result in a decrease in job satisfaction for these young high skilled workers by 1.366. Furthermore, routine cognitive tasks appear to negatively influence both young and old high-skilled workers. Noteworthy is the effect of routine cognitive on the job satisfaction of high skilled middle aged workers. The effect appears to be positive, which counters the thought of routinization negatively affecting the job satisfaction. Another interesting observation is the strong negative effect an increase in routine manual tasks has on older high-skilled workers. An increase in this value results in a decrease in job satisfaction by 2.967. This can be seen as a large decrease.

Model 2, measuring the effect of risk of automation-index on the level of job satisfaction, shows no significant effects for any of the high-skilled age-groups. An increasing risk of automation therefore shows no clear negative or positive effect.

Table 7

Task based-index and risk of automation-index on job satisfaction of high skilled workers

		High skilled		
Age		Young	Middle	Old
Model 1	Non-routine analytic	Ref.		
	Non-routine interactive	-0.730	-0.664*	-0.350
	Non-routine manual	-1.366*	-0.036	-0.659*
	Routine manual	0.547	-1.188*	-2.967***
	Routine cognitive	-0.832*	0.501*	-0.474*
Model 2	Risk of automation	0.019	0.010	0.024

Note: controlled for age, gross wage, gender and perceived job security

*p<0.05 **p<0.01 ***p<0.001

In table 8, the group of middle-skilled workers can be found. Once again, few significant effects can be found. For the entire group of middle-aged middle-skilled workers, no significant effects of the tasks or the risk of automation-index on the level of job satisfaction can be found. The category of routine manual tasks does appear to have a significant negative effect on the job satisfaction of both young and old middle-skilled workers, with an increase resulting in a decrease of 2.110 and 1.530 respectively. These negatively correlations show how routine manual tasks can be linked to a low level of job satisfaction.

The risk of automation-index also appears to influence the level of job satisfaction for young and old middle-aged workers. An increase in the index by 1 will result in a decrease in the job satisfaction by 0.078 for young middle-skilled workers, and by 0.062 for older middle-skilled workers. For the middle-aged group no significant effect can be found.

Table 8

Task based-index and risk of automation-index on job satisfaction of middle-skilled workers

		Middle-skilled		
Age		Young	Middle	Old
Model 1	Non-routine analytic	Ref.		
	Non-routine interactive	-0.211	0.162	0.002
	Non-routine manual	-0.757	-0.189	-0.222
	Routine manual	-2.110*	-0.406	-1.530***
	Routine cognitive	-0.395	-0.319	-0.497*
Model 2	Risk of automation	-0.078*	-0.026	-0.062***

Note: controlled for age, gross wage, gender and perceived job security

*p<0.05 **p<0.01 ***p<0.001

6.2 Recap, identifying the theory of SBTC

Table 6 has shown that an increase in the share of any of the categories regarding the level of routine, with the independent variable non-routine analytic being used as a variable, negatively impacts the value for job satisfaction. When split into different groups, the significance of an increase in more automatable tasks drops for most sub-groups. This gives very inconsistent results regarding the effect of routine-tasks on the level of job satisfaction, as it highly differs for each individual group.

Second, while the results regarding the routine-task intensity-index show no consistent results, an increase in the risk of automation-index has shown to decrease the value of job satisfaction by 0.026. When splitting the workers into different subgroups, based on level of skill and age, the significancy for risk of automation disappeared for many of the subgroups. While for the control group of older high-skilled workers no significant effect can be identified, the young low-skilled workers do show to experience the largest significant negative effect in comparison to the other groups.

This observation can be linked to the theory of skill-biased technological change, as put forward by Sachs & Kotlikoff (2012) and Schwabe & Castellacci (2020). The theory stated that younger low-skilled workers are more at risk for encountering negative effects due to automation, while high-skilled workers experience a positive effect due to automation being complementary to this group. Ultimately, this would result in further inequality between the groups, mainly in regards to wages. With the results indicating the largest negative effect for this young low-skilled group, while both the middle- and high-skilled groups experienced a smaller or no effect of risk of automation, automation results in a further inequality regarding the job satisfaction of these groups. Based on these findings, that an increasing risk of automation negatively influences the level of job satisfaction of young low-skilled workers, the hypotheses can be analyzed.

