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Impact of AI on worker's Job satisfaction

An analysis about the growing impact of Artificial Intelligence on job satisfaction and security

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Executive summary

Purpose: The technological world is rapidly changing with the rise of Artificial Intelligence (AI), which makes employees increasingly aware of the consequences of automation and other AI tools on their jobs. Despite their positive attitudes towards innovation and development, they only start to see the impact of AI on their jobs which leads to enthusiastic people as well as individuals who fear losing their jobs. The resulting attitude toward AI in the workforce continues to change, which is the starting point of the present research paper. This analysis aims to explore the impact of AI on the workplace, by looking at employees' responses to a survey. Moreover, by exploring the difference in attitude between employees who work with or are familiar with AI versus the ones who are not, a profile of AI-knowledgeable employees who do not fear any job dissatisfaction can be painted. The findings of this paper aim to enhance the understanding and prediction of job satisfaction caused by the rise of AI.

Research Methodology: A behavioral study was conducted on data collected by the Organisation for Economic Co-operation and Development, who conducted a survey. The survey data quantifies the individual-level familiarity, adoption, attitudes, fear, and general impact regarding AI. Since this analysis follows an inductive research approach, the paper will start with exploratory research, Heckman Selection Model, and Random Forest, which is done to find the underlying factors that influence people to use AI and to then find out what affects job satisfaction. Subsequently, the factors will be incorporated in the regressions to measure the statistical significance of the different factors on job satisfaction.

Results: We have done the Heckman Selection Model, to firstly find out who is using AI. We found that the younger males, who like technology and positively look at the rise of AI are more likely to use AI at the workplace. Furthermore, the second stage showed that using AI in the workplace really increases the job satisfaction of the employees. Furthermore, AI positively affects employee happiness even when someone is not directly using AI. We created a Random Forest Approach with which we are able to predict the happiness of an employee when someone is using AI. We found that the general views people have on AI are very important in the level of job satisfaction.

Managerial Recommendations: After all the analyses, there are recommendations for the managers to do in the future to increase efficiency as well as performance by increasing job satisfaction among its employees. Firstly, younger male employees, who like technology and positively look at the rise of AI should be motivated the most by its managers to adapt AI in their jobs. Secondly, even the other employees should be motivated to use AI as this will increase their level of happiness, except for the Human resources, customer service and reporting tasks. Thirdly, by using the Random Forest managers are able to predict who is likely to become happier by using AI. Thus, by adapting these recommendations in the company the rise of AI will positively impact the job satisfaction of employees as well as the efficiency of the tasks, this will overall increase the company performance.

Keywords: Artificial Intelligence, Workforce, Job Satisfaction, Survey Data

1. Introduction

The key concepts, the overall problem, and the research relevance for academia and managers will be evaluated in this section, before moving on to the literature and the outcomes of the recent paper.

1.1 Problem Definition

All around the world, the adoption of Artificial Intelligence (AI) and its impact on businesses and society is a main topic. The AI market is growing massively every year, with a year-over-year growth of around 47% over the last five years, and is expected to increase by 26% for 2025 again (IBM Watson, 2022). AI is providing new benefits and efficiencies to organizations worldwide through automation capabilities, a variety of virtual assistants, and implementations in IT processes. However, AI is not a new concept, since the introduction of AI in the 1950s, AI has changed and evolved. While it started with machine intelligence such as the Imitation Game[1], it rapidly grew into more advanced machine learning activities, which also came with struggles for AI research. During this time, AI became a mainstream idea, however, the U.S. government started to lose interest and cut funding (Toosi, et.al. 2021). Despite this throwback, AI kept evolving till how we know it today. Eventually for this study we use AI as a concept which represents the process of computers accomplishing tasks that traditionally require human intelligence (Chaffey, Ellis-Chadwick, 2019).

Nevertheless, besides all the benefits this new technological development generates, it also comes with fallbacks. For example, when we look back at the rise of computers, the benefits were endless and are still visible today, however, they also changed the work environment massively, which impacted certain jobs. During that time, this had led to increased fear at employees and decreased happiness at their jobs (Malamud, Pop-Eleches 2011). This fear was caused by change in job tasks due to the rise of the computer, which means that there was a change in skill requirement for the employees. This is an investment of resources for existing workers, and often older people or people who did not like the technological developments were less likely to learn these skills easily. This change led to a loss in jobs for

[1] The imitation game was proposed by Alan Turing in 1950, where he created a test that involved a human judge engaging with a computer and a human based on text. The judge's task is to find out which participant is the machine. This is a measure of what the abilities are of a computer to use intelligent behavior (Turing, 1950).

mainly the older generation of workers, as people who did not start using computers in their job were 25% less likely to continue working or did stop enjoy their tasks, while people who did use computers were even more likely to continue working happily after their retirement age (Friedberg, 2003; Autor, 2015).

History shows that technological developments can have a negative and positive impact on jobs. The last couple of years, a new technological development has risen in most companies, in the form of AI adaptation. However, with this rise, there comes uncertainty about what the consequences will be for the jobs in the future. Therefore this research focuses on the impact of AI on job satisfaction. This will be done by answering the following research question:

What is the impact of the rise of Artificial Intelligence in the workplace on job satisfaction for employees?

To address this question a database from the Organisation for Economic Co-operation and Development (OECD) has been used. This database is gathered by contacting this organization and revealing the relevance of this paper, which motivated them to provide me with their survey data on employees and their feeling toward AI at the workplace. With the use of this dataset multiple interesting questions can be answered which will finally lead to a clear answer of our research question. Firstly, I will use a Heckman Selection Model which will help me find an answer to the question: what makes people use AI? This question will help us understand the underlying motivations for people to use AI at their workplace. Afterwards the second stage of the Heckman Selection Model is used to answer questions regarding: What makes people satisfied in their job? and What makes AI users satisfied in their job? Hereby I can make a distinction on the difference and similarities on what drives job satisfaction for everyone and what drives it for AI users specifically. Lastly, a Random Forest approach is used to help policymakers and managers predict who AI users are and how we can optimize the job satisfaction for their employees?

1.2 Research Relevance - Academic and Managerial

The questions answered in this paper will help managers and policymakers to get some concrete action points which will help them to increase the level of happiness for employees. Academically, researchers will gather new insights regarding specific sectors and their ability to adapt to AI. They will read about what the real influence AI has on the wellbeing of people.

1.2.1 Academic relevance

Recent literature has explored the economic and technological implications of AI adaptation, but comprehensive research on its effects on people's psychological well-being remains limited. The positive effects of AI are often shown to give a perspective on how people will be able to adapt to a working life with AI (Autor, et.al., 2003; Korinek, 2023). However, this does not mean that the negative aspects are never addressed, but rather they mainly focus on privacy risks, ethical concerns, and biases (Du, et.al., 2021). Where most research focuses on those extinctions, there are studies that have been exploring the general implications of AI in the labor market (Strohmeier, Piazza, 2015; Pereira, et. al., 2023; Müller, et.al., 2020). However, studies do lack in giving insights on human centric outcomes, such as employee well-being and satisfaction, while mostly focusing on performance outcomes, such as economic numbers. I will help to overcome this gap by focusing on job satisfaction in correlation with AI in this study.

Moreover, there is a lack in understanding the perception of employees on AI. This gap I will fill by using specific variables that investigate the relation of the attitude, fear and expectation on AI to the happiness employees experience. Studies often use variables like real job loss, use of AI and task changes, instead of really investigating what the impact is on the feelings of employees (Jia, et.al. 2023). By looking more into the attitude towards AI, or the feeling someone has about AI will help visualize the emotional impact of AI on the people.

Lastly, researchers have been providing insights on the impact of AI that found conclusions related to lower- versus higher-skilled employees, or general insights about job redesign and workplace dynamic (Jia, et. al. 2023; Autor, 2015; Karabarbounis, 2024). None of these papers dived deeper into industry-specific differences, which could however give some very interesting insights. Therefore, in this study I will dive deeper into the difference in manufacturing and finance sector employees to see whether the impact of AI on the well-being differs across those sectors. This specification will be of great relevance to understand in what types of sectors the importance of adapting to AI will be more relevant.

1.2.2 Managerial relevance

The relevance of this research goes beyond science, it also provides managerial guidance in the relationships among AI adaptation and employee well-being. This is critical for managers to increase the value of AI in their company while encouraging employees to learn new technologies and inspire them to focus on their individual well-being. While it is critical for managers to do so, it does come with difficulties for them as it is hard to implement new technologies perfectly in their company. Thus, this research will give managers some concrete action points that will help them to adapt to this technology properly.

Firstly, I will give them tools to understand which employees are likely to use AI at the workplace. This will help managers to know what type of employees they can target to promote AI use to. Those people will increase their well-being by adapting to this new technology. Secondly, when they know who they need to target, this paper will tell them how they can promote AI use to increase job satisfaction. This means that when managers focus on those specific variables in their company, the employees who want to use AI are increasing their job satisfaction. Lastly, if managers want everyone to adapt AI in their jobs, I will tell them which changes they can make to make everyone more satisfied whether or not they are already working with AI tools.

1.3 Content of this research paper

In this paper, I will study the impact of AI on job satisfaction, by conducting a comprehensive analysis that delves into the dynamics of AI, its implementation in the workplace, the employees' satisfaction, ultimately guiding the employer toward recommendations for the future that ensures the well-being of the employee while utilizing the positive aspects of AI adaptations. The dataset used in this paper was received by the OECD library including specific descriptives as well as answers from a survey, more information is shown in the data description. In the results, this data is used to do simple regressions, a Heckman Selection Model as well as a Random Forest approach to finally answer the research question and recommend future managers.

2. Theoretical Framework

This section discusses prior literature about the fundamental concepts that are necessary to investigate to answer the research question. First, the notion of job satisfaction and the wellbeing of the employee be discussed. Next, the application of AI, its future impact, and the concepts of AI will be outlined, and lastly, this will all come together by combining job satisfaction in relation to AI.

2.1 The feelings workers experience in the workplace

Firms often say that they care about the well-being of their employees, is this just because of their good hearts, or does this make scientifically sense? Oswald, et.al. (2015) have shown that there is a link between human happiness and human productivity. This means that economists should focus on the emotional well-being of people as a causal force of productivity, as job satisfaction will give a higher productivity of the employee. This means that managers would want to do everything to increase the job satisfaction of their employees to get the best performance from its workers.

To gain competitive advantages in the manufacturing or finance industry, enhancing employees' job satisfaction is important, next to all the innovation and good work in the field. Job satisfaction can be referred to as a positive psychological feeling in relation to work performance (Schneider, 2003). There are multiple types of theories that are prominent in the literature that look at the causes of job satisfaction.

The first type are situational theories, they argue that the satisfaction is driven by the nature of someone's job (Judge, et. al 2017). Here they focus on five specific elements that will create the highest job satisfaction for someone. (1) task identity, this focuses on how much someone can identify itself with the job; (2) task significance, the degree of importance one's job feels; (3) skill variety, how varied are the tasks of someone's job; (4) autonomy, how much control does someone have over their job; and (5) feedback, how much feedback does the job itself give about the employees performance. With these five concepts the focus really is about the nature of the job, and the higher those factors score the happier the employee should be. This also really aims to look at the self-growth the individual can get from its job (Judge, et. al. 2017; Hackman, et. al. 2015).

Another theory that is often used in researching job satisfaction focuses more on the surroundings of the job and the work environment instead of the job specifically. This means that things such as salary, interpersonal relationships and working environment are at the top of increasing the level of job satisfaction. These factors are more involved with money, status, security and the conditions in which you can do the job. This focuses on the feelings you encounter while working, but not specifically on what you are working. This difference means that when someone still likes his job, however he fears losing it, this definitely influences the satisfaction level with more than only the fact that he likes it. This is in line with the study that showed that when employees know their salary as well as their colleagues and they are earning below the median, they state that they are less satisfied with their jobs, while when they did not know this, they were still satisfied (Perez-Truglia, 2020; Guerci, et. al. 2022).

