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CHANGES IN LABOR DEMAND AND SUPPLY IN THE FINNISH LABOR MARKET UNDER THE IMPACT OF DIGITAL TECHNOLOGIES

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ABSTRACT

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Artificial Intelligence, Machine learning and other automation technologies are changing the world in many ways and one of the most concerning impacts of these technologies is their effect on the labor market. Numerous research studies have been done related to the future job automation which is rather abstract due to the ambiguity and dynamics of occupation descriptions coupled with undefined possibilities of these technologies. At the same time, quite few are focusing on the actual change in occupation structures including tasks and skills which is the level at which technologies operate. Although skills have always been playing a great role in the matching process between workers and employers and therefore have always been shaping the labor market, now is the time when efficient matching of jobs and skills is becoming crucial due to the effects imposed by automation.

This study investigates occupation and skill structure in Finland and its recent changes. It is the first research in Finland that utilizes online job vacancies data – an insightful source of the skill data that comes directly from the market and provides a more comprehensive labor demand data than the one collected by statistical services. The skill analysis is completed with the factor analysis that discovers skill groups and their changes. Technology impact is analyzed with the suitability for machine learning scores for occupations in Finland.

Results of this thesis show the increased importance of interpersonal, initiative, and advanced cognitive skills, falling demand in highly automatable jobs, and deepening job polarization. They point out at considerable changes in skill factors defining occupations in 2014 and in 2020 with physical and cognitive routine skills losing their differentiating power to advanced cognitive and interpersonal skills.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI – artificial intelligence

cedefop – European Centre for the Development of Vocational Training

EU – European Union

ISCO – International Standard Classification of Occupations (EU)

ML – machine learning

O*NET – U.S. Occupational Information Network

PCA – Principal Component Analysis

SML – suitability for machine learning

SOC – Standard Occupational Classification (USA)

1. INTRODUCTION

Artificial Intelligence (AI) and its major subject Machine learning (ML) are changing the world in many ways and one of the most concerning impacts of these technologies is their effect on the labor market. While a number of research studies has been done related to the future automation of jobs which is rather abstract due to the ambiguity and dynamics of occupation descriptions coupled with undefined possibilities of AI and ML, quite few are focusing on the actual change in occupation structures including tasks and skills which can bring more specific results (see, for example, Brynjolfsson et al. 2018 and Alabdulkareem et al. 2018). Although skills have always been playing a great role in the matching process between workers and employers as shown by the 2010 Nobel Prize winners (Petrongolo and Pissarides 2001) and therefore have always been shaping the labor market, now is the time when efficient matching of jobs and skills is becoming crucial due to the effects imposed by automation with AI and ML as highlighted by Frank et al (2019, 6536).

Studying the labor market on a more granular level has been approached by several researchers and allowed them to obtain new insights rather different from the previous studies. A study conducted by Brynjolfsson et al. (2018) achieved impressive results on the impact of machine learning on the labor market from the task perspective where they calculated the suitability for machine learning (SML) scores for each task within occupations and later used them to calculate the overall SML scores for occupations and for different states in the USA. Tasks are rated by their suitability for machine learning on a scale from 1 to 5 by analysts for occupations from the American Classification of Occupations (SOC). Their results argue with the previous research studies about job automation, as their task focused approach revealed that none of the jobs can be fully automated with ML at the current level of technology development. Similar idea was developed in a study by McKinsey Global Institute where occupations were broken down by over 2 000 work activities, and it was concluded that about half of them is susceptible to automation with already existing technologies (2018). In the study done by Frank et al. (2019, 6535-6536) the importance of mapping the skill interdependencies as a way of measuring the impact of artificial intelligence and machine learning on the labor market is emphasized. According to the authors of the paper, skill study can help identify how occupations may change and are already changing in terms of augmentation and substitution with machine learning. Moreover, skill variables allow to better predict wages than a level of education, or

classification of jobs as routine/nonroutine as shown in the regression models built by Alabdulkareem et al. (2018, 5).

In one of the discussion papers by McKinsey (2018) the skill shift attributing to automation is forecasted to be accelerating until 2030 reducing demand for low-cognitive and physical skills while increasing the need for technological, social, and emotional skills. The authors of this paper highlight that skills are the main challenge of today in the face of AI and ML automation.

Results of the “skill market” analysis can be useful for policy makers to build retraining programs and build labor market development strategy in line with technological advances, for educational institutions to provide teaching of relevant skills, and for students and workers to explore their career possibilities. The research gap in and the relevance of the skills study in Finland were acknowledged by the Ministry of Economic Affairs and Employment who in 2019 organized a conference “Enhancing Sustainable Growth: Skills and Smart Work Organization in the Digital Era” where they gathered experts from several EU countries, universities and enterprises to discuss the impact digital technologies are imposing on the labor market.

1.1. Research purpose

This paper studies the recent changes in the Finnish labor market under the impact of automation technologies, machine learning, and artificial intelligence. As a geographical focus of this study Finland was chosen as one of the highly technological countries which still suffers from rather high unemployment rates. A closer look at the labor market from the skills and automation perspective should help gain new insights on how to improve its performance. Therefore, ***the purpose of this thesis is to discover the skill structure across occupations in Finland and how it can be related to automation technologies.***

The center of analysis in this paper are occupations in the Finnish labor market which are analyzed from the skills perspective.

In order to reach the purpose of this paper the following research questions are studied:

1. How has the Finnish labor market been developing in the recent years?

Answering this research question allows to build an overview of the Finnish labor market in dynamics, but as the focus of this research is specific occupations, skills and automation, the following sub questions are defined:

- Which occupations are growing and falling in demand, in employment, and in supply?
- Do the decreasing occupations fall into “highly automatable” category as suggested in the research community?
- Is there an occupational or skill mismatch between jobseekers and vacancies in the market?

2. How does the skill structure in Finland look?

There is no comprehensive skill demand data about the Finnish market collected by any agency or government statistical services. The only skill studies conducted so far on the Finnish market rely on the information obtained from the surveys. However, discovering the detailed skill structure and its development requires a more complete data, one that includes most occupations and skills. A useful but still unused data source that can provide relevant data directly from the market is the data collected from online job vacancies. To discover the skill structure at the most detailed level, the following questions are answered:

- Which skills are Finnish employers looking for the most in their employees?
- What kind of digital skills are in high demand?
- Which are the most popular complementary skills?
- What are the skill groups that define occupations and how they have been changing?
- Is there any relationship between skill groups and employment indicators?

3. Which trends in the labor and skill market can be explained with the spread of AI and ML?

The impact of AI and ML on the labor market in Finland has been assessed using the Osborne and Frey (2013) methodology which operated on the occupation level and returned rather pessimistic results. However, by now more specific

methodologies were developed which evaluate the impact of these technologies at the task level. In this thesis the impact of AI and ML is studied using this approach together with the skills analysis, and the following questions are investigated:

- How susceptible to automation with machine learning Finnish occupations are?
- Is there any relationship between job suitability for machine learning and different labor market indicators?
- Is there any relationship between skill groups across occupations and automatability?

According to Frank et al. (2019, 6532-6535), the main challenge in analyzing skills is the lack of detailed data available on skill demand and supply. Government statistics only gathers information on a very aggregated level which is insufficient to get insights about the possibility and extent of automation. One of the possible solutions to this problem offered by the authors is to gather information from job platforms which is always relevant, updated in real time, and reflects the current needs of the employers.

However, even with the lack of skill data available in some research studies it is shown that the impact of new technologies is changing the skill requirements of jobs and that the structure of the market is shifting. MacCrory, Alhammadi, Westerman, and Brynjolfsson (2014) identified the change in the skill structure from 2006 to 2014 by using principal component analysis on skill data collected by the U.S. Occupational Information Network (O*NET). Their results demonstrated that the clusters of skills between occupations were not the same for these two years meaning there was a shift in the occupation structure. The authors show that even during this rather short period the skill requirements for the same occupations have significantly changed and that this shift was to a large extent related to automation explaining it with the fact that skill clusters mostly suitable for automation named “Equipment”, “Perception” and “Vehicle operation” disappeared in 2014 and a new cluster appeared which the authors called “Cognitive”. This work provides a valuable insight into the skill structure, although it could be completed with a closer analysis of the factor composition and the changes in item loadings. In addition, the analysis can be extended now to include relevant skill data since 2014 up until 2020.

1.2. Data and methodology

All the general labor market statistics needed to describe the Finnish labor market and its development is taken from Statistics Finland (Tilastokeskus) and the Ministry of Economic Affairs and Employment of Finland (Työ- ja elinkeinoministeriö).

To study the change of the skill requirements across occupations and analyze their relationship with automation technologies O*NET skill database is used for the years 2014 and 2020 together with occupational SML scores calculated by Brynjolfsson et al. (2018) with the assumption that Finnish occupations contain similar tasks to the ones in the USA.

A different approach to the skill analysis that can provide a skill overview directly from the market will be approached with the help of online job vacancies data collected by European Centre for the Development of Vocational Training (cedefop) where one can find job advertisements data from various job platforms across 18 EU countries, which are classified by occupation, industry and skills. With the use of this data it is possible to find different trends in the skill demand than the one provided by government statistical services. Cedefop database is used to describe current skill demand in Finland as it only includes data for 2018-2020.

The research part of the thesis is built based on the research questions and includes quantitative analysis of various labor market variables: employed persons, vacancies, jobseekers, occupations, and skills. The efficiency of the skill matching in Finland is analyzed through the Beveridge curve, where unfilled vacancies are plotted against unemployment over a period of time. This provides understanding of whether the labor force possesses the skills needed by the market and how the situation has been changing over time. This first analysis part answers to research question 1. Skill demand is analyzed through mapping occupational structure in Finland to skills needed for each occupation according to O*NET database and through cedefop online job advertisements data. The test of a recent structural change in skill requirements across occupations is conducted with a factor model for skills in occupations in 2014 and 2020. This section is aimed at answering the second research question. The third research question is approached with the suitability for machine learning scores analysis recalculated for the Finnish market. Relationships between SML scores, skill groups, and employment indicators are studied with the linear regression analysis.

1.3. Definition of the key concepts

Artificial intelligence (AI) – for the purpose of this paper Artificial Intelligence is defined in the most general way as “a set of techniques used to try to imitate human intelligence” (Brynjolfsson Vipuri Prize Lecture 2019, 7)

Machine learning – “a subfield of artificial intelligence that studies the question - How can we build computer programs that automatically improve their performance at some task through experience?” (Brynjolfsson et al. 2018).

Automation – technology application aiming at the minimal human participation in the task (IBM).

Occupation – in this thesis can also be referred to as job or profession.

Skill – “ability to apply knowledge and use know-how to compete tasks and solve problems” (Cedefop, 2008).

1.4. Delimitations of the thesis

This work focuses mostly on the labor demand side as there is a difficulty finding the appropriate skill data on the supply side. Demand in this thesis is only analyzed through the statistics on jobseekers across occupations. In the previous studies it was traditionally assessed through education levels but in this thesis specific skills in occupations are of interest. Such data could be obtained, for example, from the Curriculum Vitae of jobseekers but it is not collected in Finland. Another aspect delimiting the potential of the current research is the lack of data on AI and ML implementation across companies thus the impact of these technologies cannot be rigidly and directly assessed.

1.5. Structure of the study

The thesis is structured as follows: it starts with the review of the relevant literature describing various approaches to evaluating technology impact on the labor market. It continues with the summary of the recent studies related to the Finnish labor market and artificial intelligence in the workplaces. The literature analysis is finalized with the list of propositions. The next chapter describes the data and methodology used in the thesis. followed by analysis results sections. The last chapter contains the summary of the most important results and their discussion.

2. LITERATURE REVIEW

“Seek to be a scarce complement to increasingly abundant inputs"

Hal Varian, Google Chief Economist

Artificial intelligence (AI) and machine learning (ML) have caused a tremendous interest among scientific community as well as among the biggest consulting companies and government agencies. They all study potential impact of these new technologies that are thought of as general-purpose technologies (GPT) meaning that they are expected to disrupt all the industries and sectors of life. Although many of the studies are very optimistic towards the effects of AI and ML on productivity and growth, the main concern expressed in a number of journal articles and scientific papers is linked to the future of work in the age of ubiquitous automation (see, for example, Osborne, Frey 2013) . Researchers have been coming to contrasting conclusions about how the world of work will change with AI and ML disruption. Their predictions vary from the highly pessimistic estimation of up to 47% of US jobs being under high risk of complete automation in the nearest decades (Osborne, Frey 2013) to another study giving the estimate of 9% (Arntz et al. 2016) and finally to the research where just a few or none of the jobs are considered to be fully automatable, at least with the existing technology (Brynjolfsson, Mitchell, Rock, 2018).

Such a diversity of forecasts is inherent to studies of the impact of new GPTs as they do not only depend on the technology itself, but on a number of factors including the actions of various institutions and governments, level of investments, business culture and many others (Clifton, Glasmeier, Gray 2020). However, if AI technology and its potential are not analyzed from different perspectives, its implementation can lead to serious negative consequences for society such as, for example, the type of AI which Acemoglu and Restrepo (2019) call “the wrong kind of AI”. Therefore, in this chapter various perspectives on the future of work under AI and ML impact expressed by researchers around the world will be presented. First, the studies related to the impact of AI and ML on the labor market will be discussed, then the studies containing skills analysis will be presented as skills analysis is the focus of this thesis, and, finally, recent research papers analyzing the Finnish labor market and the AI development in Finland will be summarized.

2.1. Studies related to automation, AI, and ML impact on labor market

One of the major challenges in predicting the impact of AI and ML summarized from the previous research by Clifton, Glasmeier and Gray (2020) is that there are other factors that largely affect AI adoption beside the technology itself, among which they name place, corporate culture, taxation and education systems, and several others. In the same paper the authors express their concern about the impact of the fusion of AI and automation on the jobs, especially among low- and middle-skilled workers. As for the geographical distribution of AI, they suggest that AI will develop faster in countries where labor cost is high, so companies will try to reduce the number of employees. However, this approach of cost saving through substituting machines for labor can lead to what Acemoglu and Restrepo (2019) call “the wrong kind of AI” when instead of unleashing all sides of AI potential and improving processes, productivity, and outcomes which includes human-machine cooperation and new task creation companies are only trying to replace people with computers and machines. In addition, this way of deploying AI is not efficient as currently there only exists “narrow” AI which is highly specific to the tasks and cannot perform the whole spectrum of activities performed by a single employee in any occupation, as shown by Brynjolfsson, Mitchell, and Rock (2018). Therefore, depending on the direction in which AI is being implemented and approached, its effect might not be limited to substitution or job displacement but extended to augmentation and new value creation, as stated in Brynjolfsson and Mitchell (2017).

A rather broad framework for studying the impact of AI, ML and robotics on labor market was built by Acemoglu and Restrepo (2018) where they describe several major trends created by these technologies and which influence the market either positively or negatively. The first effect is job displacement, that directly reduces demand for labor as companies would rather prefer to automate tasks with a cheaper capital where possible than to keep hiring expensive employees. Against job displacement, according to the authors, push several other trends such as productivity effect, capital accumulation, and deepening of automation. However, these three effects combined are not sufficient to outweigh the displacement effect. The most important positive trend which, from their view, can balance the situation or even turn it to the positive track, is new task creation in the areas where humans, not machines, excel. Despite the outlook being overall positive, the authors warn about the transition process that can be slow and painful, as labor markets take time to adjust and for this reason it is important to stimulate flexibility of labor market and education

and training systems. Another aspect, highlighted by the authors, is the potential mismatch between new job tasks and the skills that labor force possesses that can severely slow down technology adoption and labor market adjustment. Thus, the authors encourage further research on the skill requirements altered by AI, ML and robotics adoption.

Wisskirchen et al. (2017) in their comprehensive study covering various theories and aspects in which AI and robotics might influence the world of work anticipate a shift that is to occur in many jobs where workers will have to switch to a totally different area. In this connection, the authors highlight the need for a flexible labor market and fine-tuned education and training systems that will support workers that are left behind.

European agencies are also studying possible effects of automation on the labor market. The Organization for Economic Co-operation and Development (OECD) in their report (2018) claim that 14% of jobs are at high risk of automation in OECD countries following approach suggested by Frey and Osborne (2017), and they further suggest that another 32% of jobs are about to experience major changes due to implementation of automation technologies including robotics, machine learning and artificial intelligence.

According to this report, Finland is performing rather well in comparison to other European countries with less than 10% of jobs under high risk and about 25% of jobs being subject to a significant change meaning their content and tasks will change.

The survey analysis from the same paper related to on-the-job training brings another concern, as on average only 40% of workers in OECD countries do some yearly training with only 17% belonging to low-skilled labor group. It demonstrates than in case of rapid technological change low-skilled workers will be the most vulnerable group. Finally, another threat that comes from the impact of automation on employment expressed by the authors is that young people constitute another group at high risk. As young people usually work either at low-skilled jobs or at junior or entry positions performing mostly routine tasks, their work can be automated more easily making it more challenging for them to start their career. As for the current trends, reflecting the impact of technology, the authors compare workers at highly automatable jobs and low automatable ones and notice that the first group already experiences higher unemployment rates and declining salaries in contrast with the trends observed for the latter group.

Since retraining seems to be crucial when it comes to adapting to the technological change, several researchers have tried to model how the jobs are supposed to change and which tasks will grow in demand. Das et al. (2020) built an ARIMA model that allows to predict the demand for tasks in the US labor market. They showed that task shares within occupations were changing for the period of 2010-2017. Their results demonstrated that occupations with medium wage are experiencing decline in demand for most of the task clusters, further proving that employment market is becoming more and more polarized with technological advances. Zooming into information technology task cluster revealed that although demand for specific IT tasks, such as SQL and Java, has remained in the top during that period, it started to gradually fall. On the other hand, demand for knowledge of AI and Big Data took off, however this task cluster can only be found in high wage occupations group. Scripting languages and cloud computing which are closely related to AI were also gaining their task shares showing an increasing trend of introducing AI into workplaces, but this trend does not appear in the low-wage occupations deepening the concern about job polarization and skewed income distribution created by technological progress in AI fields.

