The London School of Economics and Political Science

Non-cognitive skills and the labour market: the past, the present and the future

Cecily Josten

This thesis was submitted to the Department of Psychological and Behavioural Science of the London School of Economics and Political Science, for the degree of Doctor of Philosophy, London, April 2023

Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I declare that my thesis consists of 60,650 words.

Statement of co-authored work

I confirm that chapter 1.2.1. and Appendix A (Paper 1) were jointly co-authored with Dr Grace Lordan. I contributed 75% and the full paper as presented in Appendix A was published in the LSE Public Policy Review. Chapter 1.2.2. and Appendix B (Paper 2) were also jointly co-authored with Dr Grace Lordan. I contributed 50% and the paper as presented in Appendix B was published in PLOS ONE.

Acknowledgments

Pursuing a PhD requires continuous effort and motivation. My key source of motivation and inspiration from start to finish has been my supervisor Grace Lordan with her captivating passion and profound knowledge spanning across so many areas. I am very grateful for her encouragement, her guidance and her expertise throughout my PhD journey. I am particularly thankful that I was able to join The Inclusion Initiative where Grace clearly followed her "mantra" in giving me opportunity, visibility, and voice.

I would also like to express my gratitude to my colleagues at The Inclusion Initiative for their collaboration and inspiration. Their diverse perspectives and expertise have enriched my research and personal growth and working together has always been great fun.

Thank you also to the Department of Psychological and Behavioural Science at LSE. Specifically, I want to thank my fellow PhD colleagues whose company and support, in both academic and practical matters, has been invaluable. Further, I would like to thank Paul Dolan for being my second supervisor, Christian Krekel and Thomas Curran for providing helpful comments during and after my Upgrade and Dario Krpan for his insights on factor analysis. Thank you also to Rebecca Lee who is the soul of the PhD group.

My heartfelt thanks go to my family and friends for their love and support; in particular for providing much welcomed distractions from academic endeavours. Lastly, I want to thank Constantin for his round-the-clock academic and moral support. His relentless optimism and his growth mindset let me think big. Thank you for being my sparring partner always.

Abstract

The aim of this PhD thesis is to shed light on the role of non-cognitive skills in the labour market in the past, the present and the future. Increasingly, research considers how non-cognitive skills determine important work outcomes, such as wages. Knowing which non-cognitive skills have an impact on such outcomes is hence helpful for individuals wanting to upskill themselves or others. In this thesis I start by highlighting the importance of non-cognitive skills in rapidly changing labour markets in paper 1 and 2, which motivate the analyses in paper 3, 4 and 5. In paper 1, I synthesise the academic evidence on the role of non-cognitive skills. In paper 2, I analyse the impact of skills and abilities on the automatability of occupations. In paper 3, I focus on how a traditional measure of non-cognitive skills, the Big Five personality inventory, determines wage outcomes for men and women differently. I find that agreeableness is punished more for men than it is for women pointing at differential rewards to personality by gender. I extend paper 3 by looking at how the demand and reward for specific non-cognitive skills changes over time in paper 4. Increasing technological innovation and disruptions to modern labour markets are changing the way we work, and the skills required at work. I study a large data set of job advertisements to analyse which non-cognitive skills are rewarded over time and find that collaborative leadership skills are increasing in importance. Also, I find that data science skills are evolving rapidly with the need to upskill on them frequently. The importance of collaborative leadership raises the question what makes collaboration successful and how to measure it. Inclusion has been shown to be a determinant of successful group outcomes. In paper 5 of this thesis, I hence develop an 'Individual Inclusiveness Inventory' that focuses on measuring what makes an individual inclusive. It does so in the vein of developing a personality trait scale like the Big Five that fits current labour market needs. The scale is developed through interviews with experts in inclusion and based on literature. It is then validated using a sample of working individuals in the UK and linked to work outcomes. The resulting 'Individual Inclusiveness Inventory' consists of two factors where one factor captures an individual's skill to foster belonging and uniqueness of co-workers and the other factor captures an individual's openness to challenge others and to be challenged. I also find that it predicts labour market outcomes. Overall, my thesis contributes to past literature on non-cognitive skills and the labour market by offering new perspectives on non-cognitive skills in rapidly changing labour markets.

Contents

List of Tables

List of Figures

Chapter 1 Introduction

The overall aim of this thesis is to improve the current understanding of non-cognitive skills in the context of labour markets. Concretely, I ask how and when non-cognitive skills are rewarded, which specific skills matter and how can they be measured. To achieve this objective, I empirically evaluate the role of non-cognitive skills in the labour market of the past, the present and the future using several data sources. The thesis consists of five stand-alone papers that each build on each other. The first two papers, presented in this chapter, motivate the subsequent analyses. The core papers of this thesis are paper 3, paper 4 and paper 5, which are presented in chapters 2, 3 and 4 respectively.

Non-cognitive skills have been increasingly incorporated into economic models concerned with the determinants of important life outcomes (Almlund *et al.*, 2011). In the context of labour markets, non-cognitive skills have been shown to impact outcomes such as wages and firm performance (Deming and Kahn, 2018). It would seem therefore that non-cognitive skills directly, or through being complements with other skills, increase productivity. However, automation, technical innovation and the recent Covid-19 pandemic are rapidly altering and disrupting labour markets thereby changing skills requirements and rewards in the labour market now and going forward. In this thesis I therefore consider both the past and the evolving role of non-cognitive skills in the labour market.

This introductory chapter is structured as follows. Section 1.1. provides background on non-cognitive skills with a focus on their applicability to the labour market. Section 1.2. is an excerpt of paper 1 (Josten and Lordan, 2021) and paper 2 (Josten and Lordan, 2022) that are both shown in full length in appendix A and B, respectively. These two papers motivate the subsequent chapters of this thesis and situate them in a wider context. Together they outline the importance of non-cognitive skills in the labour market generally and regarding the future of work. Section 1.3. outlines the aims and the research focus of this thesis together with a short summary of each chapter. Section 1.4. finishes with an outline of the thesis.

1.1. Background: What are non-cognitive skills?

Throughout this thesis I refer to the terms non-cognitive skills and cognitive skills. Non-cognitive skills include a broad range of personal attributes, habits, attitudes, and behaviours that stand in contrast to cognitive skills (Gutman and Schoon, 2013). Non-cognitive skills include traits such as emotional intelligence, communication, teamwork, flexibility, negotiation, leadership, problem-solving, and time management, amongst others. They are also commonly referred to as soft skills. Specific sub-categories of non-cognitive skills include personality traits (i.e., enduring patterns of thoughts, feelings, and behaviours that are relatively stable over time and across situations (Johnson, 1997; Borghans *et al.*, 2008)) or social skills (i.e., skills that centre around social interaction (Deming, 2017)). Sometimes the term non-cognitive skills refers exclusively to personality traits (Borghans *et al.*, 2008) but I use it as a broader term that stands in contrast to cognitive skills. That is while non-cognitive skills are not entirely devoid of cognition as Borghans et al. (2008) correctly point out, I refer to cognitive skills as skills that only centre around cognition (e.g., numeracy skills).

There are many different measures of non-cognitive skills of which I exemplarily highlight three frequently used measurement approaches. One approach is locus of control, which measures whether an individual believes that their life outcomes are due to their own efforts (Cobb-Clark, 2015). Another measurement approach concerns measuring grit, a measure of perseverance and a passion for long-term goals (Duckworth *et al.*, 2007). A third approach to measurement is the Big Five personality traits that include conscientiousness, neuroticism, openness, agreeableness, and extraversion (Costa and McCrae, 1992), which I will draw on for my analysis in chapter 2 of this thesis. These are specific examples of a multitude of psychometric personality measures that have been included in larger surveys as scales and incorporated in economic or psychological models (Nyhus and Pons, 2005; Duckworth and Quinn, 2009; Cobb-Clark, 2015). As personality traits are not directly observable, they cannot be measured straightforwardly but are often inferred through latent constructs and factor models (Almlund *et al.*, 2011). Non-cognitive skills have, however, not only been measured as self-reported scales but are also analysed through, for example, peer evaluations such as psychologist assessments (Lindqvist and Vestman, 2011) or observations such as job advertisements (Calanca *et al.*, 2019).

Non-cognitive skills in the labour market have been increasingly studied in the literature (Autor, Levy and Murnane, 2003; Weinberger, 2014; Deming, 2017, 2021; Josten and Lordan, 2021) and they are increasingly valued by employers in terms of demand and reward (Deming and Noray, 2020). Employers often require individuals to have a combination of non-cognitive and cognitive skills and this complementarity of non-cognitive and cognitive skills is increasing over time (Weinberger, 2014; Deming, 2017). That is while cognitive skills are necessary to exert technical expertise on the job, non-cognitive skills help individuals navigate increasingly complex and collaborative work environments. Changing skills requirements can be partly explained by recent labour market developments (Deming, 2021). As a result of technical innovation, routine tasks within jobs are being replaced by automation. This has caused some jobs to become obsolete, while other jobs have efficiency gains owing to their complementarity with emerging new technologies (Frey and Osborne, 2017). The skills required for jobs that are less automatable have been shown to centre around thinking and people skills (Josten and Lordan, 2020).

The mechanisms of the effect of non-cognitive skills in the labour market could be direct and/or indirect (Heineck and Anger, 2010). Non-cognitive skills could make individuals more productive at work (e.g., conscientiousness affecting the effort dedicated to tasks) or could indirectly impact education or occupational choices (Cobb-Clark and Tan, 2011), for example. Non-cognitive skills, such as self-control, have been shown to impact different labour market outcomes directly such as wages (Heineck, 2011), female labour market participation (Pohlmeier and Wichert, 2010), unemployment duration (Uysal and Pohlmeier, 2011) and occupational attainment (Heckman, Stixrud and Urzua, 2006), and also indirectly through human capital investments (Cobb-Clark, 2015), health behaviours (Hagger-Johnson *et al.*, 2012) or parenting behaviours (Lekfuangfu *et al.*, 2018). Non-cognitive skills have also been shown to explain occupational sorting. For instance, more extroverted people are more likely to become salespeople; less conscientious people are more likely to become labourers and professionals (John and Thomsen, 2014; Wells, Ham and Junankar, 2016).

Overall, non-cognitive skills are most malleable during childhood (e.g., they can be impacted by parental investments and education) while they are more stable throughout adulthood (Cobb-Clark and Schurer, 2012, 2013; Heckman and Kautz, 2013). But non-cognitive skills have also been shown to be malleable throughout the life course though there is mixed evidence on which interventions prove successful and in what context (Gutman and Schoon, 2013;

Martin-Raugh, Williams and Lentini, 2020). A better understanding of non-cognitive skills, their impact and their measurement is hence helpful for individuals and employers interested in upskilling on non-cognitive skills that foster positive life outcomes.

1.2. Motivation and context

1.2.1. The Accelerated Value of Social Skills (Paper 1)[1]

This subsection is a (slightly amended) excerpt of paper 1 shown in full length in Appendix A.

The advent of the Fourth Industrial Revolution[2] has brought with it a debate as to which skills will become redundant because of automation, and which skills will remain in demand. This study discusses the relevance of social skills[3] in this debate.

Social skills as a durable skill for knowledge workers

Historically, the Third Industrial Revolution shaped labour markets in developed countries, including the United Kingdom (UK), to further increase the importance of cognitive skills (Autor, Levy and Murnane, 2003). It is worth emphasising that there is evidence that social skills are of value to the labour market both directly and indirectly, owed to their effects on individual's education or motivation for example. Borghans et al. (2014) provide solid evidence of this in an analysis of individual-level longitudinal data from the United States (US), the UK and Germany. The authors find that individuals who score highly in people skills sort into occupations high on people tasks and end up having higher earnings in the long-term. Cortes et al. (2018) also demonstrate the growing demand for social skills by analysing a database of newspaper job advertisements from 1980 to 2000 in the US alongside information on job tasks and wages and find that the demand for social skills has increased over the study period. This in turn explains their finding that the probability of females working in cognitive/high wage occupations has increased as compared to males as females score higher in social skills.

---

[1] This subsection has been published in full as Josten C, Lordan G. The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic. LSE Public Policy Review. 2021; 1(4): 5, pp. 1–10. DOI: https://doi.org/10.31389/lseppr.31. It is shown as such in Appendix A.

[2] The Fourth Industrial Revolution describes the economic, social and political transition brought about by automation and new technologies (e.g., Internet of Things) in the 21st Century (Schwab, 2015).

[3] The focus here is on social skills that are a subset of non-cognitive skills and centre around human interaction (Deming, 2017). Social skills encompass the ability to work with others (Heckman, 2008; Deming, 2017) and include leadership, communication, and interpersonal skills more generally (Weinberger, 2014).

There is therefore a growing consensus that social skills are independently valuable in the labour market. There is also evidence that suggests that there is a complementary interactive effect between cognitive skills and social skills in terms of improved labour market outcomes (Weinberger, 2014; Deming and Kahn, 2018). Specifically, Weinberger (2014) links adolescent skills data from two longitudinal studies of high school students from the US from 1972 and 1992 to adult outcomes. They find that the earnings premium for both cognitive and social skills have increased substantially across the two cohorts. That is, while both cognitive and social skills positively affect earnings, their joint importance and complementarity has increased over time. They verify this conclusion further in an analysis that maps census data to job task measures.

There are two main points to emphasise from the discussion so far. First, the evidence suggests that social skills can be labelled as durable skills, in that there is an expectation that they will be valuable despite changes to the labour market. Second, the complementary interactive effect between cognitive and social skills demonstrates that there are gains to knowledge workers acquiring social skills.

These conclusions align well with studies demonstrating that the demand and rewards for social skills have been increasing over the past decades (Borghans, Ter Weel and Weinberg, 2014; Deming, 2017) and that they will likely continue to do so (Bode *et al.*, 2019). To consider this increasing trend, Deming (2017) establishes a model for team production, where social skills are treated as an input that reduces coordination costs and makes teamwork more efficient. Drawing on data from the US National Longitudinal Survey of Youth (NLSY) from 1979 and from 1997, Deming (2017) then tests the assumptions of the team production model and verifies that cognitive and social skills are complementary. They also find that there are positive returns to social skills in the labour market in terms of full-time employment status and wages, which have increased across the two cohorts studied. In a separate analysis, Deming (2017) also demonstrates that between 1980 and 2012 there was an increase in occupations that require high levels of social interaction by nearly 12 percentage points as a share of the US labour force. In another study evaluating social skills in the labour market, Borghans et al. (2008) also start with establishing a model that assumes that individuals differ in their level of people skills and that occupations differ in their requirements for such skills. They use individual-level longitudinal data from the US, Germany, and the UK to test their model's assumptions. Overall, they find that youth sociability is positively correlated with adult wages and affects sorting into adult occupations for which people tasks are important. Finally, in order to comment on trends of the future, Bode et al. (2019) use data from the German Socioeconomic Panel (SOEP) to empirically test the impact of personality traits on working in an occupation that is susceptible to automation. They link their data with research that establishes which occupations are most susceptible to automation, finding that jobs which are filled by individuals who are open, less neurotic and less agreeable will be less susceptible to automation in the future.

Lordan (2021) illustrates the increasing value of social skills most clearly in a quantitative analysis that relates job attributes to the probability that an individual's occupation will be automatable over the next decade. The novelty of her analysis is that it draws on a measure of automatable work constructed by Josten and Lordan (2020) which considers the changes with respect to jobs that face the risk of future automation by analysing patents. Essentially, Josten and Lordan (2020) create a classification that captures jobs that will be automatable over the next decade.

Lordan (2021) focuses on three variables that are constructed based on data that describe the skills required to do a job, along with the actual activities of the job. These three variables reasonably accurately proxy work that involves using social skills, cognitive skills and physicality. In her work, Lordan (2021) refers to these variables as people, brains and brawn respectively and each variable is constructed to have a mean of 0 and standard deviation of 1. Drawing on 2013-2016 EU Labour Force Survey data, the author then relates the classification of a job being automatable to whether work involves 'social skills,' 'cognitive skills,' and 'physicality,' as measured by these three variables. The author also considers the interaction between these three variables, which allows her to predict the usefulness of social skills, cognitive ability, and physicality independently in terms of future employability in addition to predicting the value of their interactions (i.e., the value of social skills combined with cognitive skills). A negative estimate implies that jobs that are high on a particular attribute are relatively unaffected by automation. As a result, jobs that are high on cognitive skills, for example, are relatively safe from automation.

The results for the European Union (EU) and UK analyses are re-produced in Table 1-1. The estimates point clearly to the value of cognitive skills, strongly implying that jobs which require abstract thinking will be safe from the impending wave of automation. In addition, for both the EU and the UK, the interaction between the 'social skills' and 'cognitive ability' attributes is negative and statistically significant. This signals that knowledge workers that also have high levels of social skills are even further insulated from automation. This complementarity is more pronounced in the UK as compared to the EU. Notably, evidence of the protective effect of social skills is only consistently revealed once there is an interaction with cognitive skills across both the UK and EU, suggesting that for jobs that do not also require a high level of cognitive skill, their value is less pronounced, if it exists at all. For the purposes of this section and the study in Appendix A, this emphasises clearly that the expectation was that social skills would continue to grow in value for knowledge workers.

Table 1-1: The impact of social skills, cognitive skills and physicality on automation

	EU LFS	UK – EU LFS
Social Skills	0.009***	0.006***
	(0.000)	(0.001)
Cognitive Skills	-0.070***	-0.100***
	(0.000)	(0.001)
Physicality	0.032***	0.007***
	(0.000)	(0.001)
Social Skills * Cognitive Skills	-0.002***	-0.005***
	(0.000)	(0.001)
Social Skills * Physicality	0.003***	-0.001***
	(0.000)	(0.000)
Cognitive Skills * Physicality	0.000***	-0.003***
	(0.000)	(0.001)
N	2,698,151	59575
R-squared	14%	13%

Note: The data is from the EU Labor Force survey data from 2013-2016. The stars of significance *, **, *** denote significance at the 10%, 5% and 1% levels respectively. The table shows regression results from regressing a dummy representing whether a job is automatable (as defined by Lordan and Josten (2020)) on the 'social skills,' 'cognitive skills,' and 'physicality' variables and their interactions.

The Value of Social Skills to Firms

The growing demand for social skills is without doubt linked to the added value people high in these skills bring to firms. Deming and Kahn (2018) provide evidence of this by analysing online job vacancies for a variety of professional services occupations in the US between 2010 and 2015. The authors focus on the financial returns of firms requiring certain social and cognitive skills in job adverts. They find that job adverts that include cognitive and social skills positively predict firm performance, even after controlling for education and experience requirements and occupation and industry codes. Their finding is most prominent for firms that demand both cognitive and social skills, which highlights the increasing value of social skills in knowledge work.

At the individual level, productivity in adulthood has also been credibly linked to social and emotional skills in childhood. Knudsen et al. (2006) review evidence from economics, developmental psychology, and neurobiology and highlight that early experiences during childhood have a strong effect on children's development of cognitive and social skills. Such skills in turn affect important life outcomes such as educational attainment and wages.

Kuhn and Weinberger (2005) test the impact of adolescent leadership skills on adult outcomes, drawing on three surveys of high school students in the US from 1960, 1972, and 1982 containing information on student test scores and leadership positions (e.g., acting as a team captain) as well as their labour market performance up to ten years after finishing high school. They find that students that fulfilled leadership positions during high school had significantly higher wages than those that did not. Gertler et al. (2014) test the impact of an early childhood intervention fostering cognitive and socio-emotional skills on adult outcomes. They ran a randomised controlled experiment in Jamaica between 1986–1987, in which toddlers from disadvantaged backgrounds were provided with treatments that fostered their cognitive and socio-emotional skills. They found that the children that received the treatment had higher earnings at age 22 and that the treatment reduced later-life inequality. Their findings are even larger than those of similar programmes conducted in the US, indicating potentially larger rewards for early interventions in developing countries. Edin et al. (2022) study the changing rewards for non-cognitive skills in Sweden between 1992 and 2013 using administrative data from the compulsory military draft that required men aged 18 or 19 to undergo tests on cognitive and non-cognitive skills. They find that the return in wages to non-cognitive skills doubled between 1992 and 2013 (from 7 to 14 percent for a one standard deviation increase in non-cognitive skills) and this growth was much larger than the return to cognitive skills. In an earlier study, Lindqvist and Vestman (2011) compare non-cognitive to cognitive skills of Swedish men in the military also using the enlistment data but matched with a representative sample of the Swedish population. They find that non-cognitive skills matter more for earnings at the low end of the earnings distribution and are a stronger predictor of labour force participation than cognitive skills. They argue that the reason for that is that individuals with very low non-cognitive skills are more likely to be unemployed and that non-cognitive skills are more prevalent in individuals that earn higher wages.

Overall, this evidence illustrates that there is an intrinsic value in social skills that helps individuals to thrive in the long run.

The above is an excerpt of paper 1 (which is shown in full length in Appendix A). The excerpt has emphasised the value of social skills both individually and as complements to cognitive skills. This finding is important as it motivated my interest in studying those skills in more detail in the core chapters of this study (Chapter 2, 3 and 4). Taking the finding that there is value in social skills as a foundation of this thesis, I further analyse the mechanism of the link between those skills with labour market outcomes (Chapter 2), I analyse rewards and demand for a more detailed list of skills (Chapter 3), and I develop a new measure of the non-cognitive skill of inclusiveness (Chapter 4). But first, the next subsection emphasises the importance of non-cognitive skills in the context of the future of work.

1.2.2. Automation and the changing nature of work (Paper 2)[4]

This subsection is a (slightly amended) excerpt of paper 2 shown in full length in Appendix B.

Research on the automation and the future of work has brought with it a range of research contributions which seek to determine which occupations will be lost to automation. For example, Frey and Osborne (2017) estimate the susceptibility of occupations to computerisation and find that 47% of US occupations are at risk of automation and point to service jobs as being susceptible to automation. Many other contributions in the automation literature rely on defining automatable work through measures of the tasks associated with a particular occupation rather than the occupation overall. One of the most prominent is owed to Autor and Dorn (2013) and Autor, Dorn and Hanson (2015) who define a job as automatable if it is high in routine task-intensity. Specifically, routine task-intensity is defined based on how high a job ranks on routine content, and how low it ranks on abstract and manual content.

[4] This subsection has been published in full as Josten C, Lordan G (2022) Automation and the changing nature of work. PLOS ONE 17(5): e0266326. https://doi.org/10.1371/journal.pone.0266326. It is shown as such in Appendix B.

Information on the routine, abstract and manual task content of each respective occupation comes from the US Dictionary of Occupation Titles where incumbents are asked to grade their occupation with respect to particular attributes. A job is then defined as automatable if it is in the top third of the distribution of routine task-intensity. This measure of automatable work has followed the big movements in the occupation distribution accurately over the last decades - namely the hollowing out of the middle of the occupational distribution (Acemoglu and Restrepo, 2021). To this end the types of occupations available have become more polarised, with most occupations falling into high and low skill categories, and mid skill jobs disappearing in numbers (Webb, 2019).

While much of the automation literature relies on past employment data, the rapid progress on robotics, artificial intelligence (AI) and automation technologies has also motivated predicting automation developments in the near future (Vivarelli, 2014; Josten and Lordan, 2020). The importance of this exercise is bellied in Lordan (2018) and Lordan and Neumark (2018) who suggest that new jobs are now being automated, particularly jobs traditionally at the bottom of the occupation distribution. Further, advances in AI and in particular machine learning will likely affect at least some tasks in most occupations and will hence also disrupt jobs at the top of the income distribution (Brynjolfsson, Mitchell and Rock, 2018).

Concretely, Webb (2019) studies the impact of automation on occupational tasks and matches information on job tasks to patents issued for robots, software and AI to identify which tasks can be automated by different technologies to derive an exposure to automation score. They use Google patents data, the O*NET database of occupations and tasks and US census data. O*NET is a database of occupations and tasks published by the US Department of Labor that provides detailed descriptions of a large number of occupations and has been used frequently in the literature studying the impact of automation and technical innovation on employment (Autor and Dorn, 2013; Lewandowski *et al.*, 2019; Lordan and McGuire, 2019). They first analyse the impact of this exposure to automation score on employment using historical data on robots and software patents and job descriptions and then repeats this exercise using patents on AI to predict future employment effects. AI is studied with respect to future developments as it is a relatively new phenomenon as compared to software and robotic innovations. While innovation on robots and software has mainly affected low skill and low wage occupations in the past, they find that AI is increasingly predicted to disrupt high-skill occupations. Building on this work, Tolan et al. (2021) link research intensity in AI to abilities required for specific job tasks using European survey data, O*NET data and AI benchmarking platforms. They find that jobs that were originally classified as non-automatable are increasingly affected by automation such as medical doctors. They find that abilities particularly affected by automation are abilities for idea creation while people abilities are less affected.

In an earlier study by Lordan and Josten (2020), their study is also forward-looking and takes the occupations classified by Autor and Dorn (2013) as given while reclassifying the remaining occupations as automatable depending on the number of patents recently available for each specific occupation thereby also predicting which jobs will be automatable in the near future. They aim to capture the most recent wave of automation by using patent developments in artificial intelligence, robots and automation more broadly as a proxy for technology that will be on the market shortly. If for any given occupation the authors find a large number of patents and find that successful patent pilots have been covered by the media, this occupation is classified as being on track to become automatable. Based on the number of patents filed, the classification that is a categorical variable defining an occupation as automatable, polarised automatable or non-automatable. This section and the study in Appendix B build on and use this classification of this earlier work by Lordan and Josten (2020) to analyse which job attributes and requirements predict the likelihood that a job is reclassified as automatable under their new definition. The analysis thereby speaks to the literature on the automatability of tasks, skills and abilities.

Data and Method

The analysis in this section relies on data from an earlier paper by Lordan and Josten (2020) who match data from the European Labour Force Survey (EU-LFS) between 2013–2016 to their automation classification. The automatability classification is built based on the number of patents recently available for a given occupation and then categorised into an occupation either being fully automatable, polarised automatable or not automatable. This serves as a good proxy of predicting automation of the jobs of the future as patents reflect the newest innovation available that is about to be implemented.

The EU-LFS covers quarterly employment statistics of households from EU member countries, Switzerland, Sweden and the UK. That is the analysis draws on their shares of automatable employment by EU-LFS country. This automatability classification is then matched with data on skills and abilities required on the job from O*NET. O*NET is an occupational database by the US Department of Labor that narrowly defines occupations with respect to the tasks and activities and the skills and abilities required on the job. Specifically, O*NET offers 80 distinct items in the abilities classification and offers 40 distinct items in the skills classification.

I regress the automatability classification on the skills and abilities respectively to analyse which skills and which abilities required in different occupations are susceptible to automation. Concretely, that is proceeded by regressing the classification variable on each set of job attributes and skills as provided by O*NET. It controls for differences across countries with a set of country fixed effects and for differences across time with a set of year fixed effects. There are two main sets of regressions. The first regresses the automation classification variable on the 80 ability domains and the second regresses it on the 40 skills domains. Lasso regression analysis is applied, a shrinkage and variable selection method for linear regression models. This approach is chosen to reduce the dimensionality of the abilities and skills variables under consideration. The goal of a Lasso regression is to obtain the subset of predictors that minimises prediction error for a quantitative response variable. The Lasso does this by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward zero. Variables with a regression coefficient equal to zero after the shrinkage process are excluded from the model. That is, these variables do not explain variation in the propensity for a job to be recently automatable. The remaining variables with a positive sign are those that describe the core skills and abilities that are most likely to become redundant because of the most recent wave of automation. In contrast, the remaining variables with a negative sign describe the core skills and abilities that are most likely to become more valuable. All non-zero variables are significant at the 1% significant level.

That is then further linked to work by Lordan and Pischke (2022) who capture the ‘people,’ ‘brains,’ and ‘brawn’ content of occupations with different risk of being automated, i.e., the extent to which an occupation involves people interaction, cognitive thinking skills or physicality, respectively.

Results

The detailed estimates by abilities and skills can be found in Table 2 and Table 3 respectively in Appendix B. Overall, I find that skills and abilities which relate to non-linear abstract thinking, which we term ‘brains’, are those that are the safest from automation. An example would be the skills of critical thinking and monitoring of performance that involve using information that is available to pass judgement and make decisions. Another example is fluency of ideas that is an idea generation and reasoning ability which relates to the ability to come up with a number of ideas about a topic (i.e., the number of ideas is important, not their quality, correctness, or creativity), which is highly unlikely to be automated. In this case, 'brains' is shorthand for thinking and can involve reacting to other individuals (e.g., in caring or teaching professions), performing a service (e.g., as mechanic or fine dining waiter) or engaging in agile or creative thinking (e.g., in a leadership or knowledge worker role).

Jobs that require 'brains' (i.e., abstract and non-linear thinking) are far less likely to be automated as compared to jobs which require linear and codifiable thinking skills and abilities. At the top of the income distribution, jobs that require non-linear thinking may need critical thinking, decision-making and creativity. Elsewhere in the income distribution these jobs require skills that have been traditionally delivered in apprenticeships, from mechanics and carpenters to florists and hairdressers.

I also find that jobs that require 'people' engagement interacted with 'brains' are also less likely to be automated. These jobs include management across all levels, coordinators of all types, teachers, carer and medical practitioners (including nursing). The skills and abilities that are required for these jobs include soft skills. An example are the skills of active listening, instructing, monitoring and persuasion. Finally, I find that jobs that require physicality (e.g., creating objects manually) are most likely to be automated unless they involve interaction with 'brains' and/or 'people'.

Conclusion

Information and knowledge on future job requirements by occupations and by country is essential when trying to predict the demand for skills and abilities and activities going forward. It is important knowledge for policymakers and companies who can adapt policies and organisational settings regarding the future of work accordingly and ensure that individuals are prepared for current developments and what is yet to come. It informs conversations surrounding the re-organisation of education and other development activities to ensure that the stock and flow of skills are ready for the Fourth Industrial Revolution. The returns to education are constantly increasing with the rise in technological progress with specific skills such as digital and non-cognitive skills becoming particularly important (Goos *et al.*, 2019). This information also helps to gain a more nuanced understanding of the exact aspects of the occupations at risk of automation rather than just predicting automation overall and hence extends previous work. It does, however, not answer which specific non-cognitive and cognitive skills become important and which skills are rewarded. It highlights the importance of non-linear thinking individually and jointly with people skills that involve human interaction.

The key two takeaways for the remaining chapters are the following: First, labour markets are being disrupted by automation and technological innovation. Second, there is need for additional research into what specific skills are relevant for the future of work, in addition to how they are rewarded and how they can be measured. This takeaway motivates my further research into future job requirements in chapter 3 (Paper 4) while overall highlighting the importance of improving our understanding of skills in the labour market.

To summarise, the findings of paper 1 and paper 2 summarised in sections 1.2.1. and 1.2.2. above together establish three stylised facts:

1. Non-cognitive skills are crucial for labour market outcomes both individually and alongside cognitive skills.
2. Labour markets are being disrupted by automation, technological innovation and the Covid-19 pandemic.
3. There is need for additional research into what specific skills are relevant for the future of work, in addition to how they are rewarded and how they can be measured. These are the topics that the remaining papers of this thesis focus on. Both paper 1 and paper 2 are shown in full length in Appendix A and B.

1.3. Aims and research focus

The discussion in section 1.2. above provides an overview of some of the relevant literature for this thesis. Crucially, the review and analysis highlight three key facts. First, it shows the importance of non-cognitive skills in the labour market individually and when interacted with cognitive skills. Second, it highlights that labour markets are being disrupted by automation and technological innovation and are worth studying more closely to better understand how these impact changing skills requirements and rewards. Third, while non-cognitive skills are relevant for labour market outcomes, it is less clear which non-cognitive skills matter concretely. In the remainder of this thesis, I draw on these key facts with the aim of analysing non-cognitive skills in more detail with regards to the past, the present and the future. The focus of this thesis is on the role of non-cognitive skills for professionals.

The thesis and each chapter are strongly grounded in past literature in terms of methods and data chosen but add new aspects and innovative ideas thereby contributing to the field of study. Each chapter has its own specific focus and uses a different data set that is best suited for the respective research question. However, the chapters build on each other and are closely connected by their common goal of explaining the role of non-cognitive skills in the labour market. Each chapter contributes to the literature in several distinct ways including producing a novel quantitative analysis that explores a relevant research question.

More specifically, in chapter 2 (Paper 3), I analyse the well-established Big Five personality framework in the context of gender. I study whether personality traits are rewarded differently for men and women. Using secondary data from the UK Household Longitudinal Study (UKHLS) that has been used previously to study the Big Five (Collischon, 2020), the chapter analyses the role of the Big Five for wages. This speaks to the literature on the gender pay gap and gender norms and asks whether the link of personality and wages differs by gender. While using well-established personality measures and data sets, this study brings a new aspect to this literature by looking at gender specifically. I find that being agreeable hurts men more than women across most professional occupations, which points at differential rewards to personality based on gender. Being agreeable likely disconfirms the norm of men often being the opposite of agreeable (e.g., competitive or self-interested) and is hence seen more negatively in men rather than women (Judge, Livingston and Hurst, 2012). This finding adds to the understanding of the mechanisms underlying personality effects.

Chapter 3 (Paper 4) builds on chapter 2 and focuses on the relationship between non-cognitive skills for wage outcomes. Instead of self-reported data, I use job advertisement data that captures what is being demanded in the labour market by companies. Further, I take an inductive approach in the choice of skills that I analyse by using principal component analysis. The aim is to answer the question which specific skills are becoming more relevant over time and which ones are becoming less relevant. I run a linear regression to study the link of the skills groups to wages. This results in two stylised findings: First, I find that collaborative leadership skills are increasingly demanded and rewarded over time. Second, I find that the reward to data science skills is constantly evolving with the newest data science skills being rewarded and legacy data science skills being punished. I explain this finding with technology constantly disrupting data science and with it changing the skill set demanded. I then also look at non-linear returns and interactions of skills groups using Lasso (least absolute shrinkage and selection operator) regression methods. As labour markets become more complex, skills requirements also become more complex. It is hence even more important to know which combinations of skills are relevant. I find a positive complementarity of non-cognitive and cognitive skills further reiterating previous findings in the literature.

Chapter 4 (Paper 5) builds on chapter 3. Specifically, it contributes to the literature by developing the 'Individual Inclusion Inventory' scale that captures what makes an individual inclusive of others. I do so by combining qualitative and quantitative methods. First, I interview experts to develop items for the scale. Second, I use exploratory factor analysis and confirmatory factor analysis to reduce the number of items and to validate the index. Third, I empirically test the relationship of the 'Individual Inclusion Inventory' with labour market outcomes. That way I test its predictive validity and also speak to the analyses of chapter 2 and 3. The resulting 'Individual Inclusiveness Inventory' consists of two factors where one factor captures an individual's skill to foster belonging and uniqueness of co-workers and the other factor captures an individual's openness to challenge others and to be challenged. I also find that it successfully predicts labour market outcomes such as income, people management, comparative seniority and comparative happiness.

The thesis is interdisciplinary in nature and situated at the intersection of economics, behavioural science and psychology. Papers 1 to 4 are written in the style of the field of study of economics and behavioural science while paper 5 follows the psychology literature more closely. I chose the writing style based on the topic studied (e.g., paper 5 focuses on the development of a scale that has its tradition in psychology). The thesis and each chapter are strongly grounded in past research in terms of literature and methods and data chosen but adds new aspects and innovative ideas thereby contributing to the field of study. Paper 3 is under review at the Journal of Human Capital, paper 4 is under review at the Quarterly Journal of Economics and paper 5 is under review at Management Science.

1.4. Thesis Outline

The remainder of the thesis consists of three empirical papers following the research aims highlighted above (Chapters 2-4).

In chapter 2 (Paper 3), I focus on the differential impact of the well-established Big Five personality traits on wages by gender using observational survey data from the UK Household Longitudinal Study (UKHLS). Specifically, using regression analysis, I explore whether women with the same level of personality traits (i.e., scoring high or low on a respective personality trait) have a different likelihood of making it to the top as compared to men. Chapter 2 focuses on the Big Five personality traits with the advantage that those have been studied frequently in the past and hence serve as a useful framework to analyse non-cognitive skills. With the rise of the Fourth Industrial Revolution and radical changes in the labour market, however, traditional personality measures such as the Big Five personality traits likely fail to capture all relevant skills of the future (Ghislieri, Molino and Cortese, 2018).

In chapter 3 (Paper 4), I therefore take an inductive approach and analyse the demand and reward for skills in the labour market using job advertisement data from company websites in the US. I analyse the premium that is paid to specific skills groups in the US labour market. The findings in chapter 3 highlight the changing demand and reward for skills over time. One stylised finding is that collaborative leadership skills (i.e., social skills that centre around collaboration or leadership) gain in importance over time. Social skills such as collaboration and inclusion are also increasingly discussed as drivers of success at work (Josten and Lordan, 2021; Roberson and Perry, 2022). It is, however, less clear what it means for an individual to be collaborative or inclusive of others.

In chapter 4 (Paper 5) I focus on how to measure individual inclusiveness as part of what I call the 'Individual Inclusiveness Inventory'. Through interviews and factor analysis I define, derive, and validate the 'Individual Inclusiveness Inventory' that I then further link to work outcomes and the Big Five personality traits.

In the final chapter of the thesis chapter 5, I summarise the findings and contributions of the five papers. I critically evaluate their limitations. I discuss the relevance of the findings for individuals and companies alike. I then also outline possibilities of future research.

Chapter 2 Who makes it to the top? Differential rewards to personality across gender and occupation in the UK

Abstract
This study investigates the mechanisms underlying the effect of personality traits on wages. It tests whether personality traits are legitimately rewarded in the labour market or whether there are differing rewards to personality across gender that cannot be explained with productivity. Specifically, I investigate if the Big Five personality traits affect the likelihood of making it to the top income quintile within a professional occupation differently by gender using the UK Household Longitudinal (UKHLS) data. I find that being agreeable hurts men more than women across most occupations, which points at the role of gender norms for wages. Further, female legislators and senior officials who are conscientious, extraverted, neurotic and open are more likely to be among the top earners than men. Other than that, I find small gender differences in personality rewards for professionals.

2.1. Introduction

It is often stated that specific occupations attract and retain individuals with specific personality traits; an example would be that politicians tend to be extroverted and kindergarten teachers are caring. Evidence of this can be found in Table 2-1 that shows average personality traits by five exemplary occupations. Concretely, it demonstrates that in the UK 'Legislators and senior officials' and 'Corporate managers' have markedly higher rates of extroversion as compared to 'Life science and health professionals'. Table 2-1 also suggests other differences such as that 'Teaching professionals' are significantly more open than 'Physical, mathematical and engineering science professionals'.[5]

Table 2-1: Average Big Five personality traits by five occupations

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
Legislators and senior officials	5.497	5.629	4.850	3.402	5.077
	(0.984)	(0.938)	(1.138)	(1.234)	(1.032)
Corporate managers	5.461	5.608	4.682	3.321	4.756
	(0.979)	(0.957)	(1.252)	(1.290)	(1.099)
Physical, mathematical and engineering science professionals	5.388	5.394	4.316	3.415	4.895
	(0.982)	(0.939)	(1.258)	(1.289)	(1.092)
Life science and health professionals	5.506	5.576	4.334	3.456	4.673
	(1.012)	(0.954)	(1.327)	(1.319)	(1.097)
Teaching professionals	5.702	5.610	4.711	3.662	5.107
	(0.896)	(0.970)	(1.263)	(1.358)	(1.122)

Note: The data is from the UK Household Longitudinal Study (UKHLS) that is an annual panel data set in the UK from 1991 to 2018. The sample is restricted to people with a positive amount of work hours and who have indicated their personality at least once. The table shows the average personality score among workers in white-collar occupations. Each Big Five personality trait ranges from 1 (low level) to 7 (high level). The white-collar occupations follow the ISCO-88 occupation classification in two-digit code occupations. The full set of ten white-collar two-digit code occupations are in Table 2-11 in Appendix 2.A. White-collar occupations include the top ten white-collar ISCO-88 two-digit occupations. Occupations with an ISCO-88 one-digit code of 1, 2 or 3 are regarded as high-skilled white-collar (https://www.eurofound.europa.eu/surveys/ewcs/2005/classification).

[5] The means are statistically different from each other at the 5% level when running a t-test.

The reason why individuals with specific personality traits end up more frequently in specific jobs is less clear. First, it could happen that a specific personality trait is valued within an occupation *legitimately*. One can imagine, for example, that teachers ('Teaching professionals' above) need to be more agreeable than other workers to successfully convey knowledge to pupils or that legislators and senior officials ('Legislators and senior officials' above) need to be particularly extroverted as their job involves public engagement. These intuitions are reflected in Table 2-1. Individuals may either sort into those occupations based on their personality and/or there is adaptation of personality traits to job requirements over time. The channels through which personality traits affect wages legitimately could be both direct and/or indirect (Heineck and Anger, 2010). Directly, personality traits are seen to enhance an individual's productivity (e.g., conscientious individuals may be more hard-working) and their wage bargaining power (e.g., extroverted individuals may have higher confidence that helps them bargain for higher wages). Indirectly, personality traits have been shown to impact educational attainment (Heckman and Kautz, 2012) and occupational sorting (Cobb-Clark and Tan, 2011), which in turn increase wages. Further, personality traits may predict preferences for risk or competition that differ across gender (Bertrand, 2011). Employers may value personality traits either intrinsically or because they increase productivity or workers' incentives and hence lower an employer's monitoring costs when labour effort is endogenous (John and Thomsen, 2014).

Second, it is also possible that specific personality traits are rewarded *unjustifiably*. For example, extroverted individuals are better at asking for pay rises and promotions, and as such they garner higher pay and status without adding additional value. Of course, it is not easy to observe this phenomenon. In general, it is difficult to elicit unjustifiable rewards by personality as productivity is often unobservable (Cubel *et al.*, 2014) and the direct mechanisms of personality on productivity remain largely inconclusive. However, evidence of unjustifiable rewards can be observed if one considers whether an individual's personality traits are rewarded differently depending on a person's innate characteristics. An example would be differential pay by gender for the exact same level of personality traits (i.e., scoring high or low on a respective personality trait), all else equal. Personality traits may be rewarded differently for men as compared to women with some traits being regarded positively or negatively in men but not in women (Manning and Swaffield, 2008; Blau and Kahn, 2017). Agreeableness could be, for example, seen positively in men as a sign of their empathy but negatively in women as it conveys weakness. Equally, agreeableness could also hurt men as men are usually expected to be less agreeable than women and a highly agreeable man would speak against this expectation. Also, personality could provide women with a wage advantage as compared to men, as they consistently score higher on many personality variables (Borghans, Ter Weel and Weinberg, 2014; Gensowski, Gørtz and Schurer, 2021; Li, Chen and Zhang, 2021). In this paper, I test whether personality traits are in fact unjustifiably rewarded.

Specifically, I explore whether women with the same level of personality traits (i.e., scoring high or low on a respective personality trait) have a different likelihood of making it to the top as compared to men. I estimate the probability of being in the top income quintile for men and women and compare across high versus low levels of different personality traits. I focus on the Big Five factor model as a measurement of personality, which encompasses conscientiousness, neuroticism, openness, agreeableness and extraversion and has been shown to impact labour market outcomes in a comparable way to cognitive ability (Costa and McCrae, 1992; Heckman and Kautz, 2012). I draw on the data from the UK Household Longitudinal Study (UKHLS).[6] This analysis is restricted to individuals in high-skilled white-collar occupations (i.e., professionals) as they are more homogeneous in terms of the tasks performed by men and women. The key outcome measured in this study is the likelihood of being among the top 20% income earners. Over the past decades, the gender wage gap has closed at a much slower pace at the top of the income distribution than in the middle and bottom distributions; a finding that has been attributed to the growing share of the unexplained part of the gender gap at the top (Blau and Kahn, 2017; Fortin, Bell and Böhm, 2017). While the causes for the unexplained part of the gender wage gap are multiple there is reason to believe that discrimination and differential treatment plays an important role for income gaps at the top (Blau and Kahn, 2017). I hence look at whether men and women with the same intensity in personality traits have a different likelihood of making it to the top within their occupation and calculate gender-specific personality pay differentials by occupation.

The methodology of this study broadly builds on Goldin (2014) who also focuses on within-occupation differences in earnings between men and women. In particular, they look at how within-occupation differences in earnings across gender relate to differences in hours worked using data from the American Community Survey. Similarly, I also look at the coefficient of

[6] Different waves from the UKHLS have been previously used to study the impact of personality on labour market outcomes such as on wages (Heineck, 2011), on personality pay gaps by personality quantile (Nandi and Nicoletti, 2014) and on wages across the wage distribution (Collischon, 2020).

female and occupation interacted and then add personality to the interaction to see how earnings differ across gender and personality within different occupations. Extending past empirical research, these estimates provide a nuanced insight into the premiums of each specific Big Five personality trait at the occupation level, enabling a direct comparison of rewards across occupations and gender. By including occupation fixed effects, I also hold selection into occupations by gender constant.