For hypothesis 1, H0 can be rejected, while H1 can be accepted. Based on the findings from the descriptive statistics and performed regressions, as well as the completed analysis of available literature, this paper has found that an increased risk of automation has a negative effect on the job satisfaction of young low-skilled and young and older middle-skilled Dutch workers. While the effect does differ for varying societal groups, it does show that to some degree the risk of automation influences job satisfaction.

For hypothesis 2, H0 can also be rejected, while H2 can be accepted. The findings have shown that an increase in the risk of automation for young low-skilled workers results in a larger decrease in job satisfaction in comparison to the other groups of both older and higher-skilled workers. An increase in the risk of automation-index by 1, would result in a decrease in job satisfaction by 0.377. Meanwhile, for the group of high-skilled workers the effect is not significant. The effect on young and older middle-skilled workers does appear to be negative, but as it is smaller by a large amount, it shows how The job satisfaction of young and old middle-skilled workers does also appear to be negatively influenced by an increase in the risk of automation.

7. Conclusion

Based on available scientific literature, descriptive statistics and ultimately performing multiple regression analyses, this research has tried to answer the research question: "*What is the effect of risk of automation on the job satisfaction of Dutch workers, and does it differ for high- versus low-skilled workers?"*.

To measure the risk of automation, the research has made use of multiple independent variables, being five categories of tasks based on routine-task intensity, and the risk of automation-index. When all workers are bundled together, the research found that tasks that are more subject to automation, especially routine cognitive tasks, negatively influence level of job satisfaction of Dutch workers. When level of skill and the age-group are taken into account, however, the effect of tasks on the level of job satisfaction becomes highly inconsistent.

Furthermore, the research has found that the risk of automation-index has a negative effect on young low-skilled workers, as well as young and old middle-skilled workers. These young low-skilled workers are more at risk of automation in regards to job satisfaction, as an increase in the value for the risk of automation-index by 1 would result in a decrease in job satisfaction for young low-skilled workers by 0.377. For the other subgroups, the young and old middle-skilled groups, a negative effect of 0.078 and 0.062 respectively was found.

In short, the effect of the risk of automation on the job satisfaction of Dutch workers is dependent on the level of skill and age of the individual. Young low-skilled workers appear to be more negatively influenced by exposure/risk of automation, while other groups have appeared to not be influenced/be less influenced. Furthermore, with the research looking at the effect of (non-)routine-tasks on job satisfaction, no consistent effect was found. With the inconsistency of the effect, the trend of increasing automation and its effects on the level of job satisfaction of Dutch workers should be looked at even further. Further research can therefore be deemed necessary.

8. Recommendations

8.1 Evaluation

The results from this research, gained from both the descriptive statistics as well as the several regressions, give some space to judge the current policy and give multiple policy recommendations. Since the introduction of the new forms of automation, such as artificial intelligence and machine learning, the Dutch government had been relatively welcoming to the implementation of automation. In general, with the positive effects it has on the total labor productivity and the cost-saving it brings to companies, automation has a positive effect on the economy. The results from this research show that, in particular risk of automation replacing a job, negatively influences the job satisfaction of individuals. The group of low-skilled younger workers have shown the largest negative effect on job satisfaction due to this risk. Furthermore, the research has shown that the job satisfaction for these workers is significantly lower than the job satisfaction for middle- and higher-skilled workers, as well as for middle-aged and old low-skilled workers. This trend and negative effect of automation on these young low-skilled workers in particular, require a certain level of attention.

8.2 Concrete policy measures

Based on the results, several concrete policy measures can be advised.

First, with the results indicating that younger low-skilled individuals have a lower level of job-satisfaction, regardless due to automation, the negative effects of automation on this group should be decreased. With the Covid-19 pandemic resulting in different policy measures such as Nederland Leert Door, the Dutch government should look at expanding this measure and analyze if adding it to individuals that have a high level of job insecurity could positively influence their labor market participation, security and ultimately their level of job satisfaction (Ministry of Social Affairs and Employment, 2022). Increasing this job satisfaction can result in a general increase in well-being, as well as reduce the gap between high-skilled older workers in comparison to younger low-skilled workers. All in all, advancing this already existing measure can contribute in countering the existing negative externalities induced by automation. In general, the Dutch government could provide funding for training and education programs to help low-skilled workers in the Netherlands develop new skills and knowledge. These programs could include technical training in fields such as programming or data analysis, as well as language and communication skills training.