Empirical studies are of a particular interest when it comes to AI and ML implications as they are difficult to measure due to their intangibility. Gregory, Salomons, and Zierahn (2016) built a model to analyze how the labor demand in European countries and regions was changing in 1999-2010, and they showed that although there was a significant substitution effect of the automatization from the task perspective leading to job loss, it was still outweighed by product demand effect and local demand spillover effect that led to creation of many more jobs than were lost to substitution. The authors highlight that analyzing automation effect on employment should not only include the final good produced but also the interactions present between labor and product markets. In this paper the authors tried to measure economic implications of automation technologies and showed how substitution effect can be outweighed by demand and spillover effects. However, occupations created by these effects are left to be discovered.

Bessen (2017) also analyzes the demand effects created by technological progress, and his model emphasizes the importance of looking into demand features such as elasticity. According to his model, in case AI is not a perfect substitute to humans (which is not expected to be the case in the nearest 10 to 20 years) and demand is sufficiently elastic, more jobs will be created than lost to automation, and job creation rate will become faster than previously observed. However, to which extent AI can replace human workers remains

an open question. In line with many other researchers, Bessen expects that new jobs will require new skills from the workers and that transition process might be very disruptive.

In contrast to studies focusing on job displacement, Ernst, Merola and Samaan from the International Labor Organization (ILO 2018), in line with the forecasts of Brynjolfsson, Mitchell and Rock (2018), suggest that jobs might rather be reorganized and redesigned than displaced, and they further stress the importance of institutional factors which are country-specific and which will affect the way jobs are being redesigned and hence the impact of automation technologies. Another important point mentioned in the same report is that productivity gains created by AI, ML and robotics in highly price-elastic sectors generate more labor demand in other sectors than is sufficient to offset the substituted labor. One of the examples they give is the increase in relative spending on recreation and culture in the UK from 1988 to 2017 due to lower clothes and food expenditures because their production was widely automatized leading to the price cut. Although, according to the authors, this effect takes time to uncover and in short-term technological unemployment is still a high possibility. At the same time, AI impact, as it is further discussed in the report, might differ a lot from previous waves of robotization and automation due to its ability to substitute for mental and not primitive tasks. As it is suggested in the report, the effect AI will create in the labor market will depend on the relative importance of each of the three areas of its application: matching which allows for task substitution, classification which allows for task complementarity, and process-management which generally expands the number of tasks being performed by delivering those tasks that human workers were unable to do before because of their complexity. Therefore, AI impact, the authors claim, will be the result of the direction taken by the technological change with respect to government policies and public and private investments in R&D. Moreover, there is an important aspect which differentiate AI from previous technologies, as it is stated in the same paper - AI is digital, thus its outcomes can be shared among many people usually without creating significant additional costs which means that AI technologies are highly scalable, which lets first entrants to the market, or so-called super-star firms, dominate the market creating additional inequalities and limiting entry opportunities for others. Entry barriers are further reinforced by the network effect and all these factors should also be taken into consideration while analyzing AI impact on labor market.

AI and ML are highly dependent on the level of IT development in a country and they cannot diffuse into the market unless it is highly digitized. Consequently, the impact of these

technologies can be better predicted in the countries where the infrastructure is ready for them. McKinsey & Company (2017) analyzed 9 most digitally advanced countries (including Finland) and built a forecast until 2030 based on their AI implementation stage and future strategies. Their research suggests that 44% of working hours in selected countries are automatable. In addition, it is stated that at least 10% out of all work activities that 94% of employees perform are possible to automate, although only 23% of workers are in occupations where most of the tasks are automatable. These findings further prove that most of the occupations are about to experience significant changes in their content rather than to be displaced. As for the forecast for 2030, the main trend in the base case scenario is that the net labor effect of automation will be neutral with almost the same number of jobs generated as those lost. However, this forecast can turn into reality if only analyzed countries which the authors refer to as digital front-runners will upgrade their reskilling and upskilling policies to support workers whose skills become unnecessary due to technological advances. This conclusion adds importance to the skill analysis that is crucial to successfully manage labor market in the AI age.

In the most recent MIT paper of Autor, Mindell, and Reynolds (2020) the authors bring attention to the fact that while focusing on abstract forecasts about robots taking over humans jobs, one of the most crucial problems of the technology impact is in fact that technology widens the gap between the rich and the poor by unequally distributing the gains brought by technology - the conclusion they reach based on the analysis of the U.S. market. They illustrate this problem by the decoupling trend of productivity growth and wage growth. The authors suggest that automation could strongly affect skill demand which will grow for a small group of highly specialized workers meanwhile the rest will be at risk. The wages trend, according to the report, will benefit those with formal skills while making less-educated workers replacable with machines. To handle this issue, mobility in the market should be unobstructed and retraining programs should function flawlessly, then the transition can be smooth.

It can be clearly observed from the papers discussed above that there is no single view on the impact of AI and ML on the labor market and different approaches lead to contrasting suggestions and results, although many of them agree on the necessity of adaptive and flexible education and training systems, and on the view that despite some earlier concerns jobs for humans will not disappear altogether in any near time. The next step is to zoom into tasks and skills as they seem to be the major elements of the labor market under direct

impact of AI and ML, and their analysis can help plan future education and training redesign. The next section will provide an overview on the research studies related to task- and skill-level analysis and will reveal whether this approach provided researchers with more consistent outlook on the AI and ML effect.

2.2. Studies related to skills analysis

In the recent studies a more granular approach to studying the impact of AI and ML on labor market has been taken, as it allows to empirically study ongoing changes in the market. Because many of the previously discussed studies finish with the conclusion that technologies will most probably not make jobs obsolete but will change their structure, now we will look into the studies that analyze the impact of AI and ML from the tasks and skills perspective. But before directly discussing the effect of technology on skills we will briefly introduce two research papers that empirically proved that skills can be a good predictor for workers incomes.

Alabdulkareem et al. (2018) analyze the issue of job polarization in the U.S. labor market by looking into the skill content of jobs, and they found two distinct skill clusters – cognitive and physical, transition between which is extremely limited due to completely different skillsets these clusters consist of. In addition, jobs associated with different skill clusters tend to distinguish in terms of wage differences with cognitive jobs providing much higher annual income. The authors then built a regression model to predict annual wages by using skill variables such as skill content of each occupation and cognitive skill fraction within a job, which outperformed previous models where only routine/non-routine skills were used as predictors. Another important finding of this research reveals that social and cognitive skills that are required together for a job positively correlate with the firm performance further proving their complementarity.

Deming and Kahn (2017) were also analyzing two sets of skills but they looked into the subset of labor force consisting of professionals, and utilized a different data that came from job postings and not from the government statistics like in case of Alabdulkareem et al. (2018). In this research the authors focused on cognitive and social skill groups as these are considered to be the most important for professionals. They found a positive relationship between skills and income and firm performance and highlight the heterogeneity in terms of required skills that exists among even narrow occupation groups.

Experts in the fields of labor market and technology Frank et al. (2019) insist on studying the impact of AI and ML at a task level but this opportunity, according to the authors, is limited due to the lack of detailed data about occupational requirements, lack of elaborated models for skill substitution or human-machine complementarity, and lack of macroeconomic understanding of the interaction between cognitive technologies such as AI and, for example, workers migration, job polarization, or international trade. As it is proposed in the paper, occupations can be defined as bundles of tasks which require different skills and they, not occupations, are impacted by technology. Therefore, according to the authors, a skill framework that connects skills to the whole workforce and its career mobility can help contending theories on the impact of AI and ML find a common ground.

Workers skills are one of the major elements that form the labor market, but they are characterized by persistent problems that negatively affect market performance and job satisfaction. As reported by OECD (2016), skill needs are rapidly changing due to the global trends one of which is digitalization, and in most of G20 countries this problem can be observed through skill shortages that coexist with inability to find a job that would match their degree among highly educated people. Another risk mentioned in multiple papers (see, for example, ILO 2018) is short- to medium-term unemployment caused by inability of workers to switch from their job that is automated to another one where demand is high as they lack necessary skills.

Significant results in the analysis of technology impact on skill demand were achieved in 2014 by MacCrory, Alhammadi, Westerman, and Brynjolfsson (2014) who studied how skill content of occupations was changing between 2006 and 2014 based on the O*NET database. They found that skills which were automatable had decreased in demand, while demand for those that complement machines, or where technology had not yet made its way, had escalated. They further discovered that the importance of skill complementarity had significantly increased making it crucial for workers to be flexible.

The theory suggested by the authors is based on skill biased technical change (Braverman and Marglin 1974) when the change in capital price positively affects skills that are complementary to this capital and negatively affects skills that are substituted with this capital. The need to study skill composition to evaluate technology impact, according to the authors, stems from different labor market reactions that can be characterized by either

extensive (substitution) or intensive (complementarity) margins. While the first one can result in a reduction of labor demand, the latter leads to job redefinition.

The authors managed to illustrate how the skill composition across occupations had changed from 2006 to 2014 by identifying different sets of skill clusters for these two years. In their analysis they utilized the U.S. occupational database that contain numerous skills rated by their importance in each occupation. For 2006 they extracted 7 skill factors: manual, equipment, supervision, perception, interpersonal, initiative, and vehicle operation. In 2014 using the same methodology only 5 clusters were obtained which were to some extent different from the ones of 2006 - they included cognitive, manual, supervision, interpersonal, and initiative factors. Interestingly, the content of the same skill clusters also changed. While manual skills in both years included coordination, speed of handling different objects, and dexterity, 2014 was characterized by an increased importance of skills related to machine operation and usage, at the same time skills such as stamina and strength decreased in their importance. Another meaningful finding reflecting the impact of technology extracted by the authors is that an “average” occupation in 2006 would have importance higher than the average for perception and supervision skills in 2014, but lower than the average for interpersonal and equipment skill clusters – a conclusion that the authors drew from regressing skill groups importance within occupations in 2014 on the ones from 2006. In other words, occupations in 2014 required less of perception and supervision skills and more of interpersonal and equipment skills. Therefore, the authors illustrated significant changes on the intensive margin that can be explained to a large extent by the impact of automation technologies.

Moreover, the authors found that specialization in a narrow range of skills nowadays can be harmful for workers in the long term in contrast with the past trends when specialization could guarantee income growth and employability. Although, this should not bring about much concern among those specialized in growing skills such as smart equipment operation.

Further developing Frey and Osborne (2017) approach Pouliakas (2018) estimates the relationship between work skills and automatability risk by using European Skills and Jobs Survey data from 2014 that contains information on the skill match of workers for their jobs across 28 EU countries. Results of his study mostly confirm the previous estimates with about 14% of workers in the EU being at high risk of automation. In addition, the findings

reveal that automation risk is higher among men and low-skilled labor force, and high risk is often associated with jobs where no training is provided which is mostly in private sector.

Another finding of this research concerns workers' survey responses about their job satisfaction which turns out to be lower for highly automatable jobs, as well as for the respondents' opinion on whether their major skills are likely to become outdated in the near term. Different skills are found to affect automation differently with workers under high risk of automation demonstrating digital and social skill gaps but being well equipped with basic skills and technical expertise. As for the impact of the education variable on automation risk, it is found that higher education level is associated with lower chance of automatability, which argues with job polarization theory which stated that technology mostly impact middle-skilled workers.

Ernst et al. from the ILO (2018) in their report briefly discussed in the previous section claim that due to some tasks within a job being automatized it can either disappear or be rearranged depending on whether it is profitable for companies to hire people for these "new" re-bundled jobs which also include some new tasks. A problem that arises in this sense, according to the report, is that while the number of jobs open for workers who can operate machines is growing, the supply of such workers is insufficient, thus despite generating new jobs there is still a high possibility of technological unemployment. The authors suggest that the main determinant of technology impact on labor market is the extent to which it requires skilled labor, or complementarity effect. As for AI and ML technologies, as further discussed in the paper, the situation about their capital-skill complementarity level is still unclear because their purpose is often to support decision making and offer expert knowledge to those not specialized in AI itself, thus potentially it can be widely used by low-skilled workers increasing their productivity alongside substituting in some cases tasks performed by high-skilled market participants. This position argues with the previous research where low-skilled labor is considered to be the most vulnerable group, because this theory suggests that AI can in fact cut demand for high- and medium-skilled workers and lift productivity of and demand for the low-skilled.

McKinsey & Company (2017) predict the skill demand in 2030 under automation and AI impact, and their forecast significantly differs from the Ernst et al. (2018) that AI can complement the low-skilled. The forecast of this report is that basic cognitive and physical skills will decline in terms of hours worked, while technological, social, and higher cognitive

skills will experience growth. After analizing the capabilities of current technologies the authors concluded that they still underperform humans in a considerable number of key capabilities such as problem solving, generating new patterns, coordinating, social and emotional reasoning and sensing, creativity, and some others. These are the areas where computers will most probably not replace people in the nearest decades, hence these skills are becoming crucial for labor force to acquire. Diving further in their base case scenario it is expected that demand for activities related to interaction, communication, management, physical unpredictable skills (e.g. in healthcare), and applying expertise will significantly increase. At the same time their forecast for physical skills and basic cognitive skills demand tells that they will remain at the same level or fall.

In another report of McKinsey Global Institute (2017) the study of more than 2000 work activities was conducted to evaluate their automation potential, and in the results it is stated that almost half of them could be automated with already existing technology. As for job polarization that is supposed to worsen with expanding scale of AI implelmentation, the authors of the report explain that in case a middle-skilled worker is displaced by technology, for instance, clercs whose work mostly includes highly automatable data collecting and processing, he or she might either move into lower paid (and lower skilled) occupations thus not only decreasing their own wealth but also pressing the wages downward, or if the worker is able to take some time off provided that he or she receives some social support, he or she might fall out of the labor supply for a period needed to upskill and retrain for higher positions.

The trend of climbing down the career ladder was in fact documented by Beaudry, Green, and Sand (2016) for the U.S. market from year 2000 onwards, which was characterized by a large share of high-skilled workers starting to perform lower-skilled jobs thus pushing down the income of low-skilled or even throwing them out of labor force. Beaudry et al. further discuss that this trend is inherent to all GPTs that require capital investments in the first stage which in turn increase the demand for cognitive skills, but once the new capital is well established, demand for high-skilled workers decreases as they are only needed to maintain it.

According to the results of the next year McKinsey Global Institute research (2018) where they focused on the analysis of 25 core workplace skills across 5 sectors in the U.S. and some European countries and mapped them to 2000 work activities from the O*NET

database, automation will accelerate demand for technological skills that will increase from 11% to 17% in 2030 in terms of hours worked, which include the whole range from basic digital skills to ability to program, and for social and emotional skills that will take up 22% of hours worked. As for higher cognitive skills, the authors of the research claim that it will moderately rise overall, but surge for some skills like creativity, which will become increasingly important. Skills declining in demand were also defined in the report and among these one can find basic cognitive, physical and manual skills. However, the degree of skill shift will not be the same across different sectors, as stated by the authors. According to their survey, around one fifth of companies claim that their executive teams do not have necessary knowledge to lead automation and AI adoption and even more are worried that the lack of such skills will negatively affect their future. In line with the most of the research papers mentioned above, the authors of this report conclude that displacement effect of technology will mostly concern low-skilled workers further widening the income gap. A somewhat surprising result of their research shows that physical and manual skills will remain the largest group of skills in 2030 - despite decreasing in terms of hours worked they will still take much more time than social and emotional or technological skills.

An overall more optimistic forecast for the future of skills was constructed by Bakhshi, Downing, Osborne, and Schneider (2017) whose methodology was motivated by the fact that previous studies, in their opinion, ignored the impact of some major trends like globalization, urbanisation, the rise of the “green” economy, population ageing etc. Hence, they suggested a combined approach of human expert judgement and machine learning techniques to study skill complementarities in the U.S. and the U.K. and predict future employment across occupations and new types of jobs that can arise in 2030. The model built by the authors was based on Gaussian process and heteroskedastic ordinal regression. By combining trends analysis with foresight workshops complemented by ML algorithm to predict future demand for occupations based on the skills data from O*NET database, the authors found that currently around 10% of workers are employed in occupations that are predicted to grow as a share of workforce, around 20% are in jobs that are likely to decrease, while about the rest no certain prediction can be built. In contrast to Frey and Osborne (2017) results that demonstrated the U-shaped distribution with jobs being mostly either high- or low- automatable, this approach reveals a major share of employment in occupations with very uncertain future prospects meaning they have probability of being in higher demand in the future around 0.5. Even though the future of a large share of workers cannot be predicted based on this approach, the authors are

confident that redesign of occupations and retraining programs could generate growth in these occupations.

Many of the jobs that are predicted to decrease in employment are low- and middle-skilled but not all of them will experience the fall, according to the research findings. Among the middle- and low-skill occupations those related to agriculture, construction, and skilled trade show more heterogenous trends, while food preparation and hospitality are most likely to grow as they provide differentiated services that are increasingly valued by customers. Digital technologies will, according to the authors, complement and boost demand for creative, design and engineering jobs. In addition, the authors emphasize the importance of interpersonal, higher-order cognitive and systems skills as skills of the future. The top-5 skills of the highest importance in 2030 are projected to be learning strategies, psychology, instructing, social perspectiveness, and sociology and anthropology for the U.S. market. The U.K. demonstrates slightly different list of top skills with judgement and decision-making in the first place, followed by fluency of ideas, active learning, learning strategies, and originality abilities. Among the least important are control precision, wrist finger speed, rate control, manual dexterity, and finger dexterity (in the U.S.) which is in line with overall automation trend. Consistent with the forecasts of the other studies, the authors demonstrate that in addition to specialised knowledge, broad-based knowledge is needed for the future workforce. Surprisingly, the forecasts for similar in terms of skills occupations can vary substantially, which illustrates that skills are not the only determinant of future growth or decline, as the prospects differ across sectors and specific areas. This is partly a result of automation that as the research shows, will affect even more cognitively advanced occupations (e.g. financial specialists).

Colombo, Mercorio, and Mezzanzanica (2018) discuss the limitations of using skill surveys for the analysis and suggest using online job platforms to analyze skill demand and how it is changing over time. They develop an AI technique to parse vacancies posted online in Italy and assess occupational skill needs, later mapping them to the European Standard Classification of Occupations (ESCO). This entirely data-driven approach allows new relevant insights to be sourced directly from the market. In this research the authors focused on analyzing the following skill degrees: soft skills, hard skills and their subset ICT skills, where degree means frequency of skill occurrence in an occupation. According to the results of the vacancies analysis for 2017-2018, hard skills are found to be more relevant in technical and production occupations while soft skills are more looked for in service industry

occupations. Nevertheless, soft skills play an important role in most vacancies across the market. Digital skills are not as pervasive as soft skills but they are present to some extent in almost every occupation reflecting digitalization trend across all industries. To evaluate the impact of automation on the job market the authors utilized Frey and Osborne's (2017) approach and incorporated there the data from job platforms. Probability of automation, the results show, negatively correlates with education level and experience, and with thinking and social interaction skills, supporting the theoretical literature. As for the hard skills, applied management ICT skills show positive correlation with automation potential which the authors explain by the fact that the highest probability of automation is found for middle-skill administrative occupations that require this group of skills. Their research demonstrated that soft and digital skills are the ones that complement machines and can make jobs more resilient to substitution.