This study finds that men and women face a different likelihood of making it to the top, i.e., of being among the top income quintile earners, but the differences in the likelihood across gender and personality are mostly small. For both high and low intensities of each personality trait, women are punished as compared to men; a finding that reflects the gender gap in the likelihood of making it to the top irrespective of personality traits. I do find, however, that agreeableness is more often punished for men than it is for women. This finding points at differential rewards to personality resulting from the disconfirmation of gender norms (i.e., one does not expect men to be agreeable so if they are, it plays out negatively for them). Further, I find the largest gender differences in relative rewards to personality in the 'Legislators and senior officials' occupation group, in which women are more likely to be in the top income quintile if they are conscientious, extroverted, neurotic and open as compared to men with the same traits. Men are punished for being agreeable, conscientious and extroverted. In the remaining eight two-digit code occupations I look at, having a high versus a low level of personality traits (i.e., scoring high or low on a respective personality trait) only slightly impacts the likelihood of making it to the top differently for men as compared to women with some traits being rewarded and others punished. This finding is interesting, as it shows that while the underlying mechanisms of personality are difficult to identify, personality does not affect the likelihood of making it to the top differently for women relative to men in professional occupations very much other than for agreeableness. For agreeableness, there is a likely impact of gender norms on wage outcomes; a finding that reflects differential personality expectations of men and women in the labour market. Women do not gain or lose out greatly from higher levels of non-cognitive skills as compared to men in white-collar occupations. I cannot, however, rule out that personality is rewarded differently in the recruitment process that affects sorting into specific occupations based on those traits. Though there is some evidence that finds that psychosocial traits do not influence entrance into higher paid occupations differently for men and women (Antecol and Cobb-Clark, 2013).

2.1.1. Context

The Big Five personality traits have been commonly associated with labour market outcomes. Of the Big Five, agreeableness is associated with ‘labour-friendly’ characteristics such as being compliant (John and Srivastava, 1999) but may also hamper success due to the pursuit to please others (Barrick, Mount and Judge, 2001). Conscientiousness is the “tendency to be organized, responsible, and hardworking” (Almlund *et al.*, 2011), which relates to grit or perseverance; characteristics, that tend to be demanded by employers. Extroverted individuals derive energy from social interaction and positive emotions (Borghans, Ter Weel and Weinberg, 2006), which may be helpful for some occupations. Neuroticism is the facet of the Big Five that is often negatively associated with work outcomes, as neurotic individuals are anxious (Viinikainen *et al.*, 2010). Openness to experience is the “tendency to be open to new aesthetic, cultural, or intellectual experiences” (Almlund *et al.*, 2011). The effect of openness at work is ambiguous, potentially because it is multidimensional in its facets (Griffin and Hesketh, 2004; Heineck and Anger, 2010). Of the Big Five traits, agreeableness and neuroticism exhibit the largest gender differences with women scoring higher than men on those two items (Bertrand, 2011). With the different nature of each of the Big Five personalities, their potential impact on wages is likely to differ by type of occupations that are equally diverse in terms of work characteristics and tasks (John and Thomsen, 2014).

One reason for differing likelihoods of making it to the top and occupational segregation by gender for personality could be that individuals sort into jobs that align with their identity. Akerlof and Kranton (2000) model how one’s gender identity directly influences economic decision-making and one’s utility function. They highlight that some occupations are generally regarded as male occupations, such as marines, and some generally as female, such as nurses. Being successful at a male-dominated job then comes with the expectation to act manly and to fulfil expected gender roles.

By examining whether men and women have different income premiums across five personality traits, I am essentially asking whether the phenomenon of differential expectations of male and female personality traits are observed in the labour market. Intuitively, this study, which calculates differing likelihoods of making it to the top at the occupation level, also relates to work that considers whether personality proxies reduce the gender pay gap in individual wage regressions focusing on differences in personality across gender. For example, Mueller and Plug (2006), using data from the Wisconsin Longitudinal Study of US students, estimate the impact of personality on earnings for men and women. They find that agreeableness is the only Big Five trait that has a statistically significant impact on the gender gap with men being rewarded for being antagonistic (i.e., the reverse of agreeable). Similarly, Judge, Livingston and Hurst (2012) find that agreeableness is punished for men as compared to women when using US survey data. Nyhus and Pons (2005) also analyse gender-specific returns to personality using the Big Five inventory and Dutch data from the DNB Household Survey. They find that employers are more sensitive to personality differences in women than in men. They also find strong negative effects of agreeableness and extraversion for the total and the female sample. Neuroticism has a negative impact for men and women. The authors highlight that their relatively small overall effect sizes might stem from excluding occupation-specific rewards to personality in their analysis. In a twin study in Finland, Maczulskij and Viinikainen (2018) find that while neuroticism negatively impacts long-term earnings overall, this effect is stronger for women. They also find that activity (i.e., a facet of extraversion) is positively related to long-term earnings of men. Braakmann (2009) uses data from the German Socio-Economic Panel (SOEP) and looks at how differences in personality across gender contribute to the gender gap as part of a wage decomposition. They find an overall negative effect of conscientiousness and agreeableness on wages with this negative effect being larger for men for conscientiousness and larger for women for agreeableness. Higher levels of openness are only associated with higher wages for men. Extraversion does not affect wages for either gender. Neuroticism is generally associated with negative wage effects with those being larger for women. They find that gender differences in agreeableness, neuroticism and conscientiousness explain between five percent and 18 percent of the gender pay gap.

In response to the differential effect of personality on the gender wage gap on average, Cobb-Clark and Tan (2011) highlight the importance of looking at the gendered impact of personality on wages within an occupation, as I do here. Average effects omit that sorting into occupations occurs based on personality. In their study they estimate the effect of non-cognitive skills on occupational segregation by gender and on within-occupation wage gaps using the Household, Income, and Labour Dynamics in Australia (HILDA) survey. They find that men and women enter occupations at a different rate despite having the same personalities, which does, however, not explain lower wages of women overall that stem from earning differences within occupations rather than across occupations. Controlling for occupational segregation, they do not find that non-cognitive skills help to explain the unexplained part of the gender pay gap, but women's non-cognitive skills give them a slight wage advantage. Using US data from the National Longitudinal Study of Adolescent Health, Antecol and Cobb-Clark (2013) look at masculine traits, self-esteem, analytical problem-solving approach, willingness to work hard, impulsiveness, problem avoidance and self-assessed intelligence as proxies for psychosocial traits. They find that men and women sort into occupations very differently depending on these traits, however, this gender segregation in the workplace has no effect on selection into high-paid occupations. This finding highlights the importance of studying within-occupation personality effects on job rewards. That is the approach taken in this work. I focus on white-collar occupations and the outcome of interest is the probability of being in the top income quintile. White-collar occupations are more homogeneous in terms of the tasks performed by men and women. And I focus on the probability of being in the top income quintile because the share of the unexplained gender wage gap has been growing at the top earning levels as compared to the middle and bottom distribution of incomes (Blau and Kahn, 2017).

2.2. Data and descriptive statistics

This study draws on the merged UK Household Longitudinal Study (UKHLS) from 1991 until 2018. The data set is well-suited for modelling the impact of personality on labour market outcomes given its panel nature and large sample. I restrict the sample to individuals who work a positive number of hours (i.e., part and full-time). I further restrict the sample to individuals who have indicated their personality at least once. The sample size of this restricted sample is 86,924 observations.[7]

The main outcome variable used in this study is a binary variable equal to one if an individual is in the top quintile (i.e., the top 20%) of an individual's gross hourly inflation-adjusted and within-occupation wage using CPI information from the Office of National Statistics (ONS) in 2015.[8] The analysis is clustered at the two-digit occupation level. Basic summary statistics (mean and standard deviation) of the key variables are provided separately by gender in Table 2-9 in Appendix 2.A. The UKHLS panels have been previously used to study the impact of personality on labour market outcomes such as on wages and across the wage distribution

[7] The large sample allows for a statistically meaningful analysis of personality traits with sufficiently large power. Statistical significance is discussed with the results. Given the large amount of previous research that find substantial effect sizes regarding personality and labour market outcomes, I am confident that the hypothesis of differential rewards to personality is valid. That is, statistical power is ensured.

[8] When individuals indicate that they are paid a monthly wage instead of an hourly wage, the hourly wage is computed using the gross monthly income from all labour market earnings divided by the normal and overtime hours worked per week multiplied by 4.33.

(Heineck, 2011; Nandi and Nicoletti, 2014; Collischon, 2020). I extend this research by analysing whether personality is rewarded differently for men as compared to women in white-collar occupations. White-collar occupations are defined as high skilled occupations with an ISCO-88 one-digit code of 1, 2 or 3.

Big Five personality traits

The personality variables are dummy variables equal to one if an individual is in the top tertile of the personality distribution of the Big Five personality traits and zero otherwise. Dummies are used for personality as I am interested in wage associations for individuals at the top of the personality distribution and as it makes the interaction with gender and occupation easier to interpret.

Respondents were asked a reduced version of the Big Five survey (i.e., fifteen questions, three per personality trait) with answers on a seven-point Likert-scale in 2005 and 2011 (see Table 2-10 in Appendix 2.A for the survey questions). The component score for each of the five traits is then calculated following UKHLS guidelines as "the average item response if no more than one of the three input responses is missing" (Institute for Social and Economic Research, 2020).

The Big Five traits are assumed to be constant for individuals across waves and exogenous to wages. This assumption is a limitation to this specification due to the potential reverse causality of personality and labour market outcomes (Roberts, Caspi and Moffitt, 2003). However, evidence shows that the Big Five tend to be relatively stable over time, particularly after the age of 30 (Roberts and DelVecchio, 2000). Cobb-Clark and Schurer (2012) further find that the Big Five traits remain stable during working age. To net out the linear and non-linear effects of age on individual personality, I regress personality on age and age squared. The residuals from this regression control for age effects and some of the reverse causality between the labour market and personality (Heineck, 2011; Josten and Lordan, 2020) and is used as personality measurement in the main specification. The individual age-effect-free residuals of each personality trait are standardised to have a mean of zero and a standard deviation of 1. I create five binary variables that classify individuals as scoring high in a specific personality trait if their individual standardised value is in the top tertile of this distribution. In a later robustness check, this cut-off is varied to above and below the mean of each personality trait to account for the fact that gender rewards may differ at different levels of the personality distribution.

Further, Busic-Sontic, Czap and Fuerst (2017) test for stability in the personality variable across the two waves in the UKHLS recorded in 2005 (i.e., wave 15 of the BHPS) and 2011 (i.e., wave 3 of Understanding Society). They find no systematic difference across the two waves. I hence use personality variables from 2011 for the main specification and replace it with the 2005 value only if an individual's personality trait is missing for 2011.

Overall, the mean level of all Big Five personality traits other than openness is larger for women than for men as seen in Table 2-2, which is consistent with Schmitt et al. (2008) who find women to score higher in all Big Five personality traits but openness in 55 cultures.

Table 2-2: Mean level of Big Five personality trait by gender

	Male	Female	Total
Agreeableness	5.391	5.687	5.541
	(1.008)	(0.926)	(0.979)
Conscientiousness	5.436	5.679	5.558
	(0.982)	(0.956)	(0.977)
Extraversion	4.466	4.826	4.647
	(1.264)	(1.268)	(1.279)
Neuroticism	3.216	3.731	3.476
	(1.273)	(1.330)	(1.327)
Openness	4.9	4.736	4.817
	(1.116)	(1.174)	(1.148)

Note: The table shows mean levels of the Big Five personality traits for males and females and overall. The table shows the mean and the standard deviation in brackets. The Big Five personality traits are scored on a seven-point Likert scale.

2.2.1. Likelihood of making it to the top by gender and personality

The analysis is at the two-digit occupation level.[9] This allows for job sorting based on personality and for tasks and requirements differing across occupations. I focus on white-collar occupations as they can be easily grouped and exhibit some homogeneity as regards to employees' education and tasks on the job and can hence be compared across more easily.

Table 2-3 shows the likelihood of being in the top income quintile within white-collar occupations by all five Big Five personality traits and gender. Overall, the likelihood is higher

[9] I slightly amend the ISCO-88 two-digit occupation codes by reassigning some three-digit code occupations to different two-digit occupation codes. An example would be '332: Pre-primary education teaching associate professionals' that now falls under the two-digit code '23: Teaching professionals' instead of '33: Teaching associate professionals' as that ensures a sufficient sample size of teachers. See Table 2-11 for occupation classifications.

for individuals who are in the top tertile as compared to the bottom tertile of a Big Five personality traits for all Big Five personality traits but for openness. The difference in likelihoods between the top and the bottom personality traits is not large across gender. The likelihood of being in the top 20 percent income quintile is always lower for females as compared to males.

Table 2-3: Likelihood of being in the top income quintile by Big Five tertile and gender

		Female	Male	Total
Agreeableness	Top tertile	0.195	0.290	0.249
		(0.396)	(0.454)	(0.432)
	Bottom tertile	0.106	0.168	0.131
		(0.308)	(0.374)	(0.337)
Conscientiousness	Top tertile	0.172	0.269	0.227
		(0.378)	(0.444)	(0.419)
	Bottom tertile	0.122	0.188	0.148
		(0.328)	(0.390)	(0.355)
Extraversion	Top tertile	0.150	0.250	0.204
		(0.357)	(0.433)	(0.403)
	Bottom tertile	0.160	0.245	0.193
		(0.367)	(0.430)	(0.395)
Neuroticism	Top tertile	0.159	0.246	0.208
		(0.365)	(0.431)	(0.406)
	Bottom tertile	0.142	0.256	0.183
		(0.349)	(0.436)	(0.387)
Openness	Top tertile	0.140	0.224	0.175
		(0.347)	(0.417)	(0.380)
	Bottom tertile	0.166	0.261	0.215
		(0.372)	(0.439)	(0.411)

Note: The table shows likelihood of being in the top income quintile by white-collar occupations for individuals who score high and low in each of the Big Five personality traits for males and females and overall. The table shows the mean and the standard deviation in brackets.

2.2.2. Personality by gender and occupation

Table 2-4 below shows the average personality levels of agreeableness, conscientiousness, extraversion, neuroticism and openness by gender and occupation. The largest differences between men and women are for ’Legislators and senior officials’ for extraversion and neuroticism with women scoring disproportionately higher than men and agreeableness with the difference between men and women being very small and not statistically significant. For ’Managers of small enterprises’ the difference across gender is particularly small for openness and conscientiousness as compared to other occupations and particularly large for agreeableness. In ’Life science and health professionals’ women are particularly conscientious and are similar to men in terms of neuroticism. All differences in mean for men and women are statistically significant other than those of agreeableness and openness for ’Legislators and senior officials’.

Table 2-4: Big Five personality traits by gender and occupation

	Agreeableness		Conscientiousness		Extraversion		Neuroticism		Openness	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Legislators and senior officials	5.53	5.45	5.75	5.53	5.04	4.61	3.75	3.05	4.98	5.13
Corporate managers	5.61	5.36	5.77	5.50	4.88	4.54	3.62	3.11	4.67	4.82
Managers of small enterprises	5.74	5.34	5.64	5.54	4.89	4.57	3.74	3.06	4.62	4.72
Physical, mathematical and engineering science professionals	5.50	5.37	5.53	5.37	4.66	4.26	3.85	3.34	4.68	4.93
Life science and health professionals	5.62	5.38	5.79	5.34	4.50	4.14	3.53	3.37	4.54	4.83
Teaching professionals	5.75	5.56	5.69	5.44	4.85	4.47	3.83	3.26	5.04	5.16
Other professionals	5.59	5.39	5.58	5.36	4.80	4.41	3.82	3.26	4.76	4.98
Physical and engineering science associate professionals	5.60	5.35	5.58	5.41	4.65	4.36	3.83	3.29	4.58	4.84
Life science and health associate professionals	5.79	5.52	5.71	5.39	4.76	4.40	3.66	3.23	4.57	4.98
Other associate professionals	5.69	5.39	5.68	5.39	4.83	4.60	3.73	3.27	4.74	4.95

Note: The table shows the mean of the Big Five traits by gender and occupation.

2.2.3. Correlation of personality, gender and occupation and wages

It has been argued that the unexplained gender pay gap might stem from differential rewards resulting from e.g., discrimination (Bertrand, 2011; Blau and Kahn, 2017). A ‘personality penalty' by gender hence likely exists if there are unjustifiable rewards to personality.

Before turning to the main regression analysis that tests for differential personality rewards by gender this section focuses on descriptive statistics regressions in the tables below. They highlight how the association of personality traits and wage outcomes changes when including different controls and motivate the main analysis that follows. Specifically, Table 2-5 below documents results from running a simple regression of wage (i.e. either log hourly wages or the main outcome variable top income quintile) on personality (i.e. either the standardised version of the Big Five personality traits or the main independent variable of the top tertile of personality) including all basic controls other than gender (i.e. age, age squared, an education dummy, wave fixed effects, region fixed effects and the logarithm of job hours) for white-collar occupations only. Agreeableness and neuroticism have a negative impact on wages across all four specifications. Conscientiousness is not statistically significant, which is consistent with other research using UKHLS data that find conscientiousness not to be significant for some specifications or only non-linearly related to labour market outcomes (Heineck and Anger, 2010; Heineck, 2011; Nandi and Nicoletti, 2014; Collischon, 2020). For extraversion, I find insignificant results other than for the standardised personality variable. Openness is insignificant. These individual level wage regressions match the findings of the literature of small and varying effects of personality on wages on average (Nyhus and Pons, 2005).[10]

[10] Meta-studies point to conscientiousness as the overall most frequent positive predictor of income (Barrick et al., 2001; Almlund et al., 2011). Using the UKHLS data set, agreeableness and neuroticism have been found to negatively and openness to positively impact wages (Heineck, 2011; Nandi and Nicoletti, 2014; Collischon, 2020). The impact of extraversion varied across studies. Openness was largely insignificant.

Table 2-5: Individual level regression of wages on Big Five personality traits

	(1)	(2)	(3)	(4)
Outcome:	Log hourly wage		Top income quintile	
Personality variable:	Standardised personality	Top tertile personality	Standardised personality	Top tertile personality
Agreeableness	-0.040**	-0.055**	-0.022**	-0.043**
	(0.004)	(0.008)	(0.003)	(0.005)
Conscientiousness	0.000	-0.003	-0.002	-0.014**
	(0.004)	(0.007)	(0.003)	(0.006)
Extraversion	-0.016**	-0.007	-0.009**	-0.002
	(0.004)	(0.008)	(0.003)	(0.006)
Neuroticism	-0.055**	-0.067**	-0.031**	-0.032**
	(0.004)	(0.008)	(0.003)	(0.006)
Openness	0.004	0.004	0.001	0.001
	(0.004)	(0.008)	(0.003)	(0.006)
Constant	1.078**	1.163**	-0.366**	-0.286**
	(0.065)	(0.068)	(0.036)	(0.036)
Observations	86,924	86,924	86,924	86,924
R-squared	0.184	0.176	0.102	0.098

Note: The sample is restricted to individuals that work full-time (i.e., more than 30 hours a week) and have indicated their personality at least once across the panel. The sample includes individuals in white-collar occupations only. The outcome variables are the logarithm of monthly wages (regression (1) and (2) or the probability of being in the top income quintile (i.e., the top 20% of the income distribution) (regression (3) and (4)). The independent variable are the Big Five personality traits either standardised to have a mean of 0 and a standard deviation of one (regressions (1) and (3)) or a dummy variable that equals one if the individual is in the top tertile of the respective personality trait distribution (regression (2) and (4). Basic controls include age, age squared, education, wave fixed effects, region fixed effects and the logarithm of job hours. The regressions are clustered at the individual level. Robust standard errors are in parentheses. ** p<0.01, * p<0.05

When regressing wage on gender, in Table 2-6 below, specifications (5) and (6), I find a gender wage gap of -0.197 log points and that women are 11.3% percentage points less likely to be in the top quintile of the wage distribution. When adding personality to the regression the coefficient on gender decreases slightly to -0.183 (specification (7)). The association of agreeableness and neuroticism and wages outcomes remains negative when adding gender controls. Conscientiousness changes to have a significant and positive association with the log of wages. Being in the top tertile of extraversion also changes to have a positive and significant relation to wages overall. Standardised openness has a negative association with both wage outcomes.

Table 2-6: Individual level regression of wages on gender and Big Five traits

	(5)	(6)	(7)	(8)	(9)	(10)
Outcome:	Log hourly wage	Top income quintile	Log hourly wage		Top income quintile	
Gender and personality variable:	Gender No personality	Gender No personality	Gender Standardised personality	Gender Top tertile personality	Gender Standardised personality	Gender Top tertile personality
Agreeableness			-0.029**	-0.040**	-0.015**	-0.035**
			(0.004)	(0.007)	(0.003)	(0.005)
Conscientiousness			0.013*	0.016*	0.005	-0.004
			(0.004)	(0.007)	(0.003)	(0.005)
Extraversion			0.001	0.019*	0.000	0.013*
			(0.004)	(0.008)	(0.003)	(0.006)
Neuroticism			-0.032**	-0.035**	-0.018**	-0.014*
			(0.004)	(0.008)	(0.003)	(0.006)
Openness			-0.009*	-0.013	-0.006*	-0.009
			(0.004)	(0.008)	(0.003)	(0.006)
Female	-0.197**	-0.113**	-0.183**	-0.194**	-0.105**	-0.110**
	(0.00734)	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)
		-0.229**	1.335**	1.375**	-0.219**	-0.166**
Constant	1.315**	(0.036)	(0.066)	(0.068)	(0.036)	(0.036)
	(0.0661)					
		86,937	86,924	86,924	86,924	86,924
Observations	86,937	0.113	0.209	0.206	0.116	0.115
R-squared	0.203	-0.113**	-0.183**	-0.194**	-0.105**	-0.110**

Note: The sample is restricted to individuals that work full-time (i.e., more than 30 hours a week) and have indicated their personality at least once across the panel. The sample includes individuals in white-collar occupations only. The outcome variables are the logarithm of monthly wages or the probability of being in the top income quintile (i.e., the top 20% of the income distribution). The independent variable is either being female and/or the Big Five personality traits either standardised to have a mean of 0 and a standard deviation of one or a dummy variable that equals one if the individual is in the top tertile of the respective personality trait distribution. Basic controls include age, age squared, education, wave fixed effects, region fixed effects and the logarithm of job hours. The regressions are clustered at the individual level. Robust standard errors are in parentheses. ** p<0.01, * p<0.05

In a next step, I add occupation controls to the regression to see whether the within-occupation rewards to gender and personality differ. Average effects of personality on wages do not account for the fact that occupational sorting occurs based on personality (Mueller and Plug, 2006; Cobb-Clark and Tan, 2011) and assume that personality is valued equally across occupations and person type (John and Thomsen, 2014), which seems unlikely given that occupations vary significantly in tasks and requirements. Further, average effects of personality on wages omit occupational sorting but there is evidence that, for example, risk preferences, which are more prevalent in women, impact selection into stable but lower paid occupations (Bertrand, 2011). I hence add occupation controls for all two-digit code occupations in the baseline regressions. As per Table 2-7 below, the gender gap decreases when including occupation controls in the simple regression of wages on gender from -0.197 log points without occupation controls to -0.182, which is in line with previous literature that finds even larger decreases of the gender wage gap after adding occupation controls (Goldin, 2014). Specifications (13) to (16) add either the standardised or the top tertile personality variables to the regression. I find supporting evidence that personality coefficients change once including occupation controls, which supports the hypothesis that sorting occurs based on personality and that men and women with the same personality traits sort into occupations at different rates (Cobb-Clark and Tan, 2011). The gender gap when running a regression of the main outcome variable the top income quintile including personality tertile controls and occupation is a -0.118 percentage points difference as shown in specification (16).

Table 2-7: Individual level regression of wages on gender, Big Five traits and occupation

Outcome:	(11) Log hourly wage	(12) Top income quintile	(13) Log hourly wage	(14)	(15) Top income quintile	(16)
			Standardised personality	Top tertile personality	Standardised personality	Top tertile personality
Agreeableness			-0.028**	-0.036*	-0.016**	-0.036**
			(0.005)	(0.012)	(0.003)	(0.006)
Conscientiousness			0.008*	0.012	0.005	-0.004
			(0.003)	(0.007)	(0.003)	(0.006)
Extraversion			0.001	0.021*	0.000	0.012*
			(0.004)	(0.009)	(0.002)	(0.007)
Neuroticism			-0.031**	-0.031*	-0.018**	-0.013*
			(0.005)	(0.011)	(0.002)	(0.005)
Openness			-0.005	-0.008	-0.004	-0.006
			(0.003)	(0.008)	(0.004)	(0.007)
Female	-0.182**	-0.121**	-0.168**	-0.177**	-0.113**	-0.118**
	(0.020)	(0.009)	(0.018)	(0.019)	(0.009)	(0.009)
Legislators & Senior Officials	0.176**	0.016**	0.170**	0.165**	0.013**	0.012*
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Corporate managers	0.120**	0.038**	0.109**	0.106**	0.031**	0.034**
	(0.012)	(0.007)	(0.011)	(0.011)	(0.007)	(0.007)
Managers of small enterprises	-0.244**	0.101**	-0.250**	-0.244**	0.098**	0.100**
	(0.016)	(0.007)	(0.016)	(0.015)	(0.007)	(0.007)
Physical, mathematical and engineering science professionals	0.143**	0.011	0.139**	0.140**	0.008	0.009
	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)	(0.009)
Life science and health professionals	0.276**	0.003	0.267**	0.275**	-0.003	0.002
	(0.008)	(0.005)	(0.008)	(0.007)	(0.006)	(0.006)
Other professionals	0.059**	0.029**	0.055**	0.044**	0.027**	0.027**
	(0.007)	(0.004)	(0.007)	(0.007)	(0.004)	(0.004)
Physical and engineering science associate professionals	-0.028*	0.063**	-0.034*	-0.031*	0.059**	0.061**
	(0.012)	(0.007)	(0.012)	(0.012)	(0.007)	(0.007)
Life science and health associate professionals	0.041*	0.097**	0.036	0.043*	0.094**	0.096**
	(0.016)	(0.009)	(0.016)	(0.017)	(0.008)	(0.008)
Other associate professionals	-0.058**	0.088**	-0.063**	-0.069**	0.085**	0.086**
	(0.013)	(0.006)	(0.013)	(0.013)	(0.006)	(0.006)
Constant	1.535**	-0.307*	1.546**	1.488**	-0.298*	-0.246
	(0.169)	(0.126)	(0.170)	(0.158)	(0.124)	(0.119)
Observations	86,937	86,937	86,924	86,924	86,924	86,924
R-squared	0.218	0.120	0.223	0.240	0.123	0.122

Note: The sample is restricted to working full-time, having indicated personality and white-collar occupations. Outcomes are log of wages or the probability of being in the top income quintile. The independent variable is being female and/or Big Five personality traits (standardised or a dummy for the top tertile). Basic controls are age, age squared, education, wave fixed effects, region fixed effects, occupation and the log of job hours. Regressions are clustered at the occupation level. Robust standard errors are in parentheses. ** p<0.01, * p<0.05

The findings from the above associations match findings from previous studies focusing on the effect of personality at the individual level that also find moderate but statistically significant links of all Big Five personality traits with wages (Nyhus and Pons, 2005; Heineck, 2011; Nandi and Nicoletti, 2014; Collischon, 2020). They further highlight that personality coefficients change when including gender and/or occupation controls, which motivates running subsequent analyses at the occupation level rather than on average. Individuals receive different rewards depending on their personality but regressions at the individual level fail to explain why. I hence test for differential rewards to personality by gender across occupations.

2.3. Main specification

This study tests whether there are differential rewards to personality by gender. In the main regression, the dependent variable is a dummy of the top income quintile, and the independent variable is an interaction of the dummy of the top tertile of one of the standardised Big Five traits, occupation fixed effects and gender. I run a linear regression rather than a nonlinear model as interpreting marginal effects for interactions in nonlinear models is problematic (Norton, Wang and Ai, 2004) and for straightforward interpretability of results. I further choose to analyse the top tertile of the Big Five traits for easier interpretability of the interaction and because this study focuses on rewards to strong personalities. The regression is:

$$income\ quintile_{ijt} = \chi' P_{it} * O_{ijt} * F_i + \gamma' I_{ijt} + \alpha' BigFive_{ijt} + \beta' O_{ijt} + \delta' C_{it} + e_{jit} \quad (2.1)$$

where *income quintile* is a dummy variable that equals 1 if employee *i* in occupation *j* at time t is in the top income quintile of the logarithm of inflation-adjusted hourly wages and zero otherwise. $P_{it} * O_{ijt} * F_i$ is an interaction of one of the five binary personality indicators P_{it} that equals one if an individual is in the top tertile of the respective personality trait and zero otherwise, occupation fixed effects O_{it} and a female dummy F_i that equals one if an individual is female and zero otherwise. I_{ijt} is a vector of the different sub-interactions I control for: the interaction between female and occupation fixed effects, the interaction between female and the respective personality and the interaction between occupation fixed effects and the respective personality. I restrict the analysis to white-collar occupations only because there is on average a greater homogeneity in tasks across gender in those occupations. Equation (2.1) hence relates the likelihood of being in the top 20 percent of the income bracket to one of the five personality binary indicators interacted with the individuals' own occupation fixed effects and gender. $BigFive_{it}$ is a vector all five personality binary indicators. O_{ijt} are individual occupation fixed effects for each two-digit code occupation j at the individual level. C_{it} is a vector of individual controls, namely female, age, age-squared, wave fixed effects, education, a logarithm of work hours, and region fixed effects. The standard error is ε_{jit}. Standard errors are clustered at the occupation level to control for within-occupation autocorrelation and heteroskedasticity. I run the regression five times, always controlling for all Big Five personality traits but interacting only one of these binary personality traits with occupation fixed effects and female in each regression to ensure sufficient degrees of freedom.

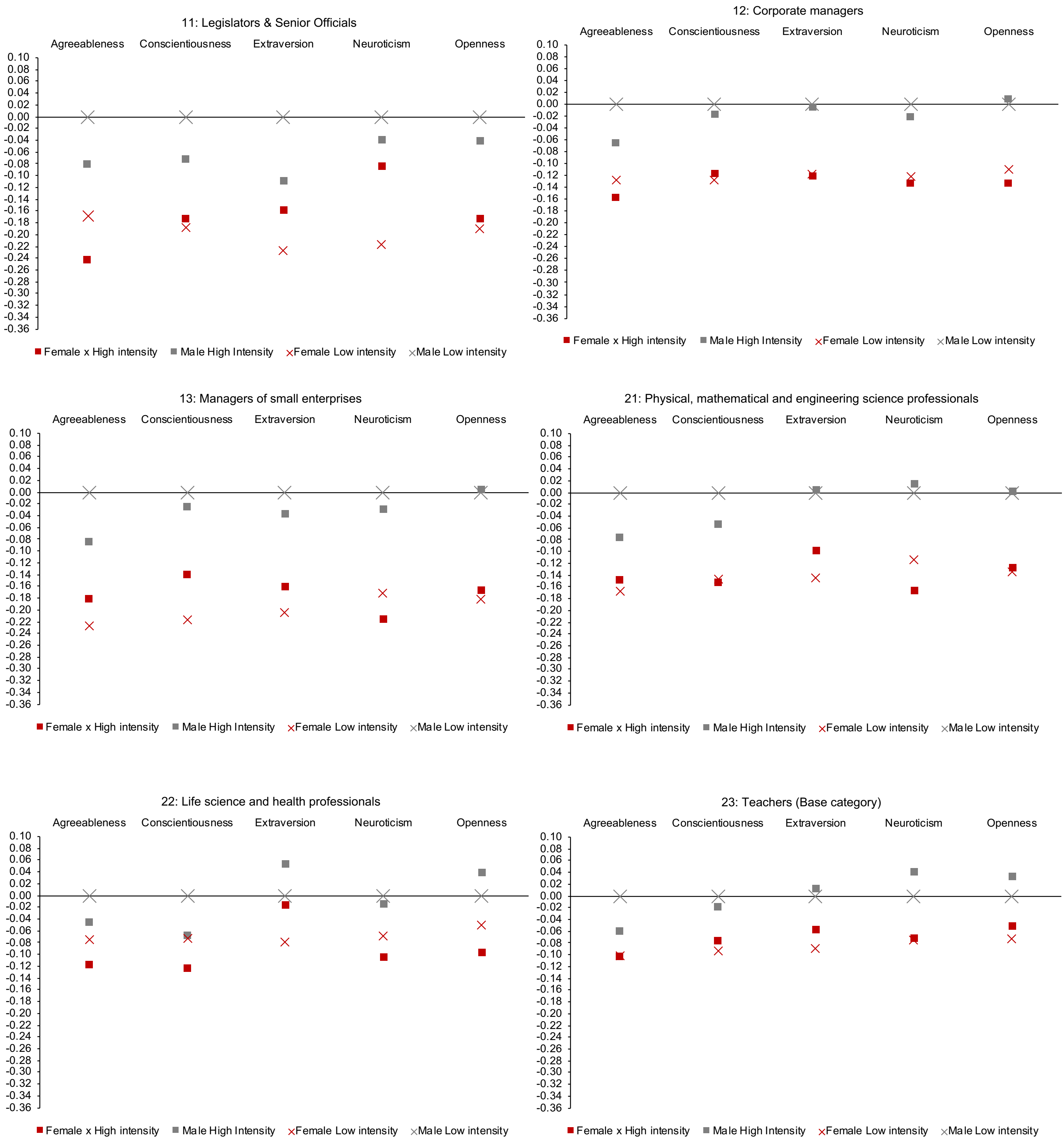
The interaction of the individual's personality trait with occupation fixed effects allows the relationship between that specific trait to differ for each occupation. The main coefficients of interest tell us whether an occupation rewards that particularly personality trait by gender. That is, they are a natural rank ordering of how each personality trait is rewarded in a particular occupation. I compare high and low intensity personality traits across men and women to ensure that I capture what is happening at the bottom of the personality variable distributions as well as at the top where high and low intensity by gender is a sum of the relevant coefficients resulting from the regression in (2.1) as explained in Table 2-12 in Appendix 2.A.

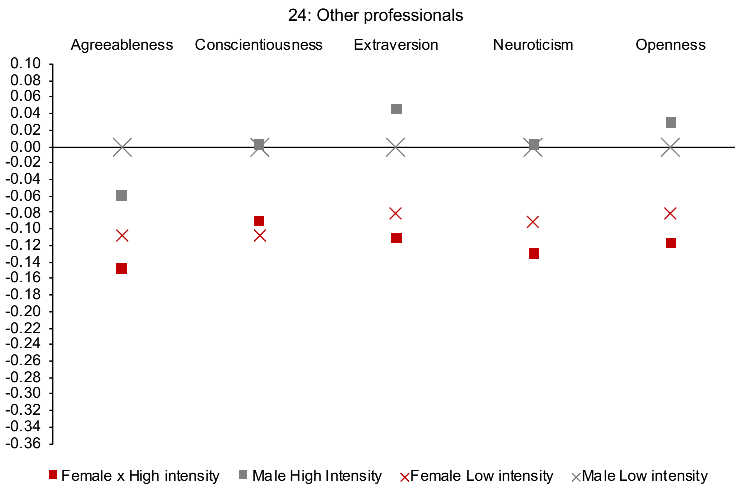
2.4. Results

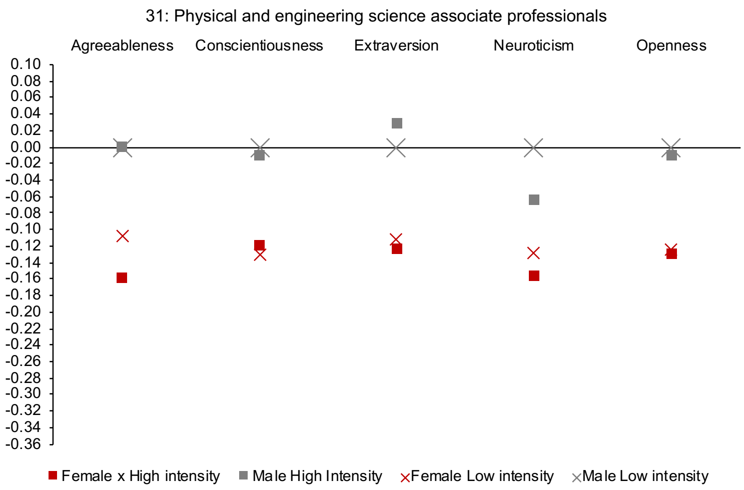
Figure 2-1 below illustrates the probability of making it to the top for each of the five personality traits of high and low intensity by gender for all two-digit occupations.[11] The larger the difference between high and low intensity across gender, the more one can say about differential rewards in an occupation. If, for example, high intensity agreeableness and low intensity agreeableness are on the same dot for men and for women (even if on a lower level), this means that while women are less likely to be in the top 20 income quintile overall, their level of agreeableness is still equally rewarded to that of men. The absolute difference between men and women then simply displays the gender wage gap. If low intensity agreeableness is more rewarded than high intensity agreeableness for men but the other way around for women, this points to systematic differences in rewards across gender.

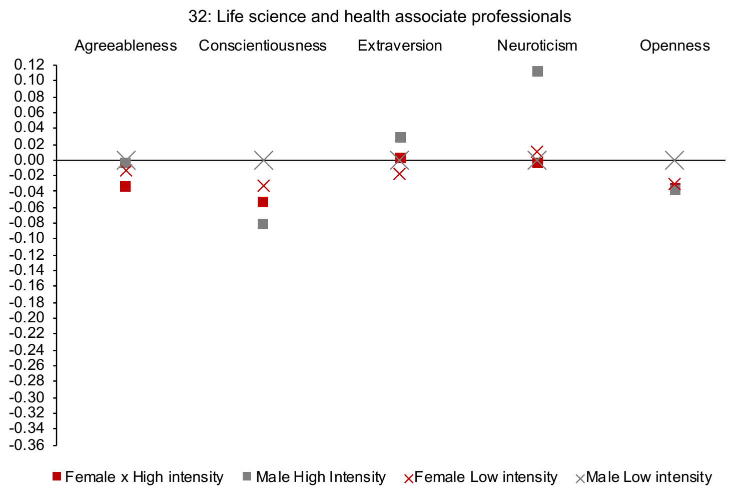
[11] The regression results can be found in Table 2-13 in Appendix 2.A. The graphs are adjusted so that 'Male low intensity' becomes the reference category at zero by subtracting the 'Male low intensity' coefficient from all coefficients. This ensures comparability across data points. The reference occupation of the analysis is teachers. The choice of base category only shifts the data points but does not affect the interpretation of rewards that are relative to 'Male low intensity'. To remove the pure occupation difference between teachers and other occupations, I subtract the coefficient on occupation (i.e., the coefficient male low intensity) from all coefficients.

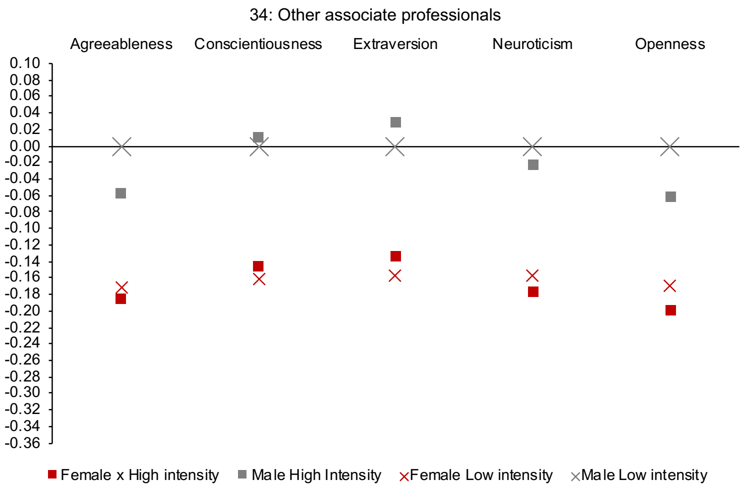
Figure 2-1: Differential rewards to Big Five traits for men and women by occupation











Note: Each graph displays one of ten two-digit code occupations. The graphs show the output of five regressions of equation (2.1); one for each Big Five trait. The grey dots display male personality of high and low intensity, and the red dots display female personality of high and low intensity. The regression coefficients show the impact of personality within an occupation and by gender on the probability of being in the top 20 percent income quintile. The y-axis shows the size of the respective coefficient, namely the probability of being in the top income quintile. The data points have been adjusted by male low intensity to ensure comparability.

Except for the occupation 'Legislators and senior officials', the graphs of Figure 2-1 show that personality is largely unimportant for differential rewards across gender as regards to the likelihood of being in the top 20% income quintile with the only exception being agreeableness that is punished more for men on average.

As regards to men, the Male high intensity coefficients are often close to zero meaning that they are valued equally to the Male low intensity coefficients in the labour market. This means it does mostly not matter for men whether they score high or low in a respective personality trait for the likelihood to be a top earner in a white-collar occupation. The exception is agreeableness that is largely punished for men but not so much for women. The punishment is as large as 0.08 percentage points for agreeable ‘Managers of small enterprises’ and on average 0.053 percentage points as compared to disagreeable men. Also, in the legislator occupation group, men are punished for scoring high in all five personality traits. For occupations with roughly similarly valued personality traits for men and women, the difference proxies the gender wage gap of between 0.11 and 0.18 percentage points in Table 2-7. An example is ‘Corporate managers’, where low levels of agreeableness are valued in the occupation for men but there are no other large differences in the likelihood of making it to the top across gender.

For ‘Managers of small enterprises’ there is a small reward for women who are highly agreeable, conscientious and extroverted, and men are punished for being agreeable. This points to men and women being systematically treated differently in this specific occupation, albeit the differences are relatively small. Science professions exhibit marginally different personality rewards across gender: In the case of ‘Physical, mathematical and engineering science professionals’, men are punished for being agreeable and conscientious while women are rewarded for being extraverted and low on neuroticism. These effects do not seem to hold for science associates as ‘Physical and engineering science associates’, where women are punished for being agreeable but there are little differential rewards for other personality traits. In the occupation ‘Life science and health professionals’, men and women scoring low in agreeableness and conscientiousness and high in extraversion benefit. Men are further rewarded for being open for which women are punished. In the corresponding associate occupation group ‘Life science and health associate professionals’ extraversion is rewarded overall while agreeableness is punished for women as compared to men and neuroticism is highly rewarded for men as compared to women. Conscientiousness and openness are punished for men. In the base category ‘Teachers’, agreeableness is punished, and neuroticism is rewarded for men. For the other personality traits, the rewards are similar across gender. In the ‘Other professionals’ occupation group, agreeableness is punished for both men and women and extraversion, neuroticism and openness are punished for women as compared to men. In the ‘Other associate professionals’ occupation, the only large difference in personality rewards is for men who are punished for being agreeable.

The most pronounced occupation in terms of differences in rewards is 'Legislators and senior officials'. As per the graph for 'Legislators and senior officials' above, extraverted and neurotic females are relatively more likely to be among the top earners within this occupation group. These traits give women a wage advantage that narrows the gender pay gap. Conscientious and open men, however, are relatively less likely to be among the top earners within this occupation group.

2.5. Discussion and Conclusion

In the workplace, personality could be rewarded because it enhances an individual's productivity and their wage bargaining power, which I call legitimate rewards. Personality could also be rewarded differently depending on a person's innate characteristics such as their gender, which I call unjustifiable rewards. Testing for unjustifiable rewards is difficult, as it is hard to disentangle which effects influence rewards. Gender is easily observable, fixed over time and the gender wage gap has been studied extensively. Further, one can imagine that there are differential rewards for men and women based on personality because of, for example, taste-based discrimination or gender norms. I hence chose gender to look at unjustifiable personality rewards.

Using the UKHLS panel data set from the UK, I explore whether women with the same level of personality traits (i.e., scoring high or low on a respective personality trait) have a different likelihood of making it to the top as compared to men. I estimate the probability of being in the top income quintile for men and women and compare across high versus low levels of different personality traits. This study looks at the likelihood of being in the top income quintile as that is where the unexplained gender wage gap has been most persistent over time (Blau and Kahn, 2017). I further focus on white-collar occupations as they are more homogeneous with respect to the tasks performed by men and women. I look at the Big Five personality traits as a measurement of personality; concretely being in the top tertile of each of the Big Five personality traits compared to the middle and bottom tertile.