The last theories combine the first two into a framework that explains job satisfaction based on the job itself as well as the surroundings. An example of this theory is Herzberg's two-factor theory. This theory shows the difference between motivation factors and hygiene factors that affect job satisfaction. The motivation factors are the most important factors related to the individual's need for self-growth and self-actualization, such as the work itself, responsibility, and achievement. Hygiene factors are related to the need of the individual to avoid unpleasantness, such as salary, working conditions, and interpersonal relationships. This means that motivation factors will lead to a positive attitude toward the job and hygiene factors lead to a positive attitude toward the surroundings of doing the jobs (Alshmemri, Akl, Maude, 2017; Herzbergm Mausner, Snydermann, 1959). Although dissatisfaction will not occur if one of the factors is not fulfilled, the attitude toward the job will be more positive if they are fulfilled. This means that factors such as these will work as moderating variables to have a larger impact in the end when looking at this research.

Many researchers support this two-factor theory, however, studies have been challenging this theory as well. The limitations include the overemphasis of the motivation factors over the hygiene factors, especially salary and status. Studies such as the one from Kotni and Karumuri (2018) show that hygiene factors have an even more significant impact on job satisfaction than motivational factors. By using these factors as indicators for happiness at the workplace, it enables researchers to have a detailed analysis of the satisfactory and unsatisfactory parts of the job and work environment. A lot of studies used this theory in combination with survey data, which did sometimes create a social desirability bias problem, which is something that should be kept in mind while using this theory in combination with surveys (Lee, et. al. 2023).

Next to factors like workplace conditions and motivation that influence job satisfaction, job insecurity significantly impacts employee well-being. Job insecurity is the perceived fear of losing one's job in the near future, and in periods where restructuring, downsizing and economic fluctuations are common feelings of insecurity have a large impact on employees across various industries (Kuvalekar, Lipnowski, 2020). Furthermore, there is a growing gap between the demand for skilled workers and the available supply.

This shortage will have a massive effect on the global economy because the lack of skilled labor will slow down economic growth and job creation in these sectors. This skill gap refers to the fact that potential and current workers do not have the required skills to perform the jobs, which is mostly quashed by the education system. The education system is not developed at the same speed as the world around them is, this means that they do not produce enough qualified specialists. Therefore, there is a big need for collaboration between companies and universities to ensure that potential employees have the necessary skills to keep up with the evolving technological landscape (Lee, Jung, 2023; McGuinness, et.al., 2018).

While companies are eager to find new employees, current workers are experiencing more job insecurity due to this occurrence. This exerts a negative impact on employees' job satisfaction through mechanisms such as psychological distress, as the fear of losing your job can lead to heightened stress levels and a reduced overall well-being (Piccoli, Reisel, Witte, 2021). Furthermore, the insecurity can impact the interpersonal relationships in the workplace, people become more guarded and therefore less collaborative leading to mistrust among colleagues. Moreover, job insecurity can impair the performance as people have a harder time concentrating on tasks, have a lower level of creativity and become less motivated (Kundi, et. al., 2020).

This gap is largely attributed to the education system's failure to keep pace with technological advancements. As digital technologies evolve rapidly and become more complex, higher education institutions are struggling to adapt accordingly. Thus, there is an urgent need for collaboration between companies and universities to ensure that employees are equipped with the necessary skills to thrive in the evolving digital landscape.

2.2 The rise of Artificial Intelligence

As already mentioned before, due to the rapid development of AI and all the different applications, it is difficult to define the concept of AI. Hence, some definitions will help gain a better understanding of this principle, and some of them will be considered here.

A well-known definition reaches back around seventy years ago, and is based on Alan Turing's ideas regarding the intelligence of the computer, who is commonly regarded as the founder of AI, in 1950 (Muggleton, 2014). The reader could be familiar with this mathematician because during World War II he successfully worked on a machine that decoded the German Enigma, which is considered one of the first Artificial Machine-like computers. He created the Turing test, in which a computer is considered artificially intelligent when it is able to imitate a human and learn like a human child. This test consisted of three participants; a computer, a human interviewer, and a human who answered. The interrogator will ask both of them questions in order to understand who the real person is. Eventually, Turing believes when there is a sufficient proportion of people who are unable to distinguish the computer from the person, then the computer can be considered intelligent (Guo, 2015; Muggleton, 2014). Thus, in his belief, AI involves natural language processing, storing knowledge, reason based on the stored data, and machine learning, as it must be able to learn from the environment and past (Brynjolfsson, 2022; Guo, et.al., 2015; Muggleton, 2014).

Another more recent definition is from Grewal (2014), who looked into all the different definitions that came around in the last seventy years. He evaluated the good aspects as well as the drawbacks to eventually come up with his recommended definition of AI. This states that AI is a system that collects knowledge and information that is used to interpret and process this into the intelligence of the universe, and it disseminates it to a form of actionable intelligence (Grewal, 2014).

Now that the definition and history of AI is clear, I will explain to you what people think about AI and the adoption of this.

2.3 Artificial Intelligence in the Workplace

There already exists an amount of literature about the effect of the adoption of new technologies and the change in work environments. This can help us understand the predicted changes that will happen due to the introduction of AI in the workplace. According to Herbert & Tuminaro (2007), employers are eager to implement new technologies to their businesses in order to increase efficiency. However, studies demonstrated that these new technologies may cause an increase in error (Haber, Carmelli, 2023). When we compare this new stage in time, with the rise of the computer and telecommunications, we see that during that period the jobs were radically transformed, resulting in boundary workplaces. This development increased the flexibility of employees, however, it also increased the transparency that put more pressure on the employee (Herbert, Tuminaro, 2007; Feigenbaum, Gross, 2024). Thus, by looking at the past, we can say that new technologies may provoke stress, and affect the employee's psychological health, which could lead to a decrease in productivity and job satisfaction (Zöllner, Sulíková, 2021; Feigenbaum, Gross, 2024).

2.3.1 Why do people use AI in their job?

AI is used in many different aspects in the work environment already and the interest is rising, however what is the reason for people to use AI in their jobs? A trend that has been seen a lot is in headhunting and job applications, often companies use AI by predicting which (potential) applicants would fit the role best. This increases the efficiency in the application process and reduces the costs of the recruitment process (van Esch, et.al., 2019). Another reason why people use AI is due to the enhanced data analysis that can be done with these models. Machine learning models currently exceed the performance of people when doing predictive tasks. This means that employees can use more advanced models to predict specific situations more clearly which reduces mistakes and improves the performance (Agarwal, 2024). Another advantage that AI can give employees is mainly for the marketing department, by personalization and getting customer insights. This process is often too time consuming or impossible without the use of AI models, thus this gave the marketing industry new interesting tools to market their products (Bleier, Eisenbeiss, 2015). These three applications of AI are only a small part of how people use AI and it shows that it will increase performance and efficiency for employees.

2.3.2 Is the resistance of most employees to use AI fair?

Recent studies show that employees have an internal resistance to adapting to new technologies, due to anxiety of being less needed or less productive as a result of the implementation of this technology (Župerkienė, 2023). Thus, it is due to the uncertainty of the improvement or pay-off of the new technology that employees tend to be resistant to this, and this causes a conflict of interest with the employer. Employers always want to improve their business's efficiency by using improved new technologies (Lameijer, Pereira, Antony, 2021). When we look at the application of AI, it is said that it is unlikely that AI will entirely replace human labor in most cases, therefore it is very important that employees accept this new technology to make it work for the employers (Clark, Gevorkyan, 2020). However, it is likely that this new technology will change the structure of jobs as some tasks will be automated in the foreseeable future. These automated tasks still need to be coordinated by real people, this will relieve employees of some demanding tasks, but it can also decrease their job satisfaction, and deskill the people (Clark, Gevorkyan, 2020; Župerkienė, 2023).

To overcome the resistance of the employees and to reach the promised benefits of AI, the drivers of the AI applications need to be understood by the employees and they should also become eager to apply this new technology in their jobs. However, when companies try to implement new technologies, it is important that the skills that are needed for this development are there on the employee's side. Unfortunately, recent studies have indicated that there is a gap between the supply and demand for technological skills in the labor market, which is even more apparent in jobs with AI skills. When looking at the evolution of the demand for AI skills between 2010-2019, it is shown that the demand for employees has increased by ten times in the United States. While this sounds like a lot, this will only keep increasing in the upcoming years in multiple sectors (Alekseeva, et. al. 2021). AI skills are mostly required in the information industry, with jobs in Scientific and technical services, just below this group are the industries of Finance, Insurance, Agriculture, and Manufacturing, which all have a share of around 2% of the AI vacancies. This shows the increasing importance (Alekseeva, et. al. 2021).

Unfortunately, still most public attention is paid to the concerns regarding the impact of AI on jobs, which is caused by the new capabilities of this technology, and the achievement of making proper predictions. The prediction technology has multiple effects on the labor market: (1) removing predicting tasks, as current predicting tasks human do can be performed by AI; (2) automated predictions can increase efficiency, as machines will respond quicker and therefore win time over people; (3) automated predictions may increase the labor productivity, with that use of AI human tasks can get more precise and better performed; and (4) automated predictions reduces the uncertainty on new tasks (Agrawal, et.al. 2019). Overall, for a company these effects can positively impact the performance, however for individual workers the impact of these effects really depends on the degree to which the skill they bring in their job is related to predictions. Therefore, it is definitely possible that people who do work a lot with predictions will experience negative impacts of AI as some of their tasks will be removed.

However, where some people fear the rise of automation and the loss of jobs or the lack of satisfaction, there are other papers that motivate why automation also comes with positive encounters and why our jobs are safe and our work life will keep improving. It is true, there are jobs changing, and being removed, however this is something that happens every time and while people think this is large, the increase in demand for other job areas is far more than for what is being removed (Autor, 2015). According to Autor (2015), the rise of automation should not be something we fear for, it is something that we should adapt to and what will make our jobs even more exciting, by asking more of our creative talents, instead of the repeated tasks which the computer can now take over. This change in job tasks will eventually improve the well-being of the employees.

2.3.3 Increase of creativity and improvement of jobs due to AI

Where research showed that AI does make the work more efficient, it is stated that AI can also generate other benefits, for example it increases the creativity of the employees (Jia, et.al., 2021). Where AI increases creativity it will make the people's mind work harder on their creative sides, which will lead to proud moments when people find solutions to problems they could not fix before, which increases job satisfaction eventually. However, there is a difference in the improvement when using AI based on the level of skills of the employee, this means that lower-skilled employees make less improvements in creativity and efficiency which will then decrease the impact of AI on job satisfaction. This knowledge will be tested during this study as well as people from different sectors with different levels of skills will be asked the same questions regarding the impact of AI on their job satisfaction.

Table 2.1 *Literature Review Table*

Study	Context	Method	Data	Type of Artificial intelligence *	Type of Job satisfaction**	Relevant findings
Feigenbaum , Gross, 2024	The impact of automation on labor market	Census-linking method	longitudinal sample of AT & T	Automation investment by AT & T	Employment change instead of jobs lost	This study found that the automation investment between 1920 and 1940 has eliminated a lot of jobs, however it positively impacted the overall employment as more new categories of work were created.
Agrawal, et.al. 2019	The impact of automated predictions.	Task-based model	Cross-sectional, interview	Automation predictions	Removement of tasks reduces satisfaction	This study found that AI in the form of prediction making is performing more human tasks which showed that there is a reformation in the jobs.
Benjamin, et.al. 2014	How can we track the well-being of people?	OLS, robustness analysis	Survey	X	Framework of how wellbeing should be tracked	This study found that the success based on GDP is not focusing on the wellbeing of people. They created a survey which helps measure the wellbeing of employees.
Autor, 2015	Future and past of automation in the workplace	Literature	Longitudinal studies	Automation of repetitive tasks	change in labor market, fear for job loss/change	This study shows that automation has not wiped out a lot of jobs and instead people are still happy working while automation tasks are performed not performed by them.
Jia, et.al., 20	Impact of AI on the creativity of the employees	Quantitative and Qualitative	Field experiment, interviews	AI assistance in repetitive tasks	Increased employee creativity	This study found that creativity is skill-biased when AI driven, with the best impact for middle- skilled employees.
This study	The impact of AI rise on job satisfaction	Heckman selection, Random Forest	Survey data	AI for different tasks	Happiness level of employee	We found that the younger males, who like technology and positively look at the rise of AI are more likely to use AI at the workplace. Furthermore, using AI increases the job satisfaction of the employees.