Narrowing down the analysis from overall technology impact to the effect created only by ML, Brynjolfsson and Mitchell (2017) explain how ML impact differs from the effect of pre-ML information technologies. While previous IT were rather narrow in terms of automation field, as they could only deliver routine, highly structured tasks, ML has a greater potential to automate a substantially broader set of tasks, including those where no clear structure or algorithm can be defined but for which large datasets with inputs and outputs are available.

Another new area where ML can demonstrate its benefits and disrupt the labor market, according to the authors, is, in contrast with many studies, creativity, as ML systems are able to design solutions that satisfy all the metrics and criteria. Hence the authors conclude that measuring ML impact will not simply repeat past automation trends, and that a new approach is needed.

One solution suggested and implemented by the authors was to create a rubric of questions that allows to understand the potential of each working activity to be automated with ML, apply it to work activities data from the American occupational database (O*NET), and obtain scores that were called suitability for machine learning (SML) for each of them. However, obtaining SML scores itself cannot predict the full impact of ML technology on the labor market, as other factors also come into play. The authors name six economic factors which should be incuded into evaluating and predicting ML impact. The first one is substitution as ML can directly substitute labor in some tasks. Then comes price elasticity

as ML automation may lower costs of tasks and lead to changes in total spending which can be higher or lower depending on price elasticity of demand. The third factor is complementarities which means that highly SML tasks can require complementary low SML tasks and the decrease in price of the former will consequently increase the demand for the latter, which can be also applied to skills. Another factor is income elasticity followed by elasticity of labor supply. Labor supply elasticity will affect the way how labor force reacts to changes in wages and depend on how many people possess the skills required by the market and whether changes in demand are reflected in employment or in wages. The last factor is business process redesign as different highly SML tasks require different adjustments in business processes, legal framework, social adaptation and many others.

Overall, ML impact usually takes time to unfold as, according to Le Chatelier's principle, elasticities are higher in the long term where society can adapt to changes and labor force becomes more mobile. According to Brynjolfsson and Mitchell (2017), the success of ML implementation depends to a large extent on complementary investments made by individuals, businesses and governments in skills, infrastructure and resources.

In another study where a task perspective approach was used (Agrawal, Gans, and Goldfarb 2019), the authors focused on the prediction power of ML and built their study based on four ML aspects that can affect labor: substitution in prediction tasks, automation in decision tasks, rise in labor productivity, and creation of new decision tasks. The authors are using new methodology dividing tasks into prediction and decision ones and highlighting complementarity of decision tasks to prediction tasks because prediction alone does not create any business value without the following decision. ML, according to the study, directly substitutes human workers for prediction tasks and also indirectly influences decision tasks. Thus, the authors conclude that automatability of a job depends on the degree to which it consists of prediction tasks. Therefore, assessing the impact of AI and ML cannot be conducted in the same way as other automation technologies because, first, prediction is always a complement to decision, then, the more accurate the prediction the better decision is taken, and finally, as decision tasks are delivered both by human workers and by machines, the net impact on labor is unclear and depends on whether technology favors capital or labor.

In contrast to Agrawal, Gans, and Goldfarb's (2019) theory that the impact of technology on labor depends on the distribution of gains from it between capital and labor, Benzell and

Brynjolfsson (2019) introduced a three factor model where in addition to labor and capital there is a third factor named “genius”, and while the first two factors became abundant due to digitalization, inelastical supply of genius factor is becoming scarcer thus limiting the growth expected from innovation. Under genius the authors understand either humans with exceptional mental capabilities or other intangible assets that are impossible to digitize such as, for example, business process reinvention. This theory can explain the coexistance of wage stagnation and low interest rates despite impressive technological progress observed in the recent decades, and also suggests a possible reason for job polarization where the genius, or an exceptional talent, “takes it all”. Therefore, the authors claim that so far the scarcity of genius has been a reason why the impact of technologies like AI and ML is not reflected in any positive trends.

This theory indirectly reveals a problem of the worker skills of the future, where income and employment growth are only possible with increasing amount of exceptionally talented labor while increasing the share of average workers will only lower the wage level. The solution offered by the authors is to focus education system on embracing skills that are difficult to digitize such as creativity; increase access to top universities that bring up brilliant minds; and support immigration of the high-skilled in order to increase the amount of top-talent.

Summing up this section, in spite of the many challenges standing in a way to study the impact of AI and ML on the labor market from the skill perspective, some researchers managed to create new or utilize existing databases and gained new insights about potential impact of automation. Opinions and results still contradict in some aspects but the overall trend is still distinguishable – workforce of the future seems to need broad range of skills rather than narrow specialization, an important share of which should be soft, as these are at the moment the hardest to automate, and technological, as workers will have to engineer and operate the machines rather than perform routine manual, physical and cognitive, or classification and data analysis tasks. In the next section we will sum up the papers related to the Finnish labor market in the AI era.

2.3. Studies of the Finnish labor market related to AI, ML, and skills

Most of the research papers studying the impact of AI and related technologies on the labor market discussed so far focus on the US, the UK, or overall European market. As the focus

of this study is Finnish labor market, in this section we analyze several recent papers studying Finland and its AI development.

Based on the work of Frey and Osborne (2013), Pajarinen, Rouvinen and Ekeland (2015) constructed a forecast for Finnish and Norwegian employment concluding that one-third in each country will be susceptible to computerization at a high risk level with low-skilled labor being threatened the most. The authors projected a considerable job destruction in the short term which, never came true – it can be seen from the national statistics on employment and unemployment rates – the former has been slightly increasing for the past 5 years (2015-2019) while the latter one was declining. Current trends might indicate that substitution and job destruction are not the prevalent effects of technology in the labor market, therefore, another approach is needed.

McKinsey & Company (2017) in their study of Europe's digital front-runners mentioned in the previous sections also forecast the changes in the Finnish labor market under the impact of AI. According to their report, Finland will have a substitution effect imposed by technology equal to 15% and new job creation or spillover effect of 16% in 2030. In an unpublished appendix to this paper presented by The Ministry of Economic Affairs and Employment of Finland (2017), two scenarios for the period until 2030 were presented. In the worst case where Finland loses its top position and builds additional barriers to AI adoption, net employment is projected to fall by 0.5% until 2030, while in the best case scenario where active participation in AI development is maintained with the focus on growth creation Finland's employment will be up to 5% higher. As for the midpoint scenario, unemployment in Finland will fall to around 8% with 25% of work activities automated and the share of educated labor force reaching the level of 51% (Table 1). This forecast clearly uncovers a vast growth potential created by AI, although it will generate some transition and education challenges.

Table 1. AI impact on the economy of Europe's digital front-runners

Overview of impact on the economy

MIDPOINT SCENARIO

Country		GDP BnEUR, real	GDP/ capita growth[1] % p.a.	Unemployment % of employees	Public sector % of employees	Automation potential % of work activities, 2016	Automated % of work activities, 2030	Impact towards 2030: Job sub-stitution % of job base	Jobs from spill over effects % of job base	New job creation % of job base	Digital jobs % of employees	High-educated labor % of employees
BEL	2016	420	1.2%	~8%	30%	42%					5%	43%
	2030	570	1.7%	~7%			25%	-15%	+10%	+6%	10%	48%
DEN	2016	280	1.2%	~6%	30%	40%					7%	35%
	2030	380	2.0%	~7%			25%	-17%	+12%	+6%	12%	39%
EST	2016	20	4.3%	~7%	21%	46%					7%	40%
	2030	30	1.8%	~6%			24%	-13%	+10%	+5%	11%	47%
IRE	2016	280	4.3%	~8%	23%	43%					7%	48%
	2030	400	2.1%	~5%			24%	-15%	+10%	+8%	13%	54%
LUX	2016	50	2.2%	~6%	29%	38%					5%	49%
	2030	80	1.6%	~5%			23%	-13%	+10%	+5%	9%	56%
NET	2016	700	1.5%	~6%	28%	45%					5%	36%
	2030	950	1.9%	~5%			28%	-17%	+12%	+7%	11%	39%
FIN	2016	220	1.2%	~9%	26%	44%					7%	44%
	2030	290	1.8%	~8%			25%	-15%	+11%	+5%	11%	51%
SWE	2016	460	1.6%	~7%	31%	46%					7%	40%
	2030	670	2.0%	~5%			28%	-17%	+12%	+6%	12%	45%
NOR	2016	340	1.5%	~5%	36%	42%					3%	43%
	2030	500	2.0%	~5%			27%	-18%	+11%	+6%	8%	45%

1 GDP/capita growth in 2016 is based on the period 1990-2015. GDP/capita growth in 2030 based on the period in 2016-2030

Source: OECD, Eurostat, McKinsey Global Institute, McKinsey analysis

Source: McKinsey (2017)

According to the ministry report (2017), Finland is about to experience the same general trends that are expected by the scientists and consulting agencies for the USA and Europe including job polarization and occupation reorganization. However, they highlight the difference in the impact of AI compared to the earlier technologies in a sense that apart from creating some negative trends such as job polarization, AI can also increase productivity of people with lower education levels, but to benefit from this opportunity, it is important to make AI available to as large group of workers as possible.

Pulkka (2018) utilized the nation-wide survey method to explore the future of the Finnish labor market and found that 71% of respondents do not expect technological unemployment in the long term, however, around three quarters agree that as a temporary trend it is possible. Most people believe that in the future jobs will become more precarious and around 70% agree that digital economy will increase inequality. Interestingly, people employed in occupations under high automation risk are more concerned about the future of work, as the survey analysis illustrates, meaning they might understand potential threats to their future workplace and get prepared for them. As for salary expectations, the survey results demonstrated that the opinions are polarized, half of the respondents believe wages will decline while the other half disagree. Overall, the survey results revealed that Finns are

rather optimistic about the future of work under the impact of automation and digital economy.

Finland has one of the most ambitious plans on AI adoption and a great potential to realize it, as it was recognized by the World Economic Forum (2016) as one of the seven countries which excels in terms of economic and digital innovation impact ranking in the top for skills and infrastructure. Therefore, it can be expected that the impact of automation technologies will be seen here sooner and will be more pronounced than in most countries. It also explains the need to carefully study the development of AI technologies, its opportunities and threats.

Another aspect related to the skill market which is worth mentioning is skill polarization. In the study conducted by Alabdulkareem et al. (2018) the authors point out at the skill polarization that underlies job polarization by discovering two distinct skill clusters, social-cognitive and sensory-physical, transitions between which are rather rare and the differences in average wages between which are significant. This trend results in the shrinking of the middle class and higher unemployment rates of workers with medium education level. The situation is further worsening with the impact of AI and ML as they usually replace tasks requiring middle-level skills, leading to long term unemployment which in Finland has the highest rate for the medium educated persons (Figure 1).

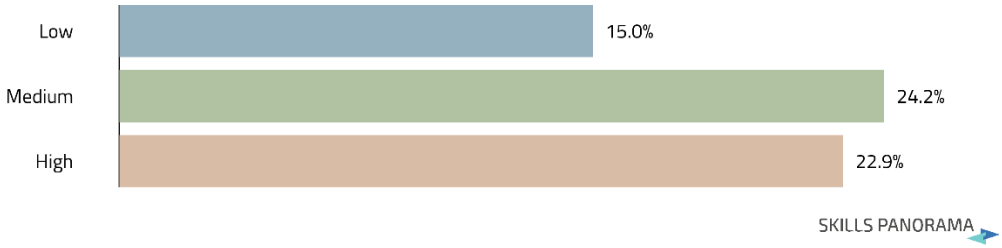

Figure 1. Long-term unemployment rate across educational levels in Finland in 2018.

Source: skillspanorama.cedefop.europa.eu

In the PWC report (2018) after interviewing Finnish companies from different sectors the authors found that for most of them AI is still in the starting phase of implementation and utilization, although there are many pilot projects, hence the impact of AI even in one of the most digitally advanced countries is still to be uncovered. As for the prospects for future jobs, the authors of the report express very optimistic views calling the outlook for Finland

“anything but bleak” despite some occupations falling into high risk category in terms of automation.

In 2018 the Ministry of Economic Affairs and Employment published a detailed report on work perspectives in the times of AI which covers employment issues, education, skills, and ethics. Overall, the authors agree that automation will most probably replace humans in many tasks, but not in occupations, and that it will substantially change jobs content.

However, there will be a lot of new tasks and jobs generated as a result of AI adoption, expects the ministry, thus predicting AI impact will always be subject to a high level of uncertainty. As for more certain aspects, artificial intelligence, the authors warn, will create an effect on income distribution, and this effect will not be the same for different occupations, as automation is extending to less routine, more high expertise tasks. Speaking of the future prospects for skills, the ministry expects that labor demand will fall for occupations where a high proportion of tasks can be performed by machines and algorithms, while it will grow for workers developing such technological solutions as well as for those whose skills complement AI. It will be important, according to the report, to educate people how to use AI technologies and what their operating principles are.

Finland’s Artificial Intelligence Accelerator (FAIA) in their report (2020) highlighted the rapid growth of firms that have implemented AI since the launch of Finnish national AI strategy in 2017. While in 2017 only 0.9% of companies applied AI in their business, in 2020 this number more than tripled with more than 1 200 companies (3.15% out of all) using AI. COVID-19 pandemic, from the authors’ point of view, should not affect further AI implementation considerably, as AI programs are mostly long-term projects and much of the investments had already been made before 2020.

2.4. Summary and propositions

Discussion about the potential disruption in the labor market caused by AI and related technologies has been sharp during the last 2 decades, and no compromise has been reached between them so far. However, several tendencies can be observed throughout most of the papers encouraging the analysis of AI impact on labor market from the skills perspective. First, the predictions of mass job displacement that was forecasted to be seen already in 2020 had clearly failed while what can be seen in the statistics of the recent

decades is the change in skill requirements for many jobs and new jobs creation. These changes can often be explained with automation. Second, skills analysis is crucial for many participants of the society including businesses, government, education and training institutions, and, clearly, for workers. Third, Finland being one of the world leaders in implementation of technology, AI readiness, and education is a perfect country to study the impact of digital technologies on the labor market. Finally, the government AI program, launched in 2017 accelerated AI implementation, and the skill study is needed to prepare the labor market for the upcoming changes.

Based on the papers analyzed in the previous section, the following ***propositions*** are suggested to be studied:

1) *Labor demand is falling in occupations highly susceptible to automation.*
2) *Soft and basic computer skills are becoming crucial for workers regardless their occupation.*
3) *AI, ML, and other automation technologies make IT and Engineering occupations more heterogeneous in terms of required skills.*
4) *Cognitive routine skills related, for example, to information gathering and processing or documenting, are losing their significance to automation technologies.*
5) *There have been some important changes in the skill structure across occupations in the recent years that can be explained by the increased use of automation technologies.*

3. DATA AND METHODOLOGY

This thesis is explorative by nature as the main goal is to discover recent trends in the labor market by using occupational and skills data where the latter is not yet structured well enough to provide a possibility of other types of analysis, and there has not been much research related to skills market done on the Finnish market. The methods chosen for the analysis are based on the fact that the data used is mostly quantitative.

3.1. Data description and summary statistics

In this thesis various data sources are used, and the summary of all the datasets and variables is presented in the following sections.

3.1.1. Statistics Finland

Statistics Finland collects general labor market data and in this thesis the time series of employed persons, vacancies, and jobseekers across occupations are used. This is the most detailed data available about occupational structure in Finland. The jobs are classified by the International Standard Classification of Occupations (ISCO) which is used across European Union countries. The summary of the data is presented in Table 1.

Table 2. Labor market data summary

	Employed persons	**Jobseekers**	**Vacancies**
Period	2010-2018	2010-2018	2010-2018
Number of occupations	545	432	432
Occupation level	up to 5-digit	up to 4-digit	up to 4-digit

In addition to these data, unemployment and vacancy rates time series based on the data provided by Statistics Finland are used. Unemployment rates are taken as they are published, and job vacancy rate was calculated as a number of open job vacancies scaled by the number of employed labor force. These datasets contain aggregated data on a country level without occupational division.

Graphical representation of all the labor market data from Statistics Finland is shown in Figure 2.

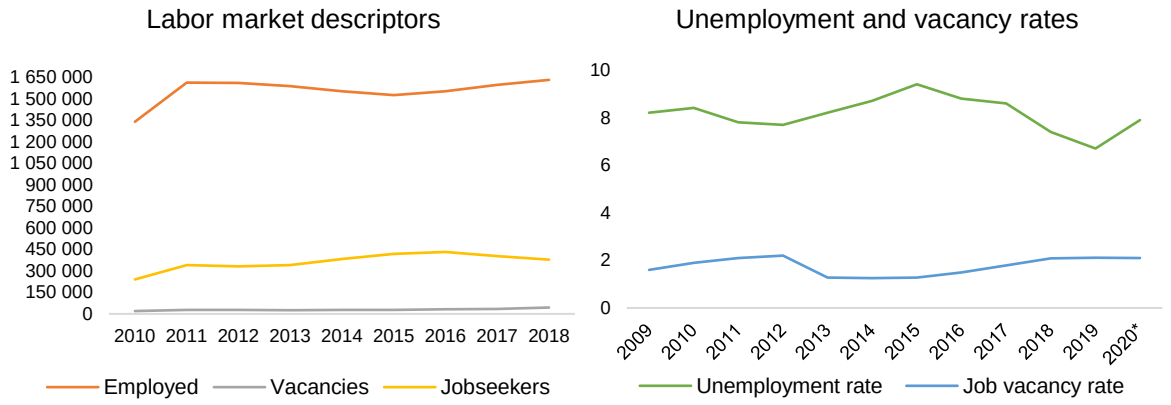

Figure 2. Labor market aggregated data.