By examining whether men and women have different likelihoods across five personality traits I am essentially asking whether the phenomenon of differential expectations of male and female personalities is observed in the labour market. The results of this study mainly suggest that personality traits are overall not unjustifiably rewarded or punished by gender. There are, however, some exceptions to this finding. First, I find that men are punished for being agreeable and often more than women while disagreeableness benefits men more than women. That is in line with previous research with similar findings (Mueller and Plug, 2006; Judge, Livingston and Hurst, 2012). In particular, Judge, Livingston and Hurst (2012) explain that this finding reflects conventional gender roles. That is, men who are agreeable disconfirm the norm of men being, for example, more competitive or self-interested than women. Women in comparison are not punished as much for being agreeable but also do not share the same gains from being disagreeable as men. This shows that being disagreeable has a different signalling effect in men than in women rather than an intrinsic value in the labour market. Though overall, agreeableness has a negative association with wages.

Second, I find that female and male 'Legislators and senior officials' with the same personality trait intensity face a different likelihood of making it to the top, an occupation that consists of the three-digit code occupations of 'Legislators and senior government officials', 'Senior officials of special-interest organisations' and 'Directors and chief executives'. The finding is that extraverted and neurotic females get rewards to personality by gender in this specific occupation. And conscientious and open males get less reward to personality. This finding is in line with the hypothesis at the start of this study that there could be unjustifiable rewards to personality due to, for example, discrimination in the labour market. The reason why I find differential rewards for men and women in the 'Legislators and senior officials' occupation specifically could be that the success of political leaders and senior officials often depends on electoral success (i.e., voters) and company shareholders rather than employers, who are bound under employment law in the UK. Personality traits have been shown to be particularly important in this specific occupation for success (Nai and Toros, 2020). Also, this occupation also has the largest difference in mean hourly wages across gender. Eagly and Sczesny (2009) argue that while there is increasing gender parity in legislator occupations, women in those occupations are still concentrated at lower-level roles in management while men occupy positions in which they themselves can determine wages, which explains large gender pay gaps (Eagly and Sczesny, 2009). This may explain why personality traits are rewarded differently for men and women. While both of those explanations require further analysis, it is important to highlight that the sample for this occupation is small with just 375 unique individual observations and the findings should hence be verified in a larger sample.

For the remaining two-digit code occupations, I do not find clear patterns in differential rewards. A limitation to this study is that two-digit code occupations consist of a multitude of often very different three-digit code occupations. As example, the 'Associate professionals' occupation group consists of a mix of eight very different three-digit code occupations. Perhaps the tasks across those occupations are not as homogeneous as previously assumed and there may be sorting based on personality into three-digit code occupations. Unfortunately, the sample size is not sufficient to run the same analysis at the three-digit code occupation level to account for such measurement issues.

Overall, I find very small differentials across gender and the gender wage gap dominates the analysis. One reason why I only find small personality differentials across gender could be the choice of the personality variable. I chose to look at the top tertile of each of the Big Five personality traits as compared to the bottom and the middle distribution as I was interested in the rewards to being highly agreeable, conscientious, extravert, neurotic or open. Past literature has, however, argued that rewards to personality traits may stem from slightly above average personality traits rather than high (or low) levels of personality traits (Mueller and Plug, 2006; Heineck, 2011). To account for effects stemming from the middle of the personality variable distribution, I change the personality variable to above and below the mean of the respective personality variable. When running equation (2.1) using a dummy for personality that is equal to one if the individual scores above average levels of the respective trait and zero if they score below, a very similar picture to Figure 2-1 above arises with personality overall not being rewarded for men, differentials for women being small and the gender wage gap dominating.

This study finds that personality is not rewarded differently across occupations for men and women in terms of the likelihood of making it to the top income quintile except for agreeableness. Both high and low levels of the other four personality trait are punished for women as compared to men; a finding that reflects the gender wage gap irrespective of personality traits. The finding is interesting, as it shows that while the underlying mechanisms of personality are difficult to identify, personality wage associations do not seem to result from differential rewards by gender. But agreeableness is punished more for men than women, which confirms the hypothesis that there are differential rewards to personality due to the expectation to adhere to one's social identity. Further research could explore whether this agreeableness gap is closing over time as gender norms become less prevalent and teamwork and sociability (i.e., skills related to high agreeableness) are increasingly demanded in the labour market.

This paper does not claim causal inference but looks at the relative importance of skills and how they predict labour market outcomes. By controlling for detailed fixed effects, I aim to control for unobserved variables. One limitation to the analysis of differential rewards to personality by gender is, however, that selection into an occupation might occur based on unobservable characteristics of the specific occupation. If an occupation strongly rewards one of the Big Five personality traits, a person who scores low on that trait but nevertheless selects into the occupation is likely to have other (unobserved) characteristics that allow her to do well in that occupation. This would bias the estimated occupation-specific effect of the studied trait on wages downwards.

Overall, my research complements the literature that analysed personality effects without looking into the mechanisms of such associations.

2.A Appendix A

Table 2-8: Average level of the Big Five personality traits by occupation

	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
11 Legislators and senior officials	5.497	5.629	4.850	3.402	5.077
	(0.984)	(0.938)	(1.138)	(1.234)	(1.032)
12 Corporate managers	5.461	5.608	4.682	3.321	4.756
13 Managers of small enterprises	(0.979)	(0.957)	(1.252)	(1.290)	(1.099)
	5.495	5.573	4.692	3.324	4.679
	(1.059)	(1.001)	(1.246)	(1.330)	(1.243)
21 Physical, mathematical and engineering science professionals	5.388	5.394	4.316	3.415	4.895
	(0.982)	(0.939)	(1.258)	(1.289)	(1.092)
22 Life science and health professionals	5.506	5.576	4.334	3.456	4.673
	(1.012)	(0.954)	(1.327)	(1.319)	(1.097)
23 Teaching professionals	5.702	5.610	4.711	3.662	5.107
	(0.896)	(0.970)	(1.263)	(1.358)	(1.122)
24 Other professionals	5.505	5.480	4.625	3.571	4.856
	(0.999)	(0.972)	(1.319)	(1.305)	(1.129)
31 Physical and engineering science associate professionals	5.428	5.460	4.452	3.453	4.755
	(0.984)	(0.938)	(1.138)	(1.234)	(1.032)
32 Life science and health associate professionals	5.758	5.669	4.720	3.606	4.619
	(0.905)	(0.965)	(1.302)	(1.312)	(1.133)
34 Other associate professionals	5.568	5.529	4.758	3.544	4.824
	(0.985)	(1.009)	(1.272)	(1.351)	(1.190)

Note: White-collar occupations include the top 10 white-collar ISCO-88 two-digit occupations. Occupations with an ISCO-88 one-digit code of 1, 2 or 3 is regarded as high skilled white-collar (https://www.eurofound.europa.eu/surveys/ewcs/2005/classification). Occupation '33: Teaching associate professionals' has been merged with occupation '23: Teaching professionals' to ensure a sufficient sample size for later analyses. Data is from 1991-2018.

Table 2-9: Summary statistics

	Male	Female	Total
Labour Market Outcomes:			
Hourly wage - inflation adjusted	18.04	14.87	16.37
	(16.66)	(11.37)	(14.21)
Log hourly wage – inflation adjusted	2.749	2.579	2.659
	(0.552)	(0.498)	(0.531)
Big Five personality traits:			
Agreeableness	5.391	5.687	5.541
	(1.008)	(0.926)	(0.979)
Conscientiousness	5.436	5.679	5.558
	(0.982)	(0.956)	(0.977)
Extraversion	4.466	4.826	4.647
	(1.264)	(1.268)	(1.279)
Neuroticism	3.216	3.731	3.476
	(1.273)	(1.330)	(1.327)
Openness	4.9	4.736	4.817
	(1.116)	(1.174)	(1.148)
Individual characteristics:			
Age	43.35	41.91	42.62
	(11.78)	(11.30)	(11.56)
Female	0.00	1.00	0.51
	0.00	0.00	(0.50)
Education: Higher/first degree	0.446	0.476	0.461
	(0.497)	(0.499)	(0.498)
Job hours	38.39	32.53	35.31
	(8.284)	(9.556)	(9.441)
Log of job hours	3.614	3.417	3.51
	(0.312)	(0.419)	(0.385)

Note: The sample is restricted to individuals that work full-time (i.e., more than 30 hours a week) and have indicated their personality at least once across the panel. The sample includes white-collar occupations only. The hourly wages are adjusted to the Consumer Price Index in the UK of 2015 as published by the ONS. The Big Five personality traits are the non-standardised version of the seven-point Likert scale. Education includes having a higher or first degree (1/0). Job hours include the hours worked regularly (including overtime work).

Table 2-10: Big Five personality questions

Personality Questions UKHLS	
	Respondent …
Conscientiousness	Does a thorough job
	Does things efficiently
	Tends to be lazy*
Extraversion	Is talkative
	Is reserved*
	Is outgoing, sociable
Agreeableness	Is sometimes rude to others*
	Has a forgiving nature
	Considerate and kind
Neuroticism	Worries a lot
	Gets nervous easily
	Is relaxed and handles stress well*
Openness	Is original, comes up with ideas
	Values artistic, aesthetic experience
	Has an active imagination

Note: All questions were answered on a scale from 1=Strongly disagree to 7=Strongly agree.
* Indicates that the answer was reversely coded.

Table 2-11: Occupation classification of ISCO-88 three-digit code occupations

Two-digit occupations	Three-digit occupations
11: Legislators and senior officials	
	111: Legislators and senior government officials
	114: Senior officials of special-interest organisations
	* 121: Directors and chief executives
12: Corporate managers	
	122: Production and operations managers
	123: Other specialist managers
13: Managers of small enterprises	
	131: Managers of small enterprises
21: Physical, mathematical and engineering science professionals	
	211: Physicists, chemists and related professionals
	212: Mathematicians, statisticians and related professionals
	213: Computing professionals
	214: Architects, engineers and related professionals
22: Life science and health professionals	
	221: Life science professionals
	222: Health professionals (except nursing)
	223: Nursing and midwifery professionals
23: Teaching professionals	
	231: College, university and higher education teaching professionals
	232: Secondary education teaching professionals
	233: Primary and pre-primary education teaching professionals
	234: Special education teaching professionals
	235: Other teaching professionals
	* 332: Pre-primary education teaching associate professionals
	* 333: Special education teaching associate professionals
	* 334: Other teaching associate professionals
24: Other professionals	
	241: Business professionals
	242: Legal professionals
	243: Archivists, librarians and related information professionals
	244: Social science and related professionals
	245: Writers and creative or performing artists
	246: Religious professionals

	247: Public service administrative professionals
31: Physical and engineering science associate professionals	
	311: Physical and engineering science technicians 312: Computer associate professionals 313: Optical and electronic equipment operators 314: Ship and aircraft controllers and technicians 315: Safety and quality inspectors
32: Life science and health associate professionals	
	321: Life science technicians and related associate professional 322: Health associate professionals (except nursing) 323: Nursing and midwifery associate professionals 331: Primary education teaching associate professionals
34: Other associate professionals	
	341: Finance and sales associate professionals 342: Business services agents and trade brokers 343: Administrative associate professionals 344: Customs, tax and related government associate professionals 345: Police inspectors and detectives 346: Social work associate professionals 347: Artistic, entertainment and sports associate professionals 348: Religious associate professionals

Note: The data is from the Eurostat ISCO-88 classification. The list excludes Armed Forces (Three-digit code =100) and agriculture occupations (Three-digit codes: 611-615) as those have been dropped given the small sample size. Occupations indicated with a * have been recoded manually.

Table 2-12: Definition of female and male high and low personality intensity

Personality intensity	Coefficients on…
Female high intensity	(Personality x Occupation x Female) + (Personality x Occupation) + (Occupation x Female) + (Personality x Female) + Occupation fixed effects + Female + Personality
Male high intensity	(Personality x Occupation) + Personality + Occupation
Female low intensity	(Occupation x Female) + Occupation + Female
Male low intensity	Occupation

Note: The table shows an overview of the relevant coefficients that fall out of regression (2.1) and how they are aggregated to show female versus male and high versus low intensity personality profiles.

Table 2-13: Main regressions

	Top 20% Income Quintile				
	Agreeableness	Conscientiousness	Extraversion	Neuroticism	Openness
11: Legislators & Senior Officials x Personality x Female	-0.050**	0.063**	0.177**	0.224**	0.083**
	(0.011)	(0.011)	(0.007)	(0.006)	(0.003)
11: Legislators & Senior Officials x Personality	-0.023*	-0.060**	-0.139**	-0.086**	-0.085**
	(0.009)	(0.007)	(0.009)	(0.005)	(0.006)
12: Corporate managers x Personality x Female	-0.023*	-0.008	-0.017**	0.049**	-0.020**
	(0.009)	(0.012)	(0.004)	(0.010)	(0.003)
12: Corporate managers x Personality	-0.005	0.002	-0.017**	-0.063**	-0.024**
	(0.009)	(0.011)	(0.003)	(0.009)	(0.004)
13: Managers of small enterprises x Personality x Female	0.070**	0.066**	0.063**	0.023*	0.023**
	(0.008)	(0.009)	(0.003)	(0.007)	(0.004)
13: Managers of small enterprises x Personality	-0.025**	-0.006	-0.049**	-0.070**	-0.028**
	(0.007)	(0.009)	(0.002)	(0.005)	(0.005)
21: Physical, mathematical and engineering science professionals x Personality x Female	0.037**	0.012	0.021**	-0.027**	0.017**
	(0.008)	(0.009)	(0.004)	(0.007)	(0.004)
21: Physical, mathematical and engineering science professionals x Personality	-0.016	-0.034**	-0.009*	-0.028**	-0.031**
	(0.007)	(0.009)	(0.003)	(0.005)	(0.005)
22: Life science and health professionals x Personality x Female	-0.056***	-0.019	-0.012	0.016	-0.072**
	(0.008)	(0.010)	(0.008)	(0.009)	(0.004)
22: Life science and health professionals x Personality	0.014	-0.048**	0.041**	-0.056**	0.005
	(0.007)	(0.011)	(0.007)	(0.006)	(0.004)
24: Other professionals x Personality x Female	-0.039**	-0.021*	-0.094**	-0.002	-0.052**
	(0.007)	(0.009)	(0.004)	(0.008)	(0.003)
24: Other professionals x Personality	-0.001	0.022*	0.032**	-0.039**	-0.005
	(0.007)	(0.009)	(0.004)	(0.006)	(0.004)

31: Physical and engineering science associate professionals x Personality x Female	-0.110**	-0.015	-0.062**	0.075**	0.018*
	(0.007)	(0.010)	(0.003)	(0.010)	(0.006)
31: Physical and engineering science associate professionals x Personality	0.060**	0.009	0.017**	-0.106**	-0.044**
	(0.007)	(0.009)	(0.003)	(0.006)	(0.004)
32: Life science and health associate professionals x Personality x Female	-0.078**	0.024*	-0.031**	-0.089**	0.046**
	(0.008)	(0.009)	(0.003)	(0.009)	(0.006)
32: Life science and health associate professionals x Personality	0.057**	-0.062**	0.017**	0.071**	-0.072**
	(0.007)	(0.009)	(0.003)	(0.008)	(0.006)
34: Other associate professionals x Personality x Female	-0.016*	-0.031**	-0.025**	0.042**	0.043**
	(0.007)	(0.009)	(0.004)	(0.007)	(0.004)
34: Other associate professionals x Personality	0.003	0.029*	0.016**	-0.065**	-0.095**
	(0.007)	(0.009)	(0.003)	(0.005)	(0.004)
Personality x Female	0.060**	0.036**	0.020**	-0.039**	-0.013**
	(0.007)	(0.010)	(0.002)	(0.007)	(0.003)
11: Legislators & Senior Officials x Female	-0.070**	-0.102**	-0.148**	-0.146**	-0.126**
	(0.011)	(0.008)	(0.007)	(0.008)	(0.008)
12: Corporate managers x Female	-0.026	-0.035*	-0.029**	-0.047**	-0.036**
	(0.012)	(0.012)	(0.008)	(0.007)	(0.010)
13: Managers of small enterprises x Female	-0.124**	-0.124**	-0.116**	-0.097**	-0.110**
	(0.009)	(0.008)	(0.006)	(0.006)	(0.008)
21: Physical, mathematical and engineering science professionals x Female	-0.066**	-0.053**	-0.055**	-0.040**	-0.061**
	(0.011)	(0.011)	(0.008)	(0.007)	(0.009)
22: Life science and health professionals x Female	0.027*	0.021	0.010	0.006	0.022*
	(0.010)	(0.010)	(0.007)	(0.006)	(0.008)
24: Other professionals x Female	-0.007	-0.015	0.008	-0.017*	-0.009
	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)
31: Physical and engineering science associate professionals x Female	-0.006	-0.037**	-0.022*	-0.054**	-0.052**

	(0.011)	(0.011)	(0.007)	(0.006)	(0.009)
32: Life science and health associate professionals x Female	0.089**	0.061**	0.073**	0.085**	0.042**
	(0.009)	(0.009)	(0.006)	(0.005)	(0.009)
34: Other associate professionals x Female	-0.070**	-0.067**	-0.068**	-0.083**	-0.096**
	(0.009)	(0.009)	(0.006)	(0.006)	(0.008)
Agreeableness dummy	-0.060**	-0.035**	-0.035**	-0.035**	-0.034**
	(0.009)	(0.006)	(0.006)	(0.006)	(0.006)
Conscientiousness dummy	-0.005	-0.019	-0.004	-0.004	-0.004
	(0.006)	(0.010)	(0.006)	(0.006)	(0.006)
Extraversion dummy	0.013	0.012	0.013*	0.012	0.012
	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)
Neuroticism dummy	-0.012*	-0.012*	-0.012*	0.042**	-0.012*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Openness dummy	-0.006	-0.005	-0.006	-0.006	0.034**
	(0.008)	(0.008)	(0.007)	(0.008)	(0.006)
11: Legislators & Senior Officials	0.063**	0.075**	0.102**	0.077**	0.100**
	(0.010)	(0.008)	(0.006)	(0.007)	(0.007)
12: Corporate managers	0.059**	0.059**	0.063**	0.074**	0.074**
	(0.012)	(0.012)	(0.009)	(0.008)	(0.011)
13: Managers of small enterprises	0.159**	0.154**	0.165**	0.167**	0.168**
	(0.011)	(0.011)	(0.008)	(0.008)	(0.010)
21: Physical, mathematical and engineering science professionals	0.041**	0.045**	0.038**	0.044**	0.054**
	(0.010)	(0.009)	(0.007)	(0.006)	(0.008)
22: Life science and health professionals	-0.003	0.016	-0.007	0.015	0.008
	(0.010)	(0.010)	(0.008)	(0.007)	(0.009)
24: Other professionals	0.043**	0.037**	0.035**	0.052**	0.050**
	(0.010)	(0.010)	(0.007)	(0.006)	(0.009)
31: Physical and engineering science associate professionals	0.070**	0.085**	0.083**	0.111**	0.109**
	(0.012)	(0.012)	(0.009)	(0.009)	(0.011)
32: Life science and health associate professionals	0.013	0.048**	0.028*	0.016	0.064**
	(0.012)	(0.012)	(0.009)	(0.008)	(0.013)
34: Other associate professionals	0.133**	0.126**	0.129**	0.149**	0.174**
	(0.011)	(0.011)	(0.008)	(0.008)	(0.011)
Female	-0.102**	-0.094**	-0.089**	-0.074**	-0.073**

	(0.012)	(0.012)	(0.009)	(0.008)	(0.011)
Age	0.029**	0.029**	0.029**	0.029**	0.029**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age squared	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education dummy	0.142**	0.141**	0.141**	0.142**	0.142**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log of job hours	-0.115**	-0.114**	-0.114**	-0.114**	-0.114**
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Constant	-0.264	-0.265	-0.274	-0.284	-0.295
	(0.126)	(0.128)	(0.127)	(0.127)	(0.132)
Observations	86,924	86,924	86,924	86,924	86,924
R-squared	0.125	0.125	0.125	0.125	0.125

Note: Robust standard errors are in parentheses. ** p<0.01, * p<0.05. The table shows the output of five regressions of equation (2.1); one for each of the Big Five personality traits. The regression coefficients show the impact of personality within an occupation and by gender on the probability of being in the top 20% income quintile. The regression includes controls age, age squared, an education dummy that is equal to one if the individual has a higher or first degree and zero otherwise, wave fixed effects, region fixed effects and the logarithm of hours worked on the job. I restrict the analysis to white-collar occupations (i.e., ISCO-88 codes 1-3).

Chapter 3 What skills pay more? The changing demand and reward to skills for professional workers[12]

Abstract

Technological innovations are disrupting labour markets and change the demand and reward for skills. I analyse how the demand and reward for skills at the occupation and state level change across two time periods, 2014-2015, shortly before the start of the Fourth Industrial Revolution and 2018-2020 Q1, during its onset, using job posting data of professionals. I extend previous literature on skills in three ways: First, I take an inductive approach to derive skills groups using principal component analysis. This results in nine skills groups: ‘collaborative leader’, ‘interpersonal & organised’, ‘big data’, ‘cloud computing’, ‘programming’, ‘machine learning’, ‘research’, ‘math’ and ‘analytical’. Second, I focus on two time frames and can hence comment on changes in the demand and reward for skills over time. Third, I analyse non-linear returns to all nine skills groups and their interactions. I find that ‘collaborative leader’ skills significantly and positively predict demand and reward over time. ‘Interpersonal & organised’ is increasingly negatively related to demand and reward over time, which I suggest is due to the automatability of the occupations requiring this skill. I also find that mature applied skills such as ‘big data’ skills are being replaced over time by more recent applied skills such as ‘machine learning’. I also granularly analyse relevant interactions and non-linear returns to the nine skills groups and confirm the complementarity of social and cognitive skills found in the literature. The analysis contributes to a detailed understanding of the future of skills requirements.

[12] This paper uses job advertisement data from LinkUp provided by Citi in the format of an Excel table. I directed the data scraping done by Citi and the use of machine learning methods for natural language processing that is described more closely in the data section below and Appendix 3.C.

3.1. Introduction

The skills demanded by the labour market are currently being shaped by the Fourth Industrial Revolution and the pace of this change has been accelerated by the Covid-19 pandemic (Frey and Osborne, 2017; Dingel and Neiman, 2020; Campello, Kankanhalli and Muthukrishnan, 2021). In the past, technological advances have led to a hollowing out of the middle of the income distribution as jobs that require routinised tasks are codified and jobs that require more complex, non-routine tasks gain in efficiency from new technologies coming on stream (Frey and Osborne, 2017; Josten and Lordan, 2022). We are currently experiencing the Fourth Industrial Revolution that started around 2015 (Schwab, 2015), which is bringing with it artificial intelligence, robotics, quantum computing, genetic engineering and the Internet of Things, all of which are disrupting the nature of work. Overall, these labour markets developments are changing the tasks performed at the occupation level, and the corresponding skills required to perform these occupations (Josten and Lordan, 2021). There is evidence that employers are increasingly demanding and rewarding social skills (e.g., leadership and communication (Josten and Lordan, 2021)), while continuing to reward cognitive skills. Examples of cognitive skills include decision-making (Deming, 2021), critical thinking (Deming and Kahn, 2018) and emerging cognitive skills such artificial intelligence skills (Alekseeva *et al.*, 2021; Deming, 2021).

Overall, the demand for skills is changing, as firms adopt available technologies that complement and substitute for tasks previously done by their workforce. In face of the Fourth Industrial Revolution and a rapidly changing market for skills, this study analyses how the price of skills (measured at the occupation and state level) changes across two time periods, namely 2014-2015 and 2018-2020 Q1 using job flow data of professionals in the United States. I choose these times periods as they frame the outbreak of the Fourth Industrial Revolution 2015. That is, the first time period 2014-2015 marks the arrival of the technologies later defining the Fourth Industrial Revolution and the second time period 2018-2020 Q1 summarises its progression.

Data on the demand for skills is obtained from a large platform of online job advertisements. I link each job advert to wage data based on the state and occupation a job was posted for. While job advert data is a proxy for the demand for skills in the labour market (Carnevale, Jayasundera and Repnikov, 2014), linking it to actual wage outcomes informs on whether the demand for skills is changing the price of skills at the state and occupation level.

The approach taken in this study builds on the research on the changing nature of work and the changing demand and reward for skills. This study is most closely related to Deming and Kahn (2018) who also analyse job advertisement data to measure the variation in skills demand for professionals. They reduce the skills keywords mentioned in job postings from Burning Glass Technologies (BGT) down to 10 broad job skills following the task literature based on their assessment of how best to divide skills. The authors link cognitive and social skills to wages and firm performance and find a positive correlation for both social and cognitive skills between 2010 and 2015. They also find a strong complementarity of social and cognitive skills with the interaction of both skills positively and significantly correlating with wage and firm outcomes. Overall, they find that the demand for cognitive and social skills accounts for around 5% of the variation in wages and firm performance when controlling for occupation, industry, education and experience requirements and eight other skills requirements. They highlight that more research is needed on alternative skills such as interpersonal skills. This study, extends and goes beyond Deming and Kahn (2018) in the following three ways:

1. I consider a more detailed list of skills groups that is statistically determined based on the skill requirements in job advertisement data rather than chosen by the author. That is, I take an inductive approach for the selection of skills groups and derive skills groups using a principal components analysis (PCA). PCA groups keywords that appear together in the skills requirement section of an advert in a meaningful way. In the choice of keywords, I follow the academic literature (Deming and Kahn, 2018) and the professional literature as defined in a report by the management consulting company McKinsey (Dondi *et al.*, 2021), in addition to the author's expertise. I refine the keyword choices based on an analysis of co-occurrences. The outcome of the PCA are nine latent factors with the following intuitive labels: 'collaborative leader', 'interpersonal & organised', 'big data', 'cloud computing', 'programming', 'machine learning', 'research', 'math' and 'analytical'.
2. I focus on two time frames for the analysis of 2014-2015 and 2018-2020 Q1[13] to comment on changes in the returns to skills over time. These two time periods are particularly

[13] The two specific times 2014-2015 and 2018-2020 Q1 frame the start of the Fourth Industrial Revolution. They are further chosen for three additional reasons: First, LinkUp only becomes sufficiently large in 2014 and I restrict the data to before the outbreak of the Covid-19 pandemic that changed labour market demand substantially from

interesting as they capture the start of the Fourth Industrial Revolution (2014-2015), with the second period allowing a sufficient lag for the new technologies to have diffused and influenced the labour market (2018-2020 Q1). Studying the returns to skills over time at the occupation/state level for these two time periods is interesting as it informs on how labour market developments, such as technological innovation, are changing the value of skills both at the occupation level, but also across geography.

3. I analyse returns to the nine skills groups, allowing for intuitive complementarities across the nine skill groupings. For example, I expect that certain cognitive skills will be more valuable if a person has high levels of leadership skills also. This aligns with Weinberger (2014) who finds an increasing complementarity of social and cognitive skills, and Deming (2021) who finds that decision-making and cognitive ability are complementary, and their rewards are increasing over time. This analysis extends these analyses by looking at the interactions of a set of nine skills groups and contributes to the existing literature by highlighting which specific skills and combinations thereof are rewarded in the labour market.

Drawing on job flow data, I relate the nine skill groups 'collaborative leader', 'interpersonal & organised', 'big data', 'cloud computing', 'programming', 'machine learning', 'research', 'math' and 'analytical' to the logarithm of hourly wage in a linear regression including a set of demographic and industry controls, and state and occupation fixed effects. Overall, I find changing prices of cognitive and non-cognitive skills over the two time periods that align with shifts in the labour market. The most interesting, stylised facts are as follows:

First, I find that the two non-cognitive skills groups 'collaborative leader' and 'interpersonal & organised' are differently rewarded. For the 'collaborative leader' skills group, I find that a 10 percentage point increase in this skill predicts an increase in wages of 0.3% in 2018-2020 Q1 (this prediction is not statistically significant in 2014-2015). This estimate implies a 0.15$ increase in hourly wages for which the mean is 49.49$ per hour in 2018-2020 Q1. For 'interpersonal & organised', a 10 percentage increase predicts a reduction in wages of -0.36% in 2014-2015 and of -0.73% in 2018-2020 Q1. This corresponds to a reduction of the mean

the end of March 2020 onwards. Second, I use two time frames that are two years apart due to the rolling averages nature of wages of the OEWS. Third, I pool the years within each time frame (e.g., 2014 and 2015) to account for changing trends in skills requirements I cannot control for such as labour market shocks (Deming and Kahn, 2018).

hourly wage of -0.16$ in 2014-2015 (with the mean hourly wage being $44.79 in 2014-2015) and of -$0.36 in 2018-2020 Q1. To summarise for non-cognitive skills, I show that the skills group 'collaborative leader' exhibits positive and increasing returns while that of 'interpersonal & organised' exhibits negative returns. Both skills groups are increasing over time in terms of demand (i.e., exhibit increasing shares). This differentiation is in line with the literature (Deming and Kahn, 2018; Calanca *et al.*, 2019). Edin et al. (2022) analyse non-cognitive skills as defined by a psychologist-assessed measure of teamwork and leadership that relates closely to the 'collaborative leader' skills group. They find a strong increase in the return to non-cognitive skills among men in the private sector using Swedish military enlistment data from 1992 to 2013 combined with administrative wage data. The return to a one standard deviation increase in non-cognitive skills increased from 7 to 14 percent with this effect being even larger at the top end of the wage distribution. Similarly, Deming (2017) analyses the returns to social skills and finds that they are increasingly valued in the labour market in terms of wages and employment when analysing US surveys from 1979 versus from 1997. Social skills refer to the ability to work with others and in particular skills related to coordination, negotiation or persuasion and are hence again closely related to the 'collaborative leader' group that entails overlapping keywords. Their finding is complemented by a later paper by Deming (2021) that focuses on decision-making skills. The author uses online job advertisement data from BGT alongside newspaper advertisement data from Atalay et al. (2020) and finds that decision-making skills have increased in importance and gain a larger wage premium. This finding points at the importance of skills that help in dealing with the increasing complexity and open-endedness of job tasks. That is like the 'collaborative leader' skills group that entails keywords such as negotiation or strategic. The finding can also be explained with the automatability of occupations requiring specific non-cognitive skills. An example are time management skills that are part of the 'interpersonal & organised' skills group and have been shown to be automatable (Josten and Lordan, 2022). That is as compared to 'collaborative leader' skills, which have been shown to be automation-proof given current technology (Atalay *et al.*, 2020; Deming, 2021).

Second, I find that the reward to data science skills is constantly evolving with the newest data science skills being rewarded and legacy data science skills being punished. This is a symptom of technology being in evolution, and with it demanding an evolving skill set. Concretely a 10 percentage point increase in the share of 'big data' is associated with an increase in wages of 1.85% in 2014-2015 (i.e., an extra 0.83$ above the mean hourly wage of 44.79$), turning negative in 2018-2020 Q1 with a 10 percentage point increase in the respective skills group predicting -1.21% lower wages in 'big data' corresponding to -0.6$. A similar trend of positive return in 2014-2015 turning negative in 2018-2020 Q1 is found for 'cloud computing' with a 10 percentage point increase in the 'cloud computing' share predicting an increase in wages by 0.57% (i.e., an increase of 1.47$ above mean hourly wages) in 2014-2015 and a decrease in wages by -0.37%. (i.e., a decrease of -0.18$ below mean hourly wages) in 2018-2020 Q1. In contrast, by 2018-2020 Q1, the skills group that has increased the most relatively in share demanded and wage premium is 'machine learning'. That is a skill grouping that did not appear in job adverts in 2014-2015 and emerged in between the periods studied. In 2018-2020 Q1, 'machine learning' gained a wage premium with a 10 percentage point increase in this skills group predicting a wage increase of 5.83%. At professionals' mean hourly wages of 49.49$ per hour in 2018-2020 Q1, this corresponds to an increase of 2.89$.

This shift across data science skills reflects a market in data science that is constantly evolving, with those that upskill in line with the sector trends being in shortage in the labour market, and as a result enjoying high wage premiums. The finding of 'machine learning' only appearing in the job advertisement data in the later time frame and exhibiting highly positive returns is also a reflection of the adoption of new technologies by companies. This is reflected in the literature on AI, which corresponds closely to the 'machine learning' group. Alekseeva et al. (2021) study skills requirements in online job advertisements between 2010 and 2019 using data from BGT with a specific focus on the demand for artificial intelligence (AI) skills in the labour market. AI skills are identified with keywords that are directly related to AI such as 'artificial intelligence' or 'keras' and the share of advertisements including at least one of these keywords is linked to shares and wages. They find an increased demand in AI skills across occupations, sectors and firms and a premium to those skills of 11% for job postings in the same firm and of 5% within the same job title. Their finding highlights developments in AI adoption in companies and shows substantial and increasing returns to AI. This study also looks at machine learning more specifically. Similarly, Squicciarini and Nachtigall (2021) study occupations requiring AI using online job postings in Canada, Singapore, the United Kingdom and the United States. They also find that an increasing number of occupations require AI skills across all four countries. They find that over time skills related to legacy computing skills such as software engineering and development decreased in importance as compared to AI-specific skills like natural language processing. Deming and Noray (2020) look at the changing returns to specific skills acquired at university over time. In their model, individuals who study applied subjects such as computer science or engineering or business (as compared to economics or biology) are required to change their skill set more often throughout their career, which leads to lower returns in the long run. Their finding again highlights that rapidly changing applied skills are rewarded initially like ‘big data’ in this analysis but turn into legacy skills over time that are not rewarded as much as compared to more stable skills.

Third, ‘programming’ has a substantive negative wage premium across both time frames (i.e., a 10 percentage point increase in ‘programming’ predicts a decrease of wages of -0.95% in 2014-2015 and of -1.09% in 2018-2020 Q1). A possible explanation is that programming skills such as java or SQL are pre-requisites in top programming occupations and are only explicitly mentioned in occupations that search for medium-skill workers familiar with low-level coding.

Fourth, the premium to ‘research’ skills increases over time with a 10 percentage point increase in the share of research skills predicting an increase in wages by 0.44% in 2014-2015 and by 0.59% in 2018-2020 Q1. Keywords that are part of the ‘research’ category overlap with the broader category of cognitive skills as for example ‘research’ or ‘statistics’ as defined by Deming and Kahn (2018). Given their finding of a positive correlation of cognitive skills on wages, it is hence not surprising that ‘research’ correlates positively with the logarithm of wages in this study.

The second set of models consider the returns to the skills interactions as identified using a Lasso (least absolute shrinkage and selection operator) regression approach. Overall, I can confirm the complementarity between soft skills and cognitive skills:

Concretely, ‘collaborative leader’ interacted with ‘research’ has a positive wage premium across both time frames (i.e., a 10 percentage point increase in the share of the ‘collaborative leader’ interaction with ‘research’ predicts an increase in wages of 0.01% in 2014-2015 that increases to 1.78% in 2018-2020 Q1). The latter effect is substantially larger and has a dollar value of 0.88$ above mean hourly wages of 2018-2020 Q1. That is, occupations that require both ‘collaborative leader’ skills and ‘research’ experience a wage premium. As highlighted above, past research mainly focused on the interaction of social skills and cognitive skills. The ‘collaborative leader’ skills group is, however, defined at a more detailed level. Specifically, this finding is in line with the findings by Deming and Kahn (2018) and Weinberger (2014) who also find a complementary effect of social and cognitive skills. Given that the skills groups in this study are more narrowly defined, the finding indicates that ‘collaborative leader’ skills are particularly valuable social skills when combined with cognitive ‘research’ skills. Such skills are centred in high-skill and high-paid occupations.

Second, there is a positive complementarity of ‘big data’ with ‘cloud computing’ in 2014-2015 but that becomes negative in 2018-2020 Q1. This finding points to the changing nature of cognitive skills that initially exhibit high rewards but for which skills requirements change frequently.

This work provides insights that are useful in several contexts. First, it provides information to firms and individuals on the skills that are becoming increasingly valuable in the advent of the Fourth Industrial Revolution. For firms this is useful in terms of hiring, planning, training and upskilling their workers for daily tasks, but equally for providing training in emerging skills as an amenity in the employee value proposition to attract and retain talent. For individuals, it is useful in terms of making choices regarding educating and upskilling themselves. Second, it provides information to firms and individuals on the volatility of prices for specific skills over time.

This paper proceeds as follows: Section 3.2. describes the data used in this study. Section 3.3. describes the methods ranging from i. principal component analysis to ii. linear regression to iii. Lasso regression. Section 3.4. summarises and discusses the results and section 3.5 concludes.

3.2. Data

3.2.1. Overview

This study draws on LinkUp (https://www.linkup.com/) provided by Citi. LinkUp is a large global job listing index of job openings with 165 million job postings listed since 2007 and sourced from employer websites worldwide (LinkUp, 2022). LinkUp contains job advertisements from websites of publicly traded companies to be used for labour market analytics.[14] The data is continuously updated through crawling of public websites. The data contains detailed information on each advertisement including the state it was posted in, its

[14] LinkUp scrapes 100% of publicly traded company websites but state that 15% of those companies do not post jobs on their website currently (LinkUp, 2021).

Occupational Information Network (O*NET) occupation code, the Global Industry Classification Standard (GICS) codes at the 2-digit level[15], job and company attributes and raw job descriptions and job records. LinkUp is unique in retaining the full job description including the section of skills requirements. LinkUp has also been previously used to study the impact of the Covid-19 pandemic on hiring (Campello, Kankanhalli and Muthukrishnan, 2021) and the demand for software testing skills (Cerioli, Leotta and Ricca, 2020). The LinkUp data has been validated and shown to be representative (Campello, Kankanhalli and Muthukrishnan, 2021).[16]

Job advertisement data more generally is a useful data source to study labour market dynamics for its large sample size and the breadth of information it contains, including the detailed description of job requirements (Faberman and Kudlyak, 2016). It further is a valuable addition to using, for example, self-reported, survey-based labour market data (Carnevale, Jayasundera and Repnikov, 2014). This is because as compared to survey data that provides a snapshot view of the labour market at the point of collection and is costly to administer, job advert data represents readily available job flow data that reflects actual employment dynamics at the point at which they occur (Faberman and Kudlyak, 2016). It also serves to make predictions into the future as it shows which skills are in demand for employees to be employed going forward (Carnevale, Jayasundera and Repnikov, 2014). Job advertisement data has also been used frequently in past research to analyse the development of skills requirements in occupations. For example, Modestino, Shoag and Balance (2020) use online job advertisement data from BGT to analyse skills requirements after the Great Recession and find that education and experience requirements increased; an effect that can be attributed to the increased supply of workers following layoffs during and after the recession. Blair and Deming (2020) also study BGT job advertisements after the Great Recession and find that skills demand has increased substantially following the recession.

LinkUp is used as data source that focuses on company websites only, as compared to the frequently studied Burning Glass Technologies data BGT (Deming and Kahn, 2018; Hershbein and Kahn, 2018; Forsythe *et al.*, 2020; Samek, Squicciarini and Cammeraat, 2021) that additionally sources from job boards. Company websites are updated frequently, there is no

[15] GICS is an industry classification developed by MSCI and S&P Dow Jones Indices that contains 11 sectors (i.e., 2-digit classifications).
[16] Campbello et al. (2021) show that job postings in LinkUp predict firm job gains in the U.S. Census Bureau's Quarterly Workforce Indicators (QWI) data and in the BLS's Job Openings and Labor Turnover Survey (JOLTS) in subsequent time periods. This is true for small and large firms and high and low skill job postings.

risk of duplicate postings across different job boards (as is the case for BGT) (Campello, Kankanhalli and Muthukrishnan, 2021). I choose to restrict the LinkUp data to occupations of professionals that account for 52.5% of all job advertisements in the period studied.[17] Research on the use of job advert data has highlighted that there is a bias of jobs posted online towards white-collar industries and occupations that seek highly skilled individuals (Carnevale, Jayasundera and Repnikov, 2014). Job advertisements from company websites are hence inappropriate to study non-professional occupations (Deming and Kahn, 2018). In addition, professional jobs are suited to the analysis of job advertisements as they have the largest variability with respect to skills requirements (Deming and Kahn, 2018). I further restrict the LinkUp data to job postings in the US by companies that are listed in the MSCI World Index. The MSCI World Index is a stock market index that includes large and mid-cap companies that operate globally (MSCI, 2022).[18] Job advert data has been shown to be less volatile and more consistent when focusing on a fixed set of job advertisement platforms (Carnevale, Jayasundera and Repnikov, 2014). To ensure stability, I hence focus on the websites of sufficiently large global companies listed in the MSCI world index even if this is traded off with coverage of a wider range of companies.

The analysis is restricted to data from 2014 to 2020 Q1. This time frame is chosen for three reasons. First, it marks the onset of the Fourth Industrial Revolution with 2014-2015 being the period shortly before the term Fourth Industrial Revolution is first coined in December 2015 and the second half until 2020 marking the rapid technological advances following its onset (Schwab, 2015). Second, given that more companies posted job advertisements online over time, 2014 is the period with comparable coverage with later years as per Table 3-5 in Appendix 3.A. Also, by 2014, between 60%-70% of all job openings are posted online (Carnevale, Jayasundera and Repnikov, 2014). Third, I also restrict the analysis to before the outbreak of the Covid pandemic as there is a large drop in advertisements from April 2020

[17] Professional occupations are restricted to the major SOC categories 11-29.

[18] The MSCI world index includes companies from 23 countries (i.e. Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US) (https://www.msci.com/documents/10199/178e6643-6ae6-47b9-82be-e1fc565ededb). The data is filtered for companies based on the MSCI World Index 2021. There are 1586 companies in total in the index; of which 853 are successfully mapped to/covered in the LinkUp job postings data feed. The MSCI World Index is updated annually (both the underlying constituents and the total number of companies in the index), however, for ease of standardisation in this analysis, the panel of companies is kept constant. The average annual panel change of the MSCI World Index is about 5-6% between 2014-2021. As compared to comparable major stock market indices, the MSCI World Index covers 94% of the companies of the NASDAQ 100, 94% of the S&P 500, 89% of the FTSE 100 and 70% of the STI 30.

onwards. In the US and worldwide, labour markets contracted towards the end of March 2020 with a sharp decline in advertised jobs and a change in the distribution of skills demanded (OECD, 2021).

3.2.2. Construction of skill groups

Keywords are selected based on three different criteria: First, I take an inductive approach and filter for keywords in the context of skills requirements and focus on those that appear frequently in adverts. Second, I include a list of keywords related to skills used in Table 1 in Deming and Kahn (2018), who base their keyword selection for social and cognitive skills on the relevant literature. Third, I additionally include keywords as defined in a recent study by the McKinsey Global Institute that consider cognitive, interpersonal, self-leadership and digital distinct elements of talent (DELTAs) (Dondi *et al.*, 2021).[19] With this keyword selection process, I try to be as inclusive of potentially relevant skills as possible by focusing on both the demand for skills as revealed by the data, in addition to the academic and professional literature. I narrow down keywords where they are too broad or ambiguous.[20] Building on the initial list of skills identified, I then expand the list to include relevant, associated skills that are similar in nature by identifying keywords that most frequently co-occur with the words in the list.[21] This selection process yields 236 underlying keywords. I then further cluster keywords that are synonyms into skills categories.[22] The final set of keywords in skills categories includes 166 keywords. A list of all keywords used for the PCA, the synonym grouping, and their source can be found in Table 3-6 in Appendix 3.B.

The keywords from the job advert data are extracted by Citi using Bidirectional Encoder Representations from Transformer (BERT). This is a machine learning method for natural

---

[19] McKinsey combines academic literature and their experience in adult training to define 56 skills and attitudes (e.g., adaptability or coping with uncertainty) that they then link to adult outcomes in a survey with 18.000 individuals. They find that individuals who score high on those skills have on average higher incomes, higher job satisfaction and are more likely to be employed.

[20] For example, I remove the word ‘management’ as it appears in about 50% of the job adverts and is an ambiguous term that can be used to describe a skill but also a person or company attributes.

[21] The fundamental statistical method used by Citi for this exercise is Pointwise Mutual Information (PMI), a measure of association between two words. Pointwise Mutual Information (PMI) is defined as the ratio of the joint distribution (coincidence) relative to the individual distributions (independence) of two words. For each word in the initial skills list, PMI is calculated against every English word that has appeared at least once across all job posting descriptions. The top 50 words with the highest PMI scores for each seed skill are manually reviewed and added to the list.

[22] Synonyms are grouped together as they likely appear in different advertisements despite describing the same skills group. The PCA would falsely classify such synonyms as being in different skills groups. An example for synonyms is strategy and strategist, which are grouped together.

language processing (Devlin *et al.*, 2019). Using BERT, 1.3 million job advertisements are analysed between 2014 and up to 2020 Q1. Job description sentences are classified into five categories: responsibilities, skills, education, (legal) requirement, others. This model has an 80-90% accuracy in correctly classifying sentences into each of these categories. However, it takes a long time (i.e., a couple of weeks) to run the classification predictions. A random stratified sample of 25% of the entire available data set of job advertisements is hence derived that is stratified keeping the same distribution of jobs per company, state, O*NET occupation code and year combination. The keyword search is restricted to the section of the job advert where candidate skills requirements are listed and derived through the BERT natural language processing technique that is explained in more detail in Appendix 3.C. A keyword is a dummy variable that equals one if the keyword appears at least once in the skills requirement section of a given job advertisement. I provide three exemplary job advertisements in Appendix 3.C.