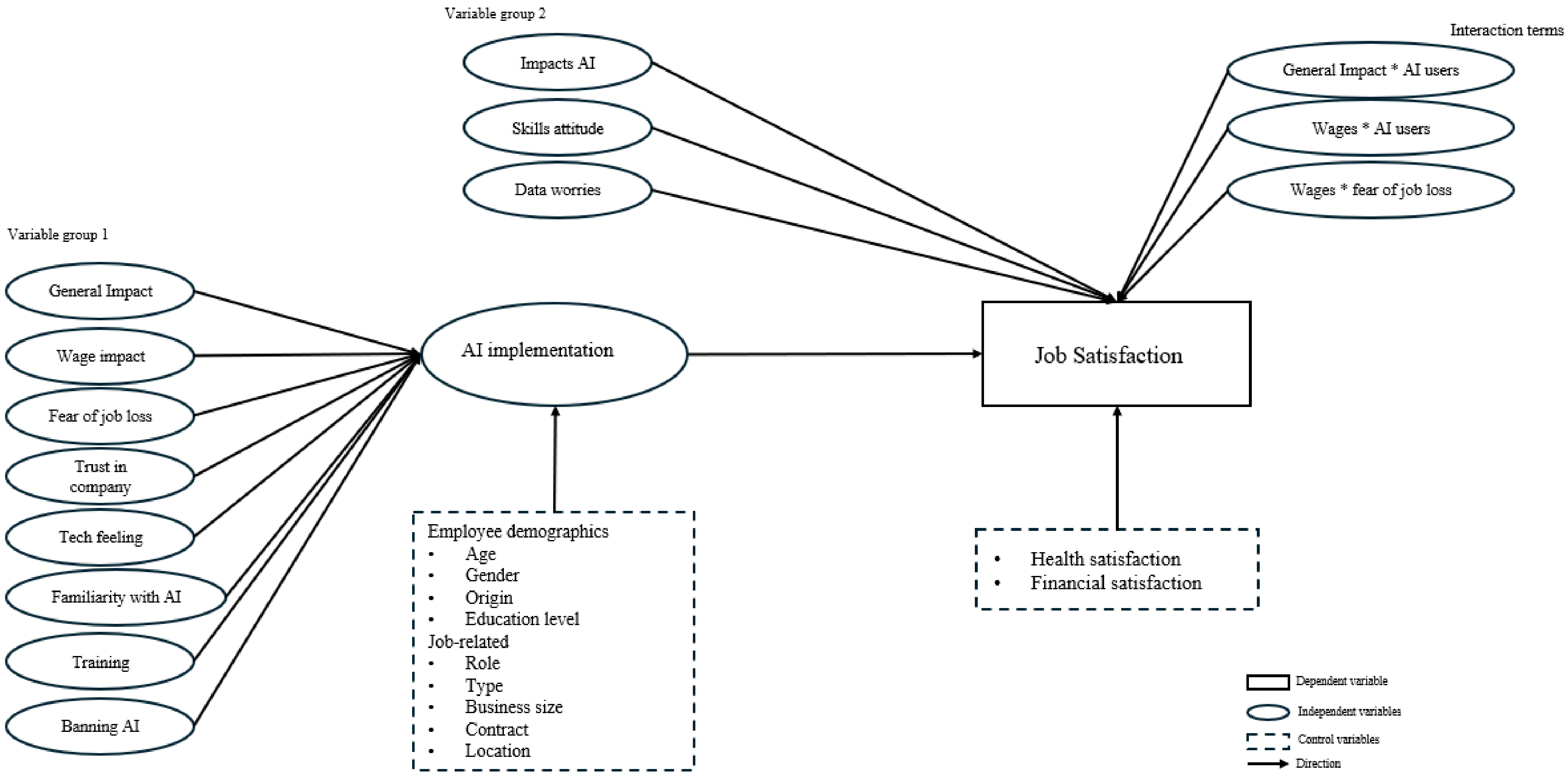
** Type of AI: How was the topic artificial intelligence adopted in the literature? In three automation as a type of articles artificial intelligence is researched. In JIa's paper, AI assistance in repetitive tasks was represented and in this paper different types of AI are analyzed such as automation, design etc.*

*** Type of job satisfaction:In the different articles different aspects of job satisfactions are layed out. Some look at job loss and the change in jobs that comes with it, while others focus on the happiness and well-being as a whole of the employee.*

2.4 Conceptual Framework

Based on the previous literature mentioned above, a conceptual framework that explains the effects that are expected is created and can be found in figure 2.1. This figure gives an overview of the effects that are expected of the impact of AI use on the overall happiness of the employees. The first group of variables is impacting the question whether or not someone is likely to use AI, which also indirectly will then impact job satisfaction. Furthermore, the second variable group are variables related to AI, which directly impact job satisfaction. Furthermore, there are some control variables incorporated in this model as well. An explanation of all the variables can be found in table 4.1. With the use of the Heckman Selection model and these different variables we are going to try to answer how AI impacts job satisfaction.

Figure 2.1: Conceptual framework based on previous studies.



3. Materials & Methods

3.1 Materials

After evaluating multiple datasets, I came in contact with employees of the Organisation for Economic Co-operation and Development (OECD), which are located in over 100 countries. After motivating the relevance of my paper, they provided me with a rich dataset on worker survey data. OECD is the Organisation for Economic Co-operation and Development and is an international organization that creates insights by analyzing different topics to build better policies in the world. The OECD conducts a survey every year, targeting specific groups of people that are relevant to that year's Economic Outlook (OECD, 2023). The Economic Outlook provides historical trends and future projections for a range of different economic statistics, which vary per year. The sample size corresponds to 5,334 employees who filled in the survey, between January and February 2022.

A sociodemographic, AI-related, and work-related data sheet was used to collect employees' information, including job, age, origin, education, familiarity with AI, attitudes toward AI, etc. Participants were also asked to report their satisfaction with their job and overall satisfaction with life. The instrument is a 90-item self-reported survey that often uses a 5-point Likert scale (1=strongly agree, 5=strongly disagree) or it uses a yes or no question. The survey was sent online to panels and individuals who have indicated a willingness to participate in surveys for compensation (Lane, et.al., 2023).

The dataset was saved in SPSS (Statistical Package for Social Science) and the study results were analyzed by using R (Programming language). Descriptive statistics were used to describe the basic descriptives of the employees in the manufacturing and finance sectors. After descriptive analyses, Pearson's correlations and model-free analysis were conducted to examine the differences and relations between the dependent and independent variables. Afterward, multiple methods were conducted over the dataset, which can be read more in-depth later.

3.1.1 Survey Data

The survey was online using panels and databases of individuals who indicated that they were willing to participate in surveys. The survey consisted of multiple sections of questions: (1) demographics, (2) adoption of AI, (3) detailed information from adopters/non-adopters, (4) AI impact for users, (5) impact on companies, (6) AI impact in general, (7) policies. Not all participants received the same questions; the questions varied based on their previous answers. For details on the survey questions, please refer to the appendix.

In order to make sure all the participants were on the same line in regards to the definition of AI, the definition was given: “AI is what enables smart computer programs and machines to carry out tasks that would typically require human intelligence”. No other definitions were specifically defined during the survey.

The provided data was collected from mid-January 2022, until mid-February 2022, consisting of worker data related to their well-being, their attitude toward AI, and some demographic questions.

3.1.2 Potential survey biases

There are some common biases that can appear when doing research based on survey data. Within this section, I will go over the different potential biases and why they are not at risk in this paper. Method biases are an issue because they are a source of measurement error, which could threaten the validity of the conclusions from the paper (Podsakoff, et.al., 2003). The first potential bias is the Common Method Bias, this can result when the method influences the relationships between variables. There are multiple potential sources of common method biases, one is that method effects are produced by a common source. This happens when a respondent provides information for both the predictor and criterion variables, as this could lead to high correlations, socially favorable answers, and mood affected information. Another source is the method effects are produced by item characteristics, which influences the respondent based on the design and wording of the survey. Furthermore effects can be produced by item context which means that the context in which the questions are shown can influence the respondents answers. Lastly, the effects produced by measurement context refers to biases from external factors that could influence the respondents answers (Podsakoff, et.al., 2003).

Now, it is important to know how we control this, and to make sure that this common method bias does not concern this research. Regarding methods effects produced by common source, this is prevented by asking questions about AI not during the same parts as job satisfaction, by separating this in the survey there is a further distinction between predictor and criterion variables. When looking at the method effects produced by item characteristics, the survey is clearly worded and neutral, as by using examples in the explanations it helps clarify AI without biasing responses. Furthermore, for method effects produced by measurement context the survey used words such as advanced technologies in the introduction which prevents biasing of respondents who have prejudices about AI. Thus, by properly designing this survey and reducing external factors by implementing this survey online this research reduces the biases from all the method effects, thereby the reliability and credibility of this data is kept at a high level.

Another type of bias that should be addressed is the non-response bias. This occurs when the individuals who respond to the survey are significantly different from those who do not. This can happen when specific demographics are underrepresented. While this may be the case there are strategies used in this survey research that reduces the risk of non-response bias. For example, the weighting adjustments, the data is weighted by age, gender and education. This makes the sample more accurately reflecting the population, which mitigates the impact of different response rates among the various demographic groups. Furthermore, targeted follow-ups were done to increase the participation rate among the underrepresented workers. These two reasons reduce the risk of non-response bias, however, there are still limitations that show a potential concern. There is no data on the non-respondent characteristics which makes comparing and analyzing the difference impossible. Furthermore, there is only one contact method used: online, which could lead to a lower audience. For instance, phone calls, and posts could have made sure we reached a broader audience. However, when concluding all the possibilities, a lot has been done to reduce the risk of this bias.

3.1.3 Construction of the dependent variable

In this study we used two-factor variables to indicate whether an individual was satisfied with their job or not. People who did not answer this question, or the ones related to this were removed from the dataset before I received it, which left me with a dataset of 5334 individuals.

The job satisfaction variable was used as dependent variable for the analysis, which had the following values, according to the 5-Point Likert-scale:

Job satisfaction

1 = Very satisfied

2 = Somewhat satisfied

3 = Neither satisfied nor dissatisfied

4 = Somewhat dissatisfied

5 = Very dissatisfied

Job satisfaction was measured by how people perceive their feelings toward their work, whether they are happy in the environment, whether they like the way they are going, and whether they believe they are actually happy with what they are doing in their job.

3.1.4 Missing values

Initially, there were 5334 respondents who participated in the survey, with many missing values. These missing values were not a result of people quitting the survey after a while or a technical error. These missing values were created due to the fact that not everyone answered the same questions, because when someone indicated that they used AI on a daily basis they were led to another group of questions in comparison with someone who never used AI before. As many machine learning methods cannot handle missing data easily, the complete data was separated into four different smaller datasets for these models. (1) Finance participants who use AI, (2) Finance participants who do not use AI, (3) Manufacturing participants who use AI, and (4) Manufacturing participants who do not use AI. In this way, no valuable information was lost and the models were able to run properly without missing data issues. It is important to note that all these participants had answers regarding the control variables as well as the dependent variable, in this way it is still possible to compare the outcomes with each other.

3.1.5 Specific variables AI users vs non-AI users

In this paper, there is a clear distinction between analyzing people who do use AI in their work environment and people who are non-AI users. This distinction is important, because with this difference we are able to see what drives people to use AI, before even looking if this makes them happier or not. This distinction can only be made if there are specific variables that are only concerning one of these groups and use them separately to compare the outcomes with each other. For example, variables such as the likelihood of the employee working with AI in the future, and the specific impact of an employee not using AI in the tasks are examples of variables that are represented only in the Non-user AI datapart. However, there are also a lot of questions the same for both groups as this will help understand the different thoughts of them. A deeper explanation of these different variables can be found in the data description section.

3.2 Methods

This part discusses the theoretical explanation of the several techniques that are used to analyze the data set and to construct a model that explains the AI factors affecting job satisfaction and job insecurity. This problem is a classification problem, as the dependent variable is measured in different categorical values, therefore multiple machine learning and simple methods can be used to analyze this issue. First, the Heckman Selection method is used to check whether the employees who use AI are significantly similar to those who do not and then a simple Ordinary Least Squares regression was done to see the first simple outcomes. Secondly, in the aim to improve the accuracy of the prediction even more than of this simple regression, a machine learning method is applied, named Random Forest approach. This method could improve the accuracy rate when predicting happiness, however this will come at the expense of the level of interpretability of the outcome. In this section, the different methods used will be explained as well as the understanding of the interpretation of the models.