Second, the Dutch government could fund job placement services, such as career counseling and resume writing assistance, to help low-skilled workers in the Netherlands find new employment opportunities in industries that are less likely to be automated. The UWV, which helps Dutch jobseekers in finding a new job, can assist as they help connect job seekers with certain potential employers.

A third option would be to increase the support for entrepreneurship. The Dutch government could encourage entrepreneurship among young low-skilled workers in the Netherlands by providing access to startup funding, business mentorship, and other resources to help them get their businesses off the ground. Currently, there are various regional programs supporting entrepreneurship for young workers, such as YES!Delft and PLNT Leiden, but they are mainly focused at individuals with a high level of education, primarily university students.

8.3 Remarks and suggestions

With this research coming across varying problems, the following remarks and suggestions for future research have to be made.

First, compiling the variable for 'automation' could be deemed as sub-optimal. It comprised of the varying routine-task intensity-index scores for the five categories and the risk of automation-index generated by Pouliakos (2018). While the risk of automation-index does reflect automation well, the relationship between automation and the task based-index can be deemed as complex. Furthermore, while the used routine-task intensity-index and risk of automation-index were of great help, they were measured at one single moment in time. If these independent variables were 'updated' for every year a more accurate relation between the dependent variable of job satisfaction and the independent variable of automation could be measured. For future research, a changing value for the independent variable of risk of automation should therefore be used.

Second, making use of a panel data regression could benefit the accuracy of the results. While the in this research used dataset of the LISS-panel is quite extensive, some of the main variables that were at the base of this research have only been included in the last few years, making it hard to conduct an accurate panel data regression. To counter having to rely on a simple cross-sectional OLS regression, a dataset with available ISCO-08 codes for a longer span of time should be used.

Literature:

1. Abeliansky, A. & Beulmann, M. (2019). Are They Coming for Us? Industrial Robots and the Mental Health of Workers. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3438287
2. Acemoglu, D., & Restrepo, P. (2016). The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment. *X*. https://doi.org/10.3386/w22252
3. Antonczyk, D., Fitzenberger, B., & Leuschner, U. (2009). Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure? *Jahrbücher Für Nationalökonomie Und Statistik*, *229*(2–3), 214–238. https://doi.org/10.1515/jbnst-2009-2-309
4. Autor, D. H., & Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *The American Economic Review*, *103*(5), 1553–1597. http://www.jstor.org/stable/42920623
5. Autor, David H. (2015). "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives*, 29 (3): 3-30.
6. Bharadwaj, A. & Dvorkin, M. A. (2021, 9 december). *The Rise of Automation: How Robots May Impact the U.S. Labor Market*. St. Louis Fed. https://www.stlouisfed.org/publications/regional-economist/second-quarter-2019/rise-automation-robots
7. Böckerman, P., Ilmakunnas, P., & Johansson, E. (2011). Job security and employee well-being: Evidence from matched survey and register data. *Labour Economics*, *18*(4), 547–554. https://doi.org/10.1016/j.labeco.2010.12.011
8. Bughin, J., Hazan, E., Lund, S., Dahlström, P., Wiesinger, A., & Subramaniam, A. (2021, January 23). *Skill shift: Automation and the future of the workforce*. McKinsey & Company. https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce
9. Burks, F. (2016, October 26). *What Is the Relationship Between Job Satisfaction & Age?* Small Business - Chron.com. https://smallbusiness.chron.com/relationship-between-job-satisfaction-age-12618.html
10. The California Business Journal Newswire. (2022, 15 november). *What is the Demand for Software Engineers and is it Expected to Rise?* California Business Journal.

https://calbizjournal.com/what-is-the-demand-for-software-engineers-and-is-it-expected-to-rise/