Data source: Statistics Finland

3.1.2. Skills data

In Finland there is no database related to skills required in occupations, thus for the purpose of this thesis it was decided to use American Occupational database (O*NET) assuming that the skills demanded in occupations in Finland are very similar to the ones required in the USA.

O*NET Skills, Abilities, and Work styles database is constructed based on the information provided by analysts and in incumbents and measured by item importance in an occupation on a scale from 1 (not important) to 5 (very important). For instance, if Numerical facility is an essential skill for a financial analyst, its importance rating will be close to 5. The database is updated several times a year with on average 80-100 occupations updated each year which accounts for around 10% of all jobs meaning that in 7 years (2014-2020) around 630 updates occurred across all occupations. Such data can be used to study the skill shift over time.

In Table 3 the main descriptive statistics of the data are presented. To keep comparability between the years only those occupations present in both years were taken for the analysis.

Table 3. Descriptive statistics of the O*NET data for the factor analysis

	2014	2020
Number of variables (skills)	145	145
Number of observations (occupations)	706	706
Mean	2.823	2.840
Median	2.880	2.950
Std	0.973	0.968

3.1.3. Online job vacancies data

Traditionally all the vacancies and skills data are collected by statistical services through conducting surveys among employers, workers, and analysts. Nowadays, a new trend is gaining popularity in the labor market — looking for and advertising jobs through online job searching platforms. Even though not all the vacancies are currently advertised online, their share is steadily increasing, and many expect this type of job search to become increasingly important. Data from these platforms has a great potential for real time labor market analysis where insights are drawn directly from the market. Although analysis of such data is a challenging task due to its rather unstructured form, technologies like AI and ML can help to parse the data, clean and structure it.

European Centre for the Development of Vocational Training (cedefop) created a tool that gathers job advertisements data across various job platforms in the EU countries and matches it to the standardized classifications of sectors (NACE rev.2), occupations (ISCO-08), and skills (ESCO version 1). The data were collected from July 2018 to September 2020 for 28 European countries and offers a valuable insight into what employers are looking for in their potential employees. It is important to mention that in contrast with the tasks and skills data collected by statistical services that contain information on a different level and include many secondary skills, online job vacancies data usually only contain information about the most crucial skills assuming the presence of others by default. Another distinctive feature is that job vacancies published online can ultimately contain skills on a more granular level such as the knowledge of specific programming languages, hardware, or software – skills that are usually not specified in the government statistics.

Data about the Finnish job advertisements come from several sources distribution of which is presented in Figure 3. The majority of job advertisements in Finland comes from job search engine and from recruitment agencies. Some vacancies are published on several resources, but they are identified and counted as one.

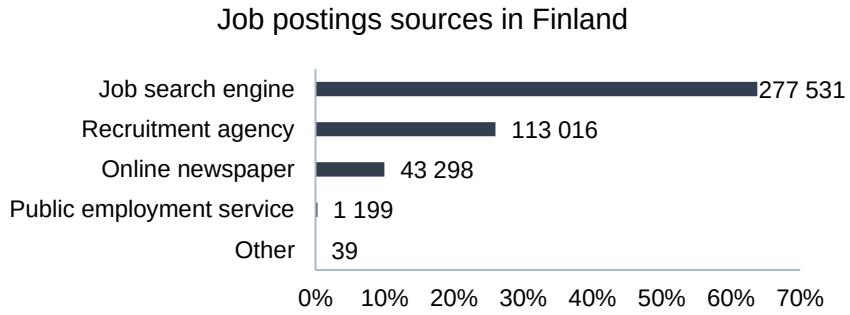

Figure 3. Job postings sources in Finland.

Data source: cedefop

Online vacancies data does not contain information about skill importance in each occupation but rather offers an overview on how many job advertisements were published for each occupation and how many and which skills were mentioned in their descriptions. The resulting dataset description is shown in Table 4.

Table 4. Finnish online vacancies data

Data type	Cross-sectional
Number of job advertisements	322 402
Number of occupations	413
Number of skills	244
Period of data collection	2018-2020

The distinct feature of the online vacancies data that limits the possibilities of the analysis is that the data is very sparse meaning that many skills mentioned in the job postings are not classified. Cleaning the dataset to only include occupations with defined skills reduces the size of the data to 110 occupations.

3.2. Methodology

The skill market analysis in this thesis is approached with several methods that were chosen depending on each dataset specifics. The order and description of each research method used is presented in this section.

The research part of this thesis starts with the time series analysis of the Finnish labor market development using the data collected by Statistics Finland. Dynamics of the labor market indicators – number of employed, jobseekers, and open vacancies over a 9-year period – are analyzed by aggregated occupation groups to find out the main labor market trends and find out the increasing and decreasing occupation groups.

To gain a better understanding of how well the labor market is functioning, job matching process in the labor market is then studied through the Beveridge curve (Petrongolo and Pissarides, 2001) based on unemployment and vacancy statistics from Statistics Finland. This analysis illustrates how the job matching in Finland was developing in the recent decades and points at the possible structural problems in the market.

The next section provides results of the statistical analysis on a more granular level and utilizes the skill data collected by cedefop for getting new insights about the skills required in the market and their relationship to automation technologies. This analysis is based on a cross-sectional data; hence it illustrates the current picture of the skill demand in Finland. In this section occupational and skill distributions are studied and the most demanded complementary skills are discovered.

As one of the purposes of this thesis is to study the skill structure and its shift, the next section presents the procedure and the results of the factor analysis used to discover skill groups that define occupations. Due to the lack of the time series of the skill data in Finland, the U.S. O*NET database is used for the analysis with the assumption that occupation descriptions (including required knowledge and skills) between the USA and Finland are close enough to use the results from the American market analysis as indicative for the Finnish market. Furthermore, there is a crosswalk between classifications of occupations used in the USA and in Europe provided by American Bureau of Labor Statistics that makes the analysis more reliable. The number of observations in the O*NET dataset is considerably larger than the number of features, items are intercorrelated but there is no

causal relationship or outliers, hence factor analysis with principal components can be utilized for discovering skill clusters. Before proceeding with the analysis, the datasets are standardized to have zero mean and standard deviation one. Factor analysis is applied separately on the skill data in 2014 and in 2020 which makes it possible to compare the results and study the skill shift over this period.

To finalize the skill analysis and map it to the Finnish labor market, weighted by employment averages are calculated for each skill for 2014 and 2020 as:

$$Skill\ importance\ in\ Finland_t = \frac{\sum skill\ importance_{it} * employment_{it}}{\sum employment_{it}}$$

where *i* is a ISCO occupation and *t* is a year.

From the changes in skills importances it can be seen which skills experienced the largest increases in importance and which are becoming less useful.

Studying the ML impact on the labor market was made possible by using suitability for machine learning (SML) scores originally calculated for American occupations by Brynjolfsson et al. (2018). For the purposes of this thesis SML scores were recalculated for the European classification of occupations by mapping the occupations from American Standard Classification of Occupations to the European ISCO using the Crosswalk provided by O*NET. However, this method leads to some information loss which is another limitation of this study.

Results of the factor analysis and SML scores are further used as regressors for various Finnish labor market indicators to study the relationship between them. In this thesis regression analysis does not aim at building a comprehensive predictive model, as it is out of the scope of the current paper. It is rather used for a preliminary study of possible relationships, impacts that SML and skills might bring to the labor market and their direction.

Each section attempts to justify, extend, or reject the suggested propositions and answer research questions. All the results are presented in the following chapter.

4. RESULTS

4.1. Labor supply and demand in Finland

To get an overview on the development of the labor market in the recent decade we first look at the general labor market trends. The labor market data is summarized in figure 4 where one can see the development of major labor demand and supply indicators in 2010-2018 at the country level.

In line with the forecasts of many researchers on the impact of AI, employment in Clerical support has been steadily declining over the observed period which supports *Proposition 1*. Although reported vacancies in this occupation group slightly increased in 2018, this increase is insignificant as the data on vacancies provided by Statistics Finland does not reflect the whole market what can be seen from the large difference in numbers between vacancies and jobseekers. Meanwhile, “Professionals” occupation group has seen the greatest increase in employment with the rest remaining largely unchanged, in contrast with the development in the number of vacancies and jobseekers.

The largest share of reported vacancies is aimed at Service and Sales workers, and this number soared in 2018 almost reaching 12 000. These are the areas where automation technologies have not succeeded much yet as they require a lot of interpersonal skills. A rapid growth in the number of vacancies was also seen among Craft and related trades workers and Plant and machine operators. The numbers of vacancies for Professionals and Elementary occupations workers have also increased but not that extensively.

Jobseekers in Service and sales occupation group follow the same trend as the vacancies and constitute the largest share among all jobseekers. A striking feature of the jobseekers data is that for the rest of occupation groups the numbers are falling indicating either a decreasing number of jobseekers in general, or a decreasing number of jobseekers reporting to employment services.

Nevertheless, there is a significant difference in numbers of vacancies and jobseekers which clearly points at the fact that vacancies data from Statistics Finland does not represent the market well. This issue serves as a further signal that labor demand data should be collected differently, for example, using job vacancies posted online.

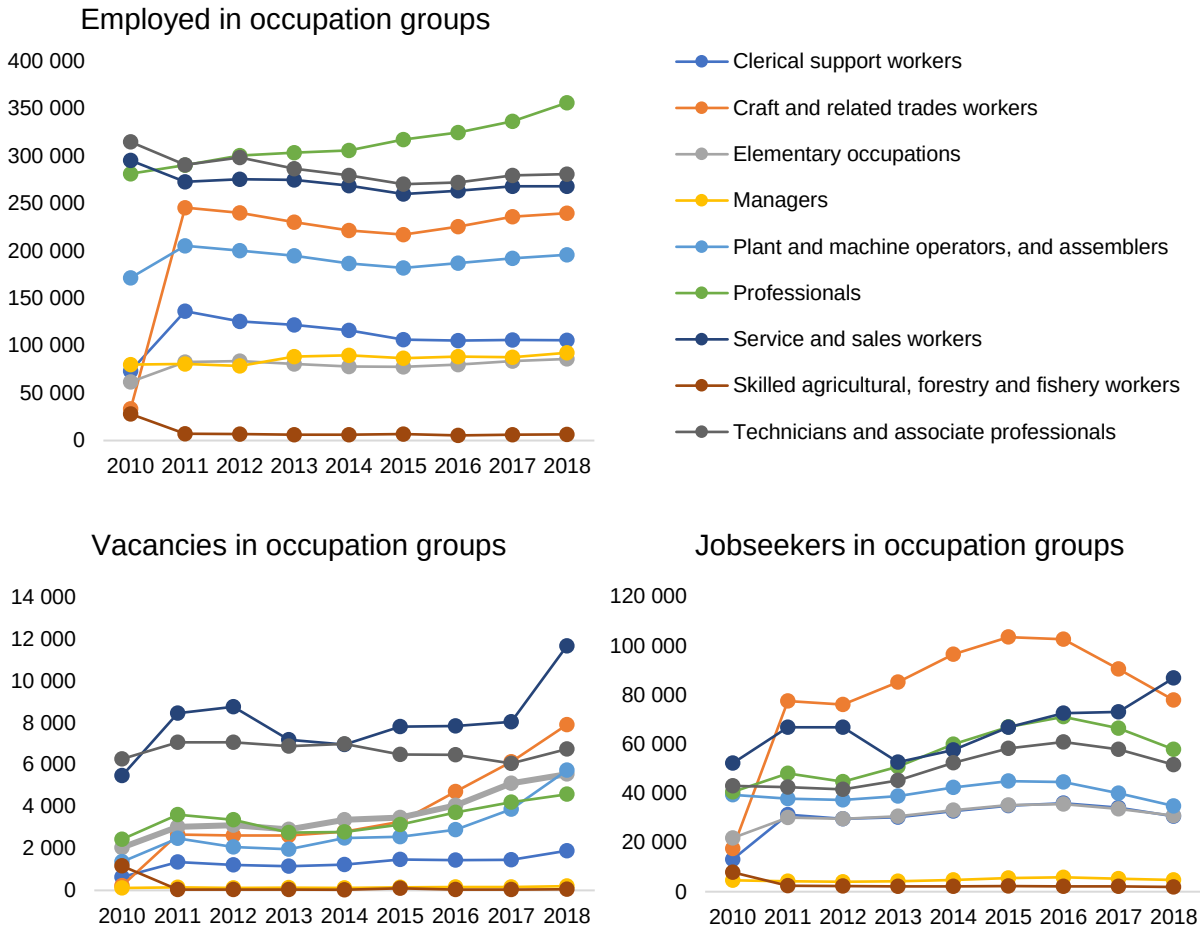

Figure 4. Labor market indicators on a 1-digit occupational level

Data source: Statistics Finland

Note: Classification of occupations has been changed in 2010, thus the data of 2010 is not fully comparable to the later years.

4.2. Job matching in Finland

One of the ways to analyze how well the labor market functions is to create a Beveridge curve model for it. This method of analysis is part of the search theories in the labor market and was first introduced by the Nobel Prize winners Petrongolo and Pissarides (2001).

Beveridge curve is a graphic representation of a functional dependence between open vacancies and unemployment. It allows to get an idea about structural problems in the market when unemployment coexist with unfilled job offerings. One of the important contributors to this group of problems is skill mismatch – a situation when employers are

looking for employees with different skillsets than those possessed by job seekers. Therefore, analyzing the Beveridge curve can provide some valuable insights about whether the labor market is balanced and on which stage of the business cycle it is. It gains additional value with the automation technologies development because they are thought to make many of the human skills obsolete.

Unemployment in Finland, although not as high as in some other European countries, still remains a daunting economic problem, especially due to its structural nature, as discussed in Kyyrä and Pesola (2018). Figure 5 presents the Beveridge Curve for the period 2009-2020 constructed based on the data provided by government statistical services. In the graph we can see that the points were mostly moving along one downward sloping line reflecting different stages of the business cycle, but 2019 seems to belong to another curve that is closer to the origin and, therefore, signals of a better functioning matching process in the market. However, it is unclear whether this was a potential long-term shift or just a temporary trend because its effect was completely wiped away by the abnormal 2020 characterized by rocketing unemployment across the whole world including Finland.

Interestingly, according to Statistics Finland, vacancy rate did not fall during 2020 but this can probably be explained by the fact that vacancy statistics in general underrepresents the real situation with many vacancies not being reported to the public employment services, hence it is difficult to tell whether the vacancy rate remained at the same level or decreased in 2020. Judging by the trends in other countries and overall economic downturn, vacancy rate in Finland should also be lower than in 2019 because many companies have become less stable in general and hiring rates in the service industry have clearly fallen.

Nevertheless, there is a significant mismatch in the Finnish labor market reflected in a rather high unemployment coexisting with increasing job vacancy rates since 2015 which may partly rise from the fact that many unemployed people do not possess the skills demanded by employers or because their skills become outdated due to broader implementation of AI and other automation technologies.

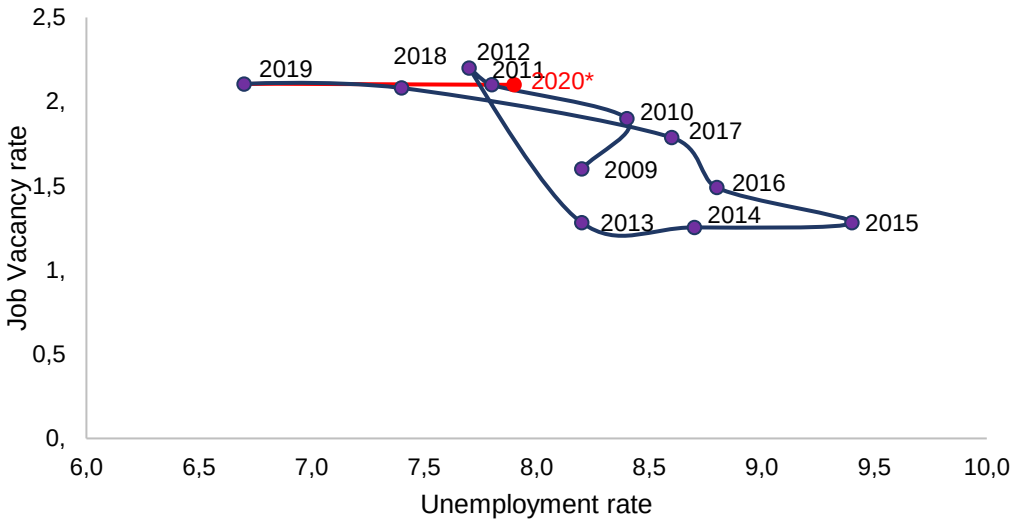

Figure 5. Beveridge Curve in Finland.

Source: Authors' own calculations based on data from Statistics Finland

Note: Vacancy rate is calculated as the annual average number of open vacancies during a month scaled by the size of employed labor force. Year 2020 estimates are based on the first three quarters of the year.

4.3. Skill market analysis

To better understand the current situation in the labor market, online job vacancies data is of a great use, although there are several occupation groups not represented in it, such as military workers, or farmers. In this section, we zoom into the skill demand in Finland based on the data from online vacancies to look for an explanation to these trends and to find out to which extent AI and ML might contribute to employment issues.

Occupational distribution of job advertisements according to 1-digit ISCO presented in Figure 6 indicates that more than a quarter of all vacancies advertised online were targeted at Professionals, second come job posts for Service and sales workers with about 17% followed by Trade workers, Associate professionals and Managers. The least advertised jobs are Elementary workers, Operators and assemblers, and Clerks all of which mostly require routine and/or manual skills. The last group is Farm workers, but this type of jobs is not widely advertised online in general.

An interesting observation is that data from Statistics Finland presented in the Figure 6 on the right for a similar timeframe (data for the same time period are not available) provide a completely different overview with Service and sales workers being reported the most, followed by Elementary and Trades workers. Professionals, according to Statistics Finland, are taking only around 10% of all vacancies. This inconsistency together with the low vacancy numbers reported by the statistical services further proves that not all open vacancies are being reported. Considering much higher numbers of vacancies published online, this data can provide a more complete picture of the labor market, at least when the interest lies in more cognitively active occupations.