3.2.3. Principal component analysis: Skills groups

Data that denotes the occurrences of the 166 keyword categories within the dataset of 1.3 million job advert are inputs for a principal component analysis (PCA). Running the wage regressions including all 166 skills keywords would lead to an overfitting of the regression and impede a straightforward interpretation of the estimates (Abdi and Williams, 2010; Lordan and Pischke, 2022b). Further, by clustering skills, I follow the literature on tasks and skills that focuses on tasks/skills groups rather than a battery of individual tasks/skills items (Weinberger, 2014; Deming and Kahn, 2018; Atalay *et al.*, 2020). Overall, with the approach taken in this study, I can comment on which keywords cluster together in the underlying data and should be combined into broader skills groups based on PCA.

For the PCA, I draw on the entire 1.3 million of LinkUp job advertisements for professionals for the years 2014 to 2020 Q1. I broadly follow the approach by Heckman et al. (2012) and succeed in reducing the 166 variables to 9 skill groupings (see Appendix 3.D for more details). Specifically, I remove items that load on more than one component (cross-loadings) and items that have a loading smaller than 0.32 (weak loadings).[23] The final components have no items that are weakly loading nor cross loading and they correlate freely. I use orthogonal rotations, that allow the components to be correlated, to find the optimal number of principal components

[23] The cut-off of 0.32 has been recommended in the literature (Tabachnick and Fidell, 2018) and the large sample size allows for choosing a relatively low loadings cut-off.

subject to the following rules for the cut-off for the components: a cumulative variance explained of the components of at least 60%, examining a jump in the scree plot (i.e., a point at which the eigenvalue of a given component falls substantially) and choosing component cut-offs that are sensible and intuitive (Bartholomew *et al.*, 2011). Each step of the PCA is explained in more detail in Appendix 3.D.

The overall PCA analysis results in nine latent factors. These represent skill groupings that are intuitively labelled based on the variables that loaded on each factor as follows: 'collaborative leader', 'interpersonal & organised', 'big data', 'cloud computing', 'programming', 'machine learning', 'research', 'math', 'analytical'.[24]

Table 3-1 below documents the nine skills components together with their underlying keywords and the corresponding loadings. I choose labels for the nine skills groups that best summarise the underlying keywords. In the case of 'collaborative leader', the group label captures keywords related to leadership (i.e., 'strategic', 'leadership', 'influence', 'negotiation') and those related to the collaborate nature of leadership (i.e., 'collaborate' 'creativity', 'coaching'). In the case of the cognitive skills groups, the labels are even more descriptive where, for example, 'big data' only captures big data applications such as 'hadoop' or 'hive'. Overall, two of nine skills groupings describe non-cognitive skills and seven describe cognitive skills. The two non-cognitive skills groups, 'collaborative leader' and 'interpersonal & organised' follow closely what Deming and Kahn (2018) describe either as social or as character skills.[25] Similarly, the skills groups 'research' and 'analytical' resemble Deming and Kahn's (2018) cognitive skills.[26] The fact that the PCA yields slightly diverging results from, for example, Deming and Kahn (2018), who choose their groups based on the task literature and categorise the keywords manually, stems from the fact that the PCA results are based on skill groupings as they appear in job advertisements.

[24] A good example of an intuitive grouping is the skills group 'machine learning' where few keywords (i.e., 'tensorflow', 'pytorch' and 'keras') that are clearly all machine learning programmes load very highly onto the component. The same is true of, for example, 'big data' and 'cloud computing'.

[25] Deming and Kahn (2018) classify social skills with the keywords: 'communication', 'teamwork', 'collaboration', 'negotiation', 'presentation'. And character skills are 'organized', 'detail oriented', 'multitasking', 'time management', 'meeting deadlines', 'energetic'.

[26] Deming and Kahn (2018) classify cognitive skills with the keywords: 'problem solving', 'research', 'analytical', 'critical thinking', 'math', 'statistics'.

Table 3-1: PCA: Cognitive and non-cognitive skills components

Collaborative leader		
Keywords	Loading	Share
strategic	0.59	24.14%
leadership	0.58	26.17%
influence	0.51	12.75%
collaborate	0.39	24.52%
creativity	0.34	13.57%
negotiation	0.33	6.57%
coaching	0.32	5.14%
Overall		58.89%

Big data		
Keywords	Loading	Share
hadoop	0.75	1.19%
spark	0.75	0.72%
hive	0.73	0.55%
hdfs	0.53	0.14%
scala	0.47	0.47%
nosql	0.34	0.81%
Overall		2.28%

Programming		
Keywords	Loading	Share
xml	0.64	1.26%
json	0.6	0.67%
javascript	0.59	2.51%
java	0.56	6.08%
sql	0.39	7.12%
git	0.38	1.16%
api	0.37	1.51%
Overall		13.45%

Interpersonal & organised		
Keywords	Loading	Share
time management	0.4	4.65%
competing priorities	0.39	12.30%
interpersonal	0.38	17.20%
organised	0.36	3.38%
Overall		29.86%

Cloud computing		
Keywords	Loading	Share
docker	0.74	0.64%
kubernetes	0.71	0.41%
amazon web services	0.48	2.32%
terraform	0.45	0.15%
azure	0.41	1.04%
jenkins	0.41	0.95%
openshift	0.35	0.06%
containerization	0.35	0.12%
openstack	0.32	0.22%
Overall		3.89%

Machine Learning		
Keywords	Loading	Share
tensorflow	0.84	0.11%
pytorch	0.76	0.04%
keras	0.73	0.03%
Overall		0.11%

Research		
Keywords	Loading	Share
quantitative	0.58	3.45%
statistics	0.54	5.48%
qualitative	0.43	1.06%
research	0.37	12.86%
Overall		18.58%

Analytical		
Keywords	Loading	Share
accounting	0.65	5.58%
finance	0.63	7.63%
common software e.g., excel	0.41	16.66%
analytical	0.33	20.78%
Overall		35.70%

Math		
Keywords	Loading	Share
calculus	0.73	0.05%
algebra	0.63	0.12%
trigonometry	0.56	0.05%
stochastic	0.47	0.05%
Overall		0.21%

Note: Loadings are the loading of each skill grouping's keywords that are larger than or equal to 0.32 and form the respective principal component. Share is the share of each keyword and component across advertisements.

Table 3-1 also illustrates the share of each keyword and the share of the overall component across advertisements. These shares capture the demand for each respective skills group. I note that non-cognitive and social skills more specifically have been found to be used very frequently in job advertisements (Calanca *et al.*, 2019), which further explains the large shares of about 59% for 'collaborative leader' and of 30% for 'interpersonal and organised' and can also explain that there is overall a larger number of items that load relatively moderately. In contrast, the cognitive skills groups have low shares as they describe more niche skills that either appear less frequently in job advertisement or are increasing over time in the case of 'machine learning'. Also, the list of related words is not exhaustive (e.g., I do not include all different programming languages as keywords or words like 'scraping', 'mining' etc.).

Table 3-2 below further shows the shares of each of the nine skills groups for the two time frames 2014-2015 and 2018-2020 Q1. There is a large variation in how often each skill grouping appears in the job adverts. For example, 'Collaborative leadership' appears in 50.14% of job adverts in 2014-2015 and 61.07% in 2018-2020 Q1. In comparison, machine learning does not appear in job advertisements in LinkUp in the earlier time frame and only appears in 0.19% of job advertisements in 2018-2020 Q1. Overall, soft skills are overused in job advertisements and also across disciplines (Calanca *et al.*, 2019), while cognitive skills are more specific. However, the demand for all skills groups is increasing over time other than for programming that remains relatively constant at 13%.

Table 3-2: Share of skills shares over time

	Collaborative leadership	Interpersonal & organised	Big data	Programming	Machine Learning	Cloud computing	Research	Math	Analytical
2014-2015	50.14%	24.70%	1.63%	13.60%	N/A	1.76%	16.19%	0.19%	31.19%
2018-2020 Q1	61.07%	30.85%	2.49%	13.03%	0.19%	4.88%	18.94%	0.21%	35.83%

Note: This table shows the share of the nine skills groups across two time frames of 2014-2015 and 2018-2020 Q1.

Table 3-11 in Appendix 3.E shows the shares of the interactions of skills groups. Overall, the share of all skills interactions and therefore the demand for all skills groups has also been increasing over the two time frames. Some interactions centre around zero in terms of shares (e.g., 'big data' interacted with math). The interaction of 'collaborative leader' and 'big data', for example, increased from 0.8% to 1.6%. The interaction of 'collaborative leader' and 'research' increases by 3.8 percentage points from 9.5% to 14.2%, which points at the fact that with increasing automation, the complementarity between social skills (i.e., 'collaborative leader') and cognitive skills (i.e., 'research') increases. For example, doctors increasingly use technology such as Clinical Decision Support Software, but still need to understand statistics, which is a facet of ‘research’ skills alongside making final decisions drawing on their ‘collaborative leader’ skills.

The shares of each skills group vary also significantly across occupations. For example, about 90% of all advertisements for marketing managers require ‘collaborative leader’ skills but only 5% of all advertisements for pharmacy technicians require the same skill. Financial examiners are among the top five highest shares in the skills group ‘interpersonal & organised’ and ‘analytical’ with 53% and 73% off all ads requiring these skills respectively. Logically, software developers for applications are required to have cognitive skills and are among the occupations with the largest shares in ‘big data’ (14%), ‘cloud computing’ (22%), ‘programming’ (63%) and ‘machine learning’ (0.4%). The skills group ‘research’ captures occupations such as statisticians or research scientists and the skills group ‘math’ is focused on occupations such as civil engineers or actuaries. A list of the top five and bottom five occupations according to their shares for each of the nine skills groups is shown in Table 3-12 in Appendix 3.E.

3.2.4. Data matching

Job advertisements in LinkUp do not state the wages paid to a given advertised role. The wage data is therefore at the six-digit occupation and state level. Concretely, I match the LinkUp data to wage data from the Occupational Employment and Wage Statistics (OEWS) from the US Bureau of Labor Statistics (BLS) based on six-digit Standard Occupational Classification (SOC) codes and US states. The OEWS wage data is well-suited as it is provided at the state and detailed occupation level annually (U.S. Department of Labor, 2022), which allows for matching it to the LinkUp data on state and detailed occupation code. I follow Deming and Kahn (2018) who also match wage data based on six-digit occupation code and geography. Their level of geography is, however, more detailed at the Metropolitan State Area that is not available in the LinkUp data set. Annual estimates of wages are adjusted to inflation using BLS consumer price index data. The OEWS wage estimates are based on rolling averages collected over three years, which it is why it is recommended to do comparisons three years apart. I hence pool the data for the regression analysis so that the data is cross-sectional but take two timeframes that are three years apart from each other with the first being 2014 to 2015 and the second being 2018 to 2020 Q1 when considering changes to the returns to skills over the time windows. Pooling the data within each time frame helps smooth changing trends in skills requirements over time that one cannot control for such labour market shocks (Deming and Kahn, 2018).[27]

I follow Deming and Kahn (2018) with respect to the control variables in the regressions. I obtain control variables from the American Community Survey (ACS) at the state level. Specifically, I control for state-level share of female, Black, Hispanic, Asian, married, moved in the last year, education (high school dropouts, exactly high school, some college, exactly BA) and age (less than 18, 19–29, 30–39, 40–49, 50–64) distributions. I further obtain data on the education and experience requirements by six-digit occupation from O*NET through the variable 'job zone' that captures how much preparation (i.e., education and experience) is needed for a given occupation.[28]

3.3. Methodology

3.3.1. Wages and skills groups

The aim in this study is to relate the share of skills demanded for nine skills groupings at an occupation/state level to wage data at the occupation/state level for two time periods 2014-2015 (shortly before start of the Fourth Industrial Revolution) and 2018-2020 Q1 (onset of the Fourth Industrial Revolution). The nine skill groupings are: 'collaborative leader', 'interpersonal & organised', 'big data', 'cloud computing', 'programming', 'machine learning', 'research', 'math' and 'analytical'. In a first instance, I run a regression of the logarithm of hourly wages on the nine skills groups as follows:

$$\log(wage)_{or} = \alpha + \beta skills_{ior} + Controls + \varepsilon_{or} \tag{3.1}$$

where $\log(wage)_{or}$ is the inflation-adjusted logarithm of mean hourly wages in occupation o in state r. The main independent variable $skills_{ior}$ is a vector of the share of the nine skills groups where i denotes the share of skills group i in occupation o in state r. The skills groups are as per Table 3-1 above derived from the PCA. A skills group is equal to one if an advert

[27] I use a crosswalk provided by the BLS to standardise the coding structure to SOC2010 as there was a change in the occupational coding structure in 2019 and 2020 in the OEWS.

[28] O*Net's job zone variable captures how much education people need to do the work, how much experience people need to do the work and how much on-the-job training people need to do the work in a respective occupation. The variable is coded from 1-5 with 1 describing occupations that need little or no preparation and 5 describing occupations that need extensive preparation. See more information here: https://www.onetonline.org/help/online/zones

contains at least one of the corresponding keywords that load onto the skills group component. The data is then matched to wage data and collapsed by state and occupation so that the skills group variable becomes a share. All regression specifications are weighted by the number of observations in each state and occupation cell.

I am interested in quantifying whether occupations pay more for some or all the nine skills groups. Wages are not, however, determined by skills requirements alone, which is why I run five specifications including increasingly detailed control variables. Specification (1) is only weighted by the number of observations in each state and occupation cell. Specification (2) additionally controls for O*Net job zone codes accounting for education and experience requirements in an occupation, basic state-level demographic controls from the American Community Service and the share of ads in each two-digit North American Industry Classification (NAICS) industry. It further includes SOC major occupation controls. Demographic controls at the state-level and education and experience requirements at the occupation level help to account for factors that drive both skills requirements and wages. Occupations with higher education requirements, for example, also likely require more skills and pay higher wages. Major occupation controls and industry shares account for occupation- and industry-specific differences in skills requirements. For example, the language used in job advertisements is likely different for the major occupation of 'Management' as compared to that of 'Computer and mathematics'. Specific skills requirements may have a different signalling effect in one industry as compared to another. Analytical thinking, for example, may be mentioned in 'Management' occupations but not in 'Computer and mathematical' occupations as it is simply assumed in the latter. In specification (3), I additionally control for minor SOC occupation fixed effects and in specification (4) for broad SOC occupation fixed effects. Specification (5) includes detailed SOC occupation fixed effects and state fixed effects. Controlling for state fixed effects in specification (5) controls for potentially higher skills requirements in states that are wealthier and have higher costs of living or pay higher wages because the workforce is more skilled overall.[29] An example is California that has the largest share of 'machine learning' skills and is a wealthy state. Controlling for increasingly detailed occupation codes from specification (2) to (5) accounts for within-occupation differences. Even at the detailed occupation code, one can imagine an advert's phrasing for marketing managers

[29] Ideally, I would control for a more detailed level of region than state such as Deming and Kahn (2018) who control for Metropolitan State Area (MSA). However, the job advert data set LinkUp does not provide data on job adverts at the MSA-level.

to be different to those of sales managers who are both part of the major occupation ‘management’.

Specification (5) is the key specification of this study as I want to avoid capturing anything that has to do with state-specific or occupation-specific differences in, for example, culture. It also accounts for unobserved skills that are required together with the nine skills groups and affect wages. However, I cannot claim causality. First, the LinkUp data set does not provide reliable information on the Metropolitan State Area an advert was posted in, which is why I match the data to wages based on the broader state variable. There may be geographical differences in the use of skills words and in wage premiums that I cannot account for. Second, even the most controlled environment may suffer from omitted variable bias in the absence of external variation. That is, there may be unobserved variables that determine both the skills demand and the wage premium. An example could be that even within the same occupation in the same state there could be cultural differences in the way skills requirements are phrased and rewarded.

I run two separate regressions for each time frame considered. That is: 2014-2015 and 2018-2020 Q1. I exclude the ‘machine learning’ skills group in 2014-2015 as there are too few job adverts for those years (i.e., less than 10).

3.3.2. Wages and skills groups: Interactions and non-linearities

I also relate log wages to interactions of the nine skill groupings, in addition to allowing for non-linear returns. That is to account for potential complementarities across skills groups as well as non-linear effects. It amounts to the inclusion of 63 skills-related variables in addition to the most detailed controls in the regressions. To avoid overfitting and for ease of interpretation, I estimate a Lasso (least absolute shrinkage and selection operator) model. Lasso is a shrinkage and variable selection method for linear regression models, that minimises prediction error for a quantitative response variable. The goal of a Lasso regression is to obtain the subset of predictors that minimises prediction error for a quantitative response variable. The Lasso does this by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward zero. Variables with a regression coefficient equal to zero after the shrinkage process are excluded from the model. That is, these variables do not explain variation in the propensity for a job to be recently automatable. The remaining variables with a positive sign are those that describe the core skills and abilities that are most likely to become redundant because of the most recent wave of automation. In contrast, the remaining variables with a negative sign describe the core skills and abilities that are most likely to become more valuable. All non-zero variables are significant at the 1% significant level.

The Lasso regression causes some regression coefficients to shrink toward zero through an imposed constraint, and therefore selects the variables that are most relevant in predicting the logarithm of wage. Specifically, I estimate the following regression:

$$\min_{\beta}\left[\sum_{i=1}^{n}\left(y_i-\beta_0-\sum_{j=1}^{p}\beta_j x_{ij}\right)^2+\lambda\sum_{j=1}^{p}\left|\beta_j x\right|\right] \tag{3.2}$$

Equation (3.2) shows the Lasso regression that minimises the prediction error from running equation (3.1) with the most detailed set of controls where all definitions are consistent with equation (3.1) and in addition it includes an interaction of the nine skills groups ‘collaborative leader’, ‘interpersonal & organised’, ‘big data’, ‘cloud computing’, ‘programming’, ‘machine learning’, ‘research’, ‘math’ and ‘analytical’ with each other and their second degree polynomial.

3.4. Results and Discussion

3.4.1. Wages and skills groups

Table 3-3 documents the results from equation (3.1), which relates log hourly wages at the occupation and state level to the share of nine skill groupings (i.e., ‘collaborative leader’, ‘interpersonal and organised’, ‘big data’, ‘cloud computing’, ‘programming’, ‘machine learning’, ‘research’, ‘math’ and ‘analytical’) demanded in job adverts in the time period 2014-2015 (specifications (1)-(5)) and then also 2018-2020 Q1 (specifications (6)-(10)). Specifications (1) and (6) show the raw unadjusted estimates for the respective time frames. Moving from specifications (2) to (5) and (7) to (10) the coefficients decrease as variation in the outcome variable of log hourly wages is picked up by the control variables. In specification (2)-(5) and (7) -(10), I include a full set of demographic controls as well as controls of job zone and industry shares and I further include occupation fixed effects at an increasing level of detail. Specifications (5) and (10) then further include detailed SOC occupation fixed effects and state fixed effects. The focus of this study is on specification (5) and (10) for 2014-2015 and 2018-

2020 Q1 respectively that each include the most detailed occupation and state controls and hence account for any state- and occupation-specific differences in skills rewards. Specification (5) and (10) control for unobserved skills that correlate with the nine skills groups in the same occupation. They also control for occupation-specific differences in the use of skills keywords. While controlling for most detailed occupation controls ensures a controlled environment in the absence of causality, I note that they likely underestimate the effects I estimate because it estimates only small changes in the rewards for skills. That is, equations (4) and (9) with region fixed effects and broad occupation fixed effects, for example, allow for more variation.

Given that the skills groups are shares, I interpret the results from Table 3-3 as the impact of a 10 percentage point increase in skills share on the percentage change in the logarithm of hourly wages.[30] To further illustrate effect sizes, I also look at the dollar value of such a 10 percentage point increase for the average hourly wage (i.e., the average wage across all occupations and states) and for exemplary occupations.

[30] To calculate the wage premium, I use the coefficient of the regression of the log of wage on the respective skills group from Table 3-3. I multiply the coefficient with the share of the skill (i.e., 0.1 for a 10 percentage point increase) and exponentiate it. I then subtract 1 and multiply by 100. That is: wage premium = (exp (coefficient β * skills group share)-1) *100.

Table 3-3: Wage premium to nine skills groups in 2014-2015 and 2018-2020 Q1

	2014-2015					2018-2020 Q1				
	Dependent variable: Log of hourly wage in occupation state cells									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Collaborative leader	0.744**	0.032**	-0.017**	0.015**	-0.001	0.951**	0.107**	0.029**	0.042**	0.031**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Interpersonal & organised	-0.122**	-0.007*	-0.033**	-0.049**	-0.036**	0.105**	-0.064**	-0.057**	-0.074**	-0.073**
	(0.006)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Big data	1.488**	0.342**	0.314**	0.316**	0.183**	0.050**	-0.440**	-0.225**	0.126**	-0.122**
	(0.033)	(0.020)	(0.016)	(0.015)	(0.019)	(0.016)	(0.010)	(0.008)	(0.007)	(0.007)
Cloud computing	1.316**	0.633**	0.501**	0.369**	0.323**	0.858**	0.245**	0.197**	0.047**	-0.037**
	(0.030)	(0.019)	(0.016)	(0.013)	(0.018)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)
Programming	-0.099**	0.149**	0.173**	-0.161**	-0.095**	-0.194**	0.174**	0.218**	-0.249**	-0.110**
	(0.006)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)
Machine learning	N/A	N/A	N/A	N/A	N/A	3.553**	1.946**	1.281**	1.081**	0.567**
						(0.051)	(0.030)	(0.026)	(0.030)	(0.025)
Research	0.024**	0.061**	0.085**	0.063**	0.044**	-0.045**	0.088**	0.095**	0.044**	0.059**
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Math	0.478**	0.309**	0.353**	0.124**	0.089**	0.907**	0.073**	0.231**	0.079**	0.250**
	(0.048)	(0.027)	(0.022)	(0.017)	(0.026)	(0.033)	(0.018)	(0.016)	(0.012)	(0.010)
Analytical	0.135**	-0.074**	-0.093**	-0.025**	-0.014**	-0.119**	-0.193**	-0.161**	-0.066**	0.002
	(0.004)	(0.003)	(0.002)	(0.002)	(0.003)	(0.033)	(0.018)	(0.016)	(0.012)	(0.010)
Weights	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
O*net job zone	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Demographics	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
State FE	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES
Occupation FE	NO	Major	Minor	Broad	Detailed	NO	Major	Minor	Broad	Detailed
Industry shares	NO	YES	YES	YES	YES	NO	YES	YES	YES	YES
Constant	3.383**	1.190**	2.132**	2.693**	3.666**	3.383**	1.190**	2.132**	2.693**	3.666**
Observations	142,284	142,284	142,284	142,284	142,284	142,284	142,284	142,284	142,284	142,284
R-squared	0.350	0.791	0.867	0.927	0.954	0.350	0.791	0.867	0.927	0.954

Note: The table displays the regression output of the inflation-adjusted logarithm of hourly wages on nine skills groups (the share of each skills group) in the years 2014-2015 and then 2018-2020 Q1. All regressions are weighted by the share of ads within each state and occupation cell. Specifications (2)-(5) and (7)-(10) further control for O*Net job zone codes accounting for education and experience requirements in an occupation, basic demographic controls from ACS and the share of ads in each two-digit North American Industry Classification (NAICS) industries. And they additionally include SOC occupation fixed effects at different levels of detail: major occupation codes, minor occupation codes, broad occupation codes and detailed occupation codes. Specification (5) and (10) are most detailed and further include state fixed effects. Standard errors in parentheses, ** p<0.01, * p<0.05

Non-cognitive skills results

First, I look at the two non-cognitive skills ‘collaborative leader’ and ‘interpersonal and organised’. The skills group ‘collaborative leader’ is not significant and centred around zero for the year 2014-2015. For the time frame of 2018-2020 Q1 the coefficient on ‘collaborative leader’ skills becomes significant in the most detailed specification (10) where a 10 percentage point increase in the share of ‘collaborative leader’ predicts an increase in wages of 0.3%. This finding is similar to Squicciarini and Nachtigall (2021) who find that non-cognitive skills such as creativity, which is also a keyword of the ‘collaborative leader’ skills group, gain in importance over time. For the mean hourly wage of 49.49$ per hour of professionals in 2018-2020 Q1, a 10 percentage point increase in ‘collaborative leader’ share corresponds to a 0.15$ increase in hourly wages. Focusing on occupations that require high levels of collaborative leadership such as marketing managers (i.e., above 90% of marketing manager job adverts require collaborative leadership), they enjoy a wage premium of $2.23 (see Table 3-12 in Appendix 3.E). Individuals are working more collaboratively than ever with collaboration becoming essential in today’s workplace. The increasing importance of collaborative leadership skills is intuitive. Facets of collaborative leadership have been previously highlighted as valuable such as creativity (Squicciarini and Nachtigall, 2021), collaboration and negotiation (Deming and Kahn, 2018), coaching (Dondi *et al.*, 2021) and strategic and leadership (Josten and Lordan, 2020).

The other non-cognitive skills group ‘interpersonal and organised’ has a negative correlation with hourly wages with the estimates implying that a 10 percentage point increase in the skills share demanded predicts an increase in hourly wages by 0.36%. This corresponds to a decrease of 0.16$ from the mean hourly wage of 48.95$. The ‘interpersonal and organised’ skills coefficient becomes even more negative in 2018-2020 Q1 despite the mean share of it increasing over the two time frames from 25% to 31%. A 10 percentage point increase in the ‘interpersonal and organised’ share in 2018-2020 Q1 predicts a -0.73% decrease in hourly wages (i.e., this corresponds to a lower hourly wage of -0.36$ as compared to the mean wage for this time frame). Looking at the occupation of financial examiners with a skill share of 49% on average over the two time frames, they would earn -$0.67 less in 2014-2015 and -$1.66 less in 2018-2020 Q1 (see Table 3-12 in Appendix 3.E).

The finding of differential rewards to different non-cognitive skills (i.e., rewards to the skills group ‘collaborative leader’ and punishment to that of ‘interpersonal and organised’) is in line with Calanca et al. (2019) who also find that skills related to leadership are rewarded while skills related to the 'interpersonal & organised' skills groups are not. It is also in line with Deming and Kahn (2018) who find social skills to have a positive effect on wages at the occupation level while character skills that are similar to the 'interpersonal & organised' skills group may be a signal of occupations that pay little and require obedience and may hence be rewarded less. The findings are also supported and even more pronounced when looking at the other regression specification including broad occupation fixed effects (specification (4) and (9)), minor occupation fixed effects (specification (3) and (8)) and major fixed effects (specification (2) and (7)). Overall, there are two main aspects that help explain the divide in the non-cognitive skills premium:

1. **Occupations that require collaborative leadership skills are less likely to be automated than those requiring individuals to be interpersonal and organised** as explained by Josten and Lordan (2022). The occupations with the highest share in leadership skills requirements all belong to management occupations (e.g., marketing managers) for which many job tasks are open-ended making them less likely to be automated (Atalay *et al.*, 2020; Deming, 2021), and most likely to evolve in response to technology. I find the other non-cognitive skills group 'interpersonal & organised' to have negative wage returns (i.e., 'interpersonal & organised' skills have a negative wage premium that increases over time from -0.16$ in 2014-2015 to -0.36$ in 2018-2020 Q1). Facets of the 'interpersonal & organised' skills group like, for example, 'time management' have been shown to have a positive effect on automation (Josten and Lordan, 2022). That is because such skills centre around setting rules and gathering information, which are tasks that are likely to be automated as they are easily codified. The 'interpersonal & organised' skills group also appears frequently as a requirement for occupations that have been previously highlighted to be at least partly automatable such as financial managers or lawyers (Lordan, 2018; Josten and Lordan, 2020). The finding of differential rewards to different non-cognitive skills, i.e., 'collaborative leadership' versus 'interpersonal & organised', is in line with Calanca et al. (2019) who find that skills related to leadership such as strategic planning are rewarded while skills related to the 'interpersonal & organised' skills groups such as 'time management' are punished.
2. **Collaborative leadership fosters individual and company performance both directly and indirectly through fostering inclusion.** Collaboration is crucial for innovation. For innovation and idea creation, working collaboratively has been shown to be crucial in

combination with working independently (Girotra, Terwiesch and Ulrich, 2010). It might be true that to solve a mathematical formula, it is enough to have one individual who is a math genius but to come up with innovative ideas, having multiple individuals working well together enhances the output (Girotra, Terwiesch and Ulrich, 2010). But the positive effect of collaboration on innovation and performance depends crucially on the quality of the collaboration. Being a 'connector' is a key trait of a collaborative leader; someone who brings people together in a way that fosters success (Ibarra and Hansen, 2011). Hence, a collaborative leader can determine the quality of collaboration by fostering creativity, diversity of thought, open discussions, debates, conflict, making decisions, amongst others. A collaborative leader can also create a safe space and inclusive environments where individuals feel safe to speak up about new ideas. Inclusion prevents groupthink and confirmation bias, which have been shown to hinder performance and innovation both in a team and at the company level.[31]

Cognitive skills results

Of the set of cognitive skills, 'machine learning' has the largest positive and significant coefficient with a 10 percentage point increase in this skills share predicting an increase in wages of 5.83% in 2018-2020 Q1. This wage increase of 10 percentage points corresponds to an increase of 2.89$ above mean hourly wages. To give some context, the estimates imply that 'Computer and Information Research Scientists' that have a relatively large demand for machine learning skills (i.e., 11% of adverts in this occupation require 'machine learning' skills) would gain a wage return of $3.93 above their mean hourly wage of $62.98 (see Table 3-12 in Appendix 3.E). These findings for 'machine learning' are comparable to Alekseeva et al. (2021) who also study the demand for AI skills as defined by overlapping keywords (i.e., keras) and using job postings data. They find a strong positive effect of AI skills on wages with an AI advert increasing wages by 5% when including firm and occupation fixed effects.

In 2014-2015, the share of 'big data' demanded, is positively related to wages. Specifically, a 10 percentage point increase predicts an increase in wages of 1.8%. This wage increase of 10 percentage points corresponds to an increase of 0.88$ above mean hourly wages. Interestingly,

[31] Groupthink is the tendency of a group of likeminded individuals to reciprocate the opinion of the other and of the individual not to challenge the group. Confirmation bias is the tendency to search for information and opinions that support one's previously held beliefs. Inclusive leadership shares many facets with the 'collaborative leader' group such as creativity, coaching and influence (Shore and Chung, 2021).

this estimate is negative in 2018-2020 Q1 with a 10 percentage point increase in the 'big data' share predicting a decrease in wage by -1.21%. This corresponds to -0.6$ below the mean hourly wage. In the context of the occupation 'Computer and Information Research Scientists' that is among the occupations that require 'big data' skills the most with 29% of adverts over the two time frames require 'big data' skills, this corresponds to a $2.90 wage premium in 2014-2015 and a -$2.46 wage decrease in 2018-2020 Q1 (see Table 3-12 in Appendix 3.E).

Similarly, 'cloud computing' has a positive coefficient in specification (5) in 2014-2015 suggesting an increase in mean hourly wages of 0.57% when the share demanded increases by 10 percentage points. However, in specification (10) in 2018-2020 Q1 this effect turns negative to -0.37%.

Decreasing returns to 'big data' over time and the appearance of 'machine learning' with a very large wage premium in the latest period is in line with the finding of Deming and Noray (2020) who find that applied computing skills are rewarded initially but turn into legacy skills more rapidly than stable skills as supply outstrips demand. In addition, trends in computing change rapidly. This is also in line with Squicciarini and Nachtigall (2021) who find that over time legacy computing skills, for example software engineering, decrease in importance as compared to newer AI skills.

'Programming' already has a wage penalty that amounts to a 10 percentage point increase in the share predicting -0.94% lower wages of occupations in 2014-2015 and -1.09% in 2018-2020 Q1. This could be because the programming skills such as java or SQL are pre-requisites in top programming occupations and are only explicitly mentioned in occupations such as web developers[32] that search for medium-skill workers familiar with low-level coding (Manyika *et al.*, 2017).

The demand for 'research' skills increases as the share rises from 16% in 2014-2015 to 19% in 2018-2020 Q1. The wage premium of a 10 percentage point increase in 'research' share also increases from 0.44% higher wages in 2014-2015 to 0.59% in 2018-2020 Q1. The occupation 'Statisticians' is among those that require 'research' skills the most with a share of 73% of job

[32] The share of 'programming' skills is highest in the occupation Web Developer with 68% over the two time frames as per Table 3-12 in Appendix 3.E.

adverts in this occupation requiring ‘research’ skills across the two time frames. The wage premium in this occupation increases from $1.45 in 2014-2015 to $1.95 in 2018-2020 Q1.

The effect of a 10 percentage point increase in ‘math’ remains small and positive predicting an increase in hourly wages from 0.89% to 2.53% between 2014-2015 and 2018-2020 Q1. The demand also increases slightly but remains very small overall (i.e., the share increases from 0.19% to 0.21% of all job adverts as per Table 3-10 in Appendix 3.E). When looking at occupations that require relatively high levels of ‘math’ skills such as ‘Chemical Technicians’ with 7% in 2014-2015 and 4% in 2018-2020 Q1, the wage premium increases from $0.14 to $0.26 over the two time frames.

‘Analytical’ has a small negative coefficient in 2014-2015 with a 10 percentage point in demand predicting a reduction of hourly wages by -0.13%. The coefficient is ‘not significant and centred around zero in the most detailed specification (10) but negative across all other specifications. The keyword ‘analytical’ is part of cognitive skills in Deming and Kahn (2018) and is positively related to wages. It is also generally highlighted as positive contributor to wages (Calanca *et al.*, 2019; Ziegler, 2021). The definition of ‘analytical’ as defined by the PCA in this study, however, also contains keywords such as ‘accounting’, ‘finance’, and common software (e.g., Excel) that may be explicitly stated in lower paid occupations and be simply assumed in higher paid occupations.

The findings across all cognitive skills are also supported and even more pronounced when looking at the other regression specification including broad occupation fixed effects (specification (4) and (9)), minor occupation fixed effects (specification (3) and (8)) and major fixed effects (specification (2) and (7)).

3.4.2. Wages and skills groups: Interactions and non-linearities

Table 3-4 below shows the results from running the Lasso regression equation (3.2) above separately for the time frames 2014-2015 and 2018-2020 Q1. The Lasso regression is run with the share of all nine skills groups, their second-degree polynomial and an interaction of all nine skills groups. It further includes basic demographic controls from ACS, industry shares, job zone codes from O*NET and state and detailed occupation code fixed effects. In Table 3-4, I document only non-zero coefficients that are selected through the Lasso shrinkage process and that are most relevant and significant in explaining the logarithm of hourly wage.

In Table 3-4, the ‘collaborative leader’ category significantly predicts variation in occupational wage in the two time periods. ‘Collaborative leader’ interacted with ‘research’ has a positive wage premium in 2018-2020 Q1. As per Table 3-11 in Appendix 3.E, the share of this interaction also increases over time from 9.5% in 2014-2015 to 13.2% in 2018-2020 Q1. This suggests that those skilled in both research and collaborative leadership skills are becoming more valuable to employers as the Fourth Industrial Revolution progresses. This is intuitive because as automation increases and advanced technologies replace human cognitive abilities, it will ultimately still be important to understand the implications of such technological tools with the help of broad cognitive research skills and convey them to others with the help of social skills.

Specifically, a 10 percentage point increase in the share of ‘collaborative leadership’ together with ‘research’ predicts an increase in occupational wages by 0.01% in 2014-2015 increasing to an estimate of 1.78% in 2018-2020 Q1. The latter effect has a dollar value of an additional 0.88$ per hour when evaluated at mean hourly wages of 49.49$ in 2018-2020 Q1. An example from the data as per Table 3-12 in Appendix 3.E is the occupation ‘Sales Managers’ for which on average 85% of all job adverts require ‘collaborative leader’ skills and 11% require ‘research’ skills. This occupation pays above average hourly wages of $63.68 in 2014-2015 (as compared to mean hourly wages of $44.79) and of $70.25 in 2018-2020 Q1 (as compared to mean hourly wages of $49.49.

The finding of an increasing wage premium and an increasing share demanded of research interacted with collaborative leadership skills is in line with the findings by Deming and Kahn (2018) and Weinberger (2014) who also find a complementary effect of social and cognitive skills. The ‘collaborative leadership’ skills group in this study is, however, defined at a more detailed level. While it contains aspects of social skills such as negotiation or collaboration, it also captures creativity or strategic skills, which have also been highlighted as crucial non-linear thinking skills (Lordan and Pischke, 2022b). Similarly, the ‘research’ skills group resembles definitions as classified in their cognitive skills definition but focuses in more detail on broad cognitive skills such as the facets ‘quantitative’ or ‘qualitative’ rather than more niche cognitive skills related to, for example, data science. This finding is in line with the automation literature that highlights that automation increases the need for social skills alongside advanced cognitive skills like logical reasoning (Manyika *et al.*, 2017). Logical reasoning is needed for the 'research' skills group as it forms part of each facet of it like 'statistics'. Professionals require soft skills but also need to understand the implications of numerical calculations (Manyika *et al.*, 2017). So even if very advanced technologies come on stream and improve and replace human cognitive abilities, it will still be important to understand the implications of such technological tools. This can be seen in LinkedIn data also where, for example, more automatable cognitive skills like accounting have been decreasing over time while less automatable skills like management have been increasing in terms of employer demand (Manyika *et al.*, 2017). The finding is also in line with Josten and Lordan (2022) who find that jobs that require 'people' skills together with 'brain' skills are less likely to be automated. Such skills are likely centred in high-skill and high-paid occupations.

Further, both 'interpersonal & organised' and 'analytical' show diminishing returns in 2014-2015 (i.e., a negative coefficient on the second-degree polynomial) but increasing returns in 2018-2020 Q1. That is despite them both having a negative wage premium in the linear regression as per Table 3-3, high shares of each of those two skills groups have a positive wage premium in 2018-2020 Q1. This finding suggests that high shares of both skills group are an indicator for higher paid occupations over time. This finding is in line with authors who highlight that non-cognitive skills are often non-linearly related to wage outcomes (Heineck and Anger, 2010; Collischon, 2020). Also, the share of 'analytical' and 'interpersonal & organised' skills is particularly high in business occupations such as Financial Examiners as per Table 3-12 in Appendix 3.E and has been increasing substantially over the two time frames. 'Analytical' shares increased for Financial Examiners from 63% to 74% and those of 'interpersonal & organised' for the same occupation group increased even more from 42% to 55%. This indicates that higher shares are both demanded and increasingly rewarded.

The Lasso output further confirms the shift in returns to applied computing skills: the interaction of 'big data' with 'cloud computing' is positive in 2014-2015 but negative in 2018-2020 Q1. As explained above, the skills required for cloud computing and big data analysis are constantly evolving, so it is important for individuals to stay up to date with the latest technologies and techniques in order to remain competitive in the job market explaining the changing returns over time (Deming and Noray, 2020). 'Cloud computing' interacted with 'analytical' has negative returns across both years. The increase of cloud computing technologies over time has come with increased automation of related tasks and outsourcing of labour that reduces wages, which is likely also true of analytical skills such as Excel skills (Berger and Frey, 2016).

'Big data' interacted with 'programming' language skills has, however, a positive return in the later time frame in 2018-2020 Q1. Machine learning occupations that are rapidly increasing in terms of demand frequently require the combination of programming together with big data skills, which may explain the positive return of the interaction of these two skills groups (Verma, Lamsal and Verma, 2022).

Table 3-4: Lasso regression output 2014-2015 and 2018-2020 Q1

Dependent variable: Log of hourly wage in occupation state cells			
2014-2015		2018-2020	
Collaborative leader	0.02	Collaborative leader	0.01
		Interpersonal & organised	-0.08
Big data	-0.04		
		Cloud computing	0.20
Research	-0.02		
		Math	0.01
		Machine Learning	0.37
Interpersonal & organised squared	-0.04	Interpersonal & organised squared	0.05
		Programming squared	-0.16
		Research squared	-0.11
Analytical squared	-0.03	Analytical squared	0.03
Collaborative leader x Research	0.001	Collaborative leader x Research	0.18
		Collaborative leader x Math	0.20
Interpersonal x Programming	-0.02		
		Interpersonal x Analytical	-0.06
Big data x Cloud computing	2.66	Big data x Cloud computing	-1.02
		Big data x Programming	0.11
Cloud computing x Programming	0.92		
		Cloud computing x Research	0.99
Cloud computing x Analytical	-1.71	Cloud computing x Analytical	-1.46
Programming x Analytical	-0.11		
Research x Analytical	0.16		
Constant	2.89	Constant	3.54
R squared	0.94	R squared	0.95

Note: The table displays the output from running the Lasso equation (3.2) above. It includes a full set of controls and state and detailed occupation fixed effects.

3.5. Conclusion

Amid a Fourth Industrial Revolution that is disrupting labour markets and the way in which we work, it becomes increasingly important to understand which skills will be in demand, and which rewarded. In this study, I analyse the skills demanded and rewarded in the labour market over time. Concretely, I look at skills as posted in job advertisements in the US shortly before the start of the Fourth Industrial Revolution 2014-2015 and compare their demand and reward to a later time period when new technologies have already settled more in 2018-2020 Q1. To do so I focus on professional occupations for the two time frames and run a regression of the logarithm of hourly wages on nine skills groups. Later, I also run a Lasso regression to test for non-linearities and interactions in the skills rewards.

This study considered nine skills groups: two non-cognitive skills ('collaborative leadership' and 'interpersonal and organised') and seven cognitive skills ('big data', 'cloud computing', 'programming', 'machine learning', 'research', 'math' and 'analytical'). Overall, I find that 'collaborative leadership' increased in importance over time in terms of predicting a positive wage premium and rising shares demanded. In contrast, the other non-cognitive skill 'interpersonal and organised' has a negative wage premium in both years, despite rising shares demanded. This difference in wages received is possibly explained by the higher automatability of occupations that require 'interpersonal and organised' skills (Josten and Lordan, 2022). It can also be explained by the fact that in professional workplaces, collaboration has increased in importance requiring leaders to master this important non-cognitive skill (Ibarra and Hansen, 2011; Allen, Belfi and Borghans, 2020). Collaborative leadership has the potential to foster individual and company performance both directly and indirectly through fostering inclusion. That is a leader that has collaborative leadership skills such as creativity also closely resembles an inclusive leader that determines the quality of collaboration by fostering these skills in others and creating an inclusive environment where individuals feel safe to speak up about new ideas (Nembhard and Edmondson, 2006; Carmeli, Reiter-Palmon and Ziv, 2010).

The findings in this study demonstrate that data science is constantly evolving. Data science skills that are in high demand and attracting a wage premium in one period lose their premium in the next period as individuals are required to upskill on new technologies. That is, given that technology is constantly evolving, so too are the skills demanded by those who work in the area. This underlines the importance of continuous learning for professional data scientists, in addition to wage premiums to encourage them to focus on learning the latest data science skills.

Concretely, in this study, I find that ‘big data’ shifts from having positive returns in the earlier time frame of 2014-2015 to having negative returns in 2018-2020 Q1 while more recent technologies such as machine learning gain a wage premium in 2018-2020 Q1.

I find a complementarity between ‘collaborative leadership’ and ‘research’ skills. This finding is in line with past research that focused on the interaction of social skills and cognitive skills (Weinberger, 2014; Deming, 2017) and the fact that non-linear thinking becomes key for the future of work (Lordan and Pischke, 2022b). The finding is also in line with Josten and Lordan (2022) who find that jobs that require ‘people’ skills together with ‘brain’ skills are less likely to be automated. Professionals require non-cognitive skills but also need to understand the implications of numerical calculations (Manyika *et al.*, 2017). Mastering even complex technologies requires a broad understanding of the underlying mechanisms and the ability to bring those across with help of social skills. With increasing complexity in labour markets due to increased technology, it becomes crucial for workers to coordinate across production processes, to be interdisciplinary skilled and to keep an overview over the many machine-driven processes (Goos *et al.*, 2019). Collaborative leaders with access to new technology can foster a culture of innovation and creative problem-solving (Goos *et al.*, 2019).

The insights from this study are useful for companies and individuals in several ways. Understanding the demand and reward for skills is crucial for firms and individuals in the face of rapidly changing labour markets due to the Fourth Industrial Revolution. They provide information on the skills that are valuable in today’s labour market such as ‘collaborative leadership’ in and of itself or in combination with broad cognitive research skills or such as up-to-date data science skills. This is useful in terms of successfully matching individuals with companies, but equally it is useful as an amenity in the employee value proposition to attract and retain talent.