3.2.1 Sample selection: Heckman's selection method

A common issue in empirical research where you compare two different groups is the issue of selection bias. Selection bias arises when the samples that are used for the analysis are not perfectly similar on all the parts except the one that differentiates them. This can happen when it is only representative of a small part of the population due to specific selection criteria. This issue can lead to an inconsistent result which will not have the correct conclusions at the end. However, to overcome this issue, the Heckman Selection model can be used. The Heckman Selection Model consists of two different stages, with the first leading to the selection equation and the second one is the outcome equation (Heckman, 1974).

The selection equation models the probability of an individual being included in the sample. This measures the chance of an individual being in the sample based on specific variables. This is specified as follows:

$$Z^* = W\gamma + v$$

Where Z^* is the latent variable, which represents the propensity to use AI. W shows the explanatory variables that influence this use of AI, which can be demographic characteristics for example. γ are the coefficients that represent the relationship of W and Z^*, and v is the error term that captures the unobserved factors. When the Z^* value is above the threshold (in this paper above zero), it indicates that the individual is likely to use AI at work (Marchenk, Genton, 2012; Heckman, 1974). This first stage is a Probit model to obtain the inverse Mills Ratio, which will correct for selection bias in the second stage. The inverse Mills Ratio is specified as:

$$\lambda = \frac{\phi(W\gamma)}{\Phi(W\gamma)}$$

Where Φ represents the probability function of the standard normal distribution, and ϕ shows the cumulative distribution of the standard normal distribution. λ is the Inverse Mills ratio that is used in the later stage to correct for the possible selection bias (Marchenk, Genton, 2012; Heckman, 1974).

The outcome equation model, the second stage, looks at the outcome of interest, job satisfaction, for those who use AI in 5.3, and for everyone in 5.2. This is specified as follows:

$$Y = X\beta + \rho\lambda + \varepsilon$$

Where Y is the outcome variable of interest, job satisfaction. $X\beta$ are the explanatory variables with their estimated coefficients and the ε is the error term. λ refers to the inverse Mills ratio. By including this coefficient the model adjusts for any selection bias (Marchenk, Genton, 2012; Heckman, 1974).

3.2.2 Random Forest

Multiple linear regressions and Ordinary Least Squares regressions are highly interpretable, however these methods could have a lower than optimal accuracy rate. Therefore, a machine learning method, Random Forest, is introduced to try to increase the accuracy of the model. This is a method that uses multiple decision trees for a classification problem to make a more accurate prediction. Random forest uses observations from the training dataset to assign them to the occurring class, and in this way the model learns to recognize which observations belong to which specific class.

Random forests consist of multiple trees, which combines the performance of numerous decision trees to predict the classification (Rodriguez-Galiano et al., 2015). Each individual decision tree is created for a bootstrap sample of the total data, which will then be resistant to overfitting. Bootstrapping is a technique of resampling with replacement from the original dataset. It starts with the original dataset with n observations and will generate multiple bootstrap samples, each consisting of n random observations from the original dataset with replacement. This new dataset is then used for the Random Forest, to be sure to reduce the chance of overfitting (Behr, Weinblat, 2017).

Multiple trees are grown, and with *K* trees grown, the regression predictor is as follows:

$$f\,(x) \;=\; \frac{1}{K}\sum_{k=1}^{K} T\,(x)$$

Where *f (x)* is the final prediction made by the random forest when the input *x* is given, with a *K* number of decision trees. The right part of the formula represents the average of the predictions made by all the different decision trees within the random forest, with *T (x)* being the prediction of a specific K-th tree. All the predictions of the multiple trees together reduces the variance in comparison with only looking at one, as with random forest they are less likely to capture the noise in the data. In combination with the diversity among the different decision trees, it will make the random forest more reliable in making predictions (Davis, Heller, 2017).

After the random forest is formed, there is a possibility to tune the hyperparameters of the model. This refers to the process in which the different parameters that control the model can be changed. These hyperparameters are set before training the random forest and by tuning them properly these changes can significantly improve the model in its accuracy as well as its efficiency. For example, the number of trees and the number of gestures at each split can be set into a specific amount that could change the performance (Coulombe, 2024). Moreover, when the model is finalized it is important to estimate the test error of the model. Without performing a cross-validation, it is possible to evaluate the performance of the Random Forest by looking at the Out-Of-Bag Error rate. This is evaluated by looking at the observations of the original data that were not selected for the training of the k-th tree process, this is the out-of-bag sample. The model will then make a separate prediction for each OOB observation and compare those predictions with the actual values. The eventual OOB rate is the average of the prediction errors across all the different OOB observations. This will then tell us more about the accuracy and quality of the model (Behr, Weinblat, 2017; Coulombe, 2024).

Where the random forest is most likely to provide a high accuracy rate, this is at the expense of the interpretability of the model. The random forest is therefore considered a black box method as it is not feasible to analyze each tree individually to understand the predictions made. One way to understand the importance of the different variables for the random forest model is to look at the variable importance measures. The Gini index and decrease in accuracy values help understand the importance of the different variables. The variables with the highest values in those measures are the most important ones and do impact the dependent variable the most (Behr, Weinblat, 2017; Coulombe, 2024).

4. Data Description

In this chapter, an explanation will be given about the data that has been used, the origin, and an overview of all the variables that were used in the analysis are presented. Afterwards, an overview of the characteristics and descriptive statistics is given together with model-free evidence.

4.1 Elaboration on the independent variables

Where the dependent variable is explained in the materials section, there are more variables that have been used in the analysis. The independent variables can be split into two different sections, the variables related to the impact of AI on employment aspects and specific AI adapter variables. Furthermore, control variables were added in the analysis as well, which are demographic variables and job related characteristic variables. All the different variables will be covered in this section, and their explanation is given in Table 4.1.This table shows more insights into what these variables mean, which will help in the future during the analysis.

Table 4.1 *Variables Operationalization*

Variable	Operationalization	Values
Dependent variable		
Job satisfaction	How satisfied is the participant with their job	(1) very satisfied, to (5) very dissatisfied
Independent variables		
AI impact on employment aspects	*These variables are available for all the individuals*	
General impact of AI	Will AI have a positive or negative impact on workers in the next 10 years	Strongly negative to strongly positive, with 5 different categories
Wages AI	The AI impact on wages, which can be negative or positive.	(1) increase wages, (2) decrease wages, (3) no changes
Fear of job loss due to AI	Worries about job loss in the next 2 or next 10 years.	(1) extremely worried to (5) not worried at all
Impact redundancies	AI impact on redundancies in the company and in the sector. Whether the participant knows someone in their company or sector who has lost their job because of AI	Binary
Impact job change	Do you know people or are you experiencing any changes in the jobs within your company because of AI.	Binary
Trust company	Do you trust the company to handle AI. (1) use AI that benefits all workers, (2) provide training for workers who will work with AI, (3) take workers' view into account when making decisions on AI, (4) only use AI that is safe en trustworthy, (5) attempt to minimize job loss due to AI.	(1) trust completely, to (4) do not trust at all
Banned AI	Thoughts about the following uses of AI about which should be banned, allowed with restrictions or allowed without restrictions. (1) AI assessing worker performance, (2) AI deciding what training workers should receive, (3) AI deciding which workers are recruited, (4) AI deciding which workers are dismissed, (5) AI deciding which workers are promoted, (6) AI monitoring workers' well-being to tackle workplace stress.	(1) banned, (2) allowed with restrictions, (3) completely allowed
Tech feel	The initial feeling about technology	Strongly negative to strongly positive, with 7 different categories

Familiarity with AI	Whether the participant did ever hear from AI and if they are able to explain the term.	Binary
AI usage in both sectors	*These variables are only available for the individuals who adapted AI in their jobs at some level.*	
How you use AI	(1) I work with AI, (2) I manage workers who work with AI, (3) I develop/maintain AI, (4) I am managed by AI, (5) I interact with AI in another way, (6) I have no interaction with AI	Binary
Worker Data	Does the participant's company collect data on them as an individual or how they do their work?	Binary
Training	Has the company provided or funded training to make working with AI easier?	Binary
Replace task	Has AI automated any tasks that you used to do in your job? (1) general, (2) Repetitive, (3) Complex, (4) Dangerous	Binary
Create task	Has AI created any tasks in your current job? (1) general, (2) Repetitive, (3) Complex, (4) Dangerous	Binary
AI impact decision making	To what extent does AI assist with decision-making. (1) AI helps me make faster decisions, (2) AI helps me make better decisions, (3) I like that AI assists me with decision-making, (4) Because of AI, I have less control over decision-making	(1) strongly agree - (5) strongly disagree
help in decisions	AI assist in decision making	Binary
Impact autonomy	How has AI changed the way you work, in terms of (1) the pace at which you perform, (2) the control you have over the sequence of tasks	(1)increased a lot - (4) decreased a lot
Impact performance	How did AI change the job performance of the participant	(1) improved a lot - (4) worsened a lot, (5) no effect
Impact enjoyment	How did AI change how much the participant enjoys their job	(1) increased a lot - (5) no effect
Impact health	How did AI change physical health and safety in the workplace?	(1) improved a lot - (4) worsened a lot, (5) no effect
Impact mental health	How did AI change mental health and well-being in the workplace?	(1) improved a lot - (4) worsened a lot, (5) no effect
Impact management fairness	How did Ai change how fairly the managers treats the participants?	(1) improved a lot - (4) worsened a lot, (5) no effect
Attitudes about AI	(1) I worry about taking instructions from an AI-powered robot or software. (2) I worry about being left behind due to AI in my workplace. (3) I worry that AI is being introduced too quickly in my workplace	(1) strongly agree - (5) strongly disagree

Skills for AI users	What skills do you need in your job? (1) AI has made some of my skills less valuable, (2) AI compliments my skills, (3) I have specialized AI skills,m such as those needed to maintain or develop AI, (4) I am enthusiastic to learn more about AI	(1) strongly agree - (5) strongly disagree
Skills non AI users	What skills do you need in your job? (1) I worry that I do not have the skills to work with new technologies, (2) I worry that new technologies will make my existing skills less valuable, (3) I feel confident that new technologies will complement my existing skills, (4) I am enthusiastic to learn how to work with new technologies.	(1) strongly agree - (5) strongly disagree
Likelihood of AI in future	How likely do you think it is that you will work with AI in the next 10 years in your job?	(1) Very likely - (4) very unlikely
Data worries	To what extent do you worry about data collection for AI by users. (1)I feel increased pressure to perform at work due to the collection of my data. (2) I worry about my privacy when my data is collected. (3) I worry that the collection of my data will lead to decisions biased against me. (4) I worry that too much of my data is being collected.	(1) strongly agree - (5) strongly disagree
Specific per sector		
AI usage in financial sector	The fact that the participant's company uses AI for (1) data analytics, (2) risk management, (3) fraud detection, (4) trading and investment, (5) administration, (6) customer service and advice, (7) reporting, (8) human resources, and (9) other areas.	Binary
AI usage in Manufacturing sector	The fact that the participant's company uses AI for (1) product design, (2) planning and scheduling, (3) production processes, (4) maintenance tasks, (5) human resources, and (6) other areas	Binary
Control variables		
Employee demographics		
Employee age category	All the participants are grouped in different age groups. People who were below 16 years old were removed from the dataset.	(1) between 16-24 years, (2) between 25-34 years, (3) between 35-49 years, (4) between 50-64 years, (5) 65 years and older
Employee sex	Gender	(1) male, (2) female
Origin	Migration background of the participant. (1) I was born in another country, (2) my mother was born in another country, (3) my father was born in another country.	Binary

Education level	University degree	Binary
Job-related characteristics		
Employee role	The role of the participant in the organization	(1) manager, (2) professional, (3) technician, (4) support worker, (5) service and sales, (6) craft and related trades, (7) plant and machine operator, (8) elementary occupation, (9) other
Employee type	Does the participant supervise or manage other workers?	Binary
Business size	The size of the company	(1) up to 19 workers, (2) 20 - 49 workers, (3) 50 - 99 workers, (4) 100 - 249 workers, (5) 250 - 499 workers, (6) 500 and more
Employment contract	The type of employment that the participant has.	(1) permanent contract, (2) temporary contract
Location	Location of work	(1) entirely at home, (2) mostly at home, (3) mostly at the office, (4) entirely at the office, (9) no answer
Health satisfaction	How satisfied is the participant with their health	(1) very satisfied, to (5) very dissatisfied
Financial satisfaction	How satisfied is the participant with their financial situation	(1) very satisfied, to (5) very dissatisfied

4.2 Data Characteristics

The sample comprises employees with an average around 35-49 with a slight majority of male respondents (57%). It is notable that most employees in the finance sector do have a university degree (65%), while the majority of the manufacturing sector do not (58%). The characteristics of this sample are specially meaningful in the analysis of job satisfaction. As literature stated, people with a higher education are often more likely to be familiar with AI and their jobs are often less insecure as it is harder to replace those skills for a company. Additionally, the younger generation of the sample size is very likely to have prior knowledge about AI and their applications, which makes it easier for them to adapt in this technological evolving environment.