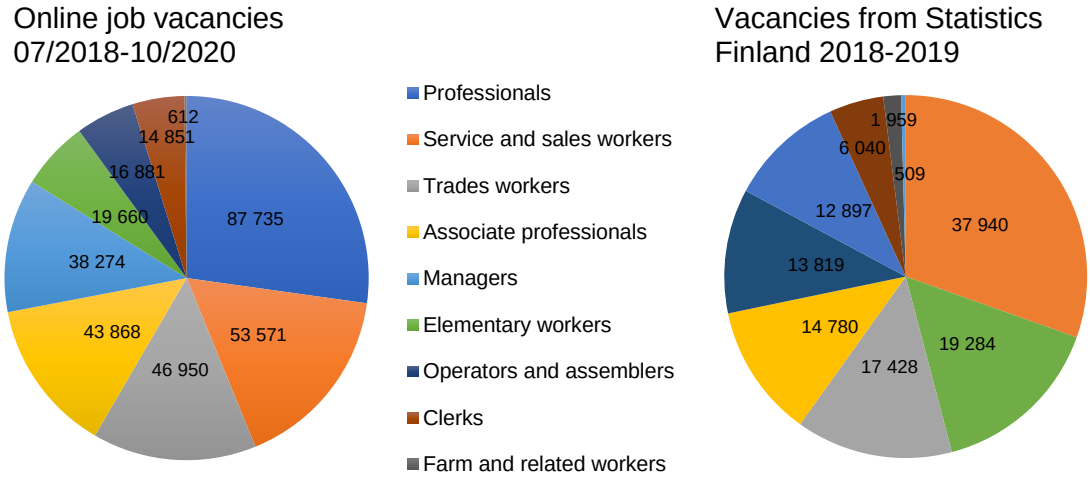

Figure 6. Occupational distribution of vacancies from online job postings and Statistics Finland.

Data source: cedefop, Statistics Finland

If we look at the most popular vacancies advertised in 2018-2020 on a 4-digit level (Figure 7), we can see that the absolute leader in Finland, according to the data from online job vacancies, is Education managers with almost 14 000 vacancies published during the period. The second and third places with around 8 000 vacancies are taken by Potters and related workers (such as Clay and brick casters and grinders), and Home-based personal care workers. Overall, the list is very heterogeneous and includes occupations of various occupation groups and diverse skill levels required which means that the market is heterogeneous as well. Top vacancies published by Statistics Finland for a similar period mostly include low skill level occupations with the highest number of vacancies reported for Shop sales assistants, Cleaners, and Health care assistants.

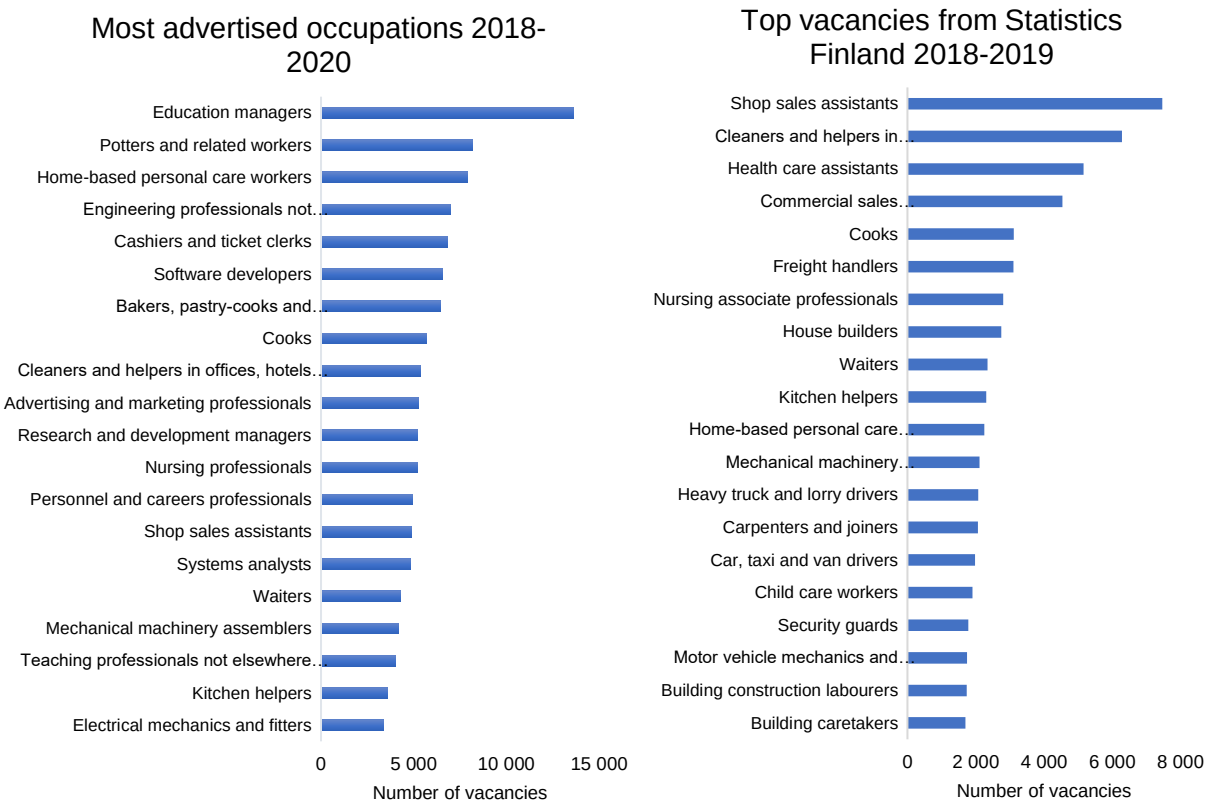

Figure 7. Most advertised occupations.

Data source: cedefop, Statistics Finland

However, the most valuable information contained in cedefop database concerns skills. Top ten skills demanded by employers regardless occupation is presented in Figure 8 (left side). Among them we can see both technical and soft skills with the majority belonging to soft skills which supports *Proposition 2*. This distribution goes in line with multiple forecasts about soft skills, and especially communication skills, being the most required by the market in the times of rapid technological progress. Being able to adapt to change is another top skill that reflects today's fast pace business environment and the changes brought by automation. As for the technical skills, in the top we can only see rather basic computer skills such as ability to use computer and Microsoft Office. This trend mostly reflects ubiquitous digitalization when the majority of jobs require some computer skills but tells nothing about the impact of AI and ML. Specific for the Finnish market "logging" appears in the top ten skills due to the large scale forestry industry in Finland.

Top 10 skills demanded in Finland mostly follow the distribution of the top skills across EU 28 (Figure 8, right side). More detailed distribution of top skills classified by 1-digit

occupation groups can be found in Appendices 1. From that table it is clear that most demanded skills are popular across different occupation groups which make them complementary as they can be transferred from one occupation to another but are not related to specialization, or industry specifics.

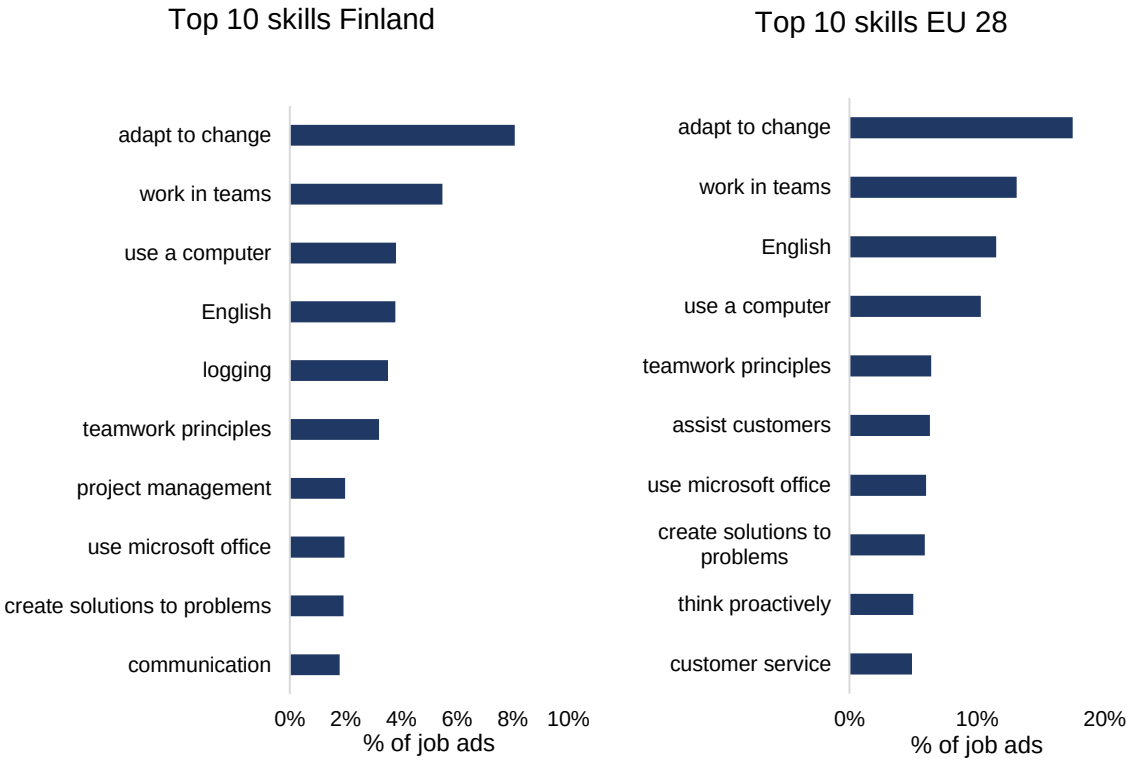

Figure 8. Top 10 skills in demand in Finland and EU 28.
Data source: cedefop

A slightly different and broader structure appears when occupational distribution across skills is built (Figure 9). In this chart only those skills that are required across at least 10 different occupations are presented, hence this distribution shows complementary skills, those that can be transferred between many different occupations. English language skills are one of the most popular across around 60 different occupations, teamwork related skills are also required in many jobs, together with communication and problem solving. As for IT skills, programming skills and ICT communications protocols also seem to be in high demand among 10-11 different occupations indicating their significant share in the total occupation structure.

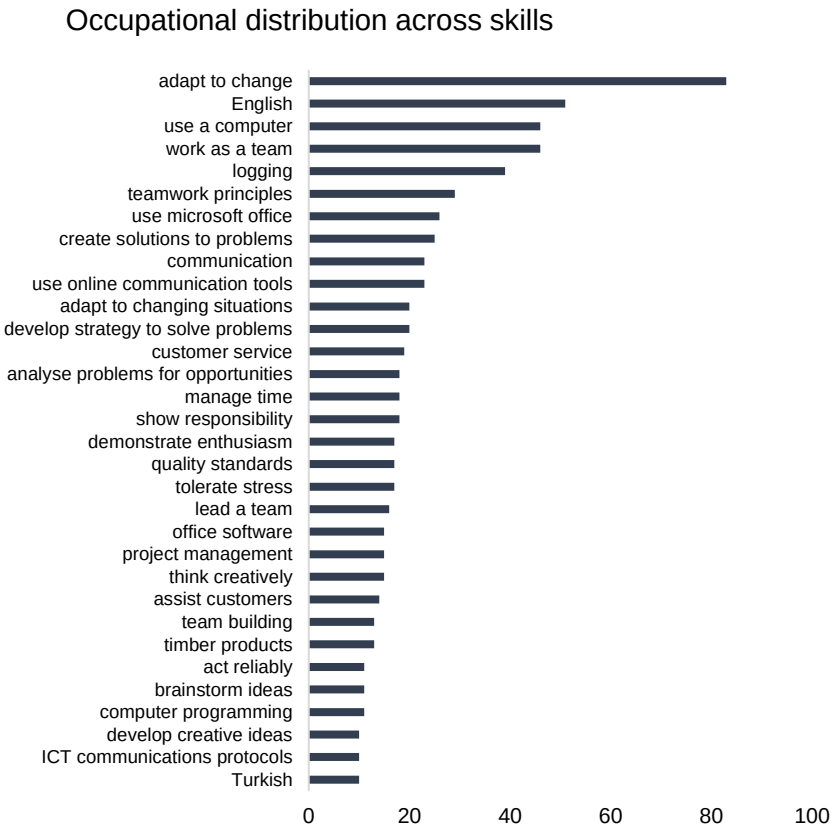

Figure 9. Occupational distribution across skills.

Data source: cedefop

Figure 10 represents the distribution of skills across occupations and indicates that some occupations are much more heterogeneous or requiring than the others. For example, job advertisements for Engineering professionals and Software developers mention up to 100 different skills which can indicate either that they are highly demanding jobs, or that 4-digit level for these occupations is not detailed enough, and there is a lot more specialization in these jobs not covered by the classification of occupations. This trend can also be partly explained with the development of digital technologies which become very diversified; thus, for example, software developers now are a very heterogeneous group that consists of jobs requiring different skillsets depending on tasks and industry specifics. This tendency was also emphasized in one of the cedefop briefing notes (cedefop, 2017) where based on the European Jobs and Skills Survey they found that around 60% of employees in ICT sector saw their jobs changing recently. Overall, in the list of occupations mentioning at least 20 different skills, one fifth refers to ICT professionals and another fifth to managers. This observation supports *Proposition 3*, but also reveals that among very requiring or

heterogeneous jobs are as well R&D, Education, and Sales managers, and Marketing professionals.

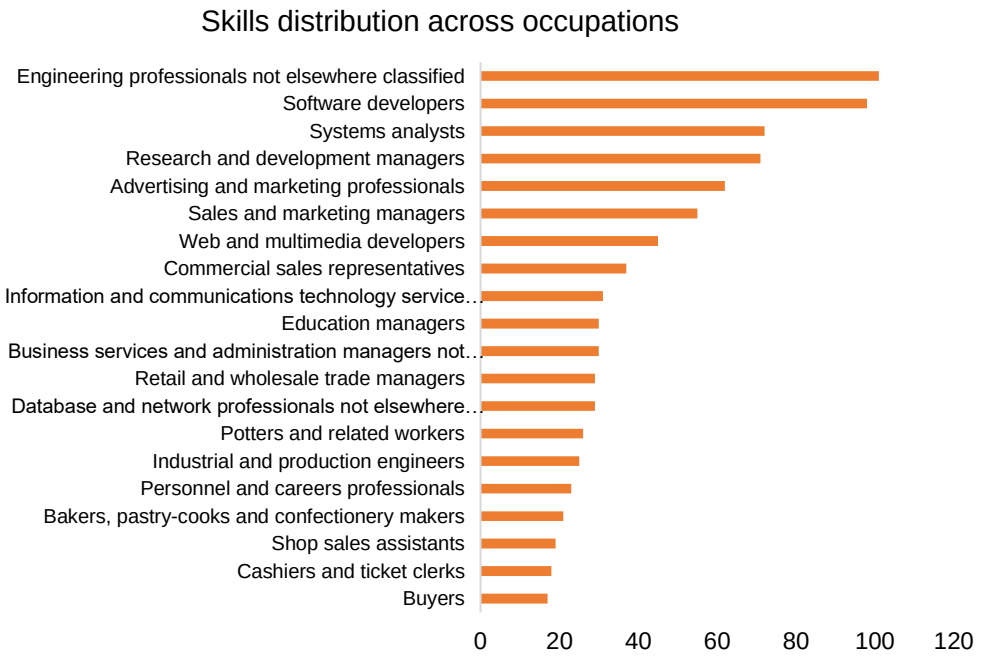

Figure 10. Skill distribution across occupations.

Data source: cedefop

4.4. Factor analysis of skills.

Analyzing skills when they are counted in hundreds is not convenient and sometimes impossible, thus some dimensionality reduction is implemented. This section presents the results of the factor analysis conducted on skills from O*NET database.

According to the very diverse list of top skills in demand in Finland, it can be concluded that using highly aggregated skill groups traditionally used in the papers, such as low, medium and high, or cognitive and manual, cannot reflect the skill structure well with computers taking over tasks from across all the groups. Therefore, in this thesis skill groups across occupations and how they have been changing over time are discovered and analyzed based on occupations and skills data with the principal component analysis (PCA) following the approach of MacCrory et al. (2014).

O*NET database can serve as a necessary complement to the online job vacancies data as it contains comprehensive sets of core skills that differentiate vacancies, while online job vacancies only contain a small number of critical skills, large share of which constitutes soft skills and work attitudes that are common in a wide range of jobs.

4.4.1. Factor analysis procedure

Factor analysis with principal component factor extraction was chosen as the most relevant one for exploratory analysis and was conducted using Stata software. Obtained factors were rotated to remove any interdependencies with orthogonal, varimax rotation and Kaiser normalization. First, factors with minimum eigenvalue = 1 were retained. Next, all the variables that loaded on factors with an absolute value below 0.6 and the factors with less than 3 variables were dropped following MacCrory et al. (2014) procedure. Then the analysis was conducted on the rest of items several times until there were no items left which were not loaded on any factor.

Factors discovered and retained after the last iteration in decreasing order of variance explained are reported in Table 5. The naming of the factors is based on those used in MacCrory et al. (2014).

Table 5. Skill factors and explained variance

factor name	2014	2020
Cognitive	24.3%	26.8%
Manual	24.0%	25.8%
Interpersonal	7.2%	7.6%
Supervision	6.2%	6,4%
Physical	5.3%	-
Vehicle operation	5.1%	5.7%
Initiative	3.3%	3.6%
Mathematical	2.8%	2,4%
(cumulative variance explained)	78.2%	78.4%

4.4.2. Reliability and validity check

Kaiser-Meyer-Olkin measure of sampling adequacy (MSA) was calculated to check validity, and MSA values indicate that both samples (2014 and 2020) are adequate, as all variables have very good MSA > 0.8, thus the calculated measures are considered valid. For reliability check Cronbach alphas were used and all of them satisfy the required condition and are higher than at least 0.8 (see Appendices 2).

4.4.3. Results discussion and analysis

Results for 2014 are mostly consistent with the factors obtained for the same year by MacCrory et al. (2014) with the exception that they did not have Physical and Vehicle operation factors separately. This might be explained by the fact that they might have used the data from another month which was somewhat different and by the different number of observations used by the authors for the analysis (674 in their paper against 706 occupations in the current thesis).

Physical factor ceased to exist in 2020 which makes it apparent that there have been significant within-occupation changes in the skills required for the same occupations in 2014 and in 2020. While 78.2% of the variance in 2014 was explained by 97 skill items, 78.4% of the variance in 2020 was explained by a smaller number of skill items - 89.