In the advent of the Fourth Industrial Revolution, human capital and the attraction thereof has come to the top of the agenda of many companies. Hiring has evolved away from very specific education and experience criteria towards detailed skills requirements (Fuller *et al.*, 2022). With a larger focus on skills-based hiring which reduces the focus on degrees, companies might hire more diversely and inclusively by broadening their talent pool to skilled non-degree holder (Fuller *et al.*, 2022). Companies can invest in task-based assessments that focus on the skills they need and those that have been highlighted as relevant in this study.

Further, companies can invest in upskilling their workforce. As regards to non-cognitive skills, Josten and Lordan (2021) highlight that they are more malleable than cognitive skills throughout an individual's lifespan. They also highlight, however, that there is mixed evidence on the impact of non-cognitive skills training for knowledge workers. They argue that it is crucial for teaching programmes to carefully design courses that are evidenced-based where possible. They also call for programmes to be vigorously evaluated for their effectiveness. This can be achieved when courses are rolled out in a manner that mimics randomised control trials, to allow for clear evidence on the causal effect of such courses on the desired outcomes.

This study further highlights that upskilling is particularly crucial in the field of data science that evolves rapidly. Examples for upskilling in data science are data coding bootcamps or short courses in data science (Deming and Noray, 2020). Such upskilling tools have been on the rise, which shows that 'lifelong learning' is already at the top of the agenda for companies and individuals alike. Upskilling also helps to tackle skills shortages (Deming and Noray, 2020). From this study, employers also learn that labour shortages are not necessarily about a shortage in workers but about a shortage in job-relevant skills. That is while employers who are skilled in legacy data science skills might lack job-relevant skills, they may still be able to upgrade their skill set to job-relevant skills that are paid well. This work provides information on the volatility of prices for specific skills.

This study does not analyse the supply side of skills as job advertisement data does not entail information about candidates. However, supply side mechanisms are still important and may have to be considered for future research. There is two ways to think about the results of this study in the context of supply. First, the reason for skills rewards increasing over time may also be that supply is not keeping pace with increases in demand. This is intuitively the case for skills like machine learning where demand for this skill exceeds supply. Second, it may also be that the supply of a skill is difficult to discern, for example, for non-cognitive skills where there is no barriers to entry, and it might be possible to mimic these skills. In this case, a price response may be muted as we see with the smaller effect sizes for 'collaborative leadership' for which there is no degree. Such supply effects might explain why we generally find larger effects for cognitive skills as compared to non-cognitive skills. For both, the demand is going up (so the share of demand is going up over time).

3.A Appendix A: Frequency job advertisements

Table 3-5: Frequency of job advertisements over time

	2013	2014	2015	2016	2017	2018	2019	2020	2021
					Frequency				
January	13	1,077	4,764	13,644	15,909	18,150	25,350	25,185	20,410
February	23	1,501	6,795	11,139	16,211	18,687	23,438	27,048	22,807
March	20	3,640	5,713	10,336	19,024	20,642	25,559	20,524	21,727
April	30	4,229	6,184	16,864	20,271	19,711	23,387	10,009	2,960
May	42	3,817	5,838	11,338	18,846	20,749	24,838	12,780	2,144
June	50	4,933	4,559	14,393	19,953	26,414	23,000	10,875	
July	57	5,214	6,102	14,877	19,746	21,125	28,885	13,712	
August	145	5,522	4,676	15,121	20,208	24,049	26,197	15,643	
September	193	4,212	12,310	15,724	17,877	22,680	11,926	16,559	
October	241	6,665	14,220	15,305	18,463	27,074	26,460	19,549	
November	750	4,196	11,191	13,718	15,574	20,221	25,394	17,788	
December	543	5,081	10,598	12,795	13,312	17,817	17,996	16,904	

Note: This table shows the number of job advertisements over time. I restrict the data to the time frame 2014-March 2020. Before 2014, the data is small and after March 2020 there is a drop in advertisements due to the outbreak of the Covid-19 pandemic.

3.B Appendix B: Keyword selection

Keyword selection

The 236 underlying keywords are chosen based on how they appear in the data, but I also follow the academic literature in the choice of the keywords (Deming and Kahn, 2018) and the professional literature as defined in a report by the management consulting company McKinsey (Dondi *et al.*, 2021). Synonymous keywords are grouped into 166 broader skills categories. See Table 3-6 below.

Table 3-6: Keyword list and source

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
1	creativity	creative	
		innovative	
		innovation	McKinsey
		ingenuity	
		creativity	McKinsey
2	thought leader	thought leader	
		thought leadership	
3	visionary	visionary	
4	disruptor	disruptor	
5	entrepreneurial	entrepreneurial	
		entrepreneurship	McKinsey
6	conscientious	conscientious	
		meticulous	
		attention to detail	
		diligent	
		rigorous	
7	reliable	reliable	
8	competent	competent	
		competency	
9	self discipline	self discipline	
		disciplined	
10	organised	organised	
		methodical	
		organized	Deming and Kahn (2018), Table 1
11	detail oriented	detail oriented	Deming and Kahn (2018), Table 1
12	attentive	attentive	
13	dependable	dependable	
14	verbal skills	verbal skills	
15	stakeholder management	stakeholder management	
16	build rapport	build rapport	
		building rapport	
17	articulate	articulate	
18	Presentation Skills	Presentation Skill	
		presentation	Deming and Kahn (2018), Table 1
19	interpersonal	interpersonal	

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
20	collaborate	collaborate	
		collaborative	
		work closely	
		collaboration	Deming and Kahn (2018), Table 1, McKinsey
21	supportive	supportive	
22	inclusive	inclusive	McKinsey
23	strategic	strategic	
		strategy	
		strategize	
		strategist	
24	influence	influence	
		influential	
		influencing	
25	negotiation	negotiation	Deming and Kahn (2018), Table 1
		negotiator	
		negotiate	
26	gravitas	gravitas	
27	networking	networking	
		Developing relationship	
28	charismatic	charismatic	
29	persuasiveness	persuasiveness	
		persuasive	
		persuade	
		persuasion	
30	confident	confident	McKinsey
31	personal brand	personal brand	
32	self starter	self starter	
33	goal orientated	goal orientated	McKinsey
34	motivated	highly motivated	
		motivated	
35	autonomous	autonomous	
36	hardworking	hardworking	
		hard working	
37	multitask	multi tasker	
		multi task	
		multi tasking	Deming and Kahn (2018), Table 1

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
		multitasker	
		multitask	
38	competing priorities	competing priorities	
		prioritise	
		prioritize	
		prioritisation	McKinsey
		prioritization	
39	juggle	juggle	
		juggling	
40	time management	time management	Deming and Kahn (2018), Table 1, McKinsey
41	curiosity	curiosity	
		curious	
42	openness	openness	
43	tenacity	tenacity	
		tenacious	
44	imaginative	imaginative	
45	inquisitive	inquisitive	
		inquisitiveness	
46	persistence	persistence	McKinsey
		persistent	
47	empathy	empathy	McKinsey
		empathetic	
48	humble	humble	
		humility	McKinsey
49	tolerant	tolerant	
50	thoughtful	thoughtful	
51	mindful	mindful	
52	accommodating	accommodating	
53	empower	empower	McKinsey
54	emotional intelligence	emotional intelligence	
		EQ	
55	leadership	leadership	Deming and Kahn (2018), Table 1
		leader	
56	critical thinking	critical thinking	Deming and Kahn (2018), Table 1
57	critical decision making	critical decision making	
58	decisive	decisive	

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
		decisiveness	
59	analytical	analytical	Deming and Kahn (2018), Table 1
60	astute	astute	
61	logical	logical	
62	judgement	judgement	
63	observant	observant	
64	research	research	Deming and Kahn (2018), Table 1
65	scientific	scientific	
66	qualitative	qualitative	
67	quantitative	quantitative	
68	experimental	experimental	
69	math	maths	
		mathematics	
		mathematical	
		math	Deming and Kahn (2018), Table 1
70	algebra	algebra	
71	calculus	calculus	
72	calculation	calculation	
73	trigonometry	trigonometry	
74	numerate	numerate	
		numerical	
		numeracy	
75	discipline	discipline	
76	statistics	statistics	Deming and Kahn (2018), Table 1
		statistical	
77	econometric	econometric	
78	multivariate	multivariate	
79	anova	anova	
80	linear models	linear models	
81	biostatistics	biostatistics	
82	bayesian	bayesian	
83	stochastic	stochastic	
84	r studio	r studio	
85	spss	spss	
86	data-driven	data driven	
87	informatics	informatics	

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
88	actuarial	actuarial	
89	bioinformatics	bioinformatics	
90	Python	Python	Deming and Kahn (2018), Table 1
91	Amazon Web Services	Amazon Web Services	
		AWS	
92	apache	apache	
93	hadoop	hadoop	
94	azure	azure	
95	bigquery	bigquery	
96	containerization	containerization	
97	docker	docker	
98	GCP	GCP	
99	Google Cloud Platform	Google Cloud Platform	
100	dynamodb	dynamodb	
101	elasticsearch	elasticsearch	
102	kubernetes	kubernetes	
103	slack	slack	
104	terraform	terraform	
105	nlp	nlp	
106	hdfs	hdfs	
107	hive	hive	
108	jupyter	jupyter	
109	keras	keras	
110	machine learning	machine learning	
111	pytorch	pytorch	
112	scala	scala	
113	spark	spark	
114	scikit learn	scikit learn	
115	tensorflow	tensorflow	
116	Java	Java	Deming and Kahn (2018), Table 1
117	SQL	SQL	Deming and Kahn (2018), Table 1
118	mongodb	mongodb	
119	nosql	nosql	
120	jenkins	jenkins	
121	git	git	
122	openshift	openshift	
123	openstack	openstack	

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
124	api	api	
125	udeploy	udeploy	
126	vmware	vmware	
127	javascript	javascript	
128	json	json	
129	nginx	nginx	
130	xml	xml	
131	teamwork	teamwork	Deming and Kahn (2018), Table 1
		team work	
		team player	
		teamplayer	
132	objectivity	objectivity	
		objective	
133	Problem solving	Problem solving	Deming and Kahn (2018), Table 1, McKinsey
134	meeting deadlines	meeting deadlines	Deming and Kahn (2018), Table 1
135	energetic	energetic	Deming and Kahn (2018), Table 1
136	writing	writing	Deming and Kahn (2018), Table 1
137	Customer	Customer	Deming and Kahn (2018), Table 1
138	sales	sales	Deming and Kahn (2018), Table 1
139	client	client	Deming and Kahn (2018), Table 1
		client relationship	
140	project management	project management	Deming and Kahn (2018), Table 1
141	Supervisory	Supervisory	Deming and Kahn (2018), Table 1
142	mentoring	mentoring	Deming and Kahn (2018), Table 1
143	budgeting	budgeting	Deming and Kahn (2018), Table 1
144	accounting	accounting	Deming and Kahn (2018), Table 1
145	finance	finance	Deming and Kahn (2018), Table 1
146	cost	cost	Deming and Kahn (2018), Table 1

Count	Skills category	Keywords of skills requirements (236 in total)	Additional source
147	computer	computer	Deming and Kahn (2018), Table 1
148	common software (e.g., Excel, PowerPoint)	Excel	Deming and Kahn (2018), Table 1
		PowerPoint	Deming and Kahn (2018), Table 1
		spreadsheets	Deming and Kahn (2018), Table 1
149	mental flexibility	mental flexibility	
150	goal achievement	goal achievement	
151	self-awareness and self-management	self awareness	McKinsey
		self management	McKinsey
		self aware	
		self manage	
152	Active listening	Active listening	McKinsey
153	Public speaking	Public speaking	McKinsey
154	Synthesizing	Synthesizing	McKinsey
155	Consensus	Consensus	
156	Logical	Logical	McKinsey
157	Adaptability	Adaptability	McKinsey
158	Agile thinking	Agile thinking	McKinsey
159	trust	trust	McKinsey
		trustworthy	
160	Sociability	Sociability	McKinsey
		sociable	
161	Role model	Role model	
162	Coaching	Coaching	McKinsey
163	risk-taking	risk taking	McKinsey
164	Conflict	Conflict	McKinsey
165	Grit	Grit	McKinsey
166	Integrity	Integrity	McKinsey

Note: This table shows the 236 keywords in the column ‘Keywords of skills requirements’. The keywords describe skills requirements from the skills requirements section in a respective job advert. For the principal component analysis, keywords that are synonyms or similar are grouped into broader skills categories highlighted in the column ‘Skill category’. I group an overall of 166 skills categories. An example is the skills category ‘trust’ that is coded as a binary variable that is equal to one if either the word trust or trustworthy appears in an advert. The column ‘Additional source’ flags if a keyword has also been mentioned by Deming and Kahn (2018) or published by Dondi et al. (2021). I exclude ambiguous words, i.e., ‘patient’ and ‘staff’ that have been used by Deming and Kahn (2018) or ‘senior’ and ‘planning and ways of working’. I further remove the keywords ‘communication’ and ‘management’ as they are frequently used in non-skills contexts (i.e., they appear in 59% of all job advertisements).

3.C Appendix C: BERT model

The BERT analysis was performed by Citi under my direction.

Description of the BERT model

The Bidirectional Encoder Representations from Transformers (BERT) model (https://arxiv.org/pdf/1810.04805.pdf) was developed by Google AI Language, published in 2018 – one of the biggest recent breakthroughs in Natural Language Processing (NLP).

Transformers are models that convert text into vector embeddings via encoding, and back via decoding. BERT is a partial example of such, as the model only generates embeddings from text (i.e., the encoding process). Fundamentally, BERT is a pre-trained model based on two tasks – Masked Language Model (Masked LM) and Next Sentence Prediction (NSP). In the first task, a proportion of word tokens in a sentence are "masked" at random – either removed, replaced with another word token, or unchanged – and the model is trained to predict the masked token. This allows the model to learn input texts in a multi-layered context through a bidirectional approach, which is more powerful than traditional unidirectional, left-to-right or right-to-left approaches. In the NSP task, BERT received pairs of sentences as input, where 50% of inputs are pairs of consecutive sentences, and the other 50% being random pairs. BERT is trained to predict if the second sentence in the pair is the subsequent sentence in the original document, and hence learns the context and association of sentences. The goal in BERT's pre-training is to minimise the overall loss function from these two tasks.

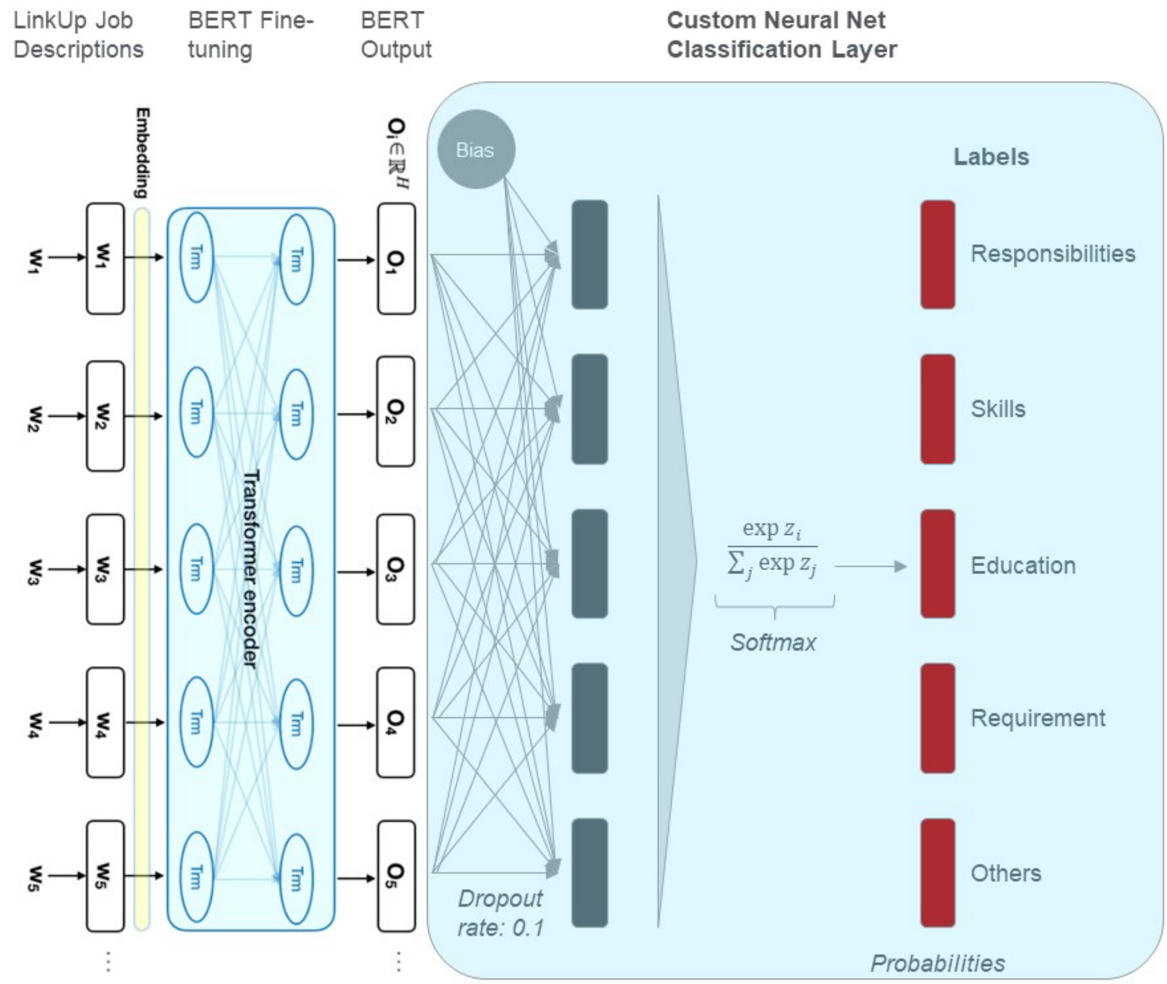
Following the pre-training, the BERT model can be adapted for downstream NLP tasks through fine-tuning, which is computationally inexpensive and straightforward. The model has been evaluated against 11 common NLP tasks – such as General Language Understanding Evaluation (GLUE) https://gluebenchmark.com/leaderboard, the Stanford Question Answering Dataset (SQuAD) v1.1 and v2.0 https://arxiv.org/pdf/1606.05250.pdf, and the Situations with Adversarial Generations (SWAG) https://arxiv.org/abs/1808.05326 – and has been shown to achieve state-of-the-art results.

Model implementation

DistilBERT (https://huggingface.co/docs/transformers/model_doc/distilbert and https://arxiv.org/abs/1910.01108), one of the many variations of BERT which features a reduced model size (40% fewer parameters) and improved speed (60% faster) while preserving 95% of BERT's performance, has been implemented in this paper. The model is used for a multi-class classification task – given any input sentence, the prediction output is to classify the sentence in one of the following five categories: responsibilities, skills, education, requirement and others. This mimics the structure and order of how a job description is typically written. Below I provide three exemplary job advertisements that are flagged for different overall keyword categories (i.e., machine leaning, collaborative leadership and cloud computing).

In the classification procedure, the pre-trained DistilBERT model is first used to generate the sentence embeddings on a small sample of manually pre-labelled dataset of 832 sentences from job descriptions, divided with an 80-20 train-test split. These embeddings and labels are then subsequently fed into a neural network architecture for the classification task training. The neural net architecture is of a standard construct with the inclusion of bias, a dropout rate of 0.1 and a softmax activation function for classification. After completion of the training phase and test data evaluation, DistilBERT is used to generate sentence embeddings at scale on the rest of the unseen data – sentences from millions of job postings – and then classified using the trained neural net model into one of the five sentence categories. This process is depicted in Figure 3-1 below.

Figure 3-1: Illustration of the DistilBERT model adapted for sentence classification



Note: The figure shows an overview (from left to right) of how the DistilBERT model is used for classifying sentences from job postings descriptions into five categories: responsibilities, skills, education, requirement and others. Words in each sentence are tokenised and fed as input to the BERT embedding layer. The output is passed into a simple neural net classifier with dropout rate 0.1 and a softmax activation function.

Model performance and accuracy

Table 3-7 below presents the classification prediction results based on the 20% test set data from the train-test split above on the format of a confusion matrix.

The precision and recall metrics across each five categories are 80%+, with the education category achieving the best prediction results due to the distinct wordings typically used in education requirements, such as BSc, MSc and PhD. There are several misclassifications between the responsibilities and other categories, which is expected as BERT create individual embeddings per sentence and is prone to losing a contextual understanding on a paragraph level (e.g., an entire paragraph on responsibilities that goes before a skills paragraph in a typical job description which could otherwise be easily identified by a human) – especially in case of generic, short sentences. Nonetheless, the overall model accuracy for the multiclass classification is 90.4%[33] on the test set, which is sufficiently accurate to be used for narrowing down job descriptions data into skill-related sections only.

Table 3-7: Classification prediction results

		Predicted					Precision	Recall
		responsibilities	skills	education	requirement	others		
Actual	responsibilities	41	0	0	2	5	85.4%	85.4%
	skills	3	27	0	0	1	96.4%	87.1%
	education	0	0	5	0	0	100%	100%
	requirement	0	1	0	9	0	81.8%	90.0%
	others	4	0	0	0	69	92.0%	94.5%

The limiting factor in this model is the runtime of DistilBERT in creating sentence embeddings and classification through neural net. A 25% stratified sample of the raw job descriptions data was extracted, and it took four weeks in total to complete the classification predictions on all sentences in the sample. Although not implemented in the paper, the model runtime can be improved through incorporating the CUDA parallel computing model where GPUs are available.

[33] If one sums up the five values along diagonal of the table (41+27+5+9+69), i.e., the correct predictions, and divides it by the total table sum (correct + incorrect predictions) this gives the overall accuracy which is 90.4%.

Skills data processing from model output

After training the BERT model and reviewing the prediction accuracy, the model is utilised to classify job posting descriptions at scale and extract skills-related sentences from the descriptions. This is a crucial process that allows the skills analysis to focus on relevant sections of the job posting description text, and discard other irrelevant parts (i.e., education, legal requirement and others) which often contain generic descriptions of the company and team. For each job posting, a dummy variable is created for each skill keyword in Table 3-6 above, representing a Boolean flag of whether that skill keyword is present for at least once in the job description (0=not represent, 1=present). Filtering out parts of the job descriptions other than skills and responsibilities prevents false positive flags that are otherwise identified from the generic company and team descriptions that bear little relevance to the actual requirements of the role.

Three examples of job advertisements by flagged keyword category

a. Machine Learning

Machine Learning Engineer - Safety Product

Amazon.com, Inc.

About US:

Launched in 2011, Twitch is a global community that comes together each day to create multiplayer entertainment: unique, live, unpredictable ex periences created by the interactions of millions. We bring the joy of co-op to everything, from casual gaming to outstanding esports to anime marathons, music, and art streams. Twitch also hosts TwitchCon, where w e bring everyone together to celebrate and grow their personal interest s and passions. We're always live at Twitch. Continually learn about al l things Twitch on Linkedin, Twitter and on our Blog.

About the Role:

Are you passionate about making Twitch safer, more inclusive, and a nic er place to enjoy? This position lets you do exactly that! You will be part of a rapidly growing Machine Learning team which develops and depl oys algorithms that are the first line of defense of users' safety at T witch. You will work with passionate co-workers who live Twitch's missi on and put their hearts into their work. If this sounds like an environ ment where you will thrive, come and join our team!

You Will:

* Build machine learning products in the safety world to protect Twitch from bad behavior such as followbotting, spam, phishing, and violent or illegal content
* Design and build scalable infrastructure that enables deploying machi ne learning models on petabytes of data
* Develop data pipelines and other modern big data processing systems
* Build distributed services to power machine learning solutions
* Design databases and make storage choices for efficient ML data manag ement
* Bring operational excellence to MLOps/DevOps
* Work on event-driven data flows to evolve machine learning applicatio ns
* Partner with fellow engineering and science teams to accomplish compl ex projects together

You Have:

* Bachelors in Computer Engineering/Science or equivalent
* Outstanding programming skills
* Demonstrated ability to understand and contribute to large software s ystems
* Experience building distributed services or backend services and unde rstand scaling computation to thousands of machines
* Passion for machine learning

Bonus Points:

* 2+ years of industry experience or equivalent internship experience
* Experience working with Amazon Web Services or other cloud solutions
* Experience with ML libraries/frameworks such as Keras, Tensorflow, and AWS Sagemaker
* Understanding of MLOps or DevOps concepts
* Experience working with large-scale data and orchestration tools such as Airflow, AWS Stepfunctions and Kubeflow
* Experience with streaming data and event-driven systems, and knowledge tools like Kinesis, Kafka, Flink, Spark, RabbitMQ and SQS
* You are a Twitch user who cares about safety

Perks:

* Medical, Dental, Vision & Disability Insurance
* 401(k), Maternity & Parental Leave
* Flexible PTO
* Commuter Benefits
* Amazon Employee Discount
* Monthly Contribution & Discounts for Wellness Related Activities & Programs (e.g., gym memberships, off-site massages, etc.),
* Breakfast, Lunch & Dinner Served Daily
* Free Snacks & Beverages

Pursuant to the San Francisco Fair Chance Ordinance, we will consider for employment qualified applicants with arrest and conviction records.

We are an equal opportunity employer and value diversity at Twitch. We do not discriminate on the basis of race, religion, color, national origin, gender, sexual orientation, age, marital status, veteran status, or disability status.

b. Collaborative Leadership

Senior Business Development Mgr, Business Electronics

Amazon.com, Inc.

The Consumer Electronics (CE) team at Amazon is looking for a Senior Business Development Manager responsible for expanding the Business Electronics (BE) categories on Amazon Business. Amazon Business is dedicated to offering a broad selection of products and supplies to business, industrial, education, government and commercial customers at competitive prices. The Business Electronics categories includes PC and office products, networking equipment, professional video / audio equipment, security, camera and imaging equipment.

This Senior Business Development Manager creates new partnerships (both internally and externally), grows existing relationships with Fortune 500 companies, and licenses assets to drive product / service improvements and innovation while reducing costs without sacrificing the customer experience. This role is an ideal next step for a leader who is looking to develop into a next career stage and to gain exposure to senior leadership both internally and externally.

This position has responsibilities that can create step-level changes t
o the business through adding strategic selection and introducing new v
endor programs and initiatives like pricing and service expansion. This
role requires an individual who can work autonomously in a highly deman
ding environment, with strong attention to detail and exceptional organ
izational skills.

The ideal candidate will have experience in negotiations, strategic pla
nning, forecasting, and a background in B2B, B2C or e-commerce business
es. The candidate must be able to work in an ambiguous but collegial en
vironment where teamwork is a priority to deliver results. The right ca
ndidate will be flexible, action and results oriented, self-starting an
d demonstrate a willingness to learn and react quickly. The candidate m
ust also be decisive and able to move with speed to implement their own
ideas. The candidate should be strong analytically and be comfortable g
enerating and evaluating forecasts and metrics to come up with recommen
dations and guidance to present to leadership. Strong communication ski
lls (both oral and written) are critical.

The Senior Business Development Manager will be responsible for the fol
lowing:

* Lead the signing, and on-boarding of new business and professional ve
ndors and expanding business and professional selection from existing C
E vendors
* Own high-level negotiations of agreements/deals with leading brands t
o drive business inputs
* Act as a leader and ambassador of Amazon and B2B across CE categories
, developing deep knowledge of supply/demand trends and success drivers
* Lead day-to-day operational aspects of the business, including gather
ing and addressing customer and vendor feedback, price management, and
business improvement initiatives
* Ability to see around corners and pioneer new initiatives with stakeh
olders across the company
* Work with a team charged with building, owning, and sharing financial
goals and deliverables for select group of vendors
* Develop and grow strong collaborative relationships internally and ex
ternally
* Bachelor's degree required
* 5+ years of relevant experience in sales, buying, account management,
consulting and/or marketing preferably in eCommerce or B2B industries
* Exceptional interpersonal and communication skills; strong writing an
d speaking skills
* Demonstrated ability to manage multiple projects - prioritization, pl
anning and time management
* Proactive attitude, detail oriented, fast learner and team player
* Strong influencing and negotiation skills
* Proven analytical skills \u2013 ability to analyze large data sets to
make strategic decisions
* Demonstrated success in situations with a high level of ambiguity
* Proven track record of delivering results in B2B or relevant category
* MBA
* Experience across categories and markets
* Business Development / Vendor Management experience

Amazon is an Equal Opportunity-Affirmative Action Employer - Minority /
Female / Disability / Veteran / Gender Identity / Sexual Orientation.

c. Cloud Computing

Application Innovation Specialist

Microsoft Corporation

We are currently looking for Application Innovation Specialists to join
our teams across our various business groups: Enterprise, Small Medium
& Corporate, as well as Regulated Industries. By applying to this r
ole, you will be considered for multiple opportunities within Microsoft
across the United States.

Microsoft is on a mission to empower every person and every organizatio
n on the planet to achieve more. Our culture is centered on embracing a
growth mindset, a theme of inspiring excellence, and encouraging teams
and leaders to bring their best each day. Growth mindset encourages eac
h of us to lean in and learn what matters most to our customers, to cre
ate the foundational knowledge that enables us to make customer-first d
ecisions in everything we do. In doing so, we create life-changing inno
vations that impact billions of lives around the world. You can help us
achieve our mission.

Are you insatiably curious? Do you embrace uncertainty, take risks, and
learn quickly from your mistakes? Do you collaborate well with others,
knowing that better solutions come from working together? Do you stand
in awe of what humans dare to achieve, and are you motivated every day
to empower others to achieve more through technology and innovation? Ar
e you ready to join the team that is at the leading edge of Innovation
at Microsoft?

To learn more about Microsoft's mission, please visit: https://careers.
microsoft.com/mission-culture

Check out all our products at: http://www.microsoft.com/en-us

We are currently hiring across a variety of teams with various levels o
f skills and experiences required. Below maps the minimum required qual
ifications to be considered for these positions.

Experiences Required: Education, Key Experiences, Skills and Knowledge:

Professional

* 5+ years of technology-related sales or account management experience
OR a Bachelor's Degree in Computer Science, Information Technology, Bus
iness Administration, or related field AND 4+ years of technology-relat
ed sales or account management experience required
* Experienced. Relevant experience selling cloud services or applicatio
n development services to medium and large enterprise customers with a
focus on cloud application development required
* Account Management. Effective territory/account management: planning,
opportunity qualification and creation, stakeholder and executive commu
nication, needs analysis, services/partner engagement, opportunity mana
gement and pipeline management required
* Executive Presence. Experience and expertise selling to LOB decision
makers, technical decision makers & enterprise solution architects
by aligning & reinforcing the value of the solution to the customer

's overall business pain and/or strategic opportunities and decision cr
iteria preferred
* Problem Solver. Ability to solve customer problems through cloud tech
nologies, specifically solutions related to cloud native apps – contain
ers & serverless, microservices, developers tools and DevOps, low c
ode, migration to cloud required
* Collaborative. Orchestrate and influence virtual teams to pursue sale
s opportunities and lead v-teams through influence required

Technical

* Enterprise-scale technical experience with cloud and hybrid infrastru
ctures, architecture designs, migrations, and technology management. Su
bject matter expertise in one or more of the following: required
* Application development platforms on public clouds and/or Azure in de
velopment languages such as Java, JavaScript, Python, PHP, C#, Node.JS
targeting Android, iOS, Linux, Windows, public clouds or Azure.
* Scalable architectures using Azure App Service, API management, serve
rless technologies, container orchestration (e.g. AKS, Kubernetes, Red
Hat OpenShift etc.), microservice frameworks etc.

* Software development practices like DevOps and CI/CD tool chains (i.e
. Jenkins, Spinnaker, Azure DevOps, GitHub). required
* Understanding of Data & AI technologies in context of app develop
ment (e.g. SQL and NoSQL Databases, Big Data, Cognitive Service, Machin
e Learning etc.). preferred
* Understanding of Low code platform and technologies such as Power Pla
tform. preferred
* Competitive Landscape. Knowledge of cloud development platforms requi
red
* Partners. Understanding of partner ecosystems and the ability to leve
rage partner solutions to solve customer needs required

Education

* Bachelor's degree or equivalent work experience required
* Certification in the following technologies preferred: Cloud, mobile,
web application development, cloud-native application architecture (i.e
. containers, microservices, API management), modern software developme
nt techniques like DevOps and CI/CD tool chains (i.e. Jenkins, Spinnake
r, Azure developer services, GitHub) and container orchestration system
s (i.e. Docker, Kubernetes, Red Hat OpenShift, Cloud Foundry, Azure Kub
ernetes Service, GitHub), Low Code (Power Platform). Required
* Certification in sales, sales management, complex sales training, sal
es methodologies, broad evangelism through events (presentation skills)
, and consultative selling preferre

Microsoft is an equal opportunity employer. All qualified applicants wi
ll receive consideration for employment without regard to age, ancestry
, color, family or medical care leave, gender identity or expression, g
enetic information, marital status, medical condition, national origin,
physical or mental disability, political affiliation, protected veteran
status, race, religion, sex (including pregnancy), sexual orientation,
or any other characteristic protected by applicable laws, regulations a
nd ordinances. We also consider qualified applicants regardless of crim
inal histories, consistent with legal requirements. If you need assista
nce and/or a reasonable accommodation due to a disability during the ap

plication or the recruiting process, please send a request via the Acco
mmodation request form.

Benefits/perks listed below may vary depending on the nature of your em
ployment with Microsoft and the country where you work.

Microsoft is uniquely positioned to win "App Innovation" workloads to h
elp with customer's Digital Transformation journey. Microsoft apps port
folio spans Azure App Platform, PowerApps, GitHub/DevOps and Visual Stu
dio. Azure App Platform is one of the fastest growing businesses inside
the Azure platform and with tighter integrations with developer tools.
Microsoft is hiring Specialist sellers for Application Innovation to de
liver on Microsoft's aspirations and sales goals in this dynamic and fa
st-growing enterprise market.

As an App Innovation Specialist, you will be a senior solution sales le
ader within our enterprise sales organization working with our most imp
ortant customers selling entire Microsoft Apps portfolio. You will lead
orchestrating a virtual team of Cloud Solution Architects, partners and
other resources to advance the sales process and achieve/exceed sales a
nd usage/consumption targets for Application Innovation related workloa
ds in your assigned accounts. You will be a trusted advisor and a cloud
application development subject matter expert.

Primary accountabilities for this role include:

* Create "buy-in" vision with the Apps Decision Makers
* Take active role in defining and influencing the customer's business
challenges and opportunities.
* Understand the financial, qualitative and competitive drivers impacti
ng customer business.
* Create "buy-in" vision and gain sponsorship by generating excitement
around Microsoft solutions value.

* Map out customer's current and desired state and expectations
* Identify customer's digital transformation needs, business drivers, t
heir perspective, and concerns.
* Collaborate effectively with the customers to outline their business
problems, opportunities.
* Establish and understand the buying decision criteria and timeline to
make decision regarding the solution.
* Establish credibility and trust by demonstrating that Microsoft solut
ions not only solve customer business problems but also the value they
realized.

* Lead the solution design by assembling and orchestrating Sales &
technical resources.
* Proficient in delivering Microsoft Apps vision, strategy, value to C-
level and Apps Decision Makers
* Orchestrate the technical experts to create the solution, validate it
via Proof of Concept, and showcase how it meets customer business and t
echnology requirements.
* Able to handle customer objections and competitive differentiation.

* Substantiate the value of the solution (commercial discussion)

* Building business cases with TCO analysis and negotiate a deal that's based on value by leveraging various MS offers and programs.
* Secure customer commitment for the business proposal.

* Drive Sales Excellence
* Drive the App Innovation business to overachieve revenue, consumption and scorecard targets.
* Maintain excellence in pipeline management, accuracy of sales forecas t, and deal close plans.

* Lead with subject matter expertise and be the Voice of the customer.
* Influence the Microsoft Application Innovation go to market strategie s by providing feedback to sales, marketing, and engineering on product requirements and sales blockers.
* Stay sharp, attaining and maintaining required certifications. We enc ourage all our employees to continuously maintain and enhance their tec hnical, sales, professional skills and competitive readiness. You will be recognized for sharing, learning and driving individual work that al l result in business impact for customers, partners and within Microsof t. We encourage thought leadership and leadership from every employee.

3.D Appendix D: Principal Component Analysis

Principal Component Analysis

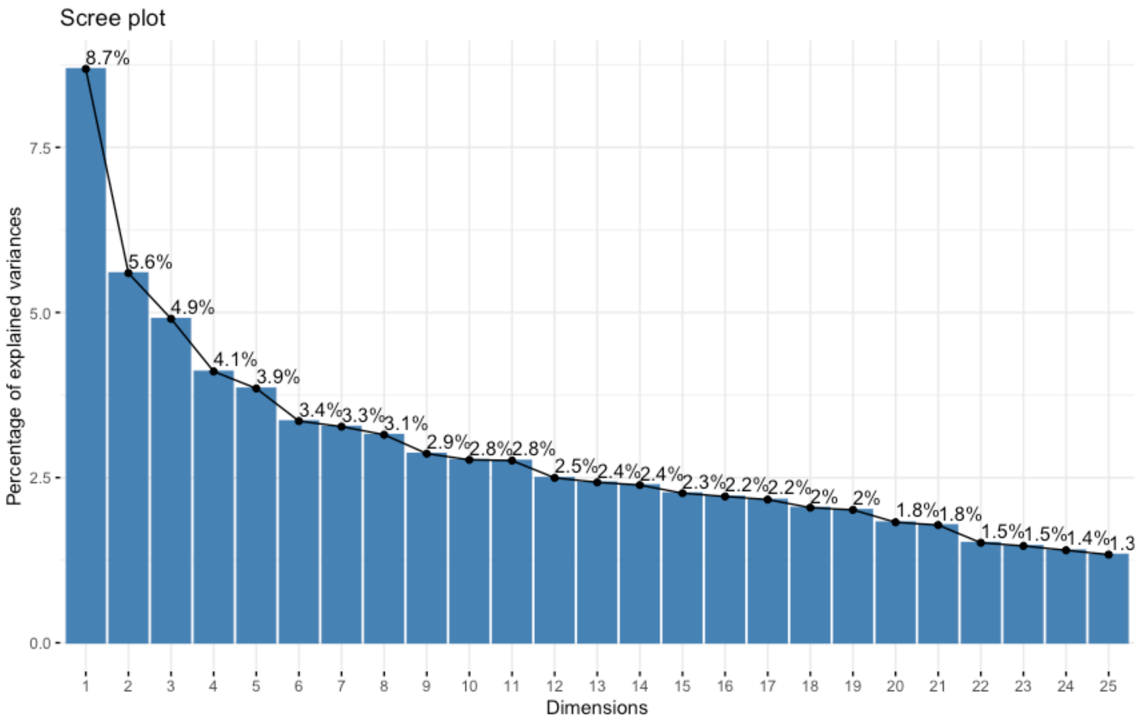
The skills requirement keywords from LinkUp are grouped using principal component analysis (PCA). PCA is a psychometric method used to reduce the dimensionality of variables (Jollife and Cadima, 2016). The aim of PCA is to define variables that are linear combinations of the keywords of skills in the data and that are uncorrelated with each other (Jollife and Cadima, 2016). It aims at simplifying the interpretation of the variables of interest, i.e., rather than analysing the impact of a large number of individual keywords I am interested in the impact of components that are representative of the original sample. The sample for the PCA includes all 1.3 million of LinkUp job advertisements for professionals for the years 2014-2020 Q1. It further includes 166 skills category variables that are used as input for the PCA (see Table 3-6 above). The analysis is run at the job advertisement level and the 166 skills category variables are coded as binary variables that are equal to one if the underlying keywords appear in the respective job advert and zero otherwise.

I run the principal component analysis initially using all 166 skill category variables. I then run oblique rotations that allows for correlation across components. If the first principal components account for a large part of the total variance, the remaining components can be dropped through rotations (Bartholomew *et al.*, 2011; Heckman *et al.*, 2012). The PCA is hence run in rotations of components to be retained to find the optimal number of principal components subject to the following rules for the cut-off for the components: a cumulative variance explained of the components of at least 60%, examining a jump in the scree plot (i.e., a point at which the eigenvalue of a given component falls substantially) and choosing component cut-offs that are sensible and intuitive (Bartholomew *et al.*, 2011). In the final step, I drop keywords that are weakly associated with the components (i.e., have a loading of less than 0.32) and those that cross-load onto multiple components. The cut-off of 0.32 has been recommended in the literature (Tabachnick and Fidell, 2018) and the large sample size allows us choosing a relatively low loadings cut-off. The overall PCA analysis results in a total number of nine skills components: ‘collaborative leadership‘, ‘interpersonal and organised‘, ‘big data‘, ‘cloud computing‘, ‘programming‘, ‘machine learning‘, ‘research‘, ‘math‘, ‘analytical‘.

Step 1: Principal Component Analysis using all 166 skills

Figure 3-2 below and Table 3-8 together show the output of running the first principal component analysis. In step 2 below, I choose to rotate with 19 components given a cumulative variance explained of greater than 60% in Table 3-8 as well as a small jump in the scree plot in Figure 3-2.

Figure 3-2: Scree plot principal component analysis with all skills keywords



Note: The figure shows the scree plot from the principal component analysis and the percentage of the explained variance. A small jump in the scree plot can be detected after 19 components where the variance levels of. The x-axis shows the number of principal components and the y-axis the percentage of explained variances.

Table 3-8: Cumulative variance explained

Importance of components

	Comp.1	**Comp.2**	**Comp.3**	**Comp.4**	**Comp.5**	**Comp.6**	**Comp.7**
Standard deviation	0.60	0.48	0.45	0.41	0.40	0.37	0.37
Proportion of Variance	0.09	0.06	0.05	0.04	0.04	0.03	0.03
Cumulative Proportion	0.09	0.14	0.19	0.23	0.27	0.31	0.34
	Comp.8	**Comp.9**	**Comp.10**	**Comp.11**	**Comp.12**	**Comp.13**	**Comp.14**
Standard deviation	0.36	0.34	0.34	0.34	0.32	0.32	0.32
Proportion of Variance	0.03	0.03	0.03	0.03	0.02	0.02	0.02
Cumulative Proportion	0.37	0.40	0.43	0.45	0.48	0.50	0.53
	Comp.15	**Comp.16**	**Comp.17**	**Comp.18**	**Comp.19**	**Comp.20**	**Comp.21**
Standard deviation	0.31	0.30	0.30	0.29	0.29	0.28	0.27
Proportion of Variance	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Cumulative Proportion	0.55	0.57	0.59	0.61	0.63	0.65	0.67

Step 2: Orthogonal rotations

I first run an orthogonal rotation reduced to 19 components, which yields a matrix of standardised factor loadings. Of those 19 components, 8 components have less than three loadings of more than 0.32 and are hence weakly loading. I therefore rotate with 11 components in the next rotation. Again, two components load weakly, so I rotate again with 9 principal components. Table 3-9 below shows the output from the rotation of 9 principal components. Any cross-loadings (loadings of greater than 0.32 on more than one component) and weak loadings (loadings of smaller than 0.32) have been removed.

Table 3-9: Cognitive skills and non-cognitive components resulting from PCA

Non-cognitive skills components			Cognitive skills components					
Collaborative leader			Big data			Programming		
Keywords	Loading	Share	Keywords	Loading	Share	Keywords	Loading	Share
strategic	0.59	24.14%	hadoop	0.75	1.19%	xml	0.64	1.26%
leadership	0.58	26.17%	spark	0.75	0.72%	json	0.6	0.67%
influence	0.51	12.75%	hive	0.73	0.55%	javascript	0.59	2.51%
collaborate	0.39	24.52%	hdfs	0.53	0.14%	java	0.56	6.08%
creativity	0.34	13.57%	scala	0.47	0.47%	sql	0.39	7.12%
negotiation	0.33	6.57%	nosql	0.34	0.81%	git	0.38	1.16%
coaching	0.32	5.14%				api	0.37	1.51%
Overall		58.89%	Overall		2.28%	Overall		13.45%
Interpersonal & organised			Cloud computing			Machine Learning		
Keywords	Loading	Share	Keywords	Loading	Share	Keywords	Loading	Share
time management	0.4	4.65%	docker	0.74	0.64%	tensorflow	0.84	0.11%
competing priorities	0.39	12.30%	kubernetes	0.71	0.41%	pytorch	0.76	0.04%
interpersonal	0.38	17.20%	amazon web services	0.48	2.32%	keras	0.73	0.03%
organized	0.36	3.38%	terraform	0.45	0.15%			
			azure	0.41	1.04%			
			jenkins	0.41	0.95%			
			openshift	0.35	0.06%			
			containerization	0.35	0.12%			
			openstack	0.32	0.22%			
Overall		29.86%	Overall		3.89%	Overall		0.11%
Research			Analytical			Math		
Keywords	Loading	Share	Keywords	Loading	Share	Keywords	Loading	Share
quantitative	0.58	3.45%	accounting	0.65	5.58%	calculus	0.73	0.05%
statistics	0.54	5.48%	finance	0.63	7.63%	algebra	0.63	0.12%
qualitative	0.43	1.06%	common software e.g., excel	0.41	16.66%	trigonometry	0.56	0.05%
research	0.37	12.86%	analytical	0.33	20.78%	stochastic	0.47	0.05%
Overall		18.58%	Overall		35.70%	Overall		0.21%

3.E Appendix E: Skills shares

Skills shares over time

There is a large variation in how often each skill grouping appears in the job adverts as seen in Table 3-10 below. For example, 'Collaborative leadership' appears in 50.14% of job adverts in 2014-2015 and 61.07% in 2018-2020 Q1. In comparison, machine learning does not appear in job advertisements in LinkUp in the earlier time frame and only appears in 0.19% of job advertisements in 2018-2020 Q1. Overall, soft skills are overused in job advertisements and also across disciplines (Calanca *et al.*, 2019), while cognitive skills are more specific.