11. Centraal Bureau voor de Statistiek. (2019, 18 oktober). *7 procent bedrijven gebruikt robots*. https://www.cbs.nl/nl-nl/nieuws/2019/42/7-procent-bedrijven-gebruikt-robots
12. Centraal Bureau voor de Statistiek. (2021, 15 oktober). *Bijna helft grote bedrijven gebruikt Artificial Intelligence*. https://www.cbs.nl/nl-nl/nieuws/2021/41/bijna-helft-grote-bedrijven-gebruikt-artificial-intelligence
13. Centraal Bureau voor de Statistiek. (2022, November 9). *Jongvolwassenen voor het eerst lager persoonlijk welzijn dan 25-plussers*. Centraal Bureau Voor De Statistiek. https://www.cbs.nl/nl-nl/nieuws/2022/45/jongvolwassenen-voor-het-eerst-lager-persoonlijk-welzijn-dan-25-plussers
14. Centraal Bureau voor de Statistiek. (2022, November 11). *Arbeidsparticipatie naar leeftijd en geslacht*. Centraal Bureau Voor De Statistiek. https://www.cbs.nl/nl-nl/visualisaties/dashboard-arbeidsmarkt/werkenden/arbeidsparticipatie-naar-leeftijd-en-geslacht
15. Centaal Planbureau. (2017). *De Introductie van dure technologie in de zorg*. https://www.cpb.nl/sites/default/files/omnidownload/CPB-Achtergronddocument-18mei2017-De-introductie-van-dure-technologie-in-de-zorg-alalysekader-en-casestudies.pdf
16. Centraal Planbureau. (2019). *Automatic Reaction – What Happens to Workers at Firms that Automate? | CPB.nl*. https://www.cpb.nl/automatic-reaction-wat-gebeurt-er-met-werknemers-als-hun-bedrijf-automatiseert
17. CHIOK FOONG LOKE, J. (2001). Leadership behaviours: effects on job satisfaction, productivity and organizational commitment. *Journal of Nursing Management*, *9*(4), 191–204. https://doi.org/10.1046/j.1365-2834.2001.00231.x
18. Chui, M., Manyika, J., & Miremadi, M. (2020, February 13). *Where machines could replace humans—and where they can't (yet)*. McKinsey & Company. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet
19. De Bie, T., De Raedt, L., Hernández-Orallo, J., Hoos, H. H., Smyth, P. & Williams, C. K. I. (2022). Automating data science. *Communications of the ACM*, *65*(3), 76–87. https://doi.org/10.1145/3495256
20. Eurofound (2018), Automation, digitisation and platforms: Implications for work and employment, Publications Office of the European Union, Luxembourg

21. Eurostat. (2022). *Statistics Explained*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Industrial_production_statistics
22. Ezzat, A., & Ehab, M. (2019). The determinants of job satisfaction in the Egyptian labor market. *Review of Economics and Political Science*, *4*(1), 54–72. https://doi.org/10.1108/reps-10-2018-012
23. Frey, C.B., & Osborne, M.A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254-280.
24. Gao, Y. (2021). *The Impact of Automation on Employee Productivity in the Banking Sector*. UTwente.
25. Goddard, W. (2020, September 9). *Where is Artificial Intelligence Used Today?* ITChronicles. https://itchronicles.com/artificial-intelligence/where-is-ai-used-today/
26. Goos, M., Manning, A. & Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review*, *104*(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509
27. Groover, Mikell (2014). Fundamentals of Modern Manufacturing: Materials, Processes, and Systems. https://www.fcusd.org/cms/lib/CA01001934/Centricity/Domain/4529/Fundamentals%20of%20Modern%20Manufacturing%20Materials%20%20Processes%20and%20Systems%20%204th%20Edition.pdf
28. Haque, M. I. (2004), "Job Satisfaction of Indian Academicians: A Study Based on Gender and Age", the Indian Journal of Commerce, vol. 57(2), 102-113.
29. Holzer, H. J. (2022, March 9). *Understanding the impact of automation on workers, jobs, and wages*. Brookings. https://www.brookings.edu/blog/up-front/2022/01/19/understanding-the-impact-of-automation-on-workers-jobs-and-wages/
30. IEEE. (2020, May 21). *Automation and the Fourth Industrial Revolution: How It Affects Your Life*. IEEE Transmitter. https://transmitter.ieee.org/how-automation-and-the-fourth-industrial-revolution-is-affecting-your-everyday-life/
31. IFR. (2021). *Robot Density nearly Doubled globally*. IFR International Federation of Robotics. https://ifr.org/ifr-press-releases/news/robot-density-nearly-doubled-globally
32. IFR. (2022). *China overtakes USA in robot density*. IFR International Federation of Robotics. https://ifr.org/ifr-press-releases/news/china-overtakes-usa-in-robot-density
33. Joseph, A.R., Richard, A. (2002), "Worker"s Evaluation in Five Countries", International Labour Review, vol. 141(4), 305-310.