Table 4.2 Descriptive Analytics Table Employee's survey

	Total		***Finance***		***Manufacturing***	
	N	**%**	**N**	**%**	**N**	**%**
Total	5,334	100%	2,562	48.0%	2,772	52.0%
Gender						
Male	3,046	57.1%	1,228	47.9%	1,818	65.6%
Female	2,265	42.5%	1,320	51.5%	945	34.1%
Other	23	0.4 %	14	0.6 %	9	0.3 %
Age						
< 16 years	0	0 %	0	0 %	0	0 %
16 - 24 years	599	11.2%	348	13.6%	251	9.1 %
25 - 34 years	1,346	25.2%	718	28.0%	628	22.7%
35 - 49 years	2,162	40.5%	979	38.3%	1,183	42.5%
50 - 64 years	1,142	21.4%	475	18.5%	667	24.1%
65 + years	85	1.7 %	42	1.6 %	43	1.6 %
Education						
University degree	2,810	52.7%	1,673	65.3%	1,137	41.0%
No university degree	2,456	46.0%	861	33.6%	1,595	57.5%

No answer	68	1.3%	28	1.1 %	40	1.5 %
Country						
Austria	747	14.0%	326	12.7%	421	15.2%
Canada	837	15.7%	412	16.1%	425	15.3%
Germany	846	15.9%	418	16.3%	428	15.4%
Ireland	442	8.3%	208	8.1 %	234	8.4 %
United Kingdom	828	15.5%	402	15.7%	426	15.4%
United States	829	15.5%	403	15.7%	426	15.4%
France	805	15.1%	393	15.3%	412	14.9%

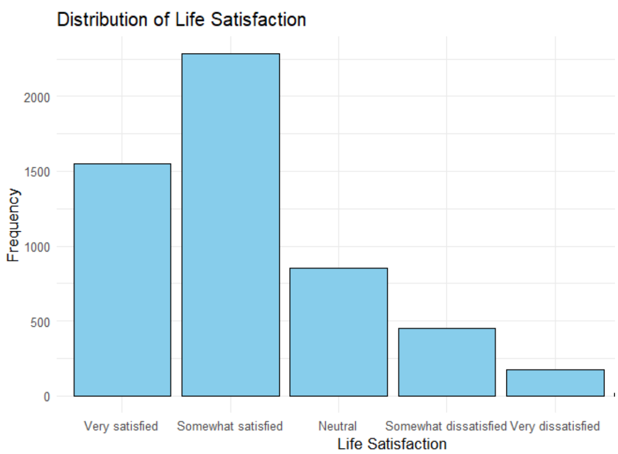
Source: OECD worker survey on the impact of AI on the workplace (2022)

4.3 Descriptive Statistics

Almost all the variables are categorical, and without running any models, it is helpful to understand the distributions of some specific variables, next to the demographic variables already shown in Table 4.1.

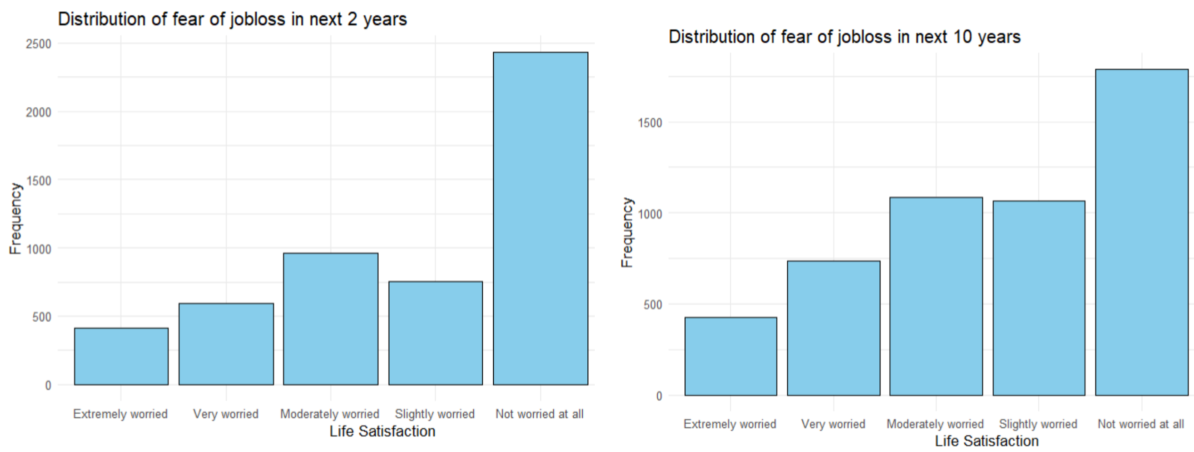
Figure 4.1 shows the distribution of Job satisfaction, as you can see clearly here is that most of the participants are very or somewhat satisfied with their jobs. This means that even though we will look at how satisfied the employees are there is a high likelihood that more are satisfied in both of the Non-user and user groups.

Figure 4.1 Distribution of the Job satisfaction for all the employees



Furthermore, in Figure 4.2 the distribution of job insecurity is made visual for the next 2 or next 10 years. As you can see, people are more worried about their jobs in the future than within the next couple of years, which is in line with the theory and the expectations. This shows that people do understand that there is a development happening that could have consequences, however it would most likely not have an impact on most people in the near future.

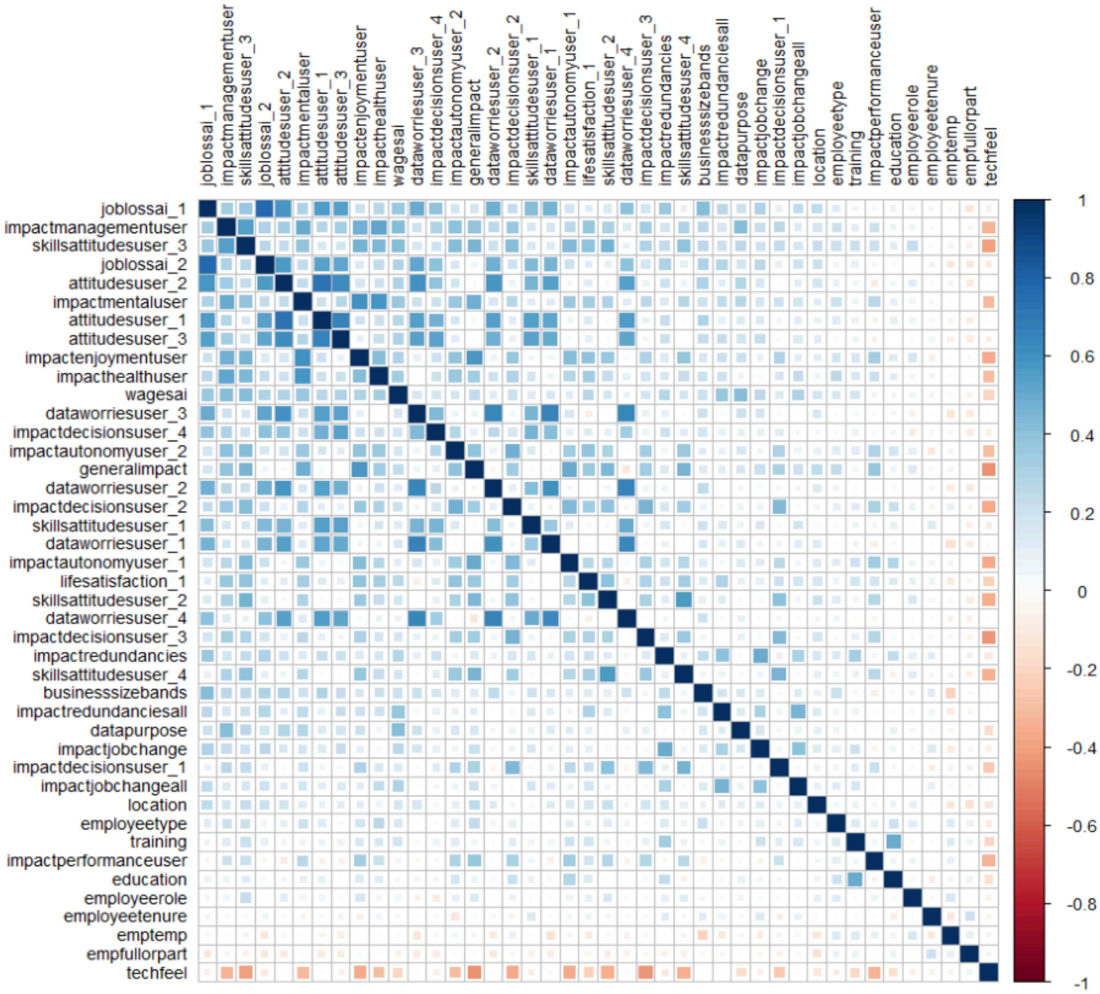
Figure 4.2 Distribution of the Job insecurity for all the employees within 2 or 10 years



4.3.1 Correlation analysis

A first impression of the possible relationships in the dataset can be obtained in Figure 4.3. Here the correlations between the independent variables are represented. This figure shows that the initial feeling about technology (tech feel) does most negatively impact the other independent variables (varies between 0 and -0.6). This is probably caused by the fact that when for example the feeling for technology is high, this will be likely leading to a positive general feeling about the impact of AI. Additionally, when looking into the positive correlations between the independent variables, it can be concluded that worries and negative feelings often positively correlate with each other. For example, the worry of losing your job positively correlates with the negative attitude toward AI and the worry about what the company will do with your data.

Figure 4.3 Correlation between the independent variables



5. Results

This section allocates the findings of the analysis conducted on the employee survey, using R, the programming software (version 2023.09.01 + 494). Firstly, we dive deeper into what makes people use AI, by looking into the first stage of Heckman's selection model. Secondly, by looking at the second stage, we answer the question: what makes people satisfied and what makes the AI-users satisfied. Lastly, we use the Random Forest Approach to make a right prediction model that can be used for managers in the future to see who will be using AI and will be satisfied more by it.

5.1 What makes employees use AI? First stage Heckman's selection model

A Heckman Selection model was computed to see who used AI and if there was no selection bias present. To answer the question of what makes employees use AI, the first stage of Heckman's selection model was used. The first step of Heckman's selection model is the probit model, with the variables shown in the conceptual framework. The results for both sectors are shown in table 5.1. Here you see the probability of using AI in their jobs when working in finance or in manufacturing, which is a binary variable.

The table shows some interesting insights. Firstly, the significant variables indicate which aspects do impact the fact whether or not someone is likely to use AI in their daily job. Insights show that people who fear the impact of AI or fear of a potential job loss or want specific parts of AI banned are less likely to use AI in their jobs. Furthermore, older people, females or people who are not familiar with AI are less likely to use AI as well. However, people who like technology, work in a larger company and work less from home are more likely to use AI in their jobs. When we look at the difference in the two sectors, you see that in finance more aspects significantly impact the chance of an individual using AI, which indicates that people who work in finance have more aspects that influences their chance of using AI in comparison with manufacturing participants.