Table 3-10: Share and observations of skills shares over time

		Collaborative leadership	Interpersonal & organised	Big data	Programming	Machine Learning	Cloud computing	Research	Math	Analytical
2014-2015	%	50.14%	24.70%	1.63%	13.60%	N/A	1.76%	16.19%	0.19%	31.19%
	#	71,718	35,335	2,325	19,448	N/A	2,524	23,152	273	44,607
2018-2020 Q1	%	61.07%	30.85%	2.49%	13.03%	0.19%	4.88%	18.94%	0.21%	35.83%
	#	374,087	188,981	15,246	79,827	1,155	29,911	115,996	1,288	219,461

Note: This table shows the share of the nine skills groups across two time frames of 2014-2015 and 2018-2020 Q1. It further shows the absolute number of observations by skills group.

Skills shares of interactions over time

Table 3-11 below documents the shares of all skills group interactions. Overall, the share of all skills interactions have been increasing over the two time frames. The interactions that centre around zero in terms of shares are not considered for the regression analysis. The interaction of 'collaborative leadership' and 'big data' for example increased from 0.8% to 1.6%. The interaction of 'collaborative leadership' and 'research' increases by 3.8 percentage points from 9.5% to 14.2%, which points at the fact that with increasing automation, the complementarity between social skills (i.e., collaborative leadership) and cognitive skills (i.e., research) increases. For example, doctors increasingly use technology such as Clinical Decision Support Software , but still need to understand statistics, which is a facet of 'research' skills alongside making final decisions drawing on their 'collaborative leadership' skills.

Table 3-11: Share of skills group interactions

Skills group interactions	2014-2015	2018-2020 Q1
Collaborative leadership x Interpersonal & organised	15.7%	22.3%
Collaborative leadership x Big data	0.8%	1.6%
Collaborative leadership x Cloud computing	1.0%	3.2%
Collaborative leadership x Programming	6.6%	8.0%
Collaborative leadership x Research	9.5%	13.2%
Collaborative leadership x Math	0.1%	0.1%
Collaborative leadership x Analytical	18.8%	24.9%
Collaborative leadership x Machine Learning	n/a	0.1%
Interpersonal & organised x Big data	0.2%	0.5%
Interpersonal & organised x Cloud computing	0.3%	0.9%
Interpersonal & organised x Programming	2.8%	3.4%
Interpersonal & organised x Research	5.1%	7.2%
Interpersonal & organised x Math	0.0%	0.1%
Interpersonal & organised x Analytical	11.9%	16.0%
Interpersonal & organised x Machine Learning	n/a	0%
Big data x Cloud computing	0.3%	0.9%
Big data x Programming	1.3%	2.0%
Big data x Research	0.4%	0.8%
Big data x Math	0.0%	0.0%
Big data x Analytical	0.4%	0.7%
Big data x Machine Learning	n/a	0.1%
Cloud computing x Programming	1.1%	2.8%
Cloud computing x Research	0.2%	0.6%
Cloud computing x Math	0.0%	0.0%
Cloud computing x Analytical	0.3%	0.9%
Cloud computing x Machine Learning	n/a	0%
Programming x Research	2.6%	3.2%
Programming x Math	0.0%	0.0%
Programming x Analytical	4.3%	4.7%
Programming x Machine Learning	n/a	0.1%
Research x Math	0.1%	0.1%
Research x Analytical	8.1%	9.8%
Research x Machine Learning	n/a	0.11%
Maths x Analytical	0.10%	0.08%
Maths x Machine Learning	n/a	0.01%
Analytical x Machine Learning	n/a	2%

Note: The table shows the skills shares by skills group interactions.

Skills shares and wage premium by occupations

To give a clearer sense of the regression estimates, I consider what these mean for a subset of occupations. I show occupations that require high versus low shares of each of the respective nine skills group and their respective skills premium in Table 3-12 below. The wage premium is calculated by multiplying the occupation share with the coefficient. So logically, the premium is larger for occupations with high shares of the respective skills group and lower for those with low shares. For the category collaborative leader, for example, job postings for managing occupations require large shares of collaborative leaders ranging from 83% to 93%. For 2014-15 the wage premium is insignificant but turns positive for 2018-2020 and makes up around 5% of the hourly wages in the top five occupations. The required shares for 'interpersonal & organised' are smaller but still between 42%-53% in the top five occupations that show increasing wage penalties over time of up to 11% of the hourly wage. An example is the occupation loan officers for which 56% of job adverts require 'interpersonal & organised' skills and the wage penalty is around 4$ of an hourly wage of 35$. An interesting case is big data: the occupations 'Computer and information research scientists' or 'Software Developer, Applications' that are large occupations in terms of absolute count show that the highest share required for 'big data' skills turn from a wage premium in 2014-2015 to a penalty in 2018-2020. The same is true for cloud computing occupations. Programming is another interesting example where the top occupations require large shares of programming skills of up to 67% of web developers but those skills are actually punished across both time frames. The wage premium to machine learning in 2018-2020 is quite large while the share required is still very low as in the 'math' skills group. Research occupations experience a wage premium. Analytical occupations have negative returns in 2014-2015 but turn insignificant in 2018-2020 Q1.

Table 3-12: Wage premium by top and bottom (in terms of share) occupations for all nine skills groups, and hourly wages and overall count by occupation

Collaborative leader	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Marketing Managers	6,042	29,844	91%	93%	$70.33	$76.15	-0.09%	2.93%	-$0.06	$2.23
Computer and Information Systems Managers	2,336	10,986	78%	88%	$69.63	$77.27	-0.08%	2.76%	-$0.05	$2.13
Human Resources Managers	1,267	5,771	80%	88%	$56.74	$63.15	-0.08%	2.76%	-$0.05	$1.74
Sales Managers	3,444	15,811	83%	87%	$63.68	$70.25	-0.08%	2.74%	-$0.05	$1.93
Graphic Designers	327	1,297	83%	85%	$26.22	$28.83	-0.08%	2.68%	-$0.02	$0.77
Bottom 5										
Medical and Clinical Laboratory Technicians	421	2,815	8%	4%	$19.30	$31.47	-0.01%	0.13%	$0.00	$0.04
Pharmacy Technicians	323	1,936	11%	9%	$14.77	$16.95	-0.01%	0.29%	$0.00	$0.05
Surgical Technologists	577	1,187	6%	7%	$20.97	$23.64	-0.01%	0.21%	$0.00	$0.05
Radiologic Technologists	356	1,142	8%	10%	$26.46	$28.94	-0.01%	0.32%	$0.00	$0.09
Medical Records and Health Information Technicians	924	3,118	16%	27%	$18.44	$21.96	-0.02%	0.85%	$0.00	$0.19

Interpersonal & organised	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Financial Examiners	387	2,272	42%	55%	$44.63	$41.82	-1.50%	-3.97%	-$0.67	-$1.66
Loan Officers	1,363	7,135	54%	55%	$37.87	$37.33	-1.93%	-3.94%	-$0.73	-$1.47
Financial Managers	5,268	22,811	35%	53%	$69.34	$75.02	-1.26%	-3.76%	-$0.88	-$2.82
Compliance Officers	417	2,349	39%	43%	$34.25	$35.39	-1.40%	-3.08%	-$0.48	-$1.09
Lawyers	477	2,636	37%	43%	$67.76	$72.73	-1.32%	-3.10%	-$0.89	-$2.25
Bottom 5										
Health Technologists and Technicians, All Other	701	6,130	4%	1%	$21.51	$22.71	-0.13%	-0.05%	-$0.03	-$0.01
Interior Designers	213	485	3%	4%	$24.32	$28.71	-0.10%	-0.30%	-$0.02	-$0.09
Nurse Practitioners	65	970	18%	3%	$48.17	$54.20	-0.66%	-0.20%	-$0.32	-$0.11
Pharmacists	265	3,424	30%	7%	$56.86	$59.98	-1.07%	-0.50%	-$0.61	-$0.30
Healthcare Social Workers	169	1,060	12%	13%	$26.03	$28.46	-0.45%	-0.97%	-$0.12	-$0.28

Big data	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Computer and Information Research Scientists	566	4,498	26%	33%	$59.67	$62.98	4.87%	-3.90%	$2.90	-$2.46
Software Developers, Applications	13,114	56,083	11%	15%	$51.93	$55.94	1.96%	-1.87%	$1.02	-$1.05
Web Developers	1,671	4,296	4%	4%	$34.80	$39.15	0.65%	-0.54%	$0.23	-$0.21
Training and Development Specialists	970	4,753	0%	0%	$30.29	$32.13	0.00%	0.00%	$0.00	$0.00
Statisticians	187	1,096	3%	3%	$41.06	$47.31	0.49%	-0.34%	$0.20	-$0.16
Bottom 5										
Interior Designers	213	485	0%	0%	$24.32	$28.71	0%	0%	$0.00	$0.00
Paralegals and Legal Assistants	167	769	0%	0%	$26.69	$27.61	0%	0%	$0.00	$0.00
Transportation, Storage, and Distribution Managers	297	1,643	0%	0%	$45.77	$50.46	0%	0%	$0.00	$0.00
Purchasing Agents, Except Wholesale, Retail, and Farm Products	1,025	4,542	0%	0%	$32.08	$34.37	0%	0%	$0.00	$0.00
Industrial Engineering Technicians	591	3,565	0%	0%	$26.85	$28.63	0%	0%	$0.00	$0.00

Cloud Computing	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Software Developers, Applications	13,114	56,083	10%	28%	$51.93	$55.94	3.24%	-1.02%	$1.68	-$0.57
Network and Computer Systems Administrators	4,998	16,116	5%	15%	$40.56	$43.32	1.76%	-0.55%	$0.71	-$0.24
Web Developers	1,671	4,296	4%	14%	$34.80	$39.15	1.44%	-0.53%	$0.50	-$0.21
Database Administrators	610	1,511	1%	12%	$41.17	$46.77	0.42%	-0.43%	$0.17	-$0.20
Computer and Information Systems Managers	2,336	10,986	4%	8%	$69.63	$77.27	1.14%	-0.29%	$0.79	-$0.23
Bottom 5										
Paralegals and Legal Assistants	167	769	0%	0%	$26.69	$27.61	0%	0%	$0.00	$0.00
Occupational Health and Safety Specialists	965	938	0%	0%	$34.87	$37.21	0%	0%	$0.00	$0.00
Chemists	373	1,855	0%	0%	$38.01	$41.00	0%	0%	$0.00	$0.00
Medical and Clinical Laboratory Technicians	421	2,815	0%	0%	$19.30	$31.47	0%	0%	$0.00	$0.00
Registered Nurses	11,101	26,025	0%	0%	$32.45	$36.44	0%	0%	$0.00	$0.00

Programming	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Web Developers	1,671	4,296	72%	64%	$34.80	$39.15	-6.57%	-6.82%	-$2.29	-$2.67
Software Developers, Applications	13,114	56,083	65%	61%	$51.93	$55.94	-5.97%	-6.46%	-$3.10	-$3.61
Computer Programmers	425	1,674	53%	47%	$40.67	$44.72	-4.91%	-5.08%	-$2.00	-$2.27
Computer Systems Analysts	4,722	13,650	32%	34%	$43.03	$46.17	-2.99%	-3.67%	-$1.29	-$1.69
Management Analysts	5,717	25,543	15%	21%	$44.67	$45.36	-1.44%	-2.27%	-$0.64	-$1.03
Bottom 5										
Registered Nurses	11,101	26,025	0%	0%	$32.45	$36.44	0%	0%	$0.00	$0.00
Health Technologists and Technicians, All Other	701	6,130	0%	0%	$21.51	$22.71	0%	0%	$0.00	$0.00
Property, Real Estate, and Community Association Managers	188	2,065	0%	0%	$35.87	$37.05	0%	0%	$0.00	$0.00
Medical and Clinical Laboratory Technicians	421	2,815	0%	0%	$19.30	$31.47	0%	0%	$0.00	$0.00
Personal Financial Advisors	948	8,018	0%	0%	$53.95	$57.26	0%	0%	$0.00	-$0.01

Machine Learning	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Computer and Information Research Scientists	566	4,498	n/a	11%	$59.67	$62.98	n/a	6.24%	n/a	$3.93
Software Developers, Applications	13,114	56,083	n/a	1%	$51.93	$55.94	n/a	0.39%	n/a	$0.22
Software Developers, Systems Software	2,303	9,870	n/a	1%	$53.29	$56.04	n/a	0.38%	n/a	$0.21
Statisticians	187	1,096	n/a	0.2%	$41.06	$47.31	n/a	0.10%	n/a	$0.05
Computer Programmers	425	1,674	n/a	0.3%	$40.67	$44.72	n/a	0.17%	n/a	$0.08
Bottom 5										
Mental Health and Substance Abuse Social Workers	594	2,124	n/a	0%	$21.19	$23.34	n/a	0.00%	n/a	$0.00
Registered Nurses	11,101	26,025	n/a	0%	$32.45	$36.44	n/a	0.00%	n/a	$0.00
Health Technologists and Technicians, All Other	701	6,130	n/a	0%	$21.51	$22.71	n/a	0.00%	n/a	$0.00
Property, Real Estate, and Community Association Managers	188	2,065	n/a	0%	$35.87	$37.05	n/a	0.00%	n/a	$0.00
Human Resources Managers	1,267	5,771	n/a	0%	$56.74	$63.15	n/a	0.00%	n/a	$0.00

Research	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Statisticians	187	1,096	79%	68%	$41.06	$47.31	3.52%	4.11%	$1.45	$1.95
Computer and Information Research Scientists	566	4,498	69%	76%	$59.67	$62.98	3.10%	4.59%	$1.85	$2.89
Natural Sciences Managers	656	3,889	75%	68%	$69.32	$76.56	3.37%	4.08%	$2.34	$3.12
Medical Scientists, Except Epidemiologists	1,016	5,944	54%	59%	$46.52	$50.48	2.42%	3.56%	$1.13	$1.80
Sales Managers	3,444	15,811	12%	9%	$63.68	$70.25	0.54%	0.52%	$0.35	$0.37
Bottom 5										
Health Technologists and Technicians, All Other	701	6,130	0%	0%	$21.51	$22.71	0.00%	0.01%	$0.00	$0.00
Registered Nurses	11,101	26,025	2%	2%	$32.45	$36.44	0.11%	0.14%	$0.04	$0.05
Pharmacists	265	3,424	6%	3%	$56.86	$59.98	0.27%	0.19%	$0.15	$0.12
Construction Managers	254	1,719	6%	4%	$46.80	$51.13	0.24%	0.21%	$0.11	$0.11
Personal Financial Advisors	948	8,018	5%	5%	$53.95	$57.26	0.23%	0.28%	$0.12	$0.16

Maths	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Chemical Technicians	129	622	7%	4%	$22.97	$25.28	0.62%	1.01%	$0.14	$0.26
Civil Engineers	108	1,224	6%	1%	$42.62	$45.44	0.58%	0.25%	$0.25	$0.11
Computer and Information Research Scientists	566	4,498	3%	2%	$59.67	$62.98	0.25%	0.52%	$0.15	$0.33
Actuaries	215	1,147	4%	2%	$53.52	$56.63	0.33%	0.48%	$0.18	$0.27
Electrical and Electronics Engineering Technicians	724	2,771	1%	2%	$29.53	$32.05	0.07%	0.56%	$0.02	$0.18
Bottom 5										
Health Technologists and Technicians, All Other	701	6,130	0%	0%	$21.51	$22.71	0.00%	0.01%	$0.00	$0.00
Public Relations and Fundraising Managers	314	1,995	0%	0%	$59.53	$67.40	0.00%	0.00%	$0.00	$0.00
Licensed Practical and Licensed Vocational Nurses	302	1,260	0%	0%	$20.29	$23.09	0.00%	0.00%	$0.00	$0.00
Lawyers	477	2,636	0%	0%	$67.76	$72.73	0.00%	0.00%	$0.00	$0.00
Personal Financial Advisors	948	8,018	0%	0%	$53.95	$57.26	0.03%	0.02%	$0.02	$0.01

Analytical	Overall count by occupation		Skills share by occupation		Hourly wage		Wage premium (%)		Wage premium ($)	
Top 5	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1	2014-2015	2018-2020 Q1
Accountants and Auditors	3,434	13,285	88%	89%	$36.20	$38.13	-1.22%	0.18%	-$0.44	$0.07
Financial Analysts	3,075	11,400	81%	85%	$46.16	$47.52	-1.13%	0.17%	-$0.52	$0.08
Financial Examiners	387	2,272	63%	74%	$44.63	$41.82	-0.87%	0.15%	-$0.39	$0.06
Actuaries	215	1,147	67%	76%	$53.52	$56.63	-0.94%	0.15%	-$0.50	$0.09
Management Analysts	5,717	25,543	62%	69%	$44.67	$45.36	-0.86%	0.14%	-$0.38	$0.06
Bottom 5										
Health Technologists and Technicians, All Other	701	6,130	0%	0%	$21.51	$22.71	0.00%	0.00%	$0.00	$0.00
Surgical Technologists	577	1,187	1%	1%	$20.97	$23.64	-0.01%	0.00%	$0.00	$0.00
Pharmacists	265	3,424	8%	6%	$56.86	$59.98	-0.11%	0.01%	-$0.06	$0.01
Registered Nurses	11,101	26,025	4%	5%	$32.45	$36.44	-0.05%	0.01%	-$0.02	$0.00
Medical and Clinical Laboratory Technicians	421	2,815	4%	5%	$19.30	$31.47	-0.05%	0.01%	-$0.01	$0.00

Note: The table displays the estimated wage premium by occupation. For each skills group, I select the top 5 and bottom 5 occupations as measured by the share within occupation. I only select occupations that have a sizeable number of total observations across the years studied and whose occupation titles are familiar. The count shows the number of observations in each occupation group. The share of skills per occupation is measured for the years 2014 to 2020 Q1. The wage premium is measured as the multiplication of the coefficient on the skills group times the skills share in the occupation.

Chapter 4 What makes an individual inclusive of others? Development and Validation of the Individual Inclusiveness Inventory

Abstract

This study develops and validates the 'Individual Inclusiveness Inventory'. Collaboration and inclusion have been frequently mentioned as key contributors to successful work outcomes in an increasingly diverse workforce. I aim to capture what makes an individual inclusive of others at work. I define an inclusive individual as someone who actively includes individuals in a group and encourages diversity of thought and background but still encourages the group in a way as to maximise performance and productivity. To develop the 'Individual Inclusiveness Inventory', I combine a deductive and inductive approach: I generate the scale items based on the existing literature on inclusion and inclusive leadership and on interviews with 14 experts in diversity and inclusion. The items are then reduced using exploratory factor analysis and confirmed using confirmatory factor analysis in two samples of working professionals in the UK. This results in a two-factor solution where Factor 1 'Belonging and Uniqueness' captures the importance of fostering belonging and uniqueness at work and Factor 2 'Challenge and Openness' captures being open to challenge and being challenged. I test the predictive validity of this two-factor solution with respect to work outcomes. I find that 'Challenge and Openness' is positively related to all work outcomes studied including income. This link to productivity is intuitive as individuals who are open to challenge are also likely competitive and innovative. 'Belonging and Uniqueness' is positively related to the number of people managed and perceived comparative seniority and happiness. This factor is less predictive of productivity as fostering belonging and uniqueness is likely more about group outcomes or happiness. Overall, this study is highly suggestive that inclusiveness in the workplace which centres around 'Belonging and Uniqueness' is not sufficient to increase productivity. Rather, 'Challenge and Openness' is also necessary.

4.1. Introduction

Workplaces are being disrupted; most recently by the Covid-19 pandemic and more generally by rapid developments in automation (Autor and Dorn, 2013; Chernoff and Warman, 2020). Hybrid work, digitisation and labour shortages, among other challenges, have changed how we work and what is required (Josten and Lordan, 2021). Further, workplaces are becoming increasingly diverse both in terms of their workforce (Shore, Cleveland and Sanchez, 2018) and in terms of tasks being performed (Deming, 2021). Specific skills have been highlighted as increasingly important for the future of work with social and interpersonal skills being particularly relevant (Deming, 2017). As concrete examples of interpersonal skills, inclusion and collaboration are frequently mentioned as contributors of successful work outcomes (Josten and Lordan, 2021).

Collaborative leadership, for example, has been highlighted as a crucial non-cognitive skill that increases in importance in terms of employer demand and gains a wage premium (Josten et al. 2023 forthcoming). Allen et al. (2020) similarly find that collaborative skills have increased in terms of employer's requirements. Cross et al. (2016) find that time spent in collaborative tasks increased by 50% over the past decades. With this rise of collaboration at work and an increasingly diverse workforce, it becomes important to understand the determinants of successful collaboration. One determinant of the quality of collaboration is inclusion (Nishii, 2013; Josten and Lordan, 2021). While team diversity has been shown to improve problem-solving ((Hong and Page, 2004) considering cognitive diversity), decision-making ((Sommers, 2006) considering ethnic diversity) and reduce bias ((Hoogendoorn and Van Praag, 2012) considering gender and ethnic diversity), there is evidence that diversity alone causes friction. For example, diversity can make teamwork costly and less efficient due to conflicts or disagreements (Azmat and Petrongolo, 2014; Bertrand and Duflo, 2016; Lyons, 2017). While diversity concerns the equal representation of different (demographic) groups, inclusion extends diversity to the active involvement and acceptance of such groups (Roberson, 2006).

I argue that inclusive employees are essential to reap the gains from diversity within firms. For example, inclusive individuals make sure all voices in a team are heard and avoid a push to consensus-based decision-making by dominant team members. This argument is supported by the literature. For example. Nishii (2013) finds that teams with an inclusive climate had less conflict. Similarly, Seong and Hong (2013) find that cooperative group norms in teams (e.g., the importance placed on shared interests) moderated negative effects of gender diversity on team commitment. Diversity alone fails to capture the sense of belongingness to a group and having a 'voice' because diverse teams can still exclude group members (Deming and Kahn, 2018).

Given that previous research highlighted that the collaborative aspect of leadership is growing in demand and reward alongside social skills generally (Deming and Kahn, 2018), this study focuses on measuring the social skill of inclusiveness. I argue that individual inclusiveness entails being a collaborative leader with additional qualities of inclusiveness. That is, I define an inclusive individual as someone who actively includes individuals in a group and encourages diversity of thought and background but still encourages the group as to maximise performance and productivity. This collaborative style of an inclusive individual bellies a strategy that puts productivity first by leveraging the voices of all talent. I propose a measurement tool thereof that I call 'Individual Inclusiveness Inventory'.

The contribution to the literature of this study is to create a measure of inclusiveness at the individual level that is increasing in demand (Josten et al. 2023 forthcoming), and its facets such as decision-making or strategic leadership are predicted to be necessary in the future of work (Atalay *et al.*, 2020; Josten and Lordan, 2020; Deming, 2021). The 'Individual Inclusiveness Inventory' builds on the inclusion literature that emphasises the importance of simultaneously satisfying an individual's need for belonging and uniqueness (Shore *et al.*, 2011; Nishii, 2013) and additionally focuses on the link between inclusion and performance (Nishii and Leroy, 2022). Its conceptualisation is most closely related to the literature on inclusive leadership that also attributes inclusion to an individual, i.e., a leader (Carmeli, Reiter-Palmon and Ziv, 2010; Randel *et al.*, 2018; Roberson and Perry, 2022; Veli Korkmaz *et al.*, 2022). This study is, however, unique in analysing inclusiveness as individual trait rather than as behaviour (Carmeli, Reiter-Palmon and Ziv, 2010) or process (Nishii and Leroy, 2022). This provides a broader understanding of what makes an individual inclusive, independent of their position in an organisation. The scale is also self-reported rather than assessed at the organisational (Mor Barak *et al.*, 2016) or the group level (Shore and Chung, 2021).[34] This way, I respond to the research on the growing importance of (specific) social skills in the labour

[34] Short self-reported scales can be administered easily (e.g., in large social surveys) and assess an individual's view of themselves but individuals may be subject to social desirability bias (Rammstedt and Beierlein, 2014). Overall, they have been accepted as form of assessing traits (Rammstedt and Beierlein, 2014).

market and can incorporate it in the Big Five framework as recommended for new scales (Bainbridge, Ludeke and Smillie, 2022).[35]

This work builds on studies that measure inclusive leadership and inclusion. Past research on inclusive leadership put emphasis on theoretical frameworks thereof (Randel *et al.*, 2018; Veli Korkmaz *et al.*, 2022) but highlighted that measurements of inclusive leadership and empirical analyses are scarce (Roberson and Perry, 2022). A study related to this one by Al-Atwi and Al-Hassani (2021) addresses this gap by deductively validating a scale that captures "subordinates' perceptions of their managers' behaviors in relation to supporting inclusion". This study shares the aim of measuring inclusiveness, but this scale differs in the following way: First, the scale is a self-reported personality test filled out by individuals, not their subordinates. I hence capture what makes individuals inclusive independent of their position within a firm. Second, the scale is not just derived in a deductive way based on the relevant literature but also in an inductive way by interviewing experts in diversity and inclusion. The inductive approach moves away from abstract concepts towards a comprehensive understanding of the construct that is grounded in the relevant context (Boateng *et al.*, 2018).

This study derives the 'Individual Inclusiveness Inventory' that is validated following recommended methods for personality scale development (Morgado *et al.*, 2017; Boateng *et al.*, 2018; Carpenter, 2018). I follow an inductive approach to derive items for the scale by conducting interviews with 14 experts in the diversity and inclusion field. The initial development of items is further guided by theory on inclusion; concretely I focus on the optimal distinctiveness theory as organising framework that highlights the need for simultaneously satisfying belongingness and uniqueness in inclusion (Nishii, 2013). After an initial reduction of items based on ambiguity, duplication or bias by academic experts on inclusion, the final set of items is validated through exploratory and confirmatory factor analysis using two large samples of working professionals in the UK. I then test for the predictive validity of the scale for work outcomes (i.e., income, managing people, comparative job seniority/happiness). First, income is a proxy for productivity, and I hypothesise that individual inclusiveness impacts individual productivity. Second, managing people and comparative seniority are both proxies for status productivity (as signals of promotions to a comparatively higher status). Third, I look

[35] The Big Five personality traits assess personality based on the following factors: conscientiousness, neuroticism, extraversion, agreeableness and openness to experience (Costa and McCrae, 1992).

at happiness at work as inclusiveness could affect individual happiness. I lastly compare the scale to the Big Five personality scale as it has been studied frequently and is one of the most all-encompassing personality frameworks that captures individual differences (Bainbridge, Ludeke and Smillie, 2022).

The resulting 'Individual Inclusiveness Inventory' is a two-factor solution. Factor 1 summarises the importance of fostering belonging and uniqueness ('Belonging and Uniqueness') and Factor 2 summarises the importance of embracing challenge ('Challenge and Openness'). Concretely, 'Belonging and Uniqueness' entails statements that centre around actively including individuals at work and being compassionate. 'Challenge and Openness' entails statements centring around inviting conflict that challenge existing viewpoints and being open for new ideas. Both factors predict work outcomes. 'Challenge and Openness' positively predicts all work outcomes including income while 'Belonging and Uniqueness' only predicts managing people and comparative seniority and happiness. That is in line with the literature that highlights two aspects of inclusion as "social inclusion" and "task-related inclusion" (Nishii and Leroy, 2022). The former closely corresponds to the 'Belonging and Uniqueness' factor and is not necessarily related to individual performance outcomes but rather group outcomes or happiness. Fostering belonging and uniqueness may create a climate of inclusion that helps the group strive. The latter corresponds to 'Challenge and Openness' that is related to tasks and productivity. A challenging environment of open discussions allows for high levels of innovation and creativity. When controlling for the Big Five personality traits in a later specification, the coefficient on 'Challenge and Openness' does not change other than for happiness indicating that it has incremental validity. 'Belonging and Uniqueness' does not have incremental validity above and beyond the Big Five. Overall, this work is highly suggestive that inclusiveness in the workplace which centres around 'Belonging and Uniqueness' is not sufficient to increase productivity. Rather, 'Challenge and Openness' is also necessary.

The 'Individual Inclusiveness Inventory' aims to fill the gap of measuring what makes an individual inclusive. It is a valuable tool that can be used by employees interested in testing and altering their level of inclusiveness. Firms can also use it to test individual inclusiveness and can offer upskilling opportunities to increase the level of inclusion in the organisation. It also informs on the skills embedded within inclusive leadership that employers can hone when upskilling their employees on the skills that are relevant in the future of work. It remains to be tested in future research to what extend and how individual inclusiveness can be taught, though there is evidence that social skills are malleable (Almlund *et al.*, 2011).

The paper proceeds as follows: Section 4.1. below summarises the relevant theory. Section 4.2. describes the data and methodology. I broadly follow Boateng et al. (2018) phases of scale development that are item generation (Study 1), scale development using exploratory factor analysis (Study 2), scale evaluation using confirmatory factor analysis (Study 3) and predictive and incremental validity using regression analysis (Study 4). Section 4.3. discusses the results and concludes.

4.1.1. Theoretical framework

Despite inclusion being increasingly mentioned as key contributor to successful work outcomes (Shore *et al.*, 2011; Jansen *et al.*, 2014; Al-Atwi and Al-Hassani, 2021; Josten and Lordan, 2021) and being intrinsically valuable (e.g. for well-being or job satisfaction) (Jansen *et al.*, 2014), the literature on inclusion at work is limited and the definition of inclusion is often confounded with definitions of diversity (Shore and Chung, 2021).

One core theory of inclusion is Brewer's optimal distinctiveness theory (Brewer, 1991). According to this theory, inclusion is achieved when an individual's need for belonging and for uniqueness are simultaneously satisfied. A member of an underrepresented minority (high levels of uniqueness), for example, may seek to belong to another group through being valued and respected whereas someone who conforms with the dominant norms (high levels of belonging) may suffer from not being unique. Individuals differ, however, in the level of need for either, which means that inclusion or exclusion is satisfied at different points for different individuals. Summarising past literature on inclusion, Roberson (2019) further highlights that inclusion entails, for example, to "feel welcomed and valued", to have "access to information, connectedness to supervisors and co-workers, and an ability to influence", to have "access to information, decision-making processes as key factors" and to have "access and influence" more generally. They also highlight that inclusion is about the connection between an individual's characteristics and their workplace environment. Shore et al., (2011) further highlight that inclusion is about "feeling comfortable voicing ideas", which closely aligns with aspects of psychological safety (Edmondson and Besieux, 2021). Inclusion may also mediate conflict, both in terms of task conflict and relationship conflict (Nishii, 2013).

Inclusion is studied in different contexts. One such context is inclusion at the organisational level, which is the individual-level perception of an organisation as being inclusive. That is, the role a company plays in fostering inclusive work outcomes and an inclusive work climate, i.e., a climate where individuals feel they are part of and share interests with other members in the organisation (Mor Barak *et al.*, 2016). Another context is inclusion at the level of the leader of an organisation or a team. That is, the role a leader plays in fostering inclusive work outcomes and how this impacts, for example, team performance (Shore and Chung, 2021). Nembhard and Edmondson (2006) define leader inclusiveness “as words and deeds by a leader or leaders that indicate an invitation and appreciation for others' contributions”. They further highlight that such leaders include others in discussions and decision-making processes and listen to their voice. Randel et al. (2018) conceptualise inclusive leadership as behaviours that foster an individual’s perception of belonginess to a work group and keep up an individual’s uniqueness. Nishii and Leroy (2022) extend the belonging and uniqueness conceptualisation of inclusion by the instrumental side of inclusion in relation to work outcomes; they define inclusive leadership as “engaging meaningfully and strategically in goal-directed behavior at work”. In a systematic literature review of the inclusive leadership literature, Veli Korkmaz et al. (2022) also highlight that inclusive leadership is more than just fostering an employee’s uniqueness and increasing belonging to a team. Concretely, they find that showing appreciation of employees is important alongside supporting organisational efforts. Roberson and Perry (2022) take an inductive approach to define inclusive leadership. They survey a sample of 27 healthcare leaders and ask them questions on inclusion such as, what inclusive leadership is. A thematic analysis of the survey yields detailed themes related to inclusive leadership such as “Recruiting, hiring, and retaining a diverse staff” or “Inviting disagreement and debate”. They also highlight the importance of leaders being open (i.e., encouraging employees to take risks, being open to other employee’s views or facilitating open conversations). Their study does not measure inclusion but highlights that it would be important for future research to do so.

The approach of developing a scale that captures what makes an individual inclusive is most closely related to the literature on inclusive leaders. The creation of inclusive environments is often unattainable for organisations but rather depends on individual agents (Shore and Chung, 2021). The scale is built on the theoretical framework of the research cited above focusing concretely on an individual’s ability to foster co-workers’ uniqueness and belonging. Similarly, to Roberson and Perry (2022), I take an inductive approach to defining inclusion. Further, I aim at defining inclusiveness as general as possible. Past literature often discusses inclusion either in relation to diversity (i.e., inclusion of diverse individuals) or in relation to leadership research more broadly (e.g., the importance of shared decision-making and empowerment of employees) (Roberson and Perry, 2022; Veli Korkmaz *et al.*, 2022). In comparison, I aim at defining inclusion more broadly. I follow an inductive approach that captures what makes an individual inclusive according to the view of experts in the field.

I assume a latent character trait of being inclusive of others as it is difficult to measure individual inclusiveness directly. As compared to inclusion at the organisational level, I am less concerned with perceptions (i.e., the perception of belonging) but focus on the active part of inclusion at the individual level (i.e., inclusive traits). This focus shifts the attention to the individual. Further, the scale is self-reported to be able to comment on the personality of individuals who promote inclusive behaviours.

Emerging research shows that the Big Five personality traits (i.e., agreeableness, conscientiousness, extraversion, neuroticism and openness to experience) relate to inclusive work climates. Nishii and Leroy (2021) collect data from employees of a wholesale distribution company who were asked about the inclusiveness of their work unit alongside the Big Five personality scale and find that there is a positive relationship between both extraversion and openness and inclusive climate. This finding can be explained with the interpersonal nature of both traits. Neuroticism was negatively related to inclusive climate and there was no significant effect of conscientiousness and agreeableness. The relationship between inclusive work climate with the Big Five motivates the analysis of inclusion at the individual level. It further motivates the study of the individual inclusiveness scale alongside the established Big Five personality traits to test for similarities. Given that the Big Five framework is among the most-established taxonomies of personality traits and many assessments of psychological traits can be located within the Big Five, I collect data on the Big Five to validate the scale (Bainbridge, Ludeke and Smillie, 2022).

Studying inclusion at the individual level helps individuals to self-assess whether they are inclusive of others in a collaborative work context and to what extent they can work on being more inclusive. While the Big Five personality traits have been shown to be malleable over the life course (Borghans *et al.*, 2008), I expect inclusiveness to be even more malleable as many of its facets such as leadership skills or communication skills have been shown to be more malleable than personality (Martin-Raugh, Williams and Lentini, 2020). Knowing which facets of individual traits influence work outcomes through inclusion can help individuals and companies in fostering inclusion at work. Ultimately, the scale can be used for experiments that test the impact of individual inclusiveness in different work contexts such as, for example, its impact on team performance. Research on the effect of inclusion on individuals and groups is limited and contributes to an improved understanding of the field (Roberson, 2019).

4.2. Data and Methodology

Development and Validation of the Individual Inclusiveness Inventory

4.2.1. Study 1: Item generation

This study aims at defining a scale that captures the latent construct of inclusion at the individual level. I assume inclusion as an individual characteristic that cannot be measured directly but indirectly through a series of items. In this first study, I generate a lengthy series of possible items to be considered as relevant for the inclusiveness scale. This is done in both a deductive way by basing the items on theory of inclusion and an inductive way by interviewing experts in diversity and inclusion. I generate a lengthy series of items through a thematic analysis of the interviews alongside a review of the inclusion and inclusive leadership literature. In this exercise I aim for completeness. I then cluster the items according to themes that align with the inclusion literature. This way an inductive and a deductive approach in scale development is combined as recommended by Morgado et al. (2017), among others. By following the content of the interviews, I follow current trends in inclusion closely and account for a novel measure of inclusiveness.

Sample

I interviewed a total of fourteen individuals who have academic and/or professional expertise in diversity and inclusion topics (see Table 4-7 in Appendix 4.A for a list of the anonymised interviewees and their roles). In total, I contacted thirty-six individuals either directly via email or via the professional networking platform LinkedIn. In the message, I indicated that I wanted to “interview thought leaders in the diversity and inclusion space to better understand how [they] understand the meaning of inclusion and what makes individuals inclusive”. I further explained the aim of this study of developing a scale and provided some information on the interviewer. Twelve individuals either did not want to be interviewed or did not reply to the message. Of the fourteen individuals interviewed, three were men and eleven were women.

Their job titles range from consultant, professor, start-up founder, diversity and inclusion officer to banker. They all have either work experience in diversity and inclusion and/or behavioural science more generally and/or have publicly talked about and/or written on diversity and inclusion topics. The average interview length was 30 minutes.

Method

The interviews were conducted as semi-structured interviews with open-ended questions. I started each interview with a question on how the interviewee understands the meaning of inclusion and on what makes individuals inclusive. The subsequent questions depended on the interview progression, but all centred around aspects of inclusion and inclusiveness. Interviewees were asked for their verbal consent to be interviewed and for the interview to be recorded at the beginning of the interview. They were also informed that no individual identifying information of the interview would be published but that the interview would be used as an input to the inclusion scale. All fourteen interviewees consented. The verbal consent form can be found in Appendix 4.A. I transcribed the interviews manually using the recordings. Transcriptions are then thematically analysed. A thematic analysis describes the analysis of qualitative data by identifying themes and organising the data (Braun and Clarke, 2006). In the case of this study, the goal is the generation of a series of items that relate to inclusion that are as complete as possible.

I followed Braun and Clarke's (2006) phases of thematic analysis. I started by familiarising myself with the transcribed data. I generated initial codes and came up with short labels for the sentences and then generated themes. When generating themes, I incorporated the theoretical framework of inclusion of belonging and uniqueness (Nishii, 2013). After reviewing the themes and adding the items based on the theoretical framework of inclusion, I came up with 150 items in total. The items were written in simple, easy to understand language that is not deceptive or ambiguous. In the original set of items, I was being overinclusive and included even items overlapping in terms of content and the way they are phrased. Further, I provided situational context for the inclusiveness items as it improves the criterion validity of inclusiveness scores (Lievens, De Corte and Schollaert, 2008). For example, I phrased some items in the context of work (e.g., "I have called out wrong behaviours and microaggressions <u>at work</u>.") as scale is later linked to work outcomes. I followed a latent rather than a fully semantic approach when analysing the transcriptions that involves reading into the transcriptions and making assumptions about the underlying the data.

Three academic experts in inclusion and inclusive leadership research screened the items for redundancy, biased language, jargon, typos and appropriateness to increase the content validity of the items as recommended (Boateng *et al.*, 2018; Kyriazos and Stalikas, 2018). There is a trade-off in the number of items to keep. While having as many items as possible improves the internal consistency and avoids item-specific measurement error (Boateng *et al.*, 2018), having too many items is impractical and may reduce response rates and the respondent's quality of reply (Stanton *et al.*, 2002). I reduced the initial sample of 150 items to 80 total items. I aimed to have a scale that is no longer than the short version of the Big Five personality traits that contain 15 items in total and five factors. Short scales of this length have high usability and compatibility for use in larger surveys while still maintaining reliability and validity if tested appropriately (Rammstedt and Beierlein, 2014). It is recommended to have about five times as many items that one aims for (i.e., 5x15=75) and 80 therefore is reasonable (Boateng *et al.*, 2018). Having fewer items reduces the time needed to take the survey from around 19 minutes to 10 minutes, which is preferable to increase participant's concentration. Of those items, seven are reverse coded. I tried to keep the reverse coded questions limited as they are less reliable than positively worded items (Jansen *et al.*, 2014). The items are input for the survey that is answered on a 7-point Likert scale ranging from strongly disagree to strongly agree.

Table 4-1 below shows the ten themes identified in the item generation process from the transcriptions of the interviews and it also shows an example survey item per theme. There are ten interconnected themes in total, which are 'openness', 'appreciation', 'authenticity', 'conflict', 'decision-making & voice', 'collaboration', 'empathetic listening', 'belonging and uniqueness', 'self-reflection' and 'embracing uncertainty/trust'.

Openness has already been highlighted in the literature as key aspect of inclusion (Nishii and Leroy, 2021). Openness to ideas and change has been pointed out in the interviews as crucial for inclusion. Appreciation entails the appreciation of co-workers, which relates to topics highlighted by Roberson (2019) on feeling valued. Authenticity was mentioned where interviewees said that being authentic helps other co-workers to speak up and thereby creates an inclusive climate, for example. The need for authenticity in inclusive leadership is also highlighted by Nishii and Leroy (2022). Embracing conflict that is not about relationships but about the task at hand was also pointed out and speaks to the literature that highlights the importance of inviting disagreement (Roberson and Perry, 2022) or mediation of conflict

(Nishii, 2013). Decision-making and giving a voice to others were highlighted as key traits of an inclusive individual. That is very closely related to the definition of an 'inclusive leader' (Roberson and Perry, 2022). Collaboration entails promoting positive team dynamics. Empathetic listening, a joint theme that focuses on the listening aspect of empathy, is also crucial for being inclusive (Nishii and Leroy, 2021). Belonging and uniqueness centres around fostering the belonging to a group for co-workers while still appreciating their uniqueness. It is in line with Brewer's optimal distinctiveness theory where an individual's need for belonging and for uniqueness are simultaneously satisfied (Shore *et al.*, 2011). Self-reflection is in a way also related to empathy and encompasses the ability to critically evaluate oneself. The final theme is embracing uncertainty and to trust. The idea is that inclusive individuals do not try to micro-manage others but trust them in what they do and thereby also embrace uncertainty, in order to give their colleagues autonomy over their own tasks (i.e., uncertainty of not knowing everything).

Table 4-1: Themes and exemplary scale items as derived from thematic analysis

Themes identified	Item example
Openness	Change makes me feel uncomfortable. (*)
Appreciation	I value the input of other people around me who are similar to myself and of those who are very different to myself.
Authenticity	I try to be authentic to myself at work.
Conflict (task versus relationship)	I raise issues with my boss even if I fear backlash.
Decision-making & voice	I value the judgement of others with different backgrounds to me before being able to make a confident decision.
Collaboration	Having a diverse group of people work together improves business outcomes.
Empathetic listening	At work I am compassionate when others tell me about their issues.
Belonging & uniqueness	I seek to work with different co-workers where possible.
Self-reflection	I seek out negative feedback.
Embracing uncertainty/trust	I encourage others around me to take risks.

Note: The table shows the themes as they are identified from a thematic analysis. The right column shows an example for each theme of an item that was derived. The items are answered on a 7-point Likert scale ranging from strongly disagree to strongly agree. The * star indicates that the item is reverse-coded.

4.2.2. Study 2: Scale Development using Exploratory Factor Analysis

To derive the 'Individual Inclusiveness Inventory', I use the 80 items derived in Study 1 above. I further reduce and validate the 80 items drawing on an exploratory factor analysis and then run a confirmatory factor analysis using data I gather from a sample of professionals residing in the UK. The goal is to further reduce the items to get a short version of the individual inclusiveness scale that can be used by firms and individuals to understand their levels of inclusiveness. Shorter self-reported scales are frequently used for measuring latent psychological constructs (Rammstedt and Beierlein, 2014). I validate the importance of this measure further in in Study 4 by linking it to work outcomes.

Sample

The sample consists of 400 individuals in total who reside in the UK and work full-time in knowledge occupations (i.e., professionals). It is recommended to have a sample to item ratio of at least 5 times the number of items, which in the case of 80 items is a sample of at least 400 (Suhr, 2006; Carpenter, 2018). I first collect 400 observations in total to run the exploratory factor analysis ('Sample 1') and then later confirm the findings in a confirmatory factor analysis using a second sample of 400 observations that are collected two months later ('Sample 2'). I recruited the sample through the online survey platform Prolific (https://www.prolific.co/) that produces high quality data for research purposes (Peer *et al.*, 2017; Palan and Schitter, 2018). The sample is restricted to professional workers who work full-time. It is gender balanced. In addition to the 80 items, I also ask for work outcomes and Big Five personality traits that are used in Study 4 below to test the scale's predictive and incremental validity.