34. Kregting, M. (2019b, December 11). *Amsterdam UMC tevreden over inzet operatierobot*. ICT&Health. https://icthealth.nl/nieuws/operatierobot/
35. Kromann, Lene & Skaksen, Jan & Sørensen, Anders. (2011). Automation, labor productivity and employment -a cross country comparison.
36. Kotlikoff, L.J. and Sachs, J.D. (2012) Smart Machines and Long-Term Misery. NBER Working 18629. http://dx.doi.org/10.3386/w18629
37. Künn-Nelen, A. & Smits, W. (2022). De impact van taken op de baan- en werkzekerheid van werknemers. *Tijdschrift voor Arbeidsvraagstukken*, *38*(2), 134–153. https://doi.org/10.5117/tva2022.2.002.kuhn
38. Lawler E (2005) Motivating and Satisfying Excellent Individuals: Management Skills: A JosseyBass Reader. San Francisco, CA: John Wiley and Sons.
39. Lim, H. S. M., & Taeihagh, A. (2019). Algorithmic Decision-Making in AVs: Understanding Ethical and Technical Concerns for Smart Cities. *Sustainability*, *11*(20), 5791. https://doi.org/10.3390/su11205791
40. LISS. (2021). *About the Panel | LISS Panel Data*. https://www.lissdata.nl/about-panel
41. Locke, E.A. (1976) The Nature and Causes of Job Satisfaction. In: Dunnette, M.D., Ed., Handbook of Industrial and Organizational Psychology, Vol. 1, 1297-1343.
42. Maurin, E. & Postel-Vinay, F. (2005). The European Job Security Gap. *Work and Occupations*, *32*(2), 229–252. https://doi.org/10.1177/0730888405274603
43. Matzliach, B., Ben-Gal, I., & Kagan, E. (2022). Detection of Static and Mobile Targets by an Autonomous Agent with Deep Q-Learning Abilities. *Entropy*, *24*(8), 1168. https://doi.org/10.3390/e24081168
44. McCarthy, J. (2007). What is artificial intelligence?.
45. Mendelson, H., & Pillai, R. R. (1999). Industry Clockspeed: Measurement and Operational Implications. *Manufacturing &Amp; Service Operations Management*, *1*(1), 1–20. https://doi.org/10.1287/msom.1.1.1
46. Mihaylov, E. S., & Tijdens, K. (2019). Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations. (035/V ed.) (TI Discussion Paper Series; Vol. 2019, No. 035/V). Tinbergen Institute. https://papers.tinbergen.nl/19035.pdf
47. Ministerie van Infrastructuur en Waterstaat. (2020, July 31). *Self-driving vehicles*. Mobility, Public Transport and Road Safety | Government.nl.

https://www.government.nl/topics/mobility-public-transport-and-road-safety/self-driving-vehicles

48. Ministerie van Sociale Zaken en Werkgelegenheid. (2022, March 16). *Nederland leert door*. Leven Lang Ontwikkelen | Rijksoverheid.nl. https://www.rijksoverheid.nl/onderwerpen/leven-lang-ontwikkelen/leven-lang-ontwikkelen-financiele-regelingen/nederland-leert-door
49. Nedelkoska, L. & Quintini, G. (2018). Automation, skills use and training. Working paper nr. 202. Parijs: OECD.
50. O'brien, G. E., & Dowling, P. (1981). Age and job satisfaction. *Australian Psychologist*, *16*(1), 49–61. https://doi.org/10.1080/00050068108254415
51. Oswald, A. J., Proto, E., & Sgroi, D. (2015). Happiness and Productivity. *Journal of Labor Economics*, *33*(4), 789–822. https://doi.org/10.1086/681096
52. Palle, A., J. Dwyer and G. David. (1995). "Productivity and Growth." Proceedings of a Conference Held at the H.C. Coombs Centre for Financial Studies, Kirribilli, Australia
53. Ploeger, M. (2022, January 27). *'Door automatisering krijgen we een grote herverdeling van werk.'* Sociale Vraagstukken. https://www.socialevraagstukken.nl/interview/door-automatisering-krijgen-we-een-grote-herverdeling-van-werk/
54. Pouliakas, Konstantinos, (2018) "Determinants of Automation Risk in the EU Labour Market: A Skills-Needs Approach,"IZA Discussion Papers 11829, Institute of Labor Economics (IZA). https://ideas.repec.org/p/iza/izadps/dp11829.html
55. Precedence Research. (2021). *Artificial Intelligence Market Size, Growth, Report 2022-2030*. https://www.precedenceresearch.com/artificial-intelligence-market
56. Rajan, K., & Saffiotti, A. (2017). Towards a science of integrated AI and Robotics. *Artificial Intelligence*, *247*, 1–9. https://doi.org/10.1016/j.artint.2017.03.003
57. Ramaswamy, K. V. (2018) "Technological Change, Automation and Employment: A Short Review of Theory and Evidence," International Review of Business and Economics: Vol. 2: Iss. 2, Article 1. Available at: https://digitalcommons.du.edu/irbe/vol2/iss2/1
58. Reinardy, S. (2012). Job security, satisfaction influence work commitment. Newspaper Research Journal, 33(1), 54-70.
59. Reynolds, M. R., Keith, T. Z., Flanagan, D. P., & Alfonso, V. C. (2013). A cross-battery, reference variable, confirmatory factor analytic investigation of the CHC