Most of the items from Cognitive and Supervision factors received slightly higher loadings indicating that the skills these factors contain stronger correlate with each other in 2020 than they did in 2014 (Appendices 2). Higher correlation between the skills within the factors also indicates increased complementarities between them.

To the Cognitive factor some new items were added: Instructing, Monitoring, Mathematics, Speaking, Fluency of Ideas, Mathematical reasoning, Oral expression, and Originality, while some others were removed: Documenting/Recording information, Getting information, Identifying objects, actions, and events, Interacting with computers, Interpreting the Meaning of Information for others, and Processing information (Appendices 2). These changes might as well be related to technological progress that automates data collection, recording and processing in many occupations as well as it allows machines to perform some identification tasks. This trend provides some evidence for *Proposition 4.* At the same

time, interacting with computers although clearly relevant in many occupations is no longer a differentiating skill for occupations which is proved by the fact that this skill is in the top ten skills regardless occupation in the online job vacancies data.

Manual factor remained largely unchanged with only some (although mostly positive) changes in item loadings. Skills in this factor related to equipment maintenance and supervision received even higher loadings in 2020 while purely physical skills like Wrist finger speed became less definitive. Items from Vehicle operation factor are also being increasingly loaded on Manual factor, so they might become one in the future.

As for Supervision skills, management of various resources was removed from it, while coaching skill was added, the rest remained largely unchanged. These trends might also be partly a consequence of implementing artificial intelligence, especially business intelligence, because while interpersonal skills remain the hardest to automate, some data processing and analytical tasks related to resource management skills are being increasingly automated. It is important to mention, though, that high level management is not being automated altogether which can be seen from high numbers in open vacancies for managerial positions, but managers start to use various decision support software more frequently, and this software is rather often built with AI and ML technologies. The increasing use of this software contributes to the changes in the skill content of such occupations.

Similar tendency to the one observed in the Vehicle operation factor can be seen in the Mathematical factor – all of its items in 2020 also loaded on the Cognitive factor reflecting the increased correlation of mathematical skills with other cognitive skills.

Initiative factor contains the same skills in both years (Appendices 2), although in 2020 the emphasis on innovation skill further increases. Persistence which is also a part of this factor was separately analyzed in Brynjolfsson, Liu, and Westerman (2018) who empirically demonstrated that computers are making persistent workers less valuable when they are occupied in routine jobs while they are not affecting persistent workers in non-routine occupations.

Factor reconfiguration that led to fewer clusters further support the theory of job polarization and increasing skill complementarity. For example, workers that mostly utilize skills from

the Cognitive factor are now generally supposed to also possess mathematical, instructing, and oratory skills. These results provide support for *Proposition 5.*

Some general trends can also be observed from the descriptive statistics of the factors. This statistic was calculated on the original data that was split into factors (Table 6 and Figure 11). In 2014 factors were generated from 97 items, while in 2020 factors consist of 89 skill items. The mean value of importance is the highest for the Initiative factor in 2014 (3.79), while in 2020 Interpersonal skills receive slightly higher importance than Initiative (3.82 and 3.81 accordingly) which makes soft skills the most important across all occupations and further supports *Proposition 2*.

Significant change in importance can be noticed in Supervision skills which gained much higher average importance in 2020. Growing importance of supervision skills was also highlighted in several papers as the consequence of automation technologies when human tasks become more and more related to supervising the machines and processes (see MacCrory et al. 2014).

Cognitive skills received slightly lower average importance in 2020 which might be related to the change in the item composition although their importance remains very high. Cognitive skills also explain the most variation in the occupation structure which puts them on the same level as interpersonal and initiative skills in the era of ubiquitous automation. This observation extends *Proposition 2* to also include cognitive skills into the most crucial skills regardless occupation. The level of cognitive skills differentiates jobs from each other.

As for the skills composition of the factors with the highest importance levels, the highest loading in Initiative factor was received by Innovation skill. Interpersonal factor includes Self Control, Concern for Others, Social Orientation, and Stress Tolerance with the highest loadings. In the Cognitive factor Inductive and Deductive Reasoning, Critical Thinking, Complex Problem-Solving, and Active Learning received the highest loadings. None of these skills is considered to be easily automatable.

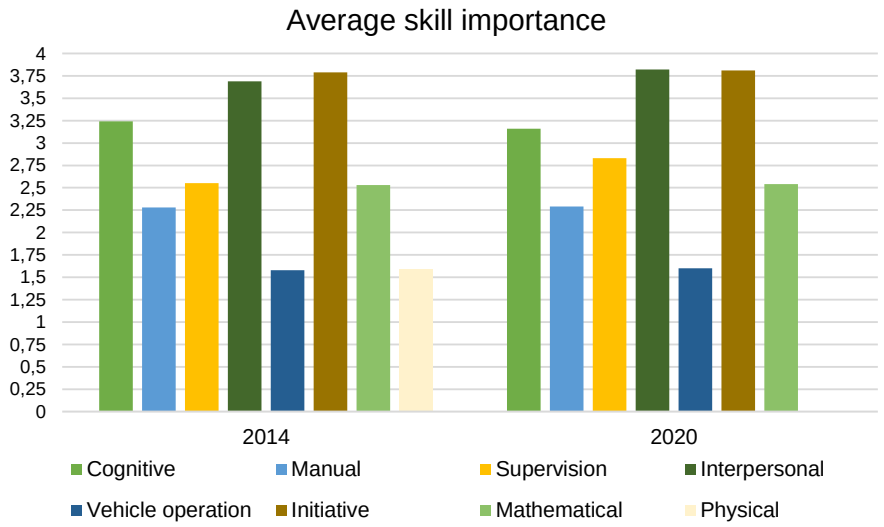

Figure 11. Average importance of different skill groups in 2014 and 2020.

*Data source: O*NET*

Table 6. Descriptive statistics of factors

	2014			2020		
Factor name	N of items	Mean	Std	N of items	Mean	Std
Cognitive	33	3.24	0.73	34	3.16	0.70
Manual	29	2.28	0.88	29	2.29	0.87
Supervision	9	2.55	0.74	7	2.83	0.68
Interpersonal	9	3.69	0.73	8	3.82	0.66
Vehicle operation	6	1.58	0.72	6	1.60	0.72
Initiative	4	3.79	0.48	4	3.81	0.45
Mathematical	3	2.53	0.59	3	2.54	0.59
Physical	6	1.59	0.67	-	-	-
N of retained skill items	97			89		
N of observations	706			706		

Note: Importance is measured on a scale 1-5.

To better understand which specific skills are growing and falling in importance across occupations in Finland, changes in the weighted by employment skill importances were calculated. The list of skills that increased and decreased in importance the most are shown in Tables 7 and 8. It is apparent from the list that Interacting with computers experienced one of the largest growths in this period reaching the weighted average importance of 3.57 and reflecting the ubiquitous digitalization across all occupations. Among other skills becoming considerably more important are controlling machines, training and coaching, teambuilding, communicating, and problem-solving. Most of them belong to the Cognitive

factor. As for the skills which are losing their importance, they appear to be mostly Physical or Manual such as finger dexterity, selective attention, and arm-hand steadiness. This trend is reflected in disappearing in 2020 Physical factor.

Table 7. Largest positive changes in skills with importance

Skill	***2014***	***2020***	***Change***
Controlling Machines and Processes	2.43	2.67	0.24
Interacting With Computers	3.34	3.57	0.23
Provide Consultation and Advice to Others	2.71	2.91	0.19
Developing Objectives and Strategies	2.89	3.07	0.19
Training and Teaching Others	3.13	3.31	0.18
Documenting/Recording Information	3.37	3.55	0.18
Scheduling Work and Activities	3.08	3.25	0.16
Developing and Building Teams	3.01	3.17	0.16
Evaluating Information to Determine Compliance with Standards	3.37	3.53	0.16
Monitoring and Controlling Resources	2.57	2.72	0.15
Communicating with Supervisors, Peers, or Subordinates	3.88	4.02	0.14
Organizing, Planning, and Prioritizing Work	3.59	3.73	0.14
Communicating with Persons Outside Organization	3.27	3.40	0.13
Coaching and Developing Others	2.97	3.10	0.13
Making Decisions and Solving Problems	3.76	3.89	0.13
Updating and Using Relevant Knowledge	3.53	3.66	0.13
Inspecting Equipment, Structures, or Material	3.03	3.15	0.12
Analyzing Data or Information	3.12	3.24	0.12

Note: only skills with importance > 2,5 in 2020 are shown

Table 8. Largest negative changes in skills with importance

Skill	***2014***	***2020***	***Change***
Finger Dexterity	2.76	2.61	-0.15
Selective Attention	3.06	2.98	-0.08
Social Orientation	3.55	3.51	-0.05
Arm-Hand Steadiness	2.52	2.48	-0.04
Speech Clarity	3.55	3.51	-0.04
Speech Recognition	3.51	3.48	-0.04
Independence	3.96	3.93	-0.03
Visual Color Discrimination	2.51	2.48	-0.03
Oral Comprehension	3.84	3.81	-0.03
Self Control	4.13	4.10	-0.02
Time Management	3.19	3.17	-0.02

Skill	2014	2020	Change
Mathematics	2.52	2.50	-0.02
Cooperation	4.18	4.16	-0.02
Oral Expression	3.78	3.76	-0.02
Flexibility of Closure	2.81	2.80	-0.02

Note: only skills with importance > 2.5 in 2014 are shown

4.5. Suitability for machine learning scores across occupations and skills.

The analysis in the previous sections presents the overall structure of occupations and skills in Finland together with their recent changes, although one of the specific goals in this thesis is to link labor market trends with the recent automation technologies, namely AI and ML. For this purpose, using the methodology of Brynjolfsson et al. (2018) suitability for machine learning scores were recalculated for the Finnish labor market to reflect how susceptible to this kind of automation different occupations are and whether occupations with lower or higher SML scores are prevalent in the market. The general description of how SML scores were calculated in the original study is presented in the Literature review chapter.

The structure of employment in Finland in 2018 results in a weighted by employment in 314 occupations average SML score of 3.48 for the whole country which tells that Finnish occupations are overall characterized by a little higher than average suitability for machine learning. The share of workers employed in high SML occupations (> 3.6) in 2018 is 16.5% which constitutes 283 485 employees. Their job tasks are likely to be substantially reorganized in the near term.

In the Figure 12 a scatter plot of SML scores against employment numbers in 2018 is presented together with a trendline showing a slight positive trend with higher employment being more associated with higher SML scores. The chart shows several distinct outliers: Shop sales assistants is the occupation with the highest employment numbers and rather high SML score (~3.6), positions of Truck drivers, Secretaries, and Accounting associate professionals employing significant number of workers also cause some concern about their jobs being considerably restructured in the nearest future due to high SML scores. At the extremes of SML range only occupations with very low employment numbers are present, so very few people in Finland are employed in the jobs with the majority of tasks being highly suitable for machine learning.

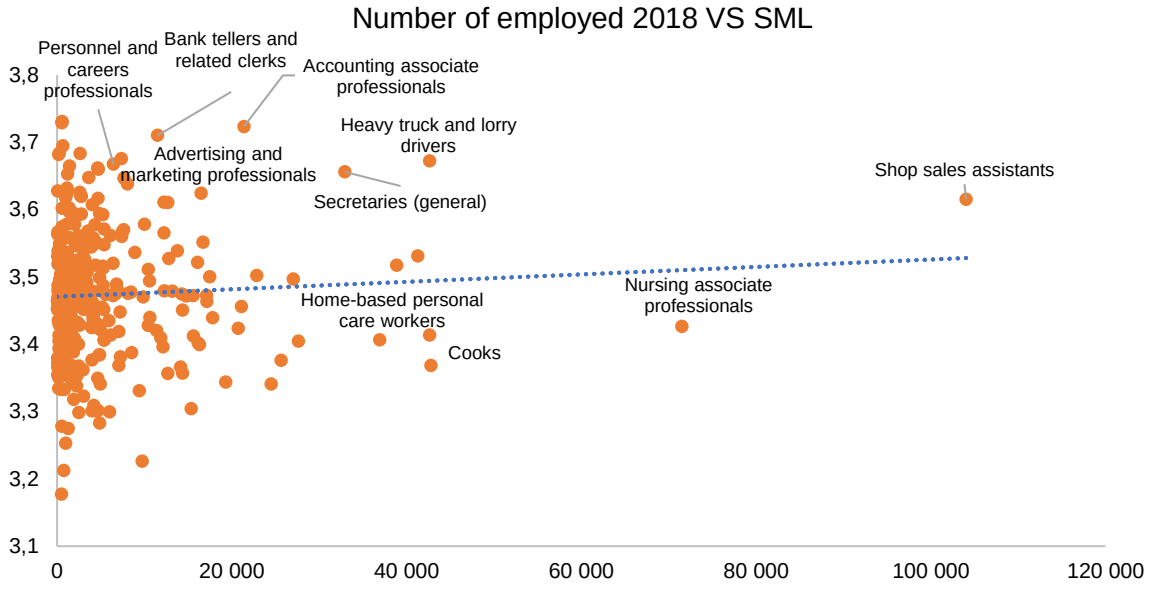

Figure 12. Scatter plot of employed 2018 versus SML.

Data source: Statistics Finland, author's own calculations based on Brynjolfsson et al. (2018)

If we look at the SML and online vacancies data (Figures 13 -14), we can see a similar trend for Accounting associate professionals, Secretaries and Truck drivers with rather high SML scores and vacancies numbers. But apart from them, there are a lot of vacancies for Advertising and marketing professionals, Cashiers and ticket clercs, and Personnel and careers professionals which all include a large share of tasks highly succeptible to automation with machine learning algorithms. In these occupations Finnish employers currently do not seem to utilize all the possibilities of ML and continue to actively hire human workers. Among low SML but popular among employers professions are personal care workers, potters and related workers, and cooks, all of which usually do not require a lot of training and are also not highly paid which further supports the theory of job polarization as one of the consequences of automation technologies.

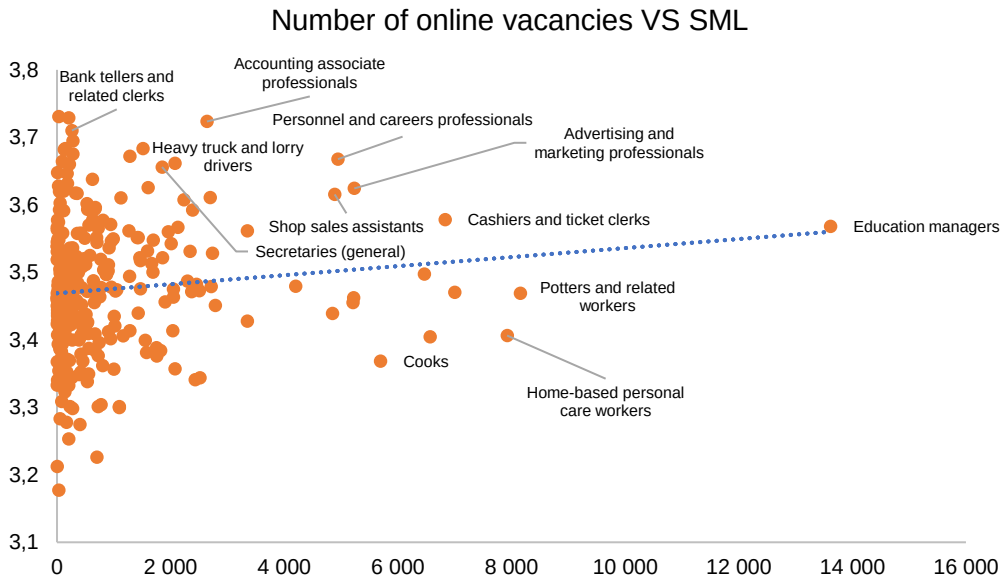

Figure 13. Scatter plot of online vacancies 2018-2020 versus SML.

Data source: Statistics Finland, author's own calculations based on Brynjolfsson et al. (2018)

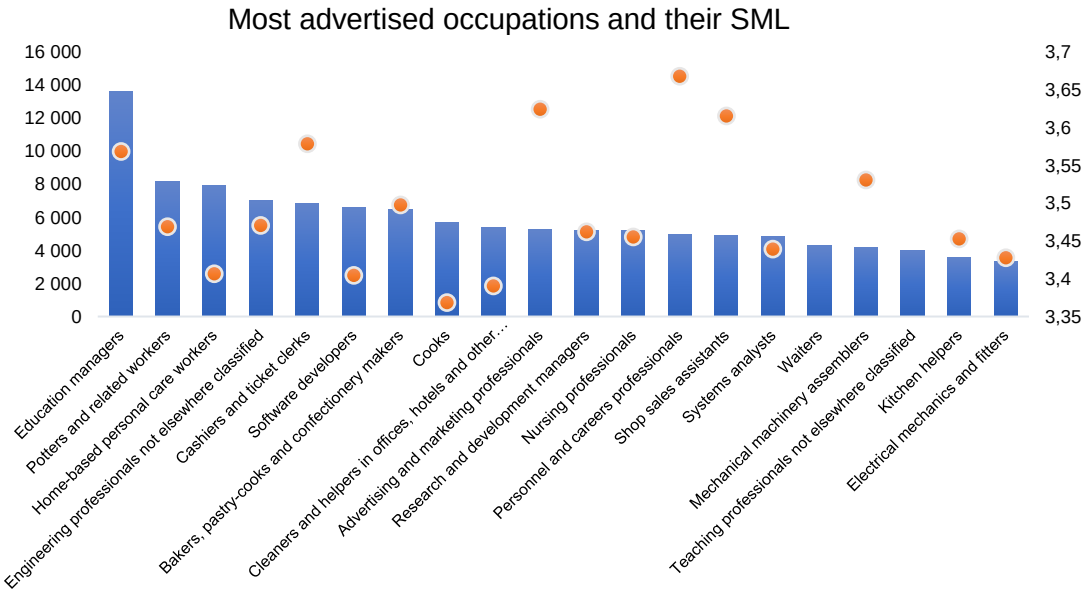

Figure 14. Most advertised occupations in Finland in 2018-2020 and their SML.