Table 5.1 First step Heckman's selection Model

	Finance participants *(Sample size 2562 participants)*			**Manufacturing participants** *(Sample size 2772 participants)*		
Variable	**Estimate**	**Pr(>|t|)**	**VIF values**	**Estimate**	**Pr(>|t|)**	**VIF values**
Intercept	1.350	<0 ***		1.245	<0 ***	
General impact	- 0.109	<0 ***	1.562	- 0.106	<0 ***	1.457
Job loss <2 years	- 0.057	0.040 *	2.496	- 0.047	0.043 .	2.690
Trust company (1)	- 0.039	0.090 .	2.022			
Trust company (2)	0.0682	0.005 **	1.890			
Trust company (4)	- 0.037	0.083 .	1.782	- 0.080	<0 ***	2.065
Trust company (5)	- 0.038	0.056 .	1.791			
Banned AI (3)	- 0.059	0.004 **	2.260			
Banned AI (5)	- 0.043	0.024 *	2.123			
Tech feeling	0.157	<0 ***	1.226	0.095	<0 ***	1.150
Familiarity	- 0.555	<0 ***	1.093	- 0.276	0.009 **	1.067
Age	- 0.097	0.004 **	1.491	- 0.151	<0 ***	1.308
Gender	- 0.166	0.002 **	1.094			
Origin (3)	0.178	0.019 *	3.169			
Employee role	- 0.094	<0 ***	1.163	- 0.032	0.002 **	1.184
Employee type				- 0.065	0.034 *	1.171
Employee tenure	0.005	0.076 .	1.435			
Business size	0.128	<0 ***	1.110	0.128	<0 ***	1.052
Contracttype	- 0.083	0.073 .	1.108			
Location	- 0.058	0.009 **	1.109	- 0.060	0.027 *	1.136
AIC	2905.9			3403.5		
Null Deviance	3363.5 on 2561 degrees of freedom			3832.4 on 2771 degrees of freedom		
Residual Deviance	2841.9 on 2530 degrees of freedom			3339.5 on 2740 degrees of freedom		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'

Insignificant variables that were used in this model and are not shown in the table are: wagesai, job loss AI <10 years, impact redundancies, impact job change, trust company (3), banned AI (1), banned AI (2), banned AI (4), banned AI (6), origin (1), origin (2), education

The lines that consist of only some values and some spaces show that for one sector the variable significantly impacts the group and for the other one not.

After evaluating the estimates and the significance of the different variables, we can answer the question regarding what makes employees use AI. However, the answer of this question is not reliable if there is a chance of multicollinearity. This means that several independent variables are highly correlated, and this will lead to a less reliable statistical result despite a good overall fit. To test for multicollinearity, we can look at the Variance Inflation Factor (VIF) values. A common rule of thumb is that when the VIF is above 10 this indicates significant multicollinearity and therefore high correlations. When looking at table 5.1 the columns 4 and 7 represent the VIF values of the different predictors. All the VIF values are below ten and thus we should not have a concern about multicollinearity when analyzing who is likely to use AI in their work.

5.2 What makes employees satisfied? Heckman's Selection model stage 2.

Furthermore, after looking at step one of the Heckman selection model, it is good to dive deeper into the results of the second step to see what makes employees satisfied, in correlation with AI. These results are present in table 5.2. This step shows the regression model of job satisfaction from the whole data set, with inclusion of the IMR to control for selection bias, which was measured in step 1.

Before looking into all the different variables, we look at the importance of the inverse Mills ratio, as this plays a role in correcting and analyzing the possibility for selection bias in this model. By accounting for the ratio, I can obtain the estimates as reliable results, which helps getting better conclusions in the other models which eventually will lead to better understanding of the impact of AI on job satisfaction for the finance and manufacturing workers. In both regressions the inverse Mills ratio (IMR) is found to be insignificant, which suggests that there is no selection bias detected. This suggests that the effects of the impact of AI on job satisfaction are consistent across the different segments of the sample.

Furthermore, when looking at the regressions some key findings are found. The use of AI, AI impact on the management and the general impact of AI all positively influence the happiness of the employees. This shows that people with positive AI views and who use AI are in general more satisfied with their jobs currently. Together with those variables, the health satisfaction and the financial satisfaction show a positive effect on job satisfaction. However, worries in relation to data use and the fear of wage change for people who use AI are negatively impacting job satisfaction.

Overall, the model performance of the different models is indicated by the R-squared values, for both regressions, the model explains a substantial portion of the variance in the job satisfaction, with finance 0.573 and for manufacturing 0.582.

After evaluating the estimates and the significance of the different variables, we can answer the question regarding what makes employees use AI. However, in this case we should also investigate the chance of multicollinearity. Table 5.2 shows the VIF outcomes and in this case there should not be a concern regarding potential multicollinearity when analyzing what makes employees satisfied.

Table 5.2 Second step Heckman's selection Model on full dataset

Variables	**Finance participants** *(Sample size 2562 participants)*		**Manufacturing participants** *(Sample size 2772 participants)*	
	Estimates	**VIF values**	**Estimates**	**VIF values**
Intercept	0.173 *** (0.154)		0.617 *** (0.195)	
AI user	0.463 *** (0.116)	1.332	0.49 *** (0.121)	5.889
AI Impact on performance	- 0.042 ** (0.016)	1.860		
AI Impact on health	0.036 ** (0.017)	2.991		
AI Impact on management fairness	0.385 ** (0.014)	2.197	0.029 * (0.016)	1.773
Skills attitude (1)			- 0.048 ** (0.019)	1.371
General impact	0.207 *** (0.046)	2.016	0.091 ** (0.051)	7.976
Fear of job loss <2 years			0.059 . (0.033)	4.234
Data worries on pressure (1)	- 0.047 * (0.020)	1.829	0.045 * (0.023)	1.694
Data worries (3)	- 0.060 ** (0.022)	2.101	- 0.068 ** (0.024)	1.917
Health satisfaction	0.304 *** (0.024)	1.509	0.239 *** (0.025)	1.435

Financial satisfaction	0.220 *** (0.023)	1.546	0.296 *** (0.023)	1.407
Trust in company (1)	0.055 ** (0.019)	1.786	0.067 ** (0.023)	1.868
Wages * AI user	-0.026 ** (0.021)	6.389	0.049* (0.022)	8.459
AI user * general Impact	- 0.098 *** (0.029)	8.110	- 0.019 ** (0.031)	7.859
IMR	- 0.098 (0.105)	2.176	- 0.058 (0.119)	2.385
R2	0.573		0.582	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’
Insignificant variables that were used in this model and are not shown in the table are: impact enjoyment, impact mental health, attitude (1), attitude (2), attitude (3), skill attitude (1), skill attitude (2), skill attitude (3), skill attitude (4), wages impact, job loss fear, data worries (2), trust in company (2/3/4), wages * fear of job loss.

The lines that consist of only some values and some spaces show that for one sector the variable significantly impacts the group and for the other one not.

IMR is shown while insignificant, because this shows that there is no selection bias.

After evaluating the estimates and the significance of the different variables, we can answer the question regarding what makes employees satisfied. However, the answer of this question is not reliable if there is a chance of multicollinearity. Thus, we look at the Variance Inflation Factor (VIF) values, while keeping in mind the rule of tumb of a VIF above 10 being significant multicollinearity. When looking at table 5.2 the columns 3 and 5 represent the VIF values of the different predictors. All the VIF values are below ten and thus we should not have a concern about multicollinearity when analyzing what makes employees satisfied. It is interesting to note that the interaction terms have larger VIF values than all the other single variables. The reason for this is that there is already a small collinearity between the variables (see table 4.3), then the product will be likely to show even a higher collinearity.

5.3 What makes employees who use AI satisfied? Heckman’s Selection model stage 2.

Furthermore, after looking at stage two of the Heckman selection model for the whole sample. It is interesting to dive deeper into the results of the second state for only the people who use AI and to see what makes them satisfied, in correlation with AI. These results are present in table 5.3. This step shows the regression model of job satisfaction from the individuals who use AI in the dataset, with inclusion of the IMR to control for selection bias, which was measured in 5.1.

Before looking into all the different variables, we look at the importance of the inverse Mills ratio again. In both regressions the inverse Mills ratio (IMR) is found to be insignificant, which suggests that there is no selection bias detected. This suggests that the effects of the impact of AI on job satisfaction are consistent across the different segments of the sample.

Furthermore, when looking at the regressions some key findings are found. When people use AI, they are most likely to look positive to the general impact and this positively impacts their happiness, as well as the impact of AI on mental health and the availability of training. Furthermore, when they work with it instead of managing it for example this positively influences their satisfaction level. This means that when people themself work with AI instead of only managing or maintaining it, it increases their satisfaction. However, when they use AI for human resources purposes as well as for customer service or reporting it will lead to a decrease in their satisfaction level. But overall, still the control variables: health satisfaction and financial satisfaction show the greatest positive effect on job satisfaction.

Overall, the model performance of the different models is indicated by the R-squared values, for both regressions, the model explains a substantial portion of the variance in the job satisfaction, with finance 0.586 and for manufacturing 0.594.

After evaluating the estimates and the significance of the different variables, we can answer the question regarding what makes employees who use AI satisfied. However, the answer of this question is not reliable if there is a chance of multicollinearity. Thus, we look at the Variance Inflation Factor (VIF) values, while keeping in mind the rule of tumb of a VIF above 10 being significant multicollinearity. When looking at table 5.3 the columns 3 and 5 represent the VIF values of the different predictors. All the VIF values are below ten and thus we should not have a concern about multicollinearity when analyzing what makes employees satisfied.

Table 5.4 Second step Heckman's selection Model on people who use AI

Variables	**Finance participants** *(sample size 1626 participants)*		**Manufacturing participants** *(sample size 1301 participants)*	
	Estimates	**VIF values**	**Estimates**	**VIF values**
Intercept	0.7025 *** (0.102)		0.689 *** (0.132)	
AI Impact on performance	- 0.043 ** (0.016)	1.659	0.023 * (0.015)	1.758
AI Impact on health	0.036 * (0.017)	1.745		
AI Impact on management fairness	0.041 ** (0.015)	1.823		
General impact	0.065 *** (0.018)	1.910	0.053 ** (0.020)	2.314
Training	0.018 * (0.019)	1.199	0.011 * (0.013)	1.096
Job loss fear < 2 years			0.050 . (0.026)	1.758
How (1)	0.046 ** (0.044)	1.853	0.112 . (0.065)	1.984
How (6)	- 0.091 * (0.061)	2.416	-0.137 * (0.079)	2.127
Data worries on pressure (1)	- 0.045 ** (0.021)	1.710	0.046 * (0.023)	1.695
Data worries (3)	- 0.059 ** (0.022)	1.929	-0.067 ** (0.024)	2.018
Health satisfaction	0.305 *** (0.024)	1.447	0.238 *** (0.025)	1.563
Financial satisfaction	0.223 *** (0.023)	1.431	0.291 *** (0.024)	1.682
Trust in company (1)	0.059 ** (0.019)	1.871	0.069 ** (0.023)	2.013
AI uses finance (6) / AI uses manufacturing (4)	- 0.022 . (0.013)	1.315	- 0.028 . (0.014)	1.462
AI uses finance (7) / AI uses manufacturing (5)	- 0.018 . (0.011)	1.504	0.028 * (0.012)	1.392
AI uses manufacturing (6)			0.018 * (0.009)	
IMR	- 0.084 (0.107)	2.389	- 0.064 (0.119)	2.674
R2	0.586		0.594	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'. IMR is shown while insignificant, because this shows that there is no selection bias.
Insignificant variables that were used in this model and are not shown in the table are: impact enjoyment, impact mental health, attitude (1), attitude (2), attitude (3), skill attitude (1), skill attitude (2), skill attitude (3), skill attitude (4), data worries (2), job loss < 10 years, wages impact, trust company (2/3/4), ai uses sector (1/2/3/5), how (2/3/4/5)
The lines that consist of only some values and some spaces show that for one sector the variable significantly impacts the group and for the other one not.

5.4 Who will use AI to get more satisfied? Random forest approach

In order to increase the representativeness of the model, other machine learning methods have been used in the hope to increase the level of reliable outcomes with it as well. Due to the factorized dependent variable, a random forest has been done on the whole sample to predict the level of job satisfaction and what variables influence this. The results of the first random forest are shown in table 5.4. This table shows a relatively high Out Of Bag error rate (OOB) which can be caused due to the imbalance of the distribution of job satisfaction, as most people are in the very positive and positive group (group 1 and 2). To account for this imbalance there are multiple techniques that can be used, for example over-sampling, undersampling or using weights on the specific classes. In this case, undersampling was used to account for the problem of imbalance in the hope to decrease the OOB error rate. In this case, all the classes will have a total of 69 observations, as this is the amount of the minority group and the outcome is shown in table 5.5. The confusion matrix, as well as the overall statistics show that when the undersampling has been done the outcomes are better and more reliable, with an accuracy level of 75.1%. Therefore, from now on the second random forest is used for analysis for the finance dataset.