taxonomy. *Journal of School Psychology*, *51*(4), 535–555. https://doi.org/10.1016/j.jsp.2013.02.003

60. Schwabe H, Castellacci F (2020) Automation, workers' skills and job satisfaction. PLoS ONE 15(11): e0242929. https://doi.org/10.1371/journal.pone.0242929
61. Sharma, R.D. & Jyoti, Jeevan. (2009). Job satisfaction of university teachers: An empirical study. Journal of Services Research. 9. 51-80.
62. Stone, V. (2000), "Job Satisfaction in Radio News", [online] Available: http:www.missouri-edu./~jourvs/rasatis/html.
63. Tool, P. (2020, June 12). *The History of Industrial Automation*. Custom Machine Builder in Holland MI. https://www.paramounttool.com/the-history-of-industrial-automation/
64. Tractica. (2016). *Artificial Intelligence Market Forecasts*. https://omdia.tech.informa.com/topic-pages/artificial-intelligence.
65. U.S. Bureau of Labor Statistics. (2022, 9 september). *Software Developers, Quality Assurance Analysts, and Testers : Occupational Outlook Handbook: : U.S. Bureau of Labor Statistics*. https://www.bls.gov/ooh/computer-and-information-technology/software-developers.htm
66. Vujičić, D., Jovičić, A., Lalić, D., Gagić, S. & Cvejanov, A. (2014). The relation between job insecurity, job satisfaction and organizational commitment among employees in the tourism sector in Novi Sad. *Economic and Industrial Democracy*, *36*(4), 633–652. https://doi.org/10.1177/0143831x14527017
67. Zulu, J.J., and Banda, B.M. (2015) "The Impact of Labour Productivity on Economic Growth: The Case of Mauritius and South Africa," Southern African Journal of Policy and Development: Vol. 2 : No. 1 , Article 6. Available at: https://scholarship.law.cornell.edu/sajpd/vol2/iss1/6

Appendix

Table 10

'Share of non-routine analytic tasks'