The survey was coded online in the survey platform Qualtrics (https://www.qualtrics.com/). I generated a link that could be opened by survey participants on both their computer and their smartphone. The survey begins with a consent form. I filter the sample for individuals who gave positive consent only. The core part of the survey consists of the items on individual inclusiveness as described in Study 1 above. Individual inclusiveness items were block randomised with a total of 10 items per block. The blocks and the item order within each block was randomised for each survey respondent to maximise item validity (Clifton, 2020). The survey included two attention checks to ensure survey quality and participant attention (Aust *et al.*, 2012; Kung, Kwok and Brown, 2018; Gummer, Roßmann and Silber, 2021). Everyone in the sample passed the attention checks. In addition to the individual inclusiveness items, I included questions on age, gender, job title, ethnicity, born in the UK, nationality, annual income, industry and education. Further, I asked whether individuals managed others at work and how many people they manage at work. I also asked individuals how their level of seniority and level of happiness compared to co-workers who started at the same time as them (i.e., higher, similar or lower). Participants also filled out the Big Five personality scale, a personality framework that captures conscientiousness, neuroticism, openness, agreeableness and extroversion (Costa and McCrae, 1992). I used the short version consisting of 15 questions answered on a 7-point Likert scale ranging from strongly disagree to strongly agree (Heineck and Anger, 2010).

Method

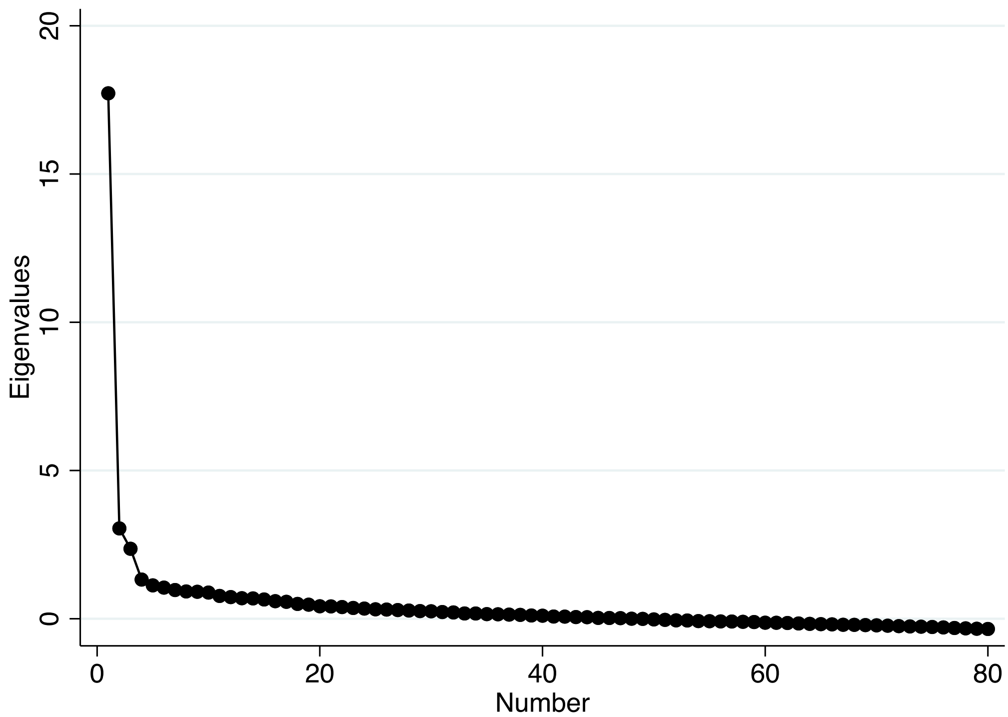
Item reduction and factor extraction is done to ensure that only relevant items are included that are functional and internally consistent (Boateng *et al.*, 2018). Exploratory factor analysis is a latent variable model that treats the observed variables (i.e., items) as measures of latent variables. It aims to find the smallest number of interpretable factors to explain the correlations among observed items sufficiently. This is ensured through high loadings of the observed items on the latent factors. The value of using exploratory factor analysis in this scenario is also practical. By reducing the dimensionality, I can create a measurement tool that can be used by firms and individuals to measure inclusive leadership.

For the exploratory factor analysis, 'Sample 1' of 400 professional workers is used. To determine the number of factors to retain I use three criteria: First, I examine the scree plot for a jump (i.e., a jump in the eigenvalue of a factor[36]), a cumulative variance explained of the components of at least 60% and choosing factor cut-offs that are sensible and intuitive (Bartholomew *et al.*, 2011). Figure 4-1 below shows the scree plot where the eigenvalue depicted on the y-axis levels off after two to three components. Two components explain 58% of the cumulative variance explained and three explain 64%. The commonly suggested threshold for the cumulative variance explained of at least 60% in the social sciences (Hair *et al.*, 2010). A fourth factor would explain 67% of the cumulative variance.

[36] An eigenvalue of a factor indicates the amount of variance the factor explains (Suhr, 2006).

Second, I perform an oblique rotation with three factors that allows factors to be correlated. I then follow the approach recommended by Heckman et al. (2012). Specifically, I remove items that load on more than one component (cross-loadings) and items that have a loading of smaller than 0.4 (weak loadings). The final factors have no items that are weakly loading nor cross loading and they correlate freely. The result of the rotation with three factors can be seen in Table 4-2 below. The third factor explains a relatively small additional proportion of variance (i.e., 6%) and as per Table 4-2 has comparatively low loadings (i.e., no loadings greater than 0.5). Further, all the items that load on the third factor are reverse coded, which may result in methodological issues (e.g., contamination of the factor structure or lower internal consistency through random measurement error) (Basso and Krpan, 2022). I hence decide to drop the third factor.[37]

Figure 4-1: Scree plot of the exploratory factor analysis



Note: The figure shows the scree plot of running an exploratory factor analysis using 80 survey items on individual inclusiveness. The y-axis depicts the eigenvalue of each factor.

[37] It is common to drop the final factor for either conceptual or statistical limitations (Basso and Krpan, 2015).

Table 4-2: Rotated factor loadings

Individual Inclusiveness Inventory items	Factor 1	Factor 2	Factor 3
I actively include individuals when working as a team.	**0.7107**		
I believe that work productivity depends strongly on a positive work climate.	**0.686**		
At work I am compassionate when others tell me about their issues.	**0.6545**		
When working as a team I promote positive team dynamics.	**0.6514**		
When leading a team, project or discussion, I want to facilitate ideas and encourage individual thinking.	**0.6215**		
Trust between co-workers is key for success.	0.6137		
I value the input of other people around me who are similar to myself and of those who are very different to myself.	0.6008		
I make conscious efforts to be inclusive.	0.5995		
I try not to exclude anyone at work.	0.5921		
I ensure everyone is able to participate and is included when sending out work emails or arranging meetings.	0.591		
I communicate and interact with individuals in my team actively.	0.566		
A leader of the future should be collaborative rather than just competent.	0.5618		
I acknowledge everyone's uniqueness when working with others	0.5553		
I am committed to listen and not just talk in meetings.	0.5539		
I engage people actively in conversations, activities, and tasks at work.	0.5387		
I provide others with opportunities where possible at work.	0.5381		
I try to allocate tasks/promotions/my time fairly to co-workers.	0.5326		
I can empathise with people who are different to myself.	0.5175		
I recognise when people are different to myself.	0.5162		
Having a diverse group of people work together improves business outcomes.	0.514		
I believe it is important to get on with colleagues.	0.5105		
I seek to hear about my colleagues' individual stories to gain new insights I am unfamiliar with.	0.5074		
I try to be authentic to myself at work.	0.502		
In a high stakes decision-making process, I value collaborative discussions even if that takes up valuable time that could otherwise speed up the process.	0.4911		
I think about how different people might be affected differently by my decisions.	0.4879		
I listen to others even if I believe my ideas are superior.	0.4715		

Individual Inclusiveness Inventory items	Factor 1	Factor 2	Factor 3
I value the judgement of others with different backgrounds to me before being able to make a confident decision.	0.4393		
At work, I admit mistakes openly and quickly.	0.4329		
I seek out data and evidence to back up decisions and work processes.	0.4137		
I am sensitive to unfair situations and try to solve such issues.	0.4054		
I communicate and interact with individuals outside of my team actively.	0.4026		
I invite conflict that challenges established viewpoints		**0.6168**	
I welcome disagreement with my own positions.		**0.6136**	
I challenge the people around me to perform at their best even if they do not ask for it.		**0.5525**	
I believe conflict is important if it is about a task at hand.		**0.5434**	
Outlier ideas excite me.		**0.5421**	
I encourage others around me to take risks.		0.5315	
At work I like to challenge myself and colleagues alike.		0.5247	
I seek out negative feedback.		0.5186	
I have recently connected individuals who I think should talk to each other.		0.4799	
I seek to work with different co-workers where possible.		0.4762	
I actively seek out disconfirming evidence to question decisions and processes at work.		0.4489	
I embrace difficult and hard conversations at work.		0.4276	
When being in charge of a task, I get easily nervous when things go unplanned.*			0.527
Change makes me feel uncomfortable.*			0.5138
There are some colleagues in my team I would not challenge.*			0.4986
Negative feedback frustrates and discourages me.*			0.4623

Note: The table shows the rotated factor loadings of a two-factor solution that are greater than 0.4. Items with no loadings of greater than 0.4 and cross-loadings were removed. Items and factors that are bold are part of the final two factor solution of the 'Individual Inclusiveness Inventory' as confirmed in the confirmatory factor analysis below. Factor 1 entails the tendency of an individual to foster other people's belonging to and uniqueness in a group while Factor 2 entails the tendency of an individual to embrace challenge and be open. * Indicates an item is reverse coded.

The two-factor solution of the 'Individual Inclusiveness Inventory' distinguishes two aspects of inclusiveness. Factor 1 that I label 'Belonging and Uniqueness' captures the social skills that are crucial for being inclusive, focusing on the extent to which an individual actively promotes inclusion with co-workers. An example is the following item: "I actively include individuals when working as a team." 31 items load highly (i.e., loadings of greater than 0.4) on Factor 1 'Belonging and Uniqueness'. All the items describe making a conscious effort to gather co-workers' ideas and empathetically facilitating positive group outcomes.

Factor 2 that I label 'Challenge and Openness' focuses on the skill of embracing challenge. There is a cluster of items that focus on the ability to speak up and to confront conflict. In other words, Factor 2 'Challenge and Openness' encourages individuals to embrace dissent. An example is: "I invite conflict that challenges established viewpoints". An inclusive individual challenges but equally wants to be challenged. 13 items load highly (i.e., loadings of greater than 0.4) on Factor 2 'Challenge and Openness'. From this initial assessment, the content validity of the new scale does reflect the desired construct of individual inclusiveness as it combines theoretical constructs and the outcome of the interviews (Morgado *et al.*, 2017).

In essence, Factor 2 'Challenge and Openness' captures an aspect of inclusion where there is a clear line to productivity. If a person is open to being challenged and challenging others it sets up an environment where, provided there is a sufficient level of cognitive diversity, discussions will allow for high levels of innovation and creativity. In contrast, Factor 1 'Belonging and Uniqueness' does not have such a clear line to productivity. For example, it might happen that individuals over-focus on shared information as a route to maintaining team harmony.

Factor 1 and Factor 2 are aggregated scores of their respective five underlying items. I choose not to aggregate the two factors to a joint higher order construct given they are distinct facets of individual inclusiveness and correlate moderately with a correlation of 0.36. I standardise the factors (i.e., mean of zero and standard deviation of one) to improve interpretation and ensure comparability with the Big Five traits in the subsequent regression analysis. Further, each of the two factors exhibits a very high scale reliability with a Cronbach's alpha of 0.93 for Factor 1 and of 0.84 for Factor 2. A Cronbach's alpha captures the extent to which items of a scale represent the latent construct measured through inter-item covariance of the items (Cronbach, 1951; Rammstedt and Beierlein, 2014). Cronbach's alpha of at least 0.7 are recommended to ensure scale reliability (Morgado *et al.*, 2017).

4.2.3. Study 3: Scale Evaluation using Confirmatory Factor Analysis

I conduct a confirmatory factor analysis to validate the fit of the two-factor solution of the 'Individual Inclusiveness Inventory'. The sample used is 'Sample 2' that consists of 400 additional individuals and was collected two months after 'Sample 1' described above. It is recommended to confirm the factor structure in a new sample (Boateng *et al.*, 2018). 'Sample 2' is collected in the same way through Prolific like 'Sample 1' and restricted to individuals who work full-time in knowledge occupations. I follow the criteria for selecting items for confirmatory factor analysis by Basso and Krpan (2022). That is, I first aim at developing a scale that meets high psychometric standards but is also easy to administer with a minimum number of three items per factor. Second, I follow their threshold for item loadings to be higher than 0.5 and not have cross-loadings higher than 0.32. Third, I also aim at choosing a broad and non-repetitive selection of items. Based on these criteria, I choose to keep five items for Factor 1 and five items for Factor 2. Five items fulfil the criteria to have at least three items per factor. In this study, the choice of five items per factor is also sensible: The first five items that load highest on Factor 1 'Belonging and Uniqueness' fit very well and comprehensively into the theoretical framework of inclusion combining uniqueness and belonging (i.e., compassionately listening to others and fostering inclusive work climates) (Veli Korkmaz *et al.*, 2022). The first five items that load highest on the Factor 2 'Challenge and Openness' fit with the aspect of inclusion that has been mentioned in the literature of mediating conflict (Nishii, 2013) and openness (Nishii and Leroy, 2021) (i.e., challenging others and being challenged). The items further overall summarise what has been said in the inductive interviews with experts very well.

Goodness of fit was assessed using the Tucker-Lewis Index (TLI), the comparative fit index (CFI), the standardized root mean square residual (SRMR) and the root mean square error of approximation (RMSEA) (Harrington, 2009). The cut-off values for these measures show that this model exhibits good fit with CFI>0.9, TLI>0.9, RMSEA close to 0.06 or less, SRMR close to 0.08 or less (Harrington, 2009). Structural equation models were run using a maximum likelihood method. This resulted in fit indexes in 'Sample 2' (N=400) of CFI=0.95; TLI=0.93; RMSEA=0.06; SRMR=0.05 as per Table 4-3. I further tested the fit of a one-factor model as compared to the hypothesised two factor solution. The alternative model had worse fit in terms of CFI, TLI, RMSEA and SRMR and fit the data significantly worse as shown by a significant chi-squared difference test ($\Delta df = 1$, $\Delta\chi^2 = 180.89$, $p < 0.001$). I also assessed whether the initial three-factor solution with a lower loading cut-off for the items of 0.4 had better fit but it also performed worse than the hypothesised model. The confirmatory factor analysis provides strong evidence supporting two factors for the 'Individual Inclusiveness Inventory'.

Table 4-3: Confirmatory factor analysis fit indices

Model specification	df	χ^2	Δdf	$\Delta\chi^2$	CFI	TLI	RMSEA	SRMR
Hypothesised model: Two factors	34	77.32			0.95	0.93	0.06	0.05
Alternative model: One factor	35	258.21	1	180.89*	0.71	0.63	0.14	0.10

Note: The table shows values for the Tucker-Lewis Index (TLI), the comparative fit index (CFI), the standardized root mean square residual (SRMR) and the root mean square error of approximation (RMSEA). df stands for degrees of freedom. *p<0.001

4.2.4. Study 4: Predictive and Incremental Validity using Regression Analysis

In Study 4, I test for the predictive validity of the 'Individual Inclusiveness Inventory' for various work outcomes. I further test for its incremental validity as compared to the Big Five personality scale.

Sample

The sample for Study 4 consists of the combined sample of 'Sample 1' (i.e., the sample used for the exploratory factor analysis in Study 2) and 'Sample 2' (i.e., the sample collected two months later for the confirmatory factor analysis in Study 3) as described in detail in Study 2 in section 4.2.2. above. The full sample consists of 800 observations of individuals residing in the UK and working full-time in professional occupations. The samples are recruited through Prolific and are gender balanced. The data includes the individual inclusiveness items in addition to information on age, gender, job title, ethnicity, born in the UK, nationality, annual income, industry and education. Further I ask whether individuals managed others at work and if yes, how many. I then asked for comparative seniority and happiness (i.e., how their level of seniority or happiness respectively compares to that of co-workers who started at the same time as them). The data also contains the Big Five personality scale. Table 4-8 in Appendix 4.A shows a table of summary statistics for the main variables studied (i.e., their mean, standard deviation, minimum and maximum).

Method

I test the predictive and incremental validity of the 'Individual Inclusiveness Inventory' using regression analysis. Concretely, I test whether the scale predicts work outcomes and how it compares to the Big Five personality scale.

The hypothesis taken in this study as regards to work outcomes is that the factors 'Belonging and Uniqueness' and 'Challenge and Openness' of the 'Individual Inclusiveness Inventory' each predict work outcomes but potentially in a different way.

First, I consider the link of both factors to income. Income is measured as the logarithm of median income within income brackets of an individual's annual salary before taxes including bonus where the brackets are £1 to £9,999, £10, 000 to £24,999, £25, 000 to £49,999, £50, 000 to £74,999, £75, 000 to £99,999, £100, 000 to £149,999 and £150,000 or more. Personal income is a proxy for productivity that has been analysed frequently to capture the direct link between non-cognitive skills and work performance (Nyhus and Pons, 2005; Heckman, Stixrud and Urzua, 2006; Borghans *et al.*, 2008). Factor 2 'Challenge and Openness' has a clear link to productivity with individuals who are open to challenge at work likely being innovative and competitive. The link of Factor 1 'Belonging and Uniqueness' to productivity is less obvious. If being cooperative is valued in an occupation, this may translate to higher earnings. However, individuals who score high on 'Belonging and Uniqueness' may also over-focus on the belonging and uniqueness of others in the team over their personal success thereby foregoing earnings. In other words, they may create happy teams that are not necessarily (individually) productive.

Second, I also analyse whether the scale predicts the number of people an individual manages. This is defined as the median number of people the respondent manages ranging from zero to more than 50 in brackets (i.e., 1-3, 4-5, 11-50, more than 50). I choose managing people as another proxy of productivity as the labour market promotes individuals to positions with higher pay and/or higher status (as expressed through more management responsibility) (Hoffman and Tadelis, 2018). Both income and managing people are noisy proxies for productivity given that there are many unobserved variables such as social background or biases that affect income and status at work (e.g., being tall affects promotions but is unrelated to productivity) (Kuhn and Weinberger, 2005). Across all specifications, I control for observable factors such as gender, age, ethnicity, born in the UK, education and industry fixed effects to account for omitted variables. Each of those control variables has a link to work outcomes. Industry fixed effects, for example, control for industry-specific differences in rewards to non-cognitive skills.

Third, I link the 'Individual Inclusiveness Inventory' to respondents' perceptions of how they compare their level of seniority to people who started working at the same time as them. The comparative seniority outcome variable is an ordered categorical variable that goes from one to three (i.e., lower, similar to higher comparative seniority). Perceived seniority is another proxy of status productivity (i.e., someone believing they have high relative seniority may capture their productivity at work). I choose comparative seniority as an outcome because inclusion at work is about connectedness to co-workers and impacts how individuals feel treated as compared to others (Nishii and Leroy, 2022).

Fourth, I link the scale to the respondent's perceptions of how they compare their level of happiness at work to people who started working at the same time as them. The comparative happiness outcome variable is an ordered categorical variable that goes from one to three (i.e., lower, similar to, higher comparative happiness). Comparing one's level of happiness to peers at work can provide insights into how social comparison processes at work impact individual well-being. Social comparison is a process where people evaluate themselves and their own abilities by comparing themselves to others (Mor Barak *et al.*, 2016). Inclusive leadership has been analysed as a behaviour that creates connectedness within organisations and the concept of inclusion is associated with an individual's need to affiliate with others (Roberson and Perry, 2022). In the workplace, people may compare their level of happiness to their colleagues to gauge their own well-being and job satisfaction. Perceived happiness is hence a proxy of job satisfaction and happiness at work. Non-cognitive skills have been linked to job satisfaction or happiness (Judge, Heller and Mount, 2002; Lee and Ohtake, 2018). I hypothesise that 'Belonging and Uniqueness' has a positive effect on comparative happiness given the link between inclusion and connectedness at work. The link of 'Challenge and Openness' for happiness is also predicted to be positive given that income positively links to overall happiness (Killingsworth, Kahneman and Mellers, 2023).

Concretely, I run the following linear regression to test the predictive validity of the two-factor solution:

$$y_i = \alpha + \beta Factor1_i + \delta\, Factor2_i + \delta Factor1_i x Factor2_i + Controls_i + \mu_i \quad (4.1)$$

where y_i is the work outcome of individual i (i.e., the logarithm of median income, managing people, comparative seniority, comparative happiness). Factor 1 and Factor 2 are the aggregated scores for the five underlying items for each factor respectively for individual i. I standardise Factor 1 and Factor 2 to have a mean of zero and a standard deviation of one to help the interpretation of the coefficients and to ensure comparability with the standardised Big Five personality traits in later specifications. The controls include gender, age, ethnicity, born in the UK, education and industry fixed effects. μ_i represents the error term.

Overall, for each of the four outcomes (i.e., logarithm of income, managing people, comparative seniority, comparative happiness), I run three specifications: First, I run the regression without controls. Second, I run the regression with controls. The controls include gender, age, ethnicity, born in the UK, education and industry fixed effects. Adding demographic controls such as gender adjusts for important observed determinants of work outcomes and hence increases the internal validity of the specification. Industry fixed effects account for within industry differences in rewards to social skills.

Third, I run the regression with controls and add the interaction of Factor 1 and Factor 2. In a separate specification, I add the interaction of the two factors Factor 1 'Belonging and Uniqueness' and Factor 2 'Challenge and Openness' to the basic specification with controls. Adding interactions allows us to explore the benefits that high levels of both traits bring in terms of explaining individual-level productivity and wellbeing. It is also an approach recommended when factors are not strongly correlated (Credé, 2018) (i.e., the correlation of Factor 1 and Factor 2 is 0.36 as per Table 4-9 in Appendix 4.A).

Fourth, I also add the Big Five personality traits conscientiousness, neuroticism, extraversion, agreeableness and openness. This approach of placing newly derived personality scales in the framework of established pre-existing scales has been recommended by Bainbridge, Ludeke and Smillie (2022) for the following advantages: First, it allows for comparison with existing research given the Big Five have been studied frequently, which makes establishing the validity and reliability of the 'Individual Inclusiveness Inventory' easier. Second, given that the Big Five personality scale comprehensively captures the major dimensions of personality, it helps to locate the 'Individual Inclusiveness Inventory' in a wider framework. It also ensures that I am measuring a new aspect of personality that is not already captured by the Big Five. Third, it makes it easier to integrate the 'Individual Inclusiveness Inventory' with existing scales given the Big Five has been administered frequently. I can thereby analyse to what extent the scale predicts work outcomes above and beyond or as part of the Big Five personality traits.

Predictive validity: Regression results

Table 4-4 documents the results from running regression (4.1) above. I start with the logarithm of median income outcome, which is a proxy for individual productivity, in the most basic regression without controls. Specification (1) highlights that Factor 1 'Belonging and Uniqueness' is not statistically significant, while a one standard deviation increase in Factor 2 'Challenge and Openness' predicts an increase the median income by 8%. Adding demographic controls in specification (2) adjusts for important observed determinants of work outcomes.

Industry fixed effects further account for within-industry differences in rewards to social skills. The impact on median income of Factor 2 reduces to 7% while Factor 1 remains insignificant. The overall conclusions are also robust to adding the interaction in specification (3) that again is insignificant. Overall, the findings highlight that Factor 2 'Challenge and Openness' is a strong and robust predictor of individual income. In contrast, Factor 1 'Belonging and Uniqueness' is not.

I now turn to the results pertaining to the number of people an individual manages, an alternative proxy of status productivity, documented in columns (4)-(6) in Table 4-4. Column (4) shows that both factors positively predict the number of people an individual manages. A one standard deviation increase in Factor 1 'Belonging and Uniqueness' predicts an increase of 0.81 people managed. A one standard deviation increase in Factor 2 'Challenge and Openness' predicts an increase of 1.15 people managed. When adding controls to column (5), Factor 1 loses its significance while the effect of Factor 2 is attenuated. This may be because the demographic controls such as gender, age, born in the UK, education affect both the outcome and the independent variable. For example, gender may be associated with other factors that affect both managing people and 'Belonging and Uniqueness' such as the choice of career paths. Industry fixed effects further control for sorting (e.g., individuals who score high on 'Belonging and Uniqueness' may choose industries that have flatter hierarchies and hence less opportunity for management). When further adding the interaction of the two factors in specification (6), Factor 1 becomes significant again with a one standard deviation increase in Factor 1 predicting an increase in the number of people managed of 1.01 and a one standard deviation increase in Factor 2 to one of 1.26. The interaction effect is also positive and significant with a coefficient of 0.74. This finding highlights the predictive validity of the two-factor solution in terms of people management.

Seniority also captures status rewards for productivity. From Table 4-4, I can conclude that both factors individually are positive and significant predictors of comparative seniority (see columns (7)-(9) in Table 4-4. For example, in the most detailed specification depicted in column (9) a one standard deviation increase in Factor 1 'Belonging and Uniqueness' predicts an increase perceived seniority compared to co-workers by 0.08 and Factor 2 'Challenge and Openness' by 0.07. This variable is ordered from one (lower seniority) to three (higher seniority).

Finally, Table 4-4 documents the results for comparative happiness in columns (10)-(12). Comparative happiness is the happiness of the individual as compared to co-workers who started at the same time as them and is ordered from one (lower happiness) to three (higher happiness). Both Factor 1 'Belonging and Uniqueness' and Factor 2 'Challenge and Openness' are positive and significant predictors of comparative happiness, while the coefficient of the interaction between the two factors is centred around zero and not significant. In the most detailed specification (12) including controls, a one standard deviation increase in Factor 1 'Belonging and Uniqueness' predicts an increase in comparative happiness by 0.05 and a one standard deviation increase in Factor 2 'Challenge and Openness' predicts an increase by 0.06.

Table 4-4: Predictive validity of the 'Individual Inclusiveness Inventory'

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log of median income			Managing people			Comparative seniority			Comparative happiness		
Factor 1	0.03	0.02	0.02	0.81*	0.65	1.01*	0.07**	0.07**	0.08**	0.05*	0.05*	0.05*
	(0.02)	(0.02)	(0.02)	(0.40)	(0.42)	(0.41)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Factor 2	0.08**	0.07**	0.07**	1.15**	1.33**	1.26**	0.09**	0.07**	0.07**	0.06*	0.06*	0.06*
	(0.02)	(0.02)	(0.02)	(0.37)	(0.40)	(0.39)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Factor 1 x Factor 2			-0.01			0.74**			0.01			-0.00
			(0.02)			(0.26)			(0.02)			(0.02)
Constant	10.68**	10.24**	10.25**	5.38**	-5.06*	-5.40*	1.07**	1.41**	1.38**	1.03**	1.32*	1.32*
	(0.02)	(0.12)	(0.12)	(0.34)	(2.43)	(2.44)	(0.02)	(0.33)	(0.33)	(0.02)	(0.63)	(0.63)
Observations	790	786	786	798	793	793	798	793	793	798	793	793
R-squared	0.03	0.20	0.21	0.03	0.14	0.14	0.04	0.10	0.10	0.03	0.07	0.07
Industry FE	NO	YES	YES	NO	YES	YES	NO	YES	YES	NO	YES	YES

Notes: The table shows the results of running regression (4.1) above. The outcomes are the median logarithm of annual income (specifications (1)-(3)), the median number of people managed (specifications (4)-(6)) and how the respondent rates their i. level of seniority (specifications (7)-(9)) and ii. level of happiness (specifications (10)-(12)) as compared to co-workers ranging from lower, similar to higher. The main independent variables are the standardised Factor 1 ('Belonging and Uniqueness') and Factor 2 ('Challenge and Openness') and their interaction. Controls include individual-level age, a gender dummy that is equal to one for females and zero otherwise, education dummies, ethnicity dummies and a dummy that equals one if an individual was born in the UK and zero otherwise. Robust standard errors are shown in parentheses. ** p<0.01, * p<0.05

Predictive validity: Discussion of regression results

The two-factor solution of the 'Individual Inclusiveness Inventory' has predictive validity. For Factor 2 'Challenge and Openness' the predictive validity is robust across all outcomes. Factor 1 'Uniqueness and Belonging' has predictive validity for all outcomes considered with the exception of individual income. I note that the variation that is explained by Factor 2 is always larger as compared to Factor 1 other than for comparative seniority. This is also true when looking at the partial R-squared (i.e., proportion of variance in the outcome variable that is explained by each factor) in Table 4-5. The partial R-squared for Factor 2 'Challenge and Openness' is always larger than that of Factor 1 'Uniqueness and Belonging' and always significant.[38]

Considering income, a one standard deviation increase in Factor 2 'Challenge and Openness', for example, predicts an increase in the logarithm of income of 7% while Factor 1 'Uniqueness and Belonging' is insignificant. The proportion of variance explained by Factor 2 'Challenge and Openness' is 1.67% as per Table 4-5 below. For the managing people outcome, Factor 1 is significant and positive with a coefficient of 1.01 people managed but smaller than for Factor 2 with a coefficient of 1.26. Here the partial R-squared is only significant for Factor 2 'Challenge and Openness' explaining 1.45% of the variation in managing people. For the comparative seniority outcome, a one standard deviation increase in Factor 1 'Uniqueness and Belonging' and in 'Challenge and Openness' predict an increase of 0.08 and 0.07 respectively. Table 4-5 below shows that the variation explained by each factor is also similar with Factor 1 explaining 1.11% and Factor 2 explaining 1.13% of the variation in comparative seniority. Finally, looking at comparative happiness, the results across factors are again similar, with a one standard deviation increase in Factor 1 and in Factor 2 being associated with an increase of 0.05 and 0.06 respectively. The partial R-squared is significant for both as per Table 4-5 and 0.61% for Factor 1 and 0.72% for Factor 2. I find no indication of a significant interaction effect between Factor 1 and Factor 2, with the one exception of managing people.

[38] Partial R-squares are calculated using a partial correlations approach where significance is determined based on the hypothesis of the change in R-squared from the inclusion of the predictor variable being significant.

Table 4-5: Partial R-squared for two-factor solution

	Partial R-squared			
	Log of median income	Managing people	Comparative seniority	Comparative happiness
Factor 1	0.21%	0.35%	1.11%*	0.61%*
Factor 2	1.67%*	1.45%*	1.13%*	0.72%*

Note: The partial R-squared is the proportion of variance in the outcome variable that is explained by each factor only when controlling for individual-level age, a gender dummy that is equal to one for females and zero otherwise, education dummies, ethnicity dummies and a dummy that equals one if an individual was born in the UK and zero otherwise. This is the decrease in the model's R-squared value that results from removing each factor respectively from the full model. The * indicates that the amount by which the partial R-squared changes is significant at the 5% level.

Overall, these results are intuitive and aligned with the literature. It is intuitive that Factor 2 'Challenge and Openness' which centres around embracing conflict and being open to be challenged and challenge actively predicts productivity outcomes strongly such as annual income, the number of people managed and seniority. To the extent that productivity is rewarded with status and higher pay, the estimates suggest that the aspect of inclusion which causes an individual to embrace being challenged themselves, in addition to challenging others, is causing them to be more productive. At the same time, I cannot rule out that an individual is getting rewarded for being confrontational and simply negotiating for higher pay or more management responsibilities (Bertrand, 2011; Collischon, 2020). There is evidence that, for example, norms around negotiation (i.e., gender norms) affect promotion while being uncorrelated to performance and that Western societies favour such form of self-promotion (Bertrand, 2011).

Factor 1 'Belonging and Uniqueness' which centres around fostering belonging and uniqueness of team members, predicts managing people, individual seniority and happiness but not income. Again intuitively, someone who is very socially inclined may not necessarily seek a higher income as a reward but succeeds in relational aspects of leadership such as managing people and self-perceived seniority and happiness. Table 4-9 in Appendix 4.A documents the correlation of the two factors of the 'Individual Inclusion Inventory' with the Big Five factors and supports those intuitions. That is Factor 1 'Belonging and Uniqueness' is correlated with conscientiousness (correlation of 0.37) and agreeableness (correlation of 0.42). These facets of the Big Five tend to be associated with cooperative and responsible behaviours (Heineck, 2011). Factor 2 'Challenge and Openness' is correlated with openness (correlation of 0.38) and extraversion (correlation of 0.27). These facets are associated with creativity, autonomy, ambition or assertiveness, among others (Heineck, 2011).

The finding is particularly interesting in the context of the inclusion literature. Much of the inclusion literature has focused strongly on the themes summarised in Factor 1; concretely there is a strong focus on, for example, an inclusive leader as someone who fosters the belonging to and the uniqueness in a team or organisation (Veli Korkmaz *et al.*, 2022). Nishii and Leroy (2022) call this "social inclusion" but argue that it is crucial to go beyond this conceptualisation and consider "informational, task-related inclusion". The link to work performance outcomes is crucial for this latter aspect of inclusion and the need for belonging and uniqueness is therefore extended by an additional need for competence or autonomy, for example. Further, inclusive leaders also challenge others and mediate conflict, in particular in diverse contexts (Nishii and Leroy, 2022). This differentiation of social and task-related inclusion fits the two-factor solution of 'Belonging and Uniqueness' and 'Challenge and Openness' very well as it resulted from the exploratory factor analysis above. It also fits to the predictive validity of the scale with Factor 2 (i.e., the scale centring around task-related inclusion) predicting the logarithm of annual income alongside all other outcomes studied. The predictive validity of Factor 1 that conceptualises "social inclusion" is slightly less straightforward as it does not predict income, however, it does predict managing people and perceived seniority and happiness as compared to co-workers. A one standard deviation increase in Factor 1 predicts an increase in one person managed, an increase of 0.08 in comparative seniority and of 0.05 in comparative happiness. Other than for comparative seniority these values are smaller than those for Factor 2. These outcomes draw on the social aspects of work in line with aspects of social inclusion that are part of Factor 1. It may also be that Factor 1 would impact co-workers' performance rather than individual performance. Past studies have focused on the effect of inclusion on group outcomes such as inclusive climate and its impact on reduced conflict (Nishii, 2013) or the effect of perceptions of inclusion on job performance (Randel *et al.*, 2018). It would hence be valuable to test the scale alongside group-level measures for team or organisational outcomes such as work climate or firm performance in a follow-up study.

Overall, this analysis is highly suggestive that inclusivity in the workplace which centres around 'Belonging and Uniqueness' is not sufficient to increase productivity. Rather, 'Challenge and Openness' is also necessary. There is likely a link of 'Challenge and Openness' to innovation and productivity given that individuals are open to be criticised and challenge others in their team. There are multiple potential mechanisms through which 'Challenge and Openness' may impact productivity. For example, it could be that when individuals are open to being challenged, they are more likely to consider alternative perspectives and ideas. This can lead to more robust problem-solving, as individuals are willing to consider different approaches. Also, it could be that individuals who challenge others actively improve group collaboration and outcomes thereby also increasing individual productivity. 'Belonging and Uniqueness' alone may not be sufficient for determining individual productivity as it centres more closely around group outcomes and group harmony (Nishii, 2013).

Finally, I analysed the interaction of the two factors to better understand the rewards to simultaneous high levels of both 'Belonging and Uniqueness' and of 'Challenge and Openness'. Other than for the managing people outcome, I do not find significant results for the interaction. Being both commanding and challenging while maintaining an environment of empathy and inclusion is difficult and requires effort. In the sample, only 5% of individuals are in the highest decile (i.e., in the top 10%) of both factors 'Belonging and Uniqueness' and 'Challenge and Openness', which may be the reason why the interaction is not significant even though it is a valuable leadership skill to have both in high numbers.

Incremental validity: Regression results

In line with the recommendation by Bainbridge, Ludeke and Smillie (2022), I also locate the 'Individual Inclusiveness Inventory' within the framework of the well-established Big Five scale.

Table 4-6 below documents the regression results for the four main outcomes (i.e., the logarithm of median income, the number of people managed, comparative seniority, comparative happiness) as in Table 4-4 before from running equation (4.1) above; but in addition, I also add the standardised Big Five personality traits to the regression. This is done to establish the validity and reliability of the 'Individual Inclusiveness Inventory', to locate the scale in the comprehensive personality framework of the Big Five and to be able to integrate the scale into surveys in the future.

Starting with the logarithm of income in columns (1) and (2) in Table 4-6, Factor 1 'Belonging and Uniqueness' becomes significant as compared to Table 4-4 above when adding the Big

Five with a one standard deviation increase in Factor 1 increasing income by 5%. This may stem from the significant negative effect of agreeableness, neuroticism or openness or the significant positive effect of extraversion on the logarithm of income that may moderate the effect of Factor 1. The coefficient on Factor 2 ‘Challenge and Openness’ remains stable at 7%. The interaction of the two factors is not significant.

Considering columns (3) and (4) in Table 4-6 which document the coefficients relating to the number of people managed outcome, Factor 1 ‘Belonging and Uniqueness’ becomes insignificant as compared to Table 4-4 in specifications (3) and (4). The reason could be that both conscientiousness and extraversion have a positive effect on managing people. A one standard deviation increase in Factor 2 ‘Challenge and Openness’ predicts a unit increase in number of people managed of 1.20. The interaction is positive and significant as above predicting a unit change of 0.66 in number of people managed in specification (4).

Turning to columns (5) and (6) in Table 4-6, I consider the coefficients that relate to the comparative seniority outcome. Notably, the coefficient for Factor 1 ‘Belonging and Uniqueness’ becomes insignificant while the coefficient for Factor 2 ‘Challenge and Openness’ reduces to 0.05. The interaction remains insignificant.

Turning to happiness in specifications (7) and (8) the effects of the two factors become insignificant when adding the Big Five personality traits indicating that the ‘Individual Inclusiveness Inventory’ has no incremental validity regarding happiness outcomes above and beyond the Big Five. Here the positive effect of conscientiousness or the negative effect of neuroticism likely play a role.

To summarise the coefficients pertaining to the Big Five personality traits in Table 4-6, conscientiousness is a positive and significant predictor of the number of people managed. Specifically, a one standard deviation increase in conscientiousness predicts an increase of 1.2 in the number of people managed (see column (4)). Conscientiousness also positively predicts happiness with a one standard deviation increase predicting an increase of 0.1 in specifications (8). A one standard deviation increase in neuroticism relates negatively to the logarithm of median income (-5%), to comparative seniority (-0.07) and to comparative happiness (-0.12). The association of extraversion is positive and significant for the productivity outcomes of income and managing people but not for seniority or happiness. Agreeableness predicts the logarithm of median income negatively (-4%) and so does openness (-6%).

Table 4-6: Divergent validity of 'Individual Inclusiveness Inventory' and the Big Five

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log of median income		Managing people		Comparative seniority		Comparative happiness	
Factor 1	0.05*	0.05*	0.08	0.47	0.05	0.05	0.01	0.00
	(0.02)	(0.02)	(0.47)	(0.48)	(0.03)	(0.03)	(0.02)	(0.03)
Factor 2	0.07**	0.07**	1.28**	1.20**	0.05*	0.05*	0.05	0.05
	(0.02)	(0.02)	(0.44)	(0.43)	(0.03)	(0.03)	(0.02)	(0.02)
Factor 1 x Factor 2		-0.01		0.66*		0.01		-0.01
Big Five		(0.02)		(0.27)		(0.02)		(0.02)
Conscientiousness	-0.02	-0.02	1.00*	0.93*	0.05	0.05	0.10**	0.11**
	(0.02)	(0.02)	(0.43)	(0.43)	(0.03)	(0.03)	(0.02)	(0.02)
Neuroticism	-0.05**	-0.05**	0.04	0.04	-0.07**	-0.07**	-0.12**	-0.12**
	(0.02)	(0.02)	(0.40)	(0.40)	(0.02)	(0.02)	(0.02)	(0.02)
Extraversion	0.03*	0.03*	0.80*	0.80*	0.04	0.04	0.03	0.03
	(0.02)	(0.02)	(0.37)	(0.37)	(0.02)	(0.02)	(0.02)	(0.02)
Agreeableness	-0.04*	-0.04*	0.21	0.12	-0.01	-0.01	0.00	0.00
	(0.02)	(0.02)	(0.40)	(0.40)	(0.03)	(0.03)	(0.02)	(0.02)
Openness	-0.06**	-0.06**	-0.09	-0.09	0.00	0.00	-0.04	-0.04
	(0.02)	(0.02)	(0.37)	(0.36)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	10.26**	10.26**	-4.83*	-5.20*	1.35**	1.34**	1.22**	1.22**
	(0.12)	(0.12)	(2.45)	(2.48)	(0.16)	(0.16)	(0.15)	(0.15)
Observations	774	774	781	781	781	781	781	781
R-squared	0.24	0.24	0.15	0.16	0.13	0.13	0.16	0.16
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: The table shows the results of running regression (4.1) above. The outcomes are the median logarithm of annual income (specifications (1)-(2)) and the median number of people managed (specifications (3)-(4)) and comparative seniority (specifications (5)-(6)) and happiness (specifications (7)-(8)). The main independent variables are the standardised Factor 1 ('Belonging and Uniqueness') and Factor 2 ('Challenge and Openness') and their interaction. Controls include individual-level age, a gender dummy that is equal to one for females and zero otherwise, education dummies, ethnicity dummies and a dummy that equals one if an individual was born in the UK and zero otherwise. The regressions include the standardised Big Five traits that are conscientiousness, neuroticism, extraversion, agreeableness and openness. Robust standard errors are shown in parentheses. ** p<0.01, * p<0.05

Incremental validity: Discussion of regression results

Including the Big Five personality traits as independent variables in the regression does not change the predictive power of Factor 2 'Challenge and Openness' on work outcomes substantively. The exception is comparative happiness, which becomes insignificant. A potential reason for this could be the positive relation of conscientiousness with comparative happiness. Conscientious individuals tend to be more organised and hardworking, which may mean that they are also be more likely to engage in challenging behaviours (i.e., 'Challenge and Openness') while simultaneously scoring high on subjective success outcomes (Duckworth *et al.*, 2012). The correlation of Factor 2 'Challenge and Openness' and conscientiousness is 0.11 (see Table 4-9 in Appendix 4.A). Overall, I conclude that Factor 2 'Challenge and Openness' has incremental validity above and beyond the Big Five personality traits.[39] This is despite this factor being positively correlated with extraversion, openness and conscientiousness and negatively with neuroticism as per Table 4-9 in Appendix 4.A (there is no correlation with agreeableness).

While Factor 1 'Belonging and Uniqueness' is generally less predictive of work outcomes, adding the Big Five further diminishes its significance indicating that it could be a facet of one of the Big Five personality traits. Its correlation is strongest with agreeableness (i.e., with a correlation of 0.42) and conscientiousness (i.e., with a correlation of 0.37). The predictive power of Factor 1 'Belonging and Uniqueness' on work outcomes is attenuated only in the case of income and diminished in the case of managing people, comparative seniority and comparative happiness when including the Big Five personality traits. The Big Five personality traits hence seem to have a confounding effect on the relationship between Factor 1 and work outcomes that differ slightly for each outcome.

In the case of individual income, there seems to be a moderating effect of the Big Five on the relationship between Factor 1 and income. Holding the Big Five constant, a one standard deviation increase in Factor 1 'Belonging and Uniqueness' predicts an increase in the logarithm of income of 5% in column (2) as compared to an insignificant effect previously. A potential reason could be the negative association of agreeableness and income that moderates this effect. Agreeable individuals may be less likely to foster uniqueness while trying to please

[39] I can rule out collinearity across the two factors and one of the Big Five factors. Table 4-9 in Appendix 4.A shows that no correlation is larger than 0.42, which rules out that collinearity explains this result.

others in fostering belonging (Judge, Livingston and Hurst, 2012), which has a negative effect on income. Holding agreeableness constant, fostering both ‘Belonging and Uniqueness’ may hence have a positive effect on income.

Regarding the managing people outcome, the Big Five mediate the effect of Factor 1 that turns insignificant. This may be due to the positive relation of conscientiousness and extraversion and income.

For comparative seniority, there is also a mediating effect of the Big Five that results in insignificant results for Factor 1. Here neuroticism predicts a significant negative effect on income.