Table 5.4 Confusion matrix of the Random forest model for the Finance dataset

Finance Participants
(Sample size 2562 participants)

	1	2	3	4	5	Class. error	Precision/Recall/F1 score per class
1	448	231	7	2	0	0.3488	0.634, 0.652, 0.643
2	173	612	55	13	3	0.2850	0.571, 0.691, 0.626
3	18	199	53	12	3	0.8140	0.324, 0.199, 0.247
4	7	105	26	9	5	0.9408	0.172, 0.057, 0.086
5	7	35	15	8	4	0.9420	0.235, 0.062, 0.098

Overall statistics
Accuracy: 0.5383 Precision: 0.387 Recall: 0.332 F1 Score: 0.340

Out-Of-Bag error rate: 52.17%

Table 5.5 Confusion matrix of the Random Forest model for the Finance dataset after undersampling to improve the imbalance

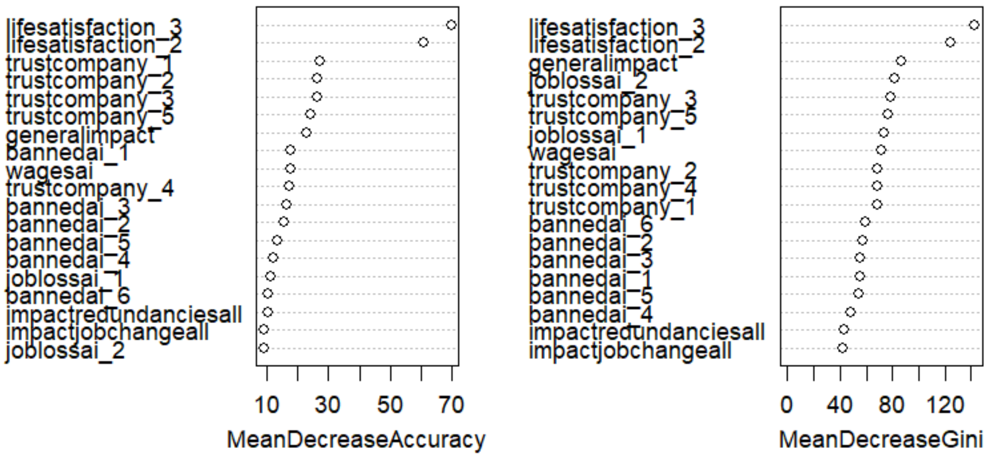
Finance Participants
(Sample size 2562 participants)

	1	**2**	**3**	**4**	**5**	**Class. error**	**Precision/Recall/F1 score per class**
1	61	4	2	3	0	0.1304	0.868, 0.854, 0.861
2	6	55	5	1	2	0.2029	0.775, 0.791, 0.783
3	1	5	52	10	1	0.2464	0.726, 0.754, 0.740
4	1	4	9	44	11	0.3623	0.598, 0.688, 0.640
5	0	3	6	13	47	0.3188	0.770, 0.681, 0.723

Overall statistics
Accuracy: 0.7507 Precision: 0.7474 Recall: 0.7536 F1 score: 0.7494
Out-Of-Bag error rate: 39,83%

When looking more into the results of the second random forest model, figure 5.4 shows the variable importance of the different variables based on the trees. The left figure shows the mean decrease accuracy, which measures how the accuracy decreases when a specific variable is permuted. As you can see, the life satisfaction variables are of great relevance for job satisfaction. This means that the overall health and the financial situation of an employee greatly influence the job satisfaction that they encounter. Furthermore, the trust in the company to handle AI properly, as well as the general impact of AI do influence the accuracy with a decent amount and therefore impact the level of job satisfaction employees experience. The second figure shows the mean decrease in gini, which represents the importance of a variable that is based on the Gini impurity criteria. Here it also states, the higher the value the more important the variable. In general the two graphs show the high importance of the same variables, however on the Gini graph you see that general AI impact and fear of job loss do have higher importance than shown on the left.

Figure 5.4 Variable importance of the second Random Forest of Finance dataset



The results of the second random forest are shown in table 5.6. This table shows a relatively high Out Of Bag error rate (OOB) again, therefore undersampling was used again to account for the problem of imbalance in the hope to decrease the OOB error rate. In this case, all the classes will have a total of 68 observations, as this is the amount of the minority group and the outcome is shown in table 5.7. The confusion matrix, as well as the overall statistics show that when the undersampling has been done the outcomes are better and more reliable, with an accuracy level of 73.2%. Therefore, from now on the second random forest is used for analysis for the finance dataset.

Table 5.6 Confusion matrix of the Random forest model for the Manufacturing dataset

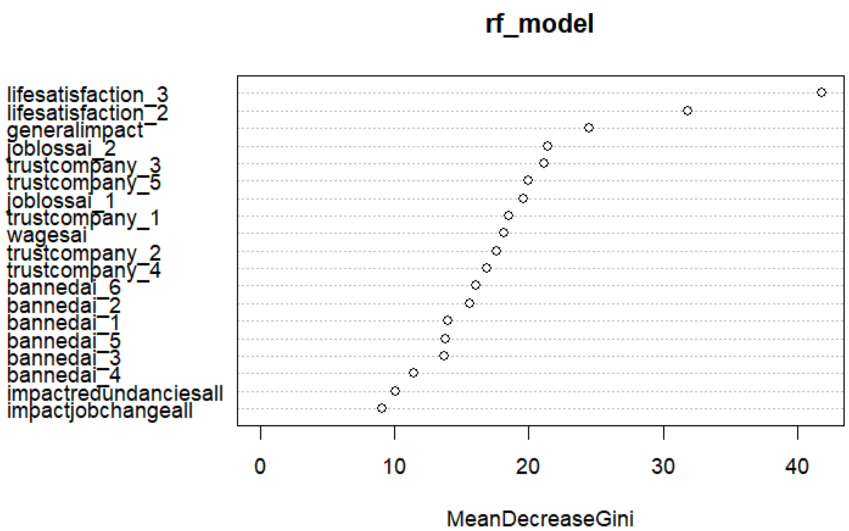
Manufacturing Participants *(Sample size 2772 participants)*							
	1	**2**	**3**	**4**	**5**	**Class. error**	**Precision/Recall/F1 score per class**
1	299	237	16	3	0	0.4613	0.722, 0.539, 0.617
2	94	795	65	19	0	0.1383	0.544, 0.817, 0.653
3	16	256	103	23	0	0.7412	0.412, 0.259, 0.319
4	4	130	55	20	3	0.9057	0.260, 0.094, 0.138
5	1	42	11	12	6	0.9167	0.231, 0.083, 0.120
Overall statistics							
Accuracy: 0.5491			Precision: 0.5745			Recall: 0.5434	F1 Score: 0.5580
Out-Of-Bag error rate: 44.66%							

Table 5.7 Confusion matrix of the Random Forest model for the Manufacturing dataset after undersampling to improve the imbalance

Manufacturing Participants *(Sample size 2772 participants)*							
	1	**2**	**3**	**4**	**5**	**Class. error**	**Precision/Recall/F1 score per class**
1	59	5	2	2	0	0.1324	0.8310, 0.8677, 0.8489
2	8	54	4	2	0	0.2058	0.7606, 0.7941, 0.7770
3	3	6	47	11	1	0.3088	0.6620, 0.6912, 0.6762
4	0	4	11	43	10	0.3676	0.6143, 0.6515, 0.6323
5	1	2	7	12	46	0.3235	0.8070, 0.6866, 0.7410
Overall statistics Accuracy: 0.7323	Precision:0.735					Recall:0.748	F1 score:0.7333
Out-Of-Bag error rate: 41.26%							

When looking more into the results of the second random forest model, figure 5.5 shows the variable importance of the different variables based on the trees. The figure shows the mean decrease in gini, which represents the importance of a variable that is based on the Gini impurity criteria. Here it also states, the higher the value the more important the variable. Here it is shown that financial stability and health satisfaction are the most important variables, with general impact following closely. Afterwards, the trust in the company and the fear of job loss due to AI are important variables in impacting the job satisfaction of an employee.

Figure 5.5 Variable importance of the second Random Forest of Manufacturing dataset



6. Discussion

The results show that younger employees, people who like technology as well as people who do not fear AI or worry about potential changes in their jobs are more likely to use AI in their jobs. This is in line with the literature and gives managers a good view on which employees are most likely to adapt to this new technology.

After analyzing the specific selection of people who participated, the second stage of the Heckman Selection Model was conducted with the use of the inverse Mills Ratio. These results confirm that there is a correlation between the job satisfaction of employees and the use of AI. Many attributes, such as general impact of AI, trust in the company, and demographics have played a significant role in the increase in job satisfaction. Based on Heckman's selection model, there are several variables that show impacts that drive AI adoption across employees. The negative relations of worries on data use, fear of wage changes and job satisfaction are in line with literature. This means that managers should focus on gaining trust of the employees who are not sure about the adaptation of AI. However, when people do have positive views on AI and generally like this, they are more satisfied with their jobs, even when they do not use AI. It is very interesting to see that people who use AI in their workplace are happier employees.

When we dive deeper into the employees who do use AI already, this gives us some interesting insights as well. Here we see that it is important for managers to look into what specific parts of their business they want to implement AI, as not every application increases the happiness of the employee and therefore their performance.

This sums up all interesting insights about the selection regression done in this study, before moving on it is good to still take a look at the quality of the model as well. The R2 of these models are around 58%, which may be less than expected in the first place. However, when keeping other literature in mind it is still a good outcome. The dependent variable, job satisfaction is a complex variable that is influenced by numerous factors, for example job insecurity. Because of its nature it is less likely to get an extremely high percentile and because of the economic relevance it is still a good outcome. However, there is always room for improvement and therefore the Random Forest models were done. After some undersampling, these models have increased the variance explained to around 70%, which is therefore the best performing model in this study.

Where the random forest models do not give a clear variable importance with their directions, it is still good to look at their insights. Because when we look at all the models in this study, we see overlap in the variable importance. This model will help managers to understand which employees will be more satisfied by using AI as this model has a higher accuracy level.

All these findings and relationships underscore the complex and diverse nature of job satisfaction as a dependent variable, however it also shows the importance of addressing the different factors to make sure that managers will be able to keep using new technologies while making sure their employees are still satisfied with their jobs which will increase their efficiency and performance eventually.

6.1 Recommendation for policymakers and managers

The results of this study will help the managers to make sure the job satisfaction of their employees stays at a high level while making their lives more efficient by adopting new technologies. Because when managers are able to increase job satisfaction as well as the efficiency, the job performance will increase which will help the future of their company. This study indicated multiple tools that will help managers in the future.

Firstly, managers should motivate their younger employees, who like technology and are familiar with AI to start using it. They should not maintain or create it themselves, but by using AI those employees will become more satisfied with their jobs. This recommendation is based on the first part of the results section, based on the first stage of the Heckman Selection model. The first stages shows that gender, age and feeling towards technology do have a significant impact on use of AI. This shows that younger male emplolyee who like technololgy are more likely to use AI. This recommendation is also in line with the previous literature and will help managers to understand which employees they should motivate to use AI.

Secondly, managers should familiarize more employees with AI and should try to remove the fear and suspicion some employees have of this new technology. This will make employees happier even when they do not start using AI right away. This recommendation is based on the second stage of the Heckman selection done on the whole sample. It showed that there are negative relations of worries on data use, fear of wage changes and job satisfaction with AI implementation and this is in line with literature. This means that managers should focus on gaining trust of the employees who are not sure about the adaptation of AI. This woulde then increase the use of AI and it will increase the overall satisfaction. However, while the fear will still be there among some employees, managers should promote the use of AI among their employees as this will increase their satisfaction with a significant large amount.

Fourtly, managers must stay away from promoting AI in human resources, customer service and in reporting. Because employees who use AI in those sectors will be less satisfied. The second stage in the Heckman selection model for the employees who use AI show that within the Human Resources department as well as customer servicve and reporting the use of AI for employees will decrease the level of satisfaction instead of increases. This indicates that by keeping the use of AI in these departments at a lower level would eventually lead to an increase in satisfaction for the employees.