Data source: cedefop, author's own calculations based on Brynjolfsson et al. (2018)

The change in occupational structure from 2011 to 2018 is presented in Figure 15. Here a slightly downward facing trend can be observed indicating that the largest positive changes

in employment occurred in lower SML occupations. Among occupations characterized by high SML and increase in employment are some sales workers, Personnel and career professionals, and Travel guides. Proving the predictions of some researchers, sport coaches and instructors experience one of the largest increases in employment being in a rapidly growing demand but not well suited for automation. Employment of software developers has seen the largest absolute increase followed by systems analysts. Both occupations are highly related to IT but are not very suitable for automation. Among occupations experiencing sharp decline and being highly suitable for machine learning are Secretaries and Clerks. Changes in high and low SML occupations separately can be found in Appendices 3.

Judging by the employment change across occupations and their SML scores *Proposition 1* about falling labor demand in highly automatable occupations is supported only partly. Although the overall tendency follows the expectations about labor demand switching towards lower SML occupations, the trend is not very pronounced, and from 2011 to 2018 some high SML occupations demonstrated significant employment growth, therefore their ML potential remains to be uncovered.

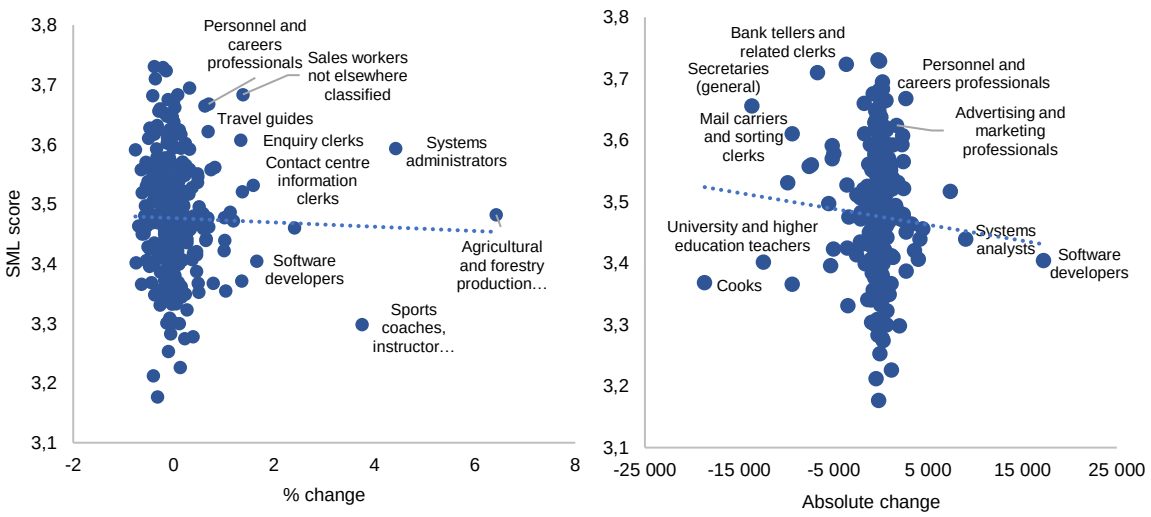

Figure 15. Scatter plot of employment change 2011-2018 against SML.

Data source: Statistics Finland, author's own calculations based on Brynjolfsson et al. (2018)

4.6. Regression analysis results

In this section regression results of various labor market variables on skill factors and SML are presented. None of the regressions have sufficient explanatory power to be used for predictions, but they are rather used to illustrate the presence of some relationship between the variables.

4.6.1. Online vacancies and skill factors

In table 9 regression results for online job vacancies regressed on factor scores are presented separately for the 2014 and 2020 factor scores. Both regressions are significant at a 10% level. Significant positive coefficients for Supervision and Mathematical factors 2014 indicate a higher demand in the vacancies that are requiring these skills while Manual factor received a negative coefficient meaning that occupations strongly relying on such skills are not that popular among employers. Regressing online vacancies on the factor scores calculated from the skill data of 2020 provides similar coefficients, but only supervision factor remains significant.

Table 9. Regression results for online vacancies

Dependent variable: Number of online job vacancies		
	2014	**2020**
Cognitive	-93.49 (91.84)	-38.25 (89.73)
Manual	-162.24 * (94.07)	-152.64 (92.91)
Supervision	172.78 * (91.54)	177.33 * (92.88)
Interpers	-27.38 (97.74)	-35.62 (93.57)
Vehicle	-105.77 (92.72)	-123.06 (91.70)
Initiative	54.93 (100.44)	127.68 (97.40)
Math	185.54 * (98.92)	156.39 (96.41)
Physical '14	-24.74 (89.00)	
(Intercept)	809.46 *** (89.60)	829.69 *** (89.35)
R^2	0.049	0.047
F-test significance	0.083	0.059
No. Observations	286	286

Note: Upper numbers are estimated regression coefficients, numbers in parentheses are standard errors

** indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01.*

4.6.2. Change in jobseekers 2011-2018 and skill factors

On a supply side of the labor market some changes have also occurred (see table 10). Using 2014 factor scores as regressors for the percentage change in a number of jobseekers from 2011 to 2018 indicates the decrease in jobseekers looking for occupations requiring a lot of physical or manual skills while the number of jobseekers from occupations requiring more supervision skills seems to increase. Using factor scores for 2020 provides very similar results with negative coefficient for manual skills and positive for supervision.

Table 10. Regression results for the change in the number of jobseekers 2011-2018 (%)

Dependent variable: Percentage change in the number of jobseekers 2011-2018		
	2014	**2020**
Cognitive	41.12 (38.18)	48.49 (37.28)
Manual	-87.17 ** (39.11)	-108.87 *** (38.60)
Supervision	74.27 * (38.06)	75.60 * (38.59)
Interpers	26.48 (40.63)	0.45 (38.88)
Vehicle	-7.40 (38.55)	-44.24 (38.10)
Initiative	-21.88 (41.76)	-35.98 (40.47)
Math	0.69 (41.12)	8.38 (40.06)
Physical '14	-77.42 ** (37.00)	
(Intercept)	137.57 *** (37.25)	139.14 *** (37.12)
R^2	0.055	0.055
F-test significance	0.045	0.027
No. Observations	286	286

Note: Upper numbers are estimated regression coefficients, numbers in parentheses are standard errors
** indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01.*

4.6.3. Vacancies change 2011-2018 (Statistics Finland) and skill factors

Changes in the demand side are captured by the regression of absolute numbers of the vacancies change on skill factors (table 11). Remembering that vacancies data from Statistics Finland mostly provide information about lower skill level occupations, it can be seen that vacancies requiring more Vehicle operation skills have increased regardless the choice of the factor scores. Using 2020 factor scores as regressors also tells that vacancies requiring

more manual and supervision skills have increased. This contradicts the results of the current research literature and theories but is probably a result of a very sparse data regarding vacancies provided by Statistics Finland.

Table 11. Regression results for the change in the number of vacancies 2011-2018

Dependent variable: absolute change in the number of vacancies 2011-2018		
	2014	**2020**
Cognitive	-12.93 (10.35)	-11.69 (10.06)
Manual	16.55 (10.60)	20.26 * (10.41)
Supervision	-0.43 (10.31)	11.34 * (10.41)
Interpers	-5.15 (11.01)	-10.87 (10.49)
Vehicle	28.97 *** (10.45)	27.93 *** (10.28)
Initiative	-16.43 (11.32)	-17.58 (10.92)
Math	5.46 (11.15)	-7.06 (10.81)
Physical '14	15.01 (10.03)	
(Intercept)	37.11 *** (10.10)	37.51 *** (10.01)
R^2	0.055	0.064
F-test significance	0.044	0.010
No. Observations	286	286

Note: Upper numbers are estimated regression coefficients, numbers in parentheses are standard errors
** indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01.*

4.6.4. SML and skill factors

In order to check whether skill factors in occupations can explain occupational suitability for machine learning, they were regressed on the skill factors. In this case O*NET database is used as it allows to keep more relevant information part of which is lost when a crosswalk between occupational classifications is used.

Two linear regressions were built separately - one for 2014 and one for 2020. The results show that both regressions are valid, although the R-squared value is not high in any of them. The highest R^2 equal to 0.204 is achieved when 2014 skill factors were used as predictors, while for the regression on 2020 skill factors R-squared drops and only reaches

0.129. Nevertheless, factors possess some explanatory power and the model is statistically significant as indicated by F-test results.

From the regression output (table 12) one can observe that Physical factor received the highest negative coefficient in 2014, followed by Initiative, Manual, and Vehicle skills all of which tend to be associated with lower SML scores. In fact, these are the skills that are the most difficult to automate using machine learning algorithms. As for the manual skills, only routine manual tasks are being currently automated.

On the other side, Mathematical skill factor has a positive coefficient meaning that occupations where mathematical skills are more important tend to have higher SML scores which comes by no surprise as computers are much better at working with numbers than humans.

Interestingly, Cognitive skill variable is not significant in both years which may indicate that cognitive skills are equally important in occupations with high and low SML scores. In 2020 Manual, Vehicle, and Initiative variables received even higher absolute coefficients, all negatively affecting SML score. The only variable positively and significantly impacting SML scores in 2020 remained Mathematical.

Table 12. Regression results for SML scores

Dependent variable: SML scores		
	2014	**2020**
Cognitive	-0.004 (0.004)	-0.002 (0.004)
Manual	-0.017 *** (0.004)	-0.023 *** (0.004)
Supervision	-0.002 (0.004)	-0.007 * (0.004)
Interpers	0.009 ** (0.004)	0.007 (0.004)
Vehicle	-0.010 *** (0.004)	-0.016 *** (0.004)
Initiative	-0.021 *** (0.004)	-0.017 *** (0.004)
Math	0.025 *** (0.004)	0.022 *** (0.004)
Physical '14	-0.033 *** (0.004)	
(Intercept)	3.462 *** (0.004)	3.462 *** (0.004)
R^2	0.204	0.129
F-test	23.586	14.767

Dependent variable: SML scores		
	2014	**2020**
No. Observations	706	706

Note: Upper numbers are estimated regression coefficients, numbers in parentheses are standard errors
** indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01.*

4.6.5. Employment change and SML

Regressing employment change on SML scores (Table 13) provides some evidence on the already existing impact of machine learning on employment. As it is seen from the high negative coefficient, a unit higher SML score decreases employment change by about 2 400 indicating that the labor market in Finland is moving towards lower SML occupations, while employment in high SML occupations is decreasing. This is an important observation as it shows the impact that machine learning has already imposed on the labor market. However, these results are only indicative as the R^2 is very low and there are multiple other factors influencing employment change which are not considered in this thesis.

Table 13. Regression results for employment change 2011-2018

Dependent variable: absolute employment change 2011-2018	
SML	-2409.65 ** (1157.92)
(Intercept)	8343.56 ** (4022.01)
R^2	0.015
F-test significance	0.038
No. Observations	281

Note: Upper numbers are estimated regression coefficients, numbers in parentheses are standard errors
** indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01.*

4.6.6. Summary of the regression analysis results

Summing up SML regression analysis, it can be said that skill factors, although possessing some explanatory power, are not very strong predictors of SML scores. Nevertheless, the drop in most of the R^2 from 2014 to 2020 might be the result of increasing skill complementarities in the job market where workers within each occupation must utilize skills from different skill groups which are in addition very different in terms of automation potential. Another possibility is that skills within a factor are changing in such a way that

highly automatable and low automatable skills now more often belong to the same factor as it occurred, for example, to the Cognitive skill factor.

Finnish employment seems to be moving to the direction of lower SML occupations with Supervision skills positively affecting both the demand side and the supply side. On the other hand, Manual skills seem to be decreasing on both sides.

5. SUMMARY AND DISCUSSION

This final chapter summarizes the most important results, analyzes the propositions, lists limitations, and offers ideas for possible related future research.

5.1. Propositions analysis

1) *Labor demand is falling in occupations highly susceptible to automation.*

   This proposition is partly supported by significant negative changes in employment in several low SML occupations, such as Secretaries and Clerks and by the current low share of these occupations in the market. In addition, regression analysis of employment change on SML scores indicated a significant negative effect of SML on the absolute change of employed persons for the period from 2011 to 2018 providing further proofs for this proposition. However, there has been an increase in some high SML occupations over the last decade, namely Sales workers and Personnel and career professionals. Overall, 16.5% of workers in 2018 were employed in high SML occupations among which a large share consists of Shop sales assistants, Accounting professionals, Bank tellers, and Secretaries.

2) *Soft and basic computer skills are becoming crucial for workers regardless their occupation.*

   Soft and basic computer skills are the ones mostly required in the Finnish market across all occupations as analysis of the online vacancies data has demonstrated. Among soft skills the leading ones are ability to adapt to change, teamwork, problem-solving, and communication skills. Assuming the similarity between American and Finnish labor market adds initiative and innovation skills to the most important ones.

   Top demanded computer skills are limited to the ability to use computer and Microsoft Office software. In addition, regression analysis showed the increasing importance of the Supervision skills which might be another indicator of extended automation as human workers tasks are being more related to machine supervision. Analysis of online job vacancies data has also revealed that programming and ICT

communication protocols skills are required across around 10 different occupations, which indicates the high importance of advanced computer skills in a significant share of occupations which judging by the employment change is likely to increase further.

3) *AI, ML, and other automation technologies make IT and Engineering occupations more heterogeneous in terms of required skills.*

The results of the analysis show that IT specialists, for example, Software developers, and Engineers are indeed very heterogeneous occupations as they require the broadest variety of skills as found in the online vacancy data. This might be related to the impact of technology as these occupations directly involve extensive use of various technologies. There seems to be a heterogeneity in these occupations not expressed on the most detailed 5-digit level in the Classification of Occupations (ESCO). Moreover, Software developers and Systems analysts being among the most heterogenous occupations have also experienced the largest absolute increase in employment during 2011-2018. However, in addition to these two groups, it was discovered that Managers and Marketing professionals are other occupation groups with a very broad diversity of required skills. Therefore, the most requiring or heterogeneous occupations are IT professionals, Engineers, Marketing professionals, and Managers.

4) *Cognitive routine skills related, for example, to information gathering and processing or documenting, are losing their significance to automation technologies.*

Skill factors defining occupations have changed from 2014 to 2020 and the changes included decreasing significance of data collection, processing, and documenting skills. However, as it can be seen from the increased overall importance of these skills, they are now inherent in a broad range of occupations and are no longer differentiating skills. This trend is directly related to automation technologies, as the volume and velocity of the data generated in this period has been only accelerating. Thus, the analysis results do not say whether such skills in humans are becoming less important, as it depends to which extent these tasks are being performed by humans or by computers.

5) *There have been some important changes in the skill structure across occupations in the recent years that can be explained by the increased use of automation technologies.*

   The skill structure has in fact changed as indicated by PCA analysis of skills across occupations in 2014 and 2020. The number of skill factors that define occupations has decreased with Physical skills no longer forming a separate group. As for the relationship of the factor changes to automation technologies, it can be seen from the structure of the factors which has also changed and is now characterized by increased emphasis on cognitive non-routine, communication, initiative, and supervision skills that are “automation cornerstones”.

5.2. Research questions summary and other important findings

The research questions defined in the introduction can be answered based on the conducted research. The answers to them are presented below. In addition, some other important findings are mentioned.

1) How has the Finnish labor market been developing in the recent years?

   There was a significant fall in employment of Clerks – a category considered to be highly automatable, and a large increase in employment of Professionals – an occupation group requiring a variety of skills and which is also characterized by lower automatability. Some mismatch was identified between the vacancies and the jobseekers which is reflected in high vacancy rates coupled with considerable unemployment. As for the current demand in the market, the largest number of vacancies published online in 2018-2020 was targeted at Education managers, followed by Potters and related workers and Home-based personal care workers. In the top were also Engineering professionals, Cashiers and ticket clerks, and Software developers. This list includes vacancies requiring very different skillsets which indicates that labor market in Finland is rather heterogeneous. The large share of job advertisements for Software developers indicates a growing IT industry and might lead to a significantly higher rates of future automation.

2) How does the skill structure in Finland look?

Soft skills are in top demand among Finnish employers, but also the ability to use a computer is required in a large share of occupations. The main skill groups defining occupations are Cognitive, Manual, Interpersonal, Supervision, Initiative, Vehicle operation, and Mathematical where half of the variation is explained by the first two skill factors. Physical skills used to be another defining category, but they have disappeared as a separate category in 2020. Some other changes in skill structure have also occurred, for example, to the Cognitive skill factor some other skills were added, namely mathematical and oratory skills, originality, and fluency of ideas. Mathematical skills have also increased in demand in Finland from 2011 to 2018. It is an interesting observation because while mathematical skills are usually easily automatable and their presence might be explained by the increased need to be able to handle and analyze numerical data across diverse range of industries and, therefore, jobs; the others are skills exclusively possessed by humans so far. This can be another trend related to the spread of automation technologies which make skills unique to humans increasingly important.

There is some relationship between skill groups and employment indicators indicated by the regression analysis results. Prevalence of the Manual skills in an occupation is associated with the lower number of online vacancies published, as well as with the decreasing number of jobseekers. At the same time, in occupations requiring more supervision skills, the number of vacancies seems to be higher, as well as there is an increasing number of jobseekers.

Another observation stemming from the factor distribution gives further support to the theories of job polarization, as around 50% of variation in skills across occupations is explained by Cognitive and Manual skill factors meaning that jobs tend to require either a lot of cognitive skills or a lot of manual. On top of that, skill complementarities within clusters have grown and the number of clusters has decreased which makes skills factors more distinct from each other than before.

3) Which trends in the labor and skill market can be explained with the spread of AI and ML?

   Decrease in demand for Secretaries and Clerks clearly reflects some automation trends as these are the occupations where most tasks can be automated. However, ML potential is not fully realized yet which can be seen by high employment numbers in some other highly suitable for ML occupations.

   Regression analysis has also illustrated strong negative correlation between SML scores and employment change which means that employment mainly falls in occupations with higher SML scores. Additionally, skill factors relationship with SML scores was also studied and the results revealed that Physical, Initiative, Manual, and Vehicle operation skill factors are associated with lower SML scores, while Mathematical skills seem to positively correlate with SML scores.

5.3. Summary, theoretical contribution and managerial implications

This work provides a valuable contribution to the empirical research of the skill market in Finland and highlights recent trends related to automation technologies. It is also the first study in Finland that utilizes online job vacancy data and although it is rather sparse, it gives new insights into the labor and skill demand which could not be revealed from the other sources. Apart from that, factor analysis of the O*NET skill data extends the previous research and includes the most relevant data up to the year 2020 which helps to discover recent skill shifts and changes in skills importance across occupations.