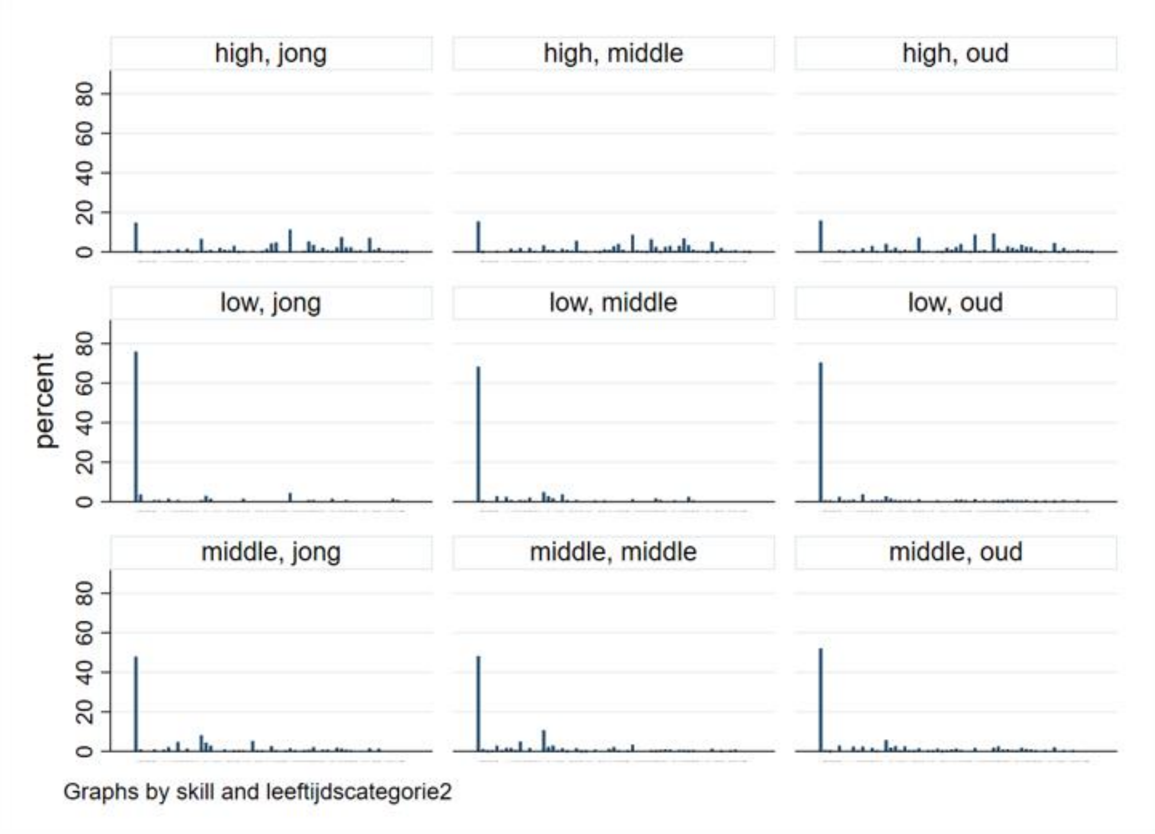


Table 11

'Share of non-routine interactive tasks'

Table 12

'Share of routine cognitive tasks'