Lastly, when managers can use the Random Forest approach in this paper to predict whether employees are becoming more satisfied by using AI. With this prediction they know if they should promote AI among those employees. The Random Forest approach made the model used more reliable and accurate, which makes the predictions better. This means that predictions based on this model will have a better accuracy level and will help managers to figure out which people would be most likely to use AI and will become happier.

6.2 Limitations

Unfortunately, there are also some limitations within this research that should be addressed. Firstly, as this paper is based on survey data, it represents the expected impact of AI, and not the real impact as it is based on people’s opinions rather than factual numbers. Furthermore, this paper is based on data from early 2022, this is already more than two years ago. Where the use of AI is rapidly changing and the new technological developments are rising, results based on data from 2024 can already represent different outcomes. Moreover, most people who filled in this survey are satisfied with their jobs, this means that the dependent variable is skewed. While we did account for this limitation it is something that we should keep in mind as the number of not satisfied employees is lower. Lastly, within the Heckman Selection Model the dependent variable is seen as a continuous variable, while in practice and in the random forest approach this is a factorized variable.

6.3 Future Research

While writing this paper, questions arose that could lead to further research in the future. Where we only focussed on the manufacturing and financial sector and a lot of research is focusing on the general impact, it could be interesting to investigate even more sectors. I think with the rise of personalization and experience marketing it would be very interesting to see how marketers look at the impact of AI on their satisfaction level, for example. Furthermore, where I already stated the limitation of survey data, I think in the future it would be really interesting to measure what the difference is between the actual data as well as the survey data and to compare whether the fears and excitement regarding AI is justified. Lastly, by adding additional variables in this paper, we could improve the explanatory power of the Heckman Selection model, which would mean that we do not need the Random Forest and we would increase the explainability while increasing the accuracy. For example, questions regarding the change in workload due to AI, or personality factors of the employees or economic conditions could all contribute towards a better explanatory power.

7. Conclusion

In conclusion, by evaluating survey data of the OECD dataset by implementing a Heckman Selection Model as well as a Random Forest Approach we have found that the use of AI in the workplace will positively influence job satisfaction. This positive impact is largest for the people who use AI and therefore managers should promote the use of AI among its employees. We found that currently, the younger males, who like technology and positively look at the rise of AI are more likely to use AI at the workplace. This section of employees should therefore be motivated to use AI even more as this will increase their level of happiness. By using the Random Forest they are able to predict who is likely to become happier by using AI. Thus, managers should promote the use of AI at specific parts of their company and to a specific selection of employees.

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Appendix: Survey

Q001 - country

1. Austria
2. Canada
3. Germany
4. Ireland
5. UK
6. USA
7. France

Q002 - Year of birth (age groups)

1. Below 16 years <u>Removed from survey</u>
2. Between 16 and 24 years
3. Between 24 and 34 years
4. Between 35 and 49 years
5. Between 50 and 64 years
6. 65 years and more

Q003 - Employment screening: What is your current employment status?

1. I am employed
2. I am self employed <u>Removed from survey</u>
3. I am currently not employed <u>Removed from survey</u>

Q004 - Sector: What sector do you work in?

1. Finance and insurance
2. Manufacturing
3. None of these <u>Removed from survey</u>

Q005 - initial feeling about technology: How would you describe your feelings about the overall impact of technology on society?

Strongly negative 1 2 3 4 5 Strongly positive

Q006 - Ever heard of AI: Have you ever heard the term **artificial intelligence** or **AI**?

1. Yes
2. No

Q007 - Familiarity with AI: Can you explain what the term artificial intelligence means?

1. I can explain well what is meant by that.
2. I know roughly what it means, but it is difficult to explain.
3. I don’t know what it means.
4. No answer

Q008 - Adoption of AI: Does your company use AI?

1. Yes
2. No
3. Don’t know

Q009 - adopter: Do you use AI in your company?

1. Adopter
2. Non-adopter

If adopter in Q009, and finance in Q004

Q010 - AI usage in financial sector: Does your company use AI for …

1. Data analytics?	Yes	No	Don’t know
2. Risk management?	Yes	No	Don’t know
3. Fraud detection?	Yes	No	Don’t know
4. Trading and investment?	Yes	No	Don’t know
5. Administration?	Yes	No	Don’t know
6. Customer service and advice?	Yes	No	Don’t know
7. Reporting?	Yes	No	Don’t know
8. Human resources?	Yes	No	Don’t know
9. Other areas?	Yes	No	Don’t know

If adopter in Q009, and manufacturing in Q004

Q011 - AI usage in manufacturing sector: Does your company use AI for …

1. Product design?	Yes	No	Don't know
2. Planning and scheduling?	Yes	No	Don't know
3. Production processes?	Yes	No	Don't know
4. Maintenance tasks?	Yes	No	Don't know
5. Human resources?	Yes	No	Don't know
6. Other areas?	Yes	No	Don't know

If adopter in Q009

Q012 - AI usage of respondent: Which statements best describe your interaction with AI?

1. I work with AI
2. I manage workers who work with AI
3. I develop/maintain AI
4. I am managed by AI
5. I interact with AI in another way
6. I have no interaction with AI at work *Fixed *Exclusive
7. Don't know *Fixed *Exclusive

Q013 - AI users vs non-users

1. AI users
2. AI non-users

If AI non-users in Q013

Q014 - Likelihood of working with AI in future. How likely do you think it is that you will work with AI or interact with it in any other way in your job in the next 10 years?

Very likely 1 2 3 4 Very unlikely

If Non-adopter in Q009, finance in Q004

Q015 - Heard of AI usage in the finance sector. In what form did companies in the finance sector use AI, according to you?

1. Data analytics?	Yes	No	Don't know
2. Risk management?	Yes	No	Don't know

3. Fraud detection?	Yes	No	Don't know
4. Trading and investment?	Yes	No	Don't know
5. Administration?	Yes	No	Don't know
6. Customer service and advice?	Yes	No	Don't know
7. Reporting?	Yes	No	Don't know
8. Human resources?	Yes	No	Don't know
9. Other areas?	Yes	No	Don't know

If Non-adopter in Q009, manufacturing in Q004

Q016 - Heard of AI usage in the manufacturing sector: In what form did companies in the manufacturing sector use AI, according to you?

1. Product design?	Yes	No	Don't know
2. Planning and scheduling?	Yes	No	Don't know
3. Production processes?	Yes	No	Don't know
4. Maintenance tasks?	Yes	No	Don't know
5. Human resources?	Yes	No	Don't know
6. Other areas?	Yes	No	Don't know

If Non-adopter in Q009

Q017 - Likelihood of a company working with AI in future: How likely do you think it is that your company will use AI in the next 10 years?

Very likely 1 2 3 4 Very unlikely

If AI users in Q013

Q018 - Replaced tasks by AI: Has AI automated any tasks that you used to do?

1. Yes
2. No

Q019 - Replaced tasks by AI, how: Were most of these tasks …

1. Repetitive?	Yes	No	Don't know
2. Complex?	Yes	No	Don't know
3. Dangerous?	Yes	No	Don't know

Q020 - Created tasks by AI: Has AI created new tasks that you did not do previously?

1. Yes
2. No

Q021 - Created tasks by AI, how: Were most of these tasks …

1. Repetitive?	Yes	No	Don't know
2. Complex?	Yes	No	Don't know
3. Dangerous?	Yes	No	Don't know

Q022 - AI help with decisions: Does AI assist you with decision-making?

1. Yes
2. No

Q023 - AI impact on decision making

1. AI helps me make faster decisions
2. AI helps me make better decisions
3. I like that AI assists me with decision-making
4. Because of AI, I have less control over decision-making

Strongly agree 1 2 3 4 5 Strongly disagree

Q024 - AI impact on autonomy of work

1. The pace at which you perform your tasks
2. The control you have over the sequence in which you perform your tasks

Increased a lot 1 2 3 4 5 No effect

Q025 - AI impact:

1. Has AI changed your job performance?
2. Has AI changed how much you enjoy your job?
3. Has AI changed your physical health and safety in the workplace?
4. Has AI changed your mental health and well-being in the workplace?
5. Has AI changed how fairly your manager treats you?

Improved a lot 1 2 3 4 5 No effect

Q026 - General Impact: In the next 10 years, do you think that AI is likely to have a positive or a negative impact on workers in your sector?

Very positive 1 2 3 4 5 Very negative

Q027 - AI impact on wages: Do you think that Ai will have an impact on wages in your sector in the next 10 years?

1. Yes, AI will increase wages
2. Yes, AI will decrease wages
3. No, AI will not impact wage
4. Don’t know

Q028 - Worries about job loss: How worried are you about losing your job as a result of AI

1. In the next 2 years?
2. In the next 10 years?

Extremely worried 1 2 3 4 5 Not worried at all

Q029 - Impact redundancies: Do you know anyone who has lost their job because of AI?

1. Yes
2. No

Q030 - Impact on job change: Do you know anyone who has job changes because of AI?

1. Yes
2. No

Q031 - AI collecting worker data: Does your company collect data on you or how you do your work?

1. Yes
2. No
3. Don’t know

Q032 - Purpose of worker data collection: Is the data used to assess worker performance?

1. Yes
2. No
3. Don't know

Q033 - Worries about data collection

1. I feel increased pressure to perform at work due to the collection of my data
2. I worry about my privacy when my data is collected.
3. I worry that the collection of my data will lead to decisions biased against me.
4. I worry that too much of my data is collected

Strongly agree 1 2 3 4 5 Strongly disagree

Q034 - Training provided: Has your company provided or funded training so that you can work with AI?

1. Yes
2. No
3. Don't know

If AI users in Q013

Q035- Attitudes on skills for AI by users

1. AI has made some of my skills less valuable
2. AI compliments my skills
3. I have specialized AI skills,m such as those needed to maintain or develop AI
4. I am enthusiastic to learn more about AI

Strongly agree 1 2 3 4 5 Strongly disagree

If AI Non-users in Q013

Q035- Attitudes on skills for AI by non-users

1. I worry that I do not have the skills to work with new technologies
2. I worry that new technologies will make my existing skills less valuable
3. I feel confident that new technologies will complement my existing skills
4. I am enthusiastic to learn how to work with new technologies.

Strongly agree 1 2 3 4 5 Strongly disagree

Q036 - Trust in the company to handle AI

1. Use AI in a way that benefits all workers?
2. Provide training for workers who will work with AI?
3. Take workers' views into account when making decisions about AI?
4. Only use AI that is safe and trustworthy?
5. Attempt to minimize job loss due to AI?

Trust completely 1 2 3 4 Do not trust at all

Q037 - Banning or regulation of AI

1. AI assessing worker performance should be …
2. AI deciding what training workers should receive should be …
3. AI deciding which workers are recruited should be …
4. AI deciding which workers are dismissed should be …
5. AI deciding which workers are promoted should be …
6. AI monitoring workers' well-being to tackle workplace stress should be …

Banned (1) Allowed with restriction (2) Allowed without restrictions (3)

Q038 - Gender: How would you describe yourself?

1. Male
2. Female
3. In another way

Q039 - Migration background: which of the following applies to you?

1. I was born in another country.	Yes	No	No answer
2. My mom was born in another country:	Yes	No	No answer
3. My dad was born in another country:	Yes	No	No answer

Q040 - Education: Have you completed at least a bachelor’s degree or equivalent?

1. Yes
2. No

Q041 - Employee role in organization: which one best describes your job?

1. Manager
2. Professional
3. Technician and associate professional
4. Clerical support worker
5. Service and sales worker
6. Craft and related trades worker
7. Plant and machine operator and assembler
8. Elementary occupation
9. Other

Q042 - Supervisory role: do you supervise or manage other workers?

1. Yes
2. No

Q043 - Business size of company: How many persons work for your company in your country?

1. Up to 19 workers
2. 20 to 49 workers
3. 50 to 99 workers
4. 100 to 249 workers
5. 250 to 499 workers
6. 500 workers or more

Q044 - Type of contract: Do you currently work …

1. Full-time
2. Part-time

Q045 -Location of work: Do you currently work …

1. Entirely at home
2. Mostly at home
3. Mostly on company premises
4. Entirely on company premises

Q046 - Satisfaction with life: How satisfied are you with …

1. Your job
2. Your health
3. Your financial situation

Very satisfied	1	2	3	4	5	Very dissatisfied