In this thesis skill structure in the Finnish labor market was analyzed together with its recent changes. Results of this study can be useful for education institutions to develop the programs in such a way that they provide students with a necessary skillset to make them successful in their future careers. As for the managerial implications, this thesis provides information about suitability for machine learning scores across occupations which can help organizations restructure positions within their organizations in a way that will promote the use of the latest technologies and make the best out of the human capital by utilizing it for the tasks where machines have not demonstrated good performance yet.

5.4. Limitations

The novelty and difficulty of skill market analysis brings some limitations which should be acknowledged when using the results of this paper. First, online job vacancies data is cross-sectional, so it does not present the development of skill demand in time. Second, the online job vacancies dataset is rather sparse in terms of skills mentioned. Many of them are not classified and not all occupations are present. Results of the factor analysis can only be reliable in case Finnish occupations are in reality very similar to American ones. Another limitation stems from the need to use a crosswalk between European and American classifications of occupations, as they cannot be completely bridged. This leads to some information loss and might confuse the results to some unknown extent. The same issue arises in suitability for machine learning calculation, some scores might be not completely truthful because of the differences in classifications.

5.5. Further research

This topic provides plenty of opportunities for further research related to either skill market or the impact of automation technologies. One suggestion would be to include the wage data into analysis and investigate the differences between wages of persons depending on their skills. Another idea is to use the supply side data from the web, for example, collect the data from online job platforms and analyze compatibility of the skills that workers possess with the ones that are requested by employers. Having both demand and supply data as a time series would reveal more patterns and trends in the structure of the Finnish labor market. As for automation technologies, occupational structure of the companies that utilize AI and ML can be compared with the ones that do not use these technologies. Although this would require detailed data on specific companies which can hardly be shared with the public.

6. CONCLUSION

This paper attempts to analyze the Finnish labor market from the skills and automation perspectives and it is the first of its kind in this region. Although it turns out that numerically measuring the impact of automation technologies in the labor market is a very challenging task, some trends related to the possible impact of AI, ML and other automation technologies are discovered. Employment in highly automatable occupations is falling, purely physical skills are losing their importance while the relevance of interpersonal, initiative, non-routine cognitive, and supervision skills is growing. Automation results are expected to appear soon, as software developers, systems analysts, and other IT specialists are experiencing the largest growth in employment and the government encourages AI implementation.

Overall, the labor market in Finland appears to be rather heterogeneous and there are no signals that many jobs will disappear in the near term. The most worrisome occupations that still employ a lot of workers and are highly susceptible to automation are various clerks, bank tellers, secretaries, and cashiers. Other than that, there is a demand for both lower skilled labor force and a steadily growing need for professionals.

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APPENDICES

APPENDIX 1. Top skills across occupation groups

Occupation group Managers	Number of job ads mentioning the skill	% of all skills in occupation	Occupation group Professionals	Number of job ads mentioning the skill	% of all skills in occupation
adapt to change	13752	0,08	adapt to change	21457	0,05
use a computer	9337	0,05	use a computer	17166	0,04
teamwork principles	7217	0,04	work as a team	15810	0,04
office administration	5792	0,03	teamwork principles	15691	0,04
project management	5706	0,03	computer programming	11423	0,03
manage time	5402	0,03	project management	10975	0,03
work as a team	5172	0,03	create solutions to problems	9234	0,02
communication	5056	0,03	business ICT systems	9171	0,02
create solutions to problems	4698	0,03	use microsoft office	8988	0,02
English	4603	0,03	develop strategy to solve problems	8085	0,02
use microsoft office	4249	0,02	English	7715	0,02
office software	4226	0,02	logging	7485	0,02
analyse problems for opportunities	3749	0,02	think creatively	7465	0,02
show responsibility	3732	0,02	analyse software specifications	6844	0,02
tolerate stress	3567	0,02	use software design patterns	6813	0,02
lead a team	3414	0,02	analyse problems for opportunities	6622	0,02
economics	3401	0,02	communication	6578	0,02
think creatively	3144	0,02	develop creative ideas	5935	0,01
develop creative ideas	3053	0,02	team building	5934	0,01
team building	2833	0,02	use online communication tools	5913	0,01

Occupation group Technicians and associate professionals	Number of job ads mentioning the skill	% of all skills in occupation	Occupation group Clerical support workers	Number of job ads mentioning the skill	% of all skills in occupation
adapt to change	7911	0,13	adapt to change	3461	0,23
use a computer	3909	0,06	English	2155	0,15
English	3496	0,06	use a computer	1735	0,12
work as a team	3260	0,05	work as a team	1230	0,08
use online communication tools	3050	0,05	use online communication tools	1000	0,07
sales activities	1814	0,03	customer service	910	0,06
customer service	1749	0,03	use microsoft office	615	0,04
quality standards	1700	0,03	sales argumentation	495	0,03
logging	1589	0,03	drive vehicles	461	0,03
graphics editor software	1529	0,02	quality standards	328	0,02

use microsoft office	1486	0,02	logging	325	0,02
manage time	1447	0,02	tolerate stress	321	0,02
ICT communications protocols	1444	0,02	adapt to changing situations	318	0,02
sales argumentation	1395	0,02	office administration	308	0,02
create solutions to problems	1369	0,02	teamwork principles	278	0,02
develop strategy to solve problems	1206	0,02	assist customers	274	0,02
think creatively	1066	0,02	office software	271	0,02
team building	1057	0,02	hotel operations	253	0,02
office software	1010	0,02			
communication	1005	0,02			

Occupation group **Service and sales workers**	**Number of job ads mentioning the skill**	**% of all skills in occupation**	**Occupation group** **Craft and related trades workers**	**Number of job ads mentioning the skill**	**% of all skills in occupation**
adapt to change	10727	0,14	English	9970	0,13
English	4947	0,07	logging	6747	0,09
customer service	4922	0,07	work as a team	5652	0,07
logging	4826	0,06	create software design	4984	0,06
present menus	4808	0,06	JavaScript Framework	4983	0,06
assist customers	3889	0,05	quality standards	3814	0,05
work in a hospitality team	3521	0,05	keep company	3287	0,04
sales activities	2720	0,04	adapt to change	3280	0,04
take food and beverage orders from customers	2550	0,03	ICT communications protocols	3001	0,04
work as a team	2071	0,03	pick orders for dispatching	2678	0,03
act reliably	1938	0,03	stay up to date with social media	2554	0,03
sales argumentation	1936	0,03	Turkish	2362	0,03
customer relationship management	1752	0,02	technical drawings	1699	0,02
tolerate stress	1401	0,02	tend CNC metal punch press	1634	0,02
adapt to changing situations	1377	0,02	tend CNC laser cutting machine	1631	0,02
merchandising techniques	1368	0,02	tend CNC drilling machine	1629	0,02
direct customers to merchandise	1359	0,02	demonstrate enthusiasm	1423	0,02
supervise merchandise displays	1348	0,02	use scripting programming	1342	0,02
use online communication tools	1226	0,02	act reliably	1140	0,01
carry out cheese production	1105	0,01	drive vehicles	1114	0,01

Occupation group Plant and machine operators, and assemblers	Number of job ads mentioning the skill	% of all skills in occupation	Occupation group Elementary occupations	Number of job ads mentioning the skill	% of all skills in occupation
adapt to change	1699	0,17	adapt to change	2779	0,15
quality standards	1361	0,14	perform warehousing operations	2182	0,12
English	1229	0,12	clean particular areas manually	1522	0,08
work as a team	757	0,08	clean surfaces	1512	0,08
manufacturing processes	519	0,05	cleaning products	1512	0,08
logging	499	0,05	cleaning techniques	1500	0,08
act reliably	418	0,04	English	1482	0,08
drive vehicles	406	0,04	work in a hospitality team	1455	0,08
mechanics	406	0,04	logging	1131	0,06
use a computer	374	0,04	act reliably	1001	0,05
online analytical processing	371	0,04	clean kitchen equipment	614	0,03
mechanics of motor vehicles	368	0,04	monitor kitchen supplies	608	0,03
engine components	366	0,04	keep company	527	0,03
create solutions to problems	337	0,03	work as a team	279	0,01
adapt to changing situations	287	0,03	present menus	272	0,01
show responsibility	249	0,03	Turkish	264	0,01
examine merchandise	234	0,02			

APPENDIX 2. Factor analysis results

a) 2014 factor loadings (rotated)

Variable	***cognitive***	***manual***	***interpers.***	***supervision***	***physical***	***vehicle***	***initiative***	***math.***	***Uniq.***
Active Learning	0.8221								0.1250
Active Listening	0.6650								0.1604
Complex Problem solving	0.8496								0.1363
CriticalThinking	0.8723								0.1153
Equipment Maintanence		0.8254							0.0674
Equipment Selection		0.8467							0.1017
Judgment and decision making	0.7911								0.1619
Learning Strategiess	0.7128								0.2393
Management of Financial Resources				0.6533					0.2122
Management of Material Resources				0.6511					0.2250
Management of personnel Resources	0.5702			0.6073					0.2028
Mathematics	0.5390							0.7199	0.1033
Operation and Control		0.8717							0.1051
Operation Monitoring		0.9062							0.1054

Quality Control Analysis		0.8525					0.2064
Reading Comprehension	0.7931						0.1167
Repairing		0.8072					0.0725
Science	0.7418						0.3288
Service Orientation			0.6190				0.2407
Systems Analysis	0.7800						0.1573
Systems Evaluation	0.7932						0.1422
Troubleshooting		0.9033					0.0887
Writing	0.7657						0.1316
Arm Hand Steadiness		0.8191					0.0910
Auditory Attention		0.7004					0.2402
Category Flexibility	0.7000						0.3024
Control Precision		0.8640					0.0901
Deductive Reasoning	0.8766						0.1237
Depth Perception		0.7880					0.1255
Dynamic Flexibility				0.7200			0.3380
Dynamic Strength		0.5601		0.6189			0.0864
Explosive Strength				0.6876			0.3878
Extent Flexibility		0.6118		0.5604			0.0930
Finger Dexterity		0.8120					0.2470
Flexibility of Closure	0.6750						0.2224
GlareSensitivity		0.5481			0.7123		0.1108
Gross Body Coordination		0.5136		0.6659			0.0778
Gross Body Equilibrium		0.5265		0.6422			0.1478
Hearing Sensitivity		0.7793					0.2166
Inductive Reasoning	0.8852						0.1248
Informatio ordering	0.7309						0.2999
Manual Dexterity		0.8122					0.0907
Mathematical Reasoning	0.5860					0.6895	0.0746
Memorization	0.7045						0.2766
Multilimb Coordination		0.7678					0.0660
Night Vision		0.5074			0.7965		0.0664
Number Facility	0.5205					0.7347	0.0961
Oral Comprehension	0.6277						0.2006
Peripheral Vision					0.7893		0.0496
Problem Sensitivity	0.7742						0.2278
Rate Control		0.7953					0.1420
Reaction Time		0.7898					0.1143
Response Orientation		0.7904					0.1228
Sound Localization		0.5711			0.7192		0.0996
Spatial Orientation					0.7741		0.0912
Speed of Closure	0.6752						0.2232
Stamina		0.5195		0.6571			0.0736
StaticStrength		0.6366		0.5309			0.0740
Visual Color Discrimination		0.7569					0.3207
Wrist Finger Speed		0.8033					0.2280

Written Comprehension	0.7670								0.1226
Written Expression	0.7569								0.1188
Analyzing Data or Information	0.7991								0.1258
Assisting and Caring for Others			0.7253						0.2341
Controlling Machines and Processes		0.8621							0.1485
Coordinating the Work and Activities of Others				0.7687					0.1852
Developing and Building Teams				0.7028					0.1960
Documenting/Recording Information	0.7135								0.2408
Getting Information	0.6781								0.2900
Guiding, Directing, and Motivating Subordinates				0.7819					0.1654
Handling and Moving Objects		0.7319							0.1122
Identifying Objects, Actions, and Events	0.6581								0.3450
Inspecting Equipment, Structures, or Material		0.8660							0.1892
Interacting with Computers	0.6310								0.1886
Interpreting the Meaning of Information for Others	0.7679								0.1968
Making Decisions and Solving Problems	0.7243								0.2764
Monitoring and Controlling Resources				0.7802					0.2407
Operating Vehicles, Mechanized Devices, or Equipment		0.6000				0.6547			0.1246
Performing General Physical Activities		0.6031			0.5149				0.1189
Processing Information	0.6976								0.1444
Repairing and Maintaining Electronic Equipment		0.7692							0.1954
Repairing and Maintaining Mechanical Equipment		0.8601							0.0973
Scheduling Work and Activities				0.6002					0.3154
Staffing Organizations				0.7771					0.2320
Updating and Using Relevant Knowledge	0.7807								0.1996
Achievement							0.6807		0.1705
Adaptability			0.6507						0.2279
Analytical Thinking	0.7167								0.1765
Concern for Others			0.8682						0.1801
Cooperation			0.8013						0.2572
Dependability			0.6781						0.3473
Initiative	0.5050						0.6353		0.1444
Innovation							0.6909		0.2512
Persistence							0.6757		0.1754
Self Control			0.8778						0.1813
Social Orientation			0.8453						0.1960
Stress Tolerance			0.7521						0.2194
Cumulative % of variance explained	**0.2431**	**0.4832**	**0.5548**	**0.6171**	**0.6704**	**0.7211**	**0.7541**	**0.7816**	
Cronbach alpha	**0.9825**	**0.9796**	**0.9331**	**0.9412**	**0.9265**	**0.9793**	**0.9286**	**0.9803**	

b) 2020 factor loadings (rotated)

Variable	cognitive	manual	interpers.	supervision	vehicle	initiative	math.	Uniq.
Active Learning	0.8322							0.1274
Active Listening	0.7144							0.1312
Complex Problem solving	0.8720							0.1451
Critical Thinking	0.8916							0.1127
Equipment Maintanence		0.8656						0.0905
Equipment Selection		0.8840						0.1274
Instructing	0.6495							0.1469
Judgment and Decision Making	0.8211							0.1777
Learning Strategies	0.7170							0.1272
Mathematics	0.5861						0.6801	0.0980
Monitoring	0.6456							0.2601
Operation and Control		0.8647						0.1212
Operation Monitoring		0.8968						0.1132
Quality Control Analysis		0.8588						0.1781
Reading Comrehension	0.8122							0.1139
Repairing		0.8495						0.1046
Science	0.7443							0.2811
Speaking	0.6441	-0.5523						0.1451
Systems Analysis	0.8291							0.1558
Systems Evaluation	0.8175							0.1492
Troubleshooting		0.9219						0.0926
Writing	0.7985							0.1230
Arm Hand Steadiness		0.8277						0.0785
Auditory Attention		0.7108						0.2560
Category Flexibility	0.7420							0.2720
Control Precision		0.8595						0.0958
Deductive Reasoning	0.8912							0.1219
Depth Perception		0.7782						0.1272
Extent Flexibility		0.6786						0.1721
Finger Dexterity		0.8128						0.1573
Flexibility of Closure	0.6839							0.2591
Fluency of Ideas	0.7245							0.1210
Glare Sensitivity		0.5628			0.7397			0.0965
Hearing Sensitivity		0.7631						0.2529
Inductive Reasoning	0.9021							0.1160
Information Ordering	0.7703							0.2647
Manual Dexterity		0.8113						0.0809
Mathematical Reasoning	0.6224						0.6560	0.0877
Memorization	0.6901							0.3117
Multilimb Coordination		0.7803						0.0665
Night Vision		0.5255			0.7843			0.0790
Number Facility	0.5647						0.7058	0.1081

Oral Comprehension	0.6907						0.1594
Oral Expresion	0.6636	-0.5179					0.1502
Originality	0.6744						0.1098
Peripheral Vision		0.5219			0.7952		0.0506
Problem Sensitivity	0.7863						0.2230
Rate Control		0.7891					0.1328
Reaction Time		0.8083					0.1014
Response Orientation		0.7711					0.1108
Sound Localization		0.5916			0.7146		0.0987
Spatial Orientation					0.7817		0.0988
Speed of Closure	0.7018						0.2733
Static Strength		0.6760					0.1345
Visual Color Discrimination		0.7121					0.2810
Visualization		0.6248					0.1844
Wrist-Finger Speed		0.7403					0.3201
Written Comrehension	0.7974						0.1242
Written Expession	0.7902						0.1114
Analyzing Data or Information	0.7794						0.1570
Assistingand Caring for Others			0.6940				0.2174
Coaching and Developing Others				0.6847			0.1517
Controlling Machines and Processes		0.8556					0.1584
Coordinating the Work and Activities of Others				0.8234			0.1673
Developing and Building Teams				0.7731			0.1810
Guiding, Directing, and Motivating Subordinates				0.8228			0.1417
Handling and Moving Objects		0.7318					0.1319
Inspecting Equipment, Structures, or Material		0.8535					0.1809
Interpreting the Meaning of Information for Others	0.7268						0.2046
Making Decisions and Solving Problems	0.7161						0.2589
Monitoring and Controlling Resources				0.7527			0.2919
Operating Vehicles, Mechanized Devices, or Equipment		0.6086			0.6486		0.1314
Repairing and Maintaining Electronic Equipment		0.7815					0.2018
Repairing and Maintaining Mechanical Equipment		0.8695					0.1003
Scheduling Work and Activities				0.6562			0.2679
Staffing Organizational Units				0.8055			0.2201
Updating and Using Relevant Knowledge	0.7442						0.2046
Achievement						0.6560	0.2018
Adaptabiliy			0.7115				0.2146
Analytical Thinking	0.7332						0.1842
Concern for Others			0.8463				0.1958
Cooperation			0.7830				0.2542
Dependability			0.7149				0.3639
Initiative						0.6321	0.1648
Innovation						0.7357	0.2428
Persistence						0.6817	0.1828

Self Control			0.8725					0.1945
Social Orientation			0.8041					0.2286
Stress Tolerance			0.7950					0.2186
Cumulative % of variance explained	0.2681	0.5263	0.6025	0.6660	0.7228	0.7592	0.7836	
Cronbach alpha	0.9842	0.9846	0.9304	0.9393	0.9803	0.9160	0.9802	

APPENDIX 3. Employment change 2011-2018 in high (>3,6) and low (< 3,4) SML occupations on a 2-digit level.