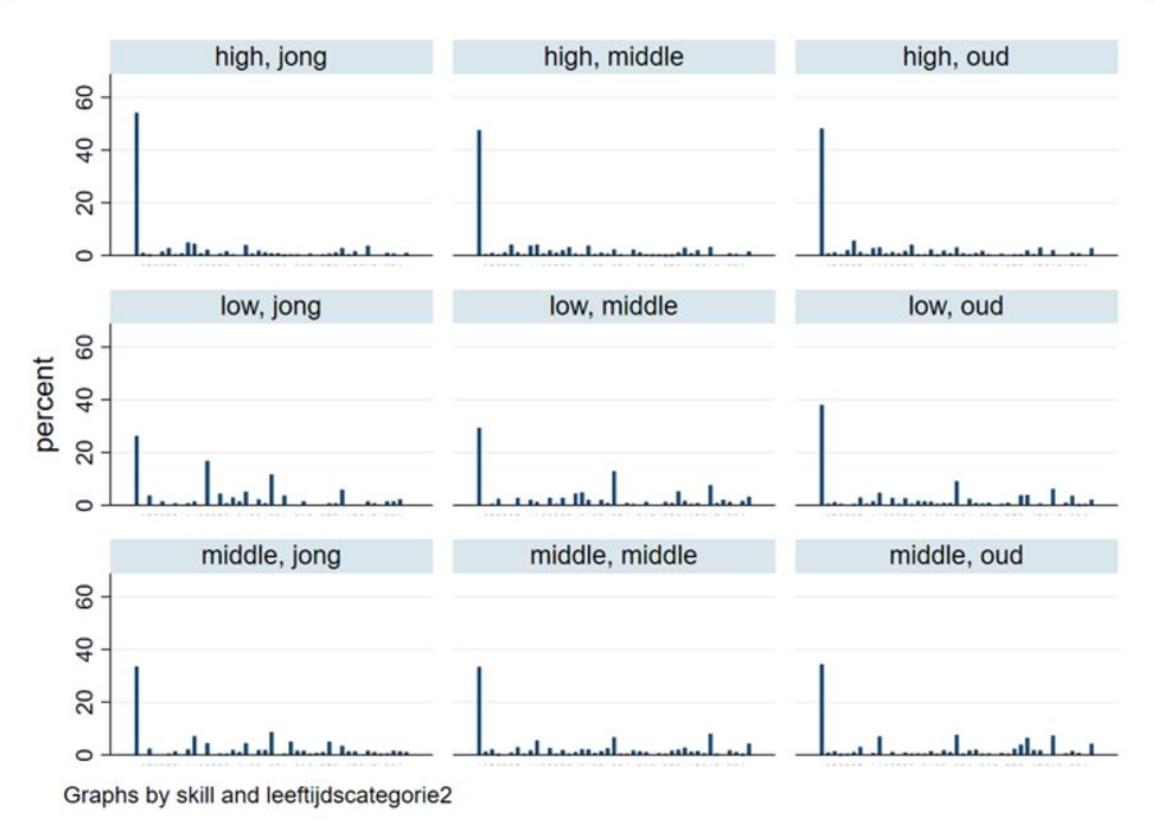


Table 13

'Share of routine manual tasks'

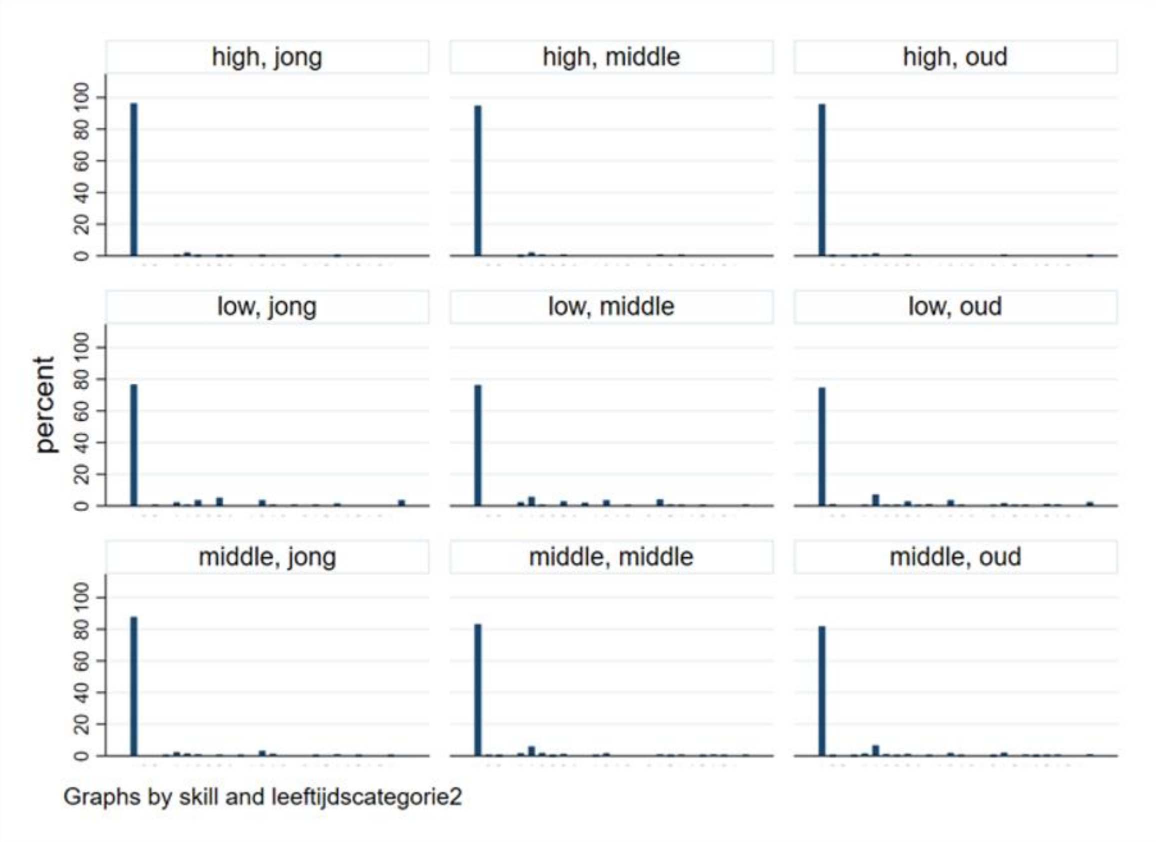


Table 14

'Share of non-routine manual tasks'