Finally, for comparative happiness there is again a mediating effect of the Big Five with the coefficient on Factor 1 becoming insignificant. Here conscientiousness is positively, and neuroticism negatively related to comparative happiness. This analysis highlights the importance of placing newly established personality inventories in the framework of the Big Five. As per Table 4-9 in Appendix 4.A, Factor 1 ‘Belonging and Uniqueness’ is positively correlated with agreeableness, conscientiousness, extraversion and openness and negatively correlated with neuroticism.

4.3. Conclusion

In this study, I developed the ‘Individual Inclusiveness Inventory’. The inventory attempts to capture the traits of what makes an individual inclusive in the workplace. As labour markets are changing with increased demand for collaboration and rising diversity, inclusion has been discussed as promising determinant of successful work outcomes (Nishii, 2013; Randel *et al.*, 2018; Al-Atwi and Al-Hassani, 2021; Nishii and Leroy, 2022). Past literature further shows the increasing importance of collaborative leadership skills both in terms of demand and returns (Josten et al. 2023 forthcoming) alongside social skills more generally (Deming and Kahn, 2018; Deming, 2021). I hence conceptualise and measure what makes an individual inclusive, defined as an individual-level trait. I define an inclusive individual as someone who actively includes individuals in a group and encourages diversity of thought and background but still encourages the group in a way as to maximise performance and productivity. The inventory adds to the existing literature in the following way: First, it uniquely defines inclusiveness as an individual trait rather than measuring inclusion at the organisational or leadership level. It can therefore also be incorporated in the well-established Big Five personality scale. Second, the approach is deductive, as I base the measure on the literature on inclusion and inclusive leadership, as well as inductive as I further derive the measure based on interviews with experts in the field of diversity and inclusion.

Using exploratory factor analysis and confirmatory factor analysis drawing on two large samples of full-time professionals in the UK, I successfully develop and validate the 'Individual Inclusiveness Inventory'. I confirm a two-factor solution with Factor 1 'Belonging and Uniqueness' capturing the aspect of inclusion that centres around satisfying co-workers' need for belonging and uniqueness in a work setting. And Factor 2 'Challenge and Openness' captures the aspect of inclusion that entails being open to be challenged by and to challenge co-workers.

I then test the predictive validity of the two-factor solution with respect to work outcomes. I hypothesise that 'Challenge and Openness' has a clear link to individual productivity as opening discussions and embracing task conflict allows for high levels of innovation and creativity and competitiveness. The link of 'Belonging and Uniqueness' and productivity is less clear as it might be that individuals favour positive group over individual outcomes. I indeed find that Factor 2 is positively related to all work outcomes studied including income while Factor 1 is positively related to the number of people managed and perceived comparative seniority and happiness. Concretely, a one standard deviation increase in 'Challenge and Openness' is associated with an increase in the logarithm of income of 7%, in the number of people managed of 1.3, in comparative seniority of 0.07 and in comparative happiness of 0.06. A one standard deviation increase in 'Belonging and Uniqueness' in comparison does not affect income but predicts an increase the number of people managed by 1, the comparative seniority by 0.08 and comparative happiness by 0.05. The findings align with previous literature. Factor 1 is about the social aspect of inclusion (Nishii and Leroy, 2022) that is not necessarily linked to individual performance outcomes such as income but rather leadership (i.e., it positively predicts managing people in the sample) or perceived comparative seniority and happiness. The comparative outcomes capture satisfaction with individual outcomes rather than actual outcomes and capture the social comparison aspect of inclusive behaviour (e.g., the need to affiliate with others) (Roberson and Perry, 2022). Overall, this work suggests that inclusivity in the workplace which centres around 'Belonging and

Uniqueness’ is not sufficient to increase productivity. Rather, ‘Challenge and Openness’ is also necessary. Factor 2 ‘Challenge and Openness’ is about the outcome-related aspect of inclusion (Nishii and Leroy, 2022) that emphasises the importance of satisfying competence needs. It is important to highlight that I cannot rule out that an individual is rewarded for factors unrelated to actual performance such as their negotiation skills or their appearance (Bertrand, 2011; Collischon, 2020). Such unjustifiable rewards to personality traits that stem from, for example, cultural norms or stereotypes would be uncorrelated to performance.

This study provides scope for future research. First, it should be tested in additional samples. Currently, the sample is restricted to full-time professionals in the UK. That way, I have a relatively homogenous group and follow the skills literature that has also focused on professional occupations initially (Deming and Kahn, 2018). Choosing a sample that resembles the target population closely is recommended (Rammstedt and Beierlein, 2014) but also diminishes the external validity of the scale. Second, testing the scale alongside additional productivity or performance outcomes would be useful to also link it to actual inclusion outcomes or organisational outcomes such as firm performance. Testing for team or organisational performance measures, for example, I could test whether ‘Belonging and Uniqueness’ indeed rather predicts group than individual outcomes. Third, the scale could be used in experiments that test the causal impact of inclusiveness on, for example, team performance. Lastly, it remains to be seen to what extent inclusiveness is malleable as a trait and how it can be taught. There is mixed evidence on how to best teach social skills (Josten and Lordan, 2021) though I do expect inclusiveness to be malleable as much of its facets such as leadership skills or communication skills have been shown to be more malleable than personality (Martin-Raugh, Williams and Lentini, 2020).

4.A Appendix A: Individual Inclusiveness Inventory

Table 4-7: List of anonymised interviewees of inclusion interviews

#	Gender	Role	Type of organisation	Date interviewed	Medium contacted
1	male	Founder	Behavioural Science Consultancy, focus on inclusion	23/03/2021	Email
2	male	Consultant	Inclusion Consultancy	23/03/2021	Email
3	female	Lead Behavioural Scientist	Consultancy, focus on inclusion	26/03/2021	Email
4	male	Diversity & Inclusion specialist	Consultancy, focus on inclusion	16/04/2021	Email
5	female	Professor, Academic expert in gender equality and Diversity & Inclusion	University	20/05/2021	Email
6	female	Associate Professor of Behavioural Science, expert inclusion	University	28/05/2021	Email
7	female	Behavioural Science Officer, expert inclusion	Executive education and Behavioural Science Consultancy	09/06/2021	Email
8	female	Founder, focus on inclusion	Hiring platform using behavioural science to remove bias	05/07/2021	LinkedIn
9	female	CEO, focus on inclusion	Finance	07/07/2021	Email
10	female	Diversity & Inclusion specialist	Consultancy	13/07/2021	LinkedIn
11	female	Co-Founder and Chief Operations, focus on inclusion	Education platform	19/07/2021	Email
12	female	Director, focus on inclusion	Consultancy	19/07/2021	Email
13	female	VP Global Community and Belonging, Founder & CEO	Diversity & Inclusion in technology	21/07/2021	Email
14	female	Global Head of Diversity & Inclusion	Banking	04/08/2021	Email

Note: The list includes all individuals interviewed for the Individual Inclusiveness Inventory. Their identity is anonymised. In their professional career they all focus or have focused on diversity and inclusion. The interviews took place between the 23/03/2021 and 04/08/2021. The interviewees were either contacted via email or through the professional platform LinkedIn.

Document A1: Verbal Information for participants: Individual inclusiveness interviews

The verbal consent form below was read out to the interviewee by the researcher at the start of each interview. While the researcher tried to follow the structure closely, the interviews were semi-structured and hence also varied slightly.

Thank you for participating in this study that runs in March/April 2021. The aim of the study is to derive an index/ that captures what makes an individual inclusive in a team or a group.

As you know I am Cecily Josten and a PhD candidate at the London School of Economics. My expertise lies in studying the impact of personality traits on labour market outcomes and I am also involved in the Inclusion Initiative as a researcher officer. The Inclusion Initiative aims at promoting inclusive workplaces and tries to apply behavioural science insights to work.

This interview is entirely voluntary, and you can withdraw at any point in time. To make the interview process go as conversational as possible, I would like to record this interview. Do you consent for it to be recorded? The recording will be transcribed and used to define the inclusion index. Once the index is set up the recording and its transcript will be deleted. If you do not wish to be recorded, I will take notes of our discussion.

No individual identifying information of the interview will be published but rather it will only be used as an input to the inclusion index.

The collected information will be used in an academic paper and for future research projects.

Table 4-8: Summary statistics

	Summary statistics (N=800)			
	mean	sd	min	max
Factor 1 "Belonging and Uniqueness"	29.65	3.80	5	35
Factor 2 "Challenge and Openness"	24.02	4.82	5	35
Outcome variables:				
Median annual income	48,810	25,505	5,000	150,000
Median number of people managed	5.38	9.78	0	50
Comparative salary	1.06	0.62	0	2
Comparative seniority	1.07	0.61	0	2
Comparative happiness	1.03	0.58	0	2
Big Five personality scale:				
Conscientiousness	16.60	3.02	5	21
Neuroticism	11.97	4.27	3	21
Extraversion	12.78	4.10	3	21
Agreeableness	16.28	3.02	8	21
Openness	15.12	3.42	3	21
Controls:				
Age	39	10	18	70
Female	0.50	0.50	0	1
Education: O-levels	0.08	0.28	0	1
Education: A-Levels	0.23	0.42	0	1
Education: Undergraduate	0.48	0.50	0	1
Education: Postgraduate	0.20	0.40	0	1
Ethnicity: White	0.84	0.36	0	1
Ethnicity: Mixed / Multiple ethnic groups	0.03	0.17	0	1
Ethnicity: Asian / Asian British	0.07	0.25	0	1
Ethnicity: Black / African / Caribbean / Black British	0.04	0.18	0	1
Ethnicity: Chinese	0.01	0.11	0	1
Ethnicity: Arab	0.00	0.06	0	1
Ethnicity: Other ethnic group	0.01	0.08	0	1
Born in the UK	0.90	0.31	0	1
Industry:				
Forestry, fishing, hunting or agriculture support	0.00	0.06	0	1
Real estate or rental and leasing	0.02	0.13	0	1
Mining	0.00	0.04	0	1
Professional, scientific or technical services	0.16	0.37	0	1
Utilities	0.01	0.11	0	1
Management of companies or enterprises	0.04	0.19	0	1
Construction	0.02	0.14	0	1

Admin, support, waste management or remediation services	0.04	0.20	0	1
Manufacturing	0.04	0.19	0	1
Educational services	0.03	0.16	0	1
Wholesale trade	0.01	0.09	0	1
Health care or social assistance	0.04	0.20	0	1
Retail trade	0.03	0.18	0	1
Arts, entertainment or recreation	0.02	0.14	0	1
Transportation or warehousing	0.01	0.09	0	1
Accommodation or food services	0.00	0.06	0	1
Information	0.04	0.19	0	1
Other services (except public administration)	0.08	0.27	0	1
Finance or insurance	0.41	0.49	0	1
Unclassified establishments	0.01	0.09	0	1

Note: The table shows the summary statistics for the key variables used in the predictive validity regression analysis using the full sample that is 'Sample 1' and 'Sample 2' of full-time professionals in the UK from Prolific of 800 observations in total. Median annual income is the median of income brackets ranging from 5,000£ to 150,000£. The median number of people managed is also the median of people managing brackets ranging from 0 to 50. Female is a dummy that is equal to one for female gender and zero otherwise. For education, ethnicity and industry, I show dummies for each category. Born in the UK is a dummy equal to one if the individual was born in the UK and zero otherwise.

Table 4-9: Correlation Matrix of 'Individual Inclusiveness Inventory' with Big Five

	Factor 1	Factor 2	Conscientiousness	Neuroticism	Extraversion	Agreeableness	Openness
Factor 1	1.00						
Factor 2	0.36	1.00					
Conscientiousness	0.37	0.11	1.00				
Neuroticism	-0.10	-0.17	-0.25	1.00			
Extraversion	0.21	0.27	0.06	-0.25	1.00		
Agreeableness	0.42	0.03	0.34	-0.15	0.10	1.00	
Openness	0.28	0.38	0.10	-0.10	0.19	0.08	1.00

Note: The table shows the correlations across Factor 1 and Factor 2 and the Big Five personality traits.

Chapter 5 Conclusion

The overall aim of this thesis is to improve our understanding of the role of non-cognitive skills in the labour market in the past, present and future. Non-cognitive skills have become increasingly important at work. This increase in importance has been driven in part by automation. Automation and technological innovation (e.g., the introduction of the computer) increasingly substituted cognitively challenging tasks while complementing humans in performing interactive work (Deming and Kahn, 2018). This development increased the complementarity of cognitive and non-cognitive skills. The Covid-19 pandemic further sped up trends related to automation and emphasised the importance of non-cognitive skills, for example, for successful collaboration (Josten and Lordan, 2021).

This thesis consists of five stand-alone papers that each consider one aspect of non-cognitive skills and the labour market. In this chapter, I summarise the main results of each paper consecutively and outline their contributions to the literature. I then discuss the key limitations of this thesis. Lastly, I delve into the overall conclusions of my work, discussing its practical implications and areas of future research. I finish with concluding remarks.

5.1. Main Findings and Contributions

5.1.1. The relevance of social skills for labour market outcomes

In chapter 1.1.1. and Appendix A (Paper 1), I highlight the importance of social skills for labour market outcomes. Social skills are a subset of non-cognitive skills that entail skills related to human interaction; examples are leadership, collaboration and communication skills. The Fourth Industrial Revolution increased the importance of social skills given that they complement new technological innovation. Building on this, this chapter analyses why social skills are relevant for knowledge worker specifically.

The aim of chapter 1.1.1. is to motivate the subsequent empirical analysis of non-cognitive skills in the labour market. It highlights the need for more research on which specific non-cognitive skills matter at work. Further, it also clearly links non-cognitive skills to the future of work. It also highlights that improving the measurement of non-cognitive skills is crucial (e.g., to then be able to measure whether such skills can in fact be taught).

In chapter 1.1.1. I begin by summarising the academic literature on non-cognitive skills of the past (before the outbreak of the Covid-19 pandemic). The evidence clearly shows that non-cognitive skills, including social skills specifically, have become more important over time both individually and also when interacted with cognitive skills (Weinberger, 2014; Deming, 2017). Further, they are also intrinsically valuable given their effect on labour market outcomes directly (e.g., on productivity) and indirectly (e.g., through sorting into higher paid occupations) (Borghans *et al.*, 2008). First, this finding highlights that social skills are durable skills, i.e., they are valuable in and of themselves. Second, the complementarity of non-cognitive and cognitive skills emphasises the importance of social skills for knowledge workers. The academic evidence also shows that non-cognitive skills impact wages and likely continue to do so in the future (Borghans, Ter Weel and Weinberg, 2014; Deming, 2017; Bode *et al.*, 2019). To stress further that non-cognitive skills are important for the future of work, I document a table and data by Lordan (2021) and Josten and Lordan (2020). Lordan (2021) quantitatively relates the probability that an occupation is automatable to an occupation's attributes (i.e., their level of social skills, cognitive skills and physicality) using EU Labour Force Survey data from 2013–2016. Automatability of an occupation is defined based on a classification by Josten and Lordan (2020) who combine previous research on automatability of specific occupations with patent data (i.e., they additionally classify an occupation as automatable depending on the number of patents recently available for each specific occupation). The estimates clearly show that cognitive skills and also the interaction of cognitive skills with social skills negatively impact the automatability of an occupation. Social skills also negatively predict automatability when an interaction is included. That is, they are relevant in knowledge work of the future. The chapter further highlights that social skills are also relevant for firms in that they predict firm performance (Deming and Kahn, 2018) or productivity (Knudsen *et al.*, 2006) and help individuals to thrive in the long run.

In Appendix A, the remainder of paper 1 continues with an analysis of social skills during and after the Covid-19 pandemic. Specifically, collaboration has become more essential as skill. Also, inclusion has become more important as it promotes successful collaboration (i.e., inclusive work environments improve collaboration). Working virtually during the pandemic has challenged the way in which we collaborate and has affected individuals differently, which in turn requires managers to have social skills for managing effectively. The paper uses evidence from interviews with 35 leaders in the UK working at large companies to show that social skills may have increased their premium during and also after the pandemic. Lastly, this paper discusses the evidence on whether social skills can be taught. While social skills have been shown to be malleable, the evidence on how to best teach them is mixed and research is limited. This paper is documented in full length in Appendix A and the first part of the paper in the introduction motivates the papers that follow in the remainder of the thesis.

Overall, paper 1 contributes to the literature in synthesising the academic evidence on the role of non-cognitive skills and on whether they can be taught. Further, it studies these social skills in the context of the pandemic and looks at them before, during and after the outbreak of Covid-19. It reproduces quantitative and qualitative evidence to present evidence that social skills may have increased their premium during the pandemic.

5.1.2. Automation and non-cognitive skills

In chapter 1.1.2. and Appendix B (Paper 2), I further highlight the importance of non-cognitive skills for labour markets with a specific focus on the role of automation. As for paper 1, I show the full length of paper 2 in Appendix B and draw on it partially in chapter 1.1.2. to motivate subsequent chapters. Concretely, in paper 2, I identify skills, abilities and job attributes that predict the likelihood of an occupation becoming recently automatable. Overall, I find that skills and abilities which relate to non-linear abstract thinking are those that are the safest from automation. The paper then looks at the 'people', 'brains' and 'brawn' content of an occupation, which entails the extent to which an occupation involves people interactions, abstract thinking and physicality respectively. I find that jobs that require the interaction of 'people' and 'brains' are less likely to be automated, which are activities that require soft skills. Finally, jobs that require high levels of physicality are likely to be automated unless it is interacted with 'brains' and/or 'people'.

Overall, paper 2 makes the following contributions. First, it provides information and knowledge on future job requirements by occupation and by country. This helps policymakers and companies to make predictions on the demand for skills and abilities by occupations. Second, it provides information to policymakers and companies interested in preparing individuals for the future of work (e.g., through the reorganisation of education to include, for example, non-cognitive skills). Third, it increases the nuanced understanding of the specific aspects of occupations that are at risk of automation. Fourth, in Appendix B, the paper also runs the analysis of linking skills, abilities and job attributes to the likelihood of an occupation becoming recently automatable for all European countries, which is useful for policymakers interested in understanding the impact of country-specific policies on the share of automatable occupations.

The aim of chapter 1.1.2. is to analyse the impact of skills and abilities on the automatability of occupations. This way it contributes to the overall aim of this thesis of shining light on the increasing importance of non-cognitive skills in the labour market, particularly in professional jobs. While paper 2 is shown in full length in Appendix B, an excerpt of it is presented in chapter 1.1.2. and motivates subsequent papers by showing the importance of non-cognitive skills in the context of automation.

5.1.3. The differential return to personality traits across gender

Chapter 2 (Paper 3) of this thesis speaks to the literature on the role that personality traits play in determining labour market outcomes, with a specific focus on the well-established Big Five personality traits that have been studied frequently in the past. It draws on a large secondary data set of the UK Household Longitudinal data panel (UKHLS) to study personality traits. Concretely, I analyse the differential impact of the Big Five personality traits for the likelihood of making it to the top income quintile within an occupation, comparing males to females. Personality traits may be rewarded differently for men as compared to women with some traits being regarded positively or negatively in men but not in women (Blau and Kahn, 2017). This would point at unjustifiable rewards to personality due to, for example, social norms or discrimination as compared to legitimate rewards that would be based on, for example, productivity.

I find that being agreeable hurts men more than women across most occupations. I explain this gap with the norm that agreeableness in men is expected to be low. That is, for men to score high on agreeableness goes against this gender norm, causing them to be punished in the labour market. In addition, I also find that female legislators and senior officials who are conscientious, extraverted, neurotic and open are more likely to be among the top earners than men. Across all other occupations, I find a gender gap in pay but the likelihood of making it to the top is the same for men and for women.

Overall, paper 3 makes the following contributions. First, it extends previous literature by analysing the association of personality and wages in the context of gender norms. This way it tests whether personality traits are legitimately rewarded (i.e., whether the link between personality traits and wages is the same for men and women) and studies the mechanisms behind the effect of personality on labour market outcomes. Second, it provides information on a gap in rewards to agreeableness that can be analysed further going forward.

5.1.4. The changing demand and rewards to skills for professional workers

In chapter 3 (Paper 4) of this thesis, I analyse the changing demand and reward to skills at the occupation and state level over time using job advertisement data from the US. Concretely, I study the period shortly before the outbreak of the Fourth Industrial Revolution 2014-2015 and the period at its onset when new technologies had already started to diffuse in 2018-2020 Q1. I choose these times periods as they frame the outbreak of the Fourth Industrial Revolution in 2015 very well and are also restricted to the time before the outbreak of the Covid-19 pandemic following the first quarter of 2020.[40] I analyse skills requirements as they are posted in a large data set of job advertisements called LinkUp. First, I use principal component analysis to derive meaningful skills groups that are: 'collaborative leader', 'interpersonal & organised', 'big data', 'cloud computing', 'programming', 'machine learning', 'research', 'math' and 'analytical'. Second, I use those nine skills groups in a linear regression to test their impact on wages. I find that the two non-cognitive skills groups of 'collaborative leader' and 'interpersonal & organised' are rewarded differently. Over time, 'collaborative leader' skills gain in importance with a positive link to the logarithm of hourly wage in the later time frame of 2018-2020 Q1. 'Interpersonal & organised', in comparison, exhibits negative returns across both time frames. I explain this difference with the difference in automatability of occupations requiring those skills.

Further, I also find that the reward to data science skills is constantly evolving. Mature skills such as 'big data' are initially rewarded but punished over time while newer skills such as 'machine learning' are rewarded highly in the later time frame. Notably, I find that big data links positively to the logarithm of wages in the earlier time frame of 2014-2015 but this link turns negative in 2018-2020 Q1. The same is true of the skill cloud computing. In contrast,

[40] The first time period (2014-2015) marks the arrival of the technology later defining the Fourth Industrial Revolution and the second time period (2018-2020 Q1) summarises its progression.

machine learning that does not appear frequently in job advertisements in 2014-2015 has a positive and significant link to wages in 2018-2020 Q1. This finding is a symptom of technology being currently in evolution, and with it demanding an evolving skill set.

Third, using Lasso regressions, I further find a complementary effect of ‘collaborative leader’ with ‘research’ skills across both time frames. There is a positive association of the combined ‘collaborative leader’ and ‘research’ skills. This finding is in line with previous research that also find a complementary effect of non-cognitive with cognitive skills for wage outcomes (Weinberger, 2014; Deming, 2017).

Overall, paper 3 contributes to previous literature in the following ways. First, I take an inductive approach in choosing skills keywords by using principal component analysis. This way I use a more detailed list of skills groups for analysing changes in demand and reward as compared to previous literature that focused on keywords based on academic literature. A more detailed skills list provides helpful insights for individuals, companies and policymakers on the relevance of specific skills for, for example, upskilling or in the hiring process. Second, I frame the analysis around the onset of the Fourth Industrial Revolution. I am hence analysing labour market developments over time and how they impact the value of skills at the occupation and the state level at a time of technological disruption. The specified time periods are particularly interesting as they capture the start (2014-2015) of the Fourth Industrial Revolution, with the second period (2018-2020 Q1) allowing a sufficient lag for the new technologies to have diffused and influenced the labour market. Third, I analyse complementarities across all nine skills groups thereby providing a more detailed understanding of non-linearities and interactions of skills.

5.1.5. Measurement of non-cognitive skills: ‘Individual Inclusiveness Inventory’

Measuring non-cognitive skills and the impact thereof is a core aim of this thesis. Chapter 4 (Paper 5) aims to fill the gap of measuring what makes an individual inclusive of others. With an increasingly diverse workforce and an increasing demand for social skills at work, inclusion and inclusive leadership have been pointed out as core skills to achieve positive group outcomes and successful collaboration (Josten and Lordan, 2021). Chapter 4 develops and validates what I call the ‘Individual Inclusiveness Inventory’. For the scale item generation, I interview 14 experts in diversity and inclusion alongside revisiting the relevant literature on inclusion and inclusive leadership. The items are then reduced using exploratory factor analysis and confirmed using confirmatory factor analysis using two samples of working professionals in the UK. I find a two-factor solution with Factor 1 entailing an individual's ability to foster belonging and uniqueness in human interactions that I call 'Belonging and Uniqueness' and Factor 2 entailing an individual's openness to challenge that I call 'Challenge and Openness'. Testing the predictive validity of the two factors, I find that Factor 2 'Challenge and Openness' is positively related to all work outcomes studied including productivity while Factor 1 'Belonging and Uniqueness' is positively related to the number of people managed and perceived comparative seniority and happiness. I also locate the inventory in the well-established Big Five personality framework and find that it has some incremental validity beyond the Big Five.

This paper has the following contributions to the literature. First, it is the first paper to my knowledge to measure what makes an individual inclusive irrespective of, for example, their leadership status. Uniquely, it defines inclusion as a trait rather than as a behaviour or process. Second, the measurement is a self-reported measure of a trait rather than measured at the group level. This way it can be easily administered and can be incorporated into well-established personality frameworks such as the Big Five traits. Third, I improve knowledge on inclusion and the measurement thereof. While inclusion is increasingly being investigated, there is still limited research on how it can actually be measured. Going forward the scale can be used to measure work outcomes and can be administered in experiments. This is a useful tool for individuals and companies alike interested in testing their personal or their employees' level of inclusiveness.

5.1.6. Overall contributions

As highlighted above, each individual paper makes its own contribution to the literature, while they are also tied together by the overall aim of increasing our understanding of non-cognitive skills in the labour market. Overall, my thesis contributes to past literature on non-cognitive skills and the labour market. It analyses non-cognitive skills in more detail than has been done before. While past literature has frequently analysed non-cognitive skills broadly, I zoom into specific aspects thereof, enabling me to provide more nuanced insights. Papers 1 and 2 highlight the importance of non-cognitive skills in rapidly changing labour markets. In paper 3, I extend the previously studied link between non-cognitive skills and wage outcomes by looking at the role of context (i.e., social norms). In paper 4, I extend the list of skills studied to include a more detailed account of skills to then analyse the demand and reward to those specific skills. In paper 5, I develop a new measurement of a specific non-cognitive skill that has not been measured before that captures what makes an individual inclusive. In each paper, I attempt to capture 'what is being talked about' and 'am taking a closer look'.

Further, this thesis also extends the literature on the impact of automation in the labour market. I go further from stating which occupations are prone to be automated to actually improving our understanding of the skills that have been highlighted as relevant for the future. Paper 4 takes an inductive approach in choosing specific skills groups that are relevant. This extends previous accounts of, for example, social skills or personality traits more broadly. Paper 5 builds on this analysis and tries to capture a non-cognitive skill that is increasingly talked about. Inclusion, diversity and collaboration are 'buzzwords' but it is less clear how we can measure them and whether measuring them actually has incremental validity above and beyond existing scales like the Big Five personality scale. With a narrow focus on specific skills such as 'collaborative leader' skills, data science skills or 'individual inclusiveness', this thesis is a guide to policymakers, companies and individuals alike trying to future-proof careers and work more generally.

This thesis focuses on professional occupations concretely and studies those across different countries, i.e., the UK, the European Union and the US. This specific focus has the advantage of providing guidance to policymakers, companies and individuals concerned with labour markets in those specific contexts. Further, non-cognitive skills have been pointed out to be particularly relevant in professional occupations (e.g., due to their likely broader variation in skills requirements) and have also been studied in this context in past research (Deming and Kahn, 2018). Further, paper 4 uses job advertisement data from the US to study changing skills requirements. Job advertisement data has been shown to be biased toward professional occupations further justifying the choice (Carnevale, Jayasundera and Repnikov, 2014)

Overall, this thesis synthesises the role of non-cognitive skills in the labour market of the past, present and future. It also provides opportunities for future research that can build firmly on my thesis. Areas of future research are outlined below.

5.2. Limitations

This section discusses the overall limitations of the research that broadly centre around limitations of causality, external validity and data and measurement.

Causality

The thesis does not claim to make causal inferences. While I follow (econometric) methods strictly when using regression analysis or factor analysis, I am not claiming causality as established through, for example, randomised controlled trials or quasi-experiments. Instead, I am interested in the relative importance of skills and how they predict labour market outcomes. This is particularly relevant for chapter 2 (Paper 3) and chapter 3 (Paper 4) where I link non-cognitive skills to wages. It is also relevant when establishing the predictive validity of the 'Individual Inclusiveness Inventory' in chapter 4 (Paper 5). In those analyses, I include detailed controls. To control for unobserved variables that are linked to both non-cognitive skills and wages and labour market outcomes more broadly I further include detailed occupation, industry and/or state fixed effects. Such fixed effects account for, for example, the fact that both skills demand and skills rewards differ across occupations, industry and geography. The level of detail of these controls depends on data availability. Throughout the thesis I am building my analysis on previous studies in the field that have addressed research questions in similar methodological ways.

External validity

This thesis is restricted to data from the UK, the European Union and the US. It remains to be tested whether the same findings hold across different countries and can be generalised across geography, particularly developing countries. All samples are restricted to WEIRD countries (i.e., Western, Educated, Industrialized, Rich and Democratic countries), which are not representative for humans in general (Henrich, Heine and Norenzayan, 2010). Concretely, in chapter 4 (Paper 5) I interview individuals from the UK and the US who are experts in diversity and inclusion to then derive scale items that are validated in a UK sample. It is, however, established that culture affects workplace processes (Randel *et al.*, 2018). In the case of individual inclusiveness, there may be cultural nuances as to definitions of what makes an individual inclusive. Confirming the 'Individual Inclusiveness Inventory' in additional international samples may improve the external validity of the scale. The same applies for the analysis of non-cognitive skills for labour market rewards in Chapter 2 (Paper 3) and Chapter 3 (Paper 4).

Further, the analyses across all chapters are restricted to professional occupations. Non-cognitive skills have been frequently discussed in the context of professional occupations (Spurk and Abele, 2011; Deming and Kahn, 2018; Cerioli, Leotta and Ricca, 2020). While analysing professional occupations only is a deliberate choice, future research could expand or replicate the same analyses in a sample of non-professionals, which would add valuable information to the study of non-cognitive skills in the labour market as a whole.

Data and measurement

Across all papers I analysed a variety of data sources including secondary data (Paper 3), job advertisement data (Paper 4) and interview and survey data (Paper 5). The data is sufficiently large across all studies. However, there are still limitations. In Chapter 2 (Paper 3), the analysis is at the 2-digit occupation level because the sample is too small to run the same analysis using 3-digit occupations. Such an analysis would, however, potentially provide more detailed explanations as to why there are differential rewards to personality within occupations. Further, in Chapter 2 and Chapter 4, I assume that self-reported data on non-cognitive skills (i.e., the Big Five personality traits and the 'Individual Inclusiveness Inventory') accurately reflects individual traits. Self-reported data does, however, potentially exhibit reporting bias (Morgado *et al.*, 2017). At the same time, self-reported data has the advantage of being easy to administer and provides valuable insights into individuals' subjective perspectives (Stanton *et al.*, 2002) and has been primarily used by psychologists to study character skills (Heckman and Kautz, 2013). This trade-off has been considered when designing my studies and choosing self-reported scales to measure non-cognitive skills. Measuring non-cognitive skills is generally difficult as they are not readily observable and more subjective than is the case for, for example, cognitive skills (Thiel and Thomsen, 2013). Methods of factor analysis that aim to explain latent constructs are used to overcome this bias in measurement.

To conclude, it is important to highlight that by no means I am analysing all relevant aspects of non-cognitive skills in the labour market. There is a variety of important aspects to non-cognitive skills that are not discussed in this thesis such as the role of non-cognitive skills for self-selection into occupations. Further, the specific non-cognitive skills I discuss such as 'collaborative leader' skills or the Big Five personality traits are not a comprehensive list of all non-cognitive skills that matter for work outcomes. They are selected based on previous research findings or 'what is being talked about' but do not aim to be comprehensive of all skills that exist and are important.

5.3. Practical Implications

The topics studied throughout this thesis are of a practical nature and relate closely to current labour market trends. In this respect, the insights gained from this thesis have practical implications for companies and individuals alike regarding today's labour markets in all countries studies. While the implications would also likely be interesting for an audience of policymakers, my focus in this thesis was primarily on the impact of my analyses for companies and individuals across all chapters, which is why providing concrete policy implications is beyond the scope of this thesis. I do, however, emphasise the importance for governments worldwide to adapt their skills agendas subject to the major disruptions to labour markets outlined in this thesis.

Chapter 1.1.1. (Paper 1 and Appendix A) reviews the academic evidence on the relevance of social skills before, during and after the Covid-19 pandemic. It further outlines actions to overcome obstacles to virtual inclusion (i.e., ensuring inclusion when working remotely). While the paper does not provide concrete actions, it highlights the importance of social skills that in turn serve as motivation for companies and individuals to invest in upskilling. Further, I outline that the existing evidence on teaching social skills is mixed. Companies interested in teaching social skills are hence encouraged to implement and evaluate teaching programmes, ideally in a randomised controlled setting.

Chapter 1.1.2. (Paper 2 and Appendix B) starts by providing information on how the skills content of occupations affects the automatability of an occupation. That is, it identifies future job requirements by occupations. Understanding how automation affects skills demand is crucial for governments, companies and individuals. First, it improves the knowledge of the skills and abilities required of workers in the future and on the activities, they will likely be engaged in. Second, like in Chapter 1.1.1., it emphasises the need for reorganising education and upskilling going forward with increasing returns to education due to an increasing demand for skills. Third, it outlines the specific aspects of occupations that are at risk of automation rather than analysing occupations as a whole thereby providing a more nuanced view on the impact of automation.

Chapter 2 (Paper 3) provides insights into whether personality traits are legitimately rewarded or whether gender norms determine personality rewards as it has been hypothesised previously (Blau and Kahn, 2017). Overall, I find small differences in the likelihood of making it to the top income quintile by gender. This finding helps in directing the efforts of companies and governments in closing the gender pay gap to different aspects other than personality. The finding that agreeableness is punished for men as compared to women is further interesting for companies interested in changing their company culture so that there is no differential in reward to personality traits. They can focus on agreeableness specifically and could change the standard according to which individuals are evaluated (Judge, Livingston and Hurst, 2012). Increasing the awareness around unjustifiable rewards is helpful in alleviating mechanisms that are not related to productivity outcomes.

The findings in Chapter 3 (Paper 4) are again relevant to both companies and individuals. I focus on the demand and reward for detailed skills groups and thereby add to previous literature that analyses non-cognitive skills more broadly (Deming and Kahn, 2018). First, knowing which specific skills are becoming increasingly important in terms of demand and reward is essential in the context of the Fourth Industrial Revolution. Firms can adapt training and upskilling agendas for their employees accordingly. Such activities also add to companies' value proposition when trying to attract and retain talent. With the help of my research output, individuals can also adapt their education and upskilling decisions. For example, the findings regarding data science skills may speak against the common intuition that data science pays always. Knowing that the premium to specific data science skills changes rapidly and that one needs to upskill regularly to stay up to the date with the newest technology is helpful in differentiating the advantages from potential caveats of data science education. Second, the insights inform on the volatility of prices for specific skills over time, which is relevant information for both wage-setting companies and wage-receiving employees. Third, the analysis provides valuable information for the hiring process. With the rapidly progressing Fourth Industrial Revolution, hiring has shifted increasingly away from education towards skills-based hiring (Sadun *et al.*, 2022). Companies hence have an incentive to invest in task-based assessments that focus on the skills they need and those highlighted as relevant in this study.

Chapter 4 (Paper 5) creates a new scale that captures what makes an individual inclusive of others at work that I call 'Individual Inclusiveness Inventory'. It is a self-reported measurement of inclusion. Individuals can use the 'Individual Inclusiveness Inventory' to self-assess their level of inclusiveness. This may help to increase self-awareness and to understand one's strengths and weaknesses. Companies can use the 'Individual Inclusiveness Inventory' when assessing the level of inclusiveness of their workforce. Companies have an interest in capturing what makes individuals inclusive given that I show that it links positively with income and also comparative salary, happiness and seniority. It can hence be used in the hiring process as assessment. It can also be tested as part of the promotion process when considering employees for upcoming promotions. Companies are increasingly using innovative tools that assesses a worker's soft skills profile in the hiring and also team allocation process; an example of which is the talent matching platform Pymetrics (Sadun *et al.*, 2022). Further, the 'Individual Inclusiveness Inventory' can also be used by companies for training and development when aiming to enhance their workers' inclusiveness.

5.4. Future Research

The conclusions of this thesis carry interesting possibilities for future research on the impact of non-cognitive skills in the labour market. In chapters 1.1.1. (Paper 1) and 1.1.2. (Paper 2), I argued that social skills have become increasingly important over time and that automation affects the demand for specific skills. This motivated the subsequent analyses in Chapter 2 (Paper 3), Chapter 3 (Paper 4) and Chapter 4 (Paper 5) taking a closer look at specific non-cognitive skills, the mechanisms and measurement thereof. Chapter 1.1.1. additionally makes the case for future research on how to effectively teach social skills. I argue that teaching programmes should be carefully designed in an evidence-based way so that they can be evaluated for their effectiveness. Such an evaluation (i.e., in a way that mimics a randomised controlled trial) would be highly valuable for future research to be able to make causal claims on what works in what context.

Chapter 2 provides evidence on the differential rewards to personality by gender. It motivates future research analysing the mechanisms of the effect of the Big Five personality traits on labour market outcomes more closely. Replicating the analysis in a larger sample that allows for an analysis at the 3-digit occupation level would be valuable to improve the interpretation of occupation-specific differences in differential rewards. Replicating the analysis in a non-UK sample would further be valuable to test for differences across countries with different social norms. Further, more research is needed that analyses the reason for differential rewards to agreeableness more closely. It would be particularly interesting to analyse to what extent the gap in reward by gender regarding agreeableness changes with changing labour market trends. Specifically, is the agreeableness gap closing over time as gender norms become less prevalent and as, for example, teamwork and collaboration (i.e., skills that correlate with agreeableness) are increasingly demanded in the labour market? Such an analysis would also fit nicely with the analyses in Chapter 3 and 4 where I focus on the increasing importance of 'collaborative leader' skills and inclusiveness.

Chapter 3 provides evidence on the demand and reward to specific skills over time. Extending this analysis to include more recent data would be interesting to incorporate the impact of the Covid-19 pandemic on skills requirements and also to confirm that the predictions hold with new technologies being implemented and on the horizon. The Fourth Industrial Revolution has progressed rapidly with new technologies being introduced such as the advanced AI chatbot ChatGPT that was launched in November 2022 that changes how we work and potentially substitutes labour, complements it or creates new work (Zarifhonarvar, 2023). Such technological developments also likely change the demand and reward for the skills I analysed in Chapter 3. Analysing how these developments affect skills requirements by using job advertisement data is hence valuable to analyse the dynamic nature of non-cognitive skills in the labour market. Further, in Chapter 3, I argue for the importance of upskilling and the reorganisation of education to account for the findings on which skills are demanded and rewarded. Future research would need to analyse how important skills such as 'collaborative leader' skills can be effectively taught. Again, implementing programmes in an experimental or randomised controlled setting would be appreciated to be able to comment on causality.

Chapter 4 provides evidence on how we can measure what makes an individual inclusive of others at work. Future research is necessary to better understand the relevance of the 'Individual Inclusiveness Inventory' that I validated. First, confirming the scale in additional samples would be highly appreciated. Extending the analysis to different countries other than the UK or different target populations (i.e., non-professional occupations) would also be interesting to analyse whether the scale can be applied universally. Second, analysing the link of the 'Individual Inclusiveness Inventory' to work outcomes more closely would also be valuable.

Third, using the scale in experiments that test the impact of inclusion programmes on group outcomes would be valuable to see whether individual inclusiveness predicts group outcomes in an experimental setting. In the vein of Chapter 2, it would also be interesting to test the mechanisms behind the effect of the 'Individual Inclusiveness Inventory' for work outcomes.

5.5. Concluding remarks

In this thesis, I aimed to improve our understanding of non-cognitive skills in the labour market. I am interested in non-cognitive skills at work. First, because I firmly believe in their importance in a work context jointly with cognitive skills having worked myself across different settings with different colleagues. Second, because I believe many aspects of non-cognitive skills have not yet been sufficiently studied or incorporated in work settings. As I progressed with my thesis, I explored and discovered new avenues for research, which is why each chapter of this thesis builds at least partly on the previous one. The thesis is a snapshot of this process. Going forward, there are multiple opportunities for studying additional aspects of non-cognitive skills that build on my thesis as outlined in the previous section. The research field is rapidly developing with new technologies being implemented and trends changing how we work. For example, I have been fascinated by the fact that there appears to be a 'labour market paradox' where on the one hand, many large companies are laying off staff (e.g., big tech companies in 2023) but at the same time there are talent shortages across many occupations (e.g., in healthcare occupations). While the reasons for such developments are manifold and will likely be persistent given changing demographic structures, this paradox implies and highlights once again the importance for governments, companies and individuals to develop successful and evidence-based talent strategies that are future-proof. I am hoping that my thesis has at least partly contributed to this understanding.

Bibliography

Abdi, H. and Williams, L.J. (2010) ‘Principal component analysis’, *Wiley Interdisciplinary Reviews: Computational Statistics*, 2(4), pp. 433–459. Available at: https://doi.org/10.1002/wics.101.

Acemoglu, D. and Restrepo, P. (2021) ‘Tasks, automation, and the rise in US wage inequality’, *NBER Working Paper*, w28920. Available at: http://www.nber.org/papers/w28920.

Akerlof, G.A. and Kranton, R.E. (2000) ‘Economics and Identity’, *The Quarterly Journal of Economics*, 115(3), pp. 715–753. Available at: https://doi.org/https://doi.org/10.1162/003355300554881.

Al-Atwi, A.A. and Al-Hassani, K.K. (2021) ‘Inclusive leadership: scale validation and potential consequences’, *Leadership and Organization Development Journal*, 42(8), pp. 1222–1240. Available at: https://doi.org/10.1108/LODJ-08-2020-0327.

Alekseeva, L. *et al.* (2021) ‘The demand for AI skills in the labor market’, *Labour Economics*, 71(May), p. 102002. Available at: https://doi.org/10.1016/j.labeco.2021.102002.

Allen, J., Belfi, B. and Borghans, L. (2020) ‘Is There a Rise in the Importance of Socioemotional Skills in the Labor Market? Evidence From a Trend Study Among College Graduates’, *Frontiers in Psychology*, 11. Available at: https://doi.org/10.3389/fpsyg.2020.01710.

Almlund, M. *et al.* (2011) ‘Personality Psychology and Economics’, *NBER Working Paper Series*, w16822. Available at: https://doi.org/10.3386/w16822.

Antecol, H. and Cobb-Clark, D.A. (2013) ‘Do psychosocial traits help explain gender segregation in young people’s occupations?’, *Labour Economics*, 21, pp. 59–73. Available at: https://doi.org/10.1016/j.labeco.2012.12.005.

Atalay, E. *et al.* (2020) ‘The Evolution of Work in the United States’, *American Economic Journal: Applied Economics*, 12(2), pp. 1–34. Available at: https://doi.org/10.1257/APP.20190070.

Aust, F. *et al.* (2012) ‘Seriousness checks are useful to improve data validity in online research’, *Behavior Research Methods*, 45, pp. 527–535. Available at: https://doi.org/10.3758/s13428-012-0265-2.

Autor, D. and Dorn, D. (2013) ‘The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market’, *The American Economic Review*, 103(5), pp. 1553–1597. Available at: https://doi.org/10.1257/aer.103.5.1553.

Autor, D.H., Dorn, D. and Hanson, G.H. (2015) ‘Untangling Trade and Technology: Evidence from Local Labour Markets’, *Economic Journal*, 125(584), pp. 621–646. Available at: https://doi.org/10.1111/ecoj.12245.

Autor, D.H., Levy, F. and Murnane, R.J. (2003) ‘The Skill Content of Recent Technological Change: An Empirical Exploration’, *The Quarterly Journal of Economics*, 118(4), pp. 1279–1333. Available at: https://doi.org/https://doi.org/10.1162/003355303322552801.

Azmat, G. and Petrongolo, B. (2014) 'Gender and the labor market: What have we learned from field and lab experiments?', *Labour Economics*, 30, pp. 32–40. Available at: https://doi.org/10.1016/j.labeco.2014.06.005.

Bainbridge, T.F., Ludeke, S.G. and Smillie, L.D. (2022) 'Evaluating the Big Five as an Organizing Framework for Commonly Used Psychological Trait Scales', *Journal of Personality and Social Psychology*, 122(4), pp. 749–777. Available at: https://doi.org/10.1037/pspp0000395.

Barrick, M.R., Mount, M.K. and Judge, T.A. (2001) 'Personality and Performance at the Beginning of the New Millennium: What Do We Know and Where Do We Go Next?', *International Journal of Selection and Assessment*, 9(1 & 2), pp. 9–30. Available at: https://doi.org/https://doi.org/10.1111/1468-2389.00160.

Bartholomew, D.J. *et al.* (2011) 'Principal Component Analysis', in *Analysis of Multivariate Social Science Data*. Second Edi, pp. 117–144.

Basso, F. and Krpan, D. (2022) 'Supplementary appendix: Measuring the transformative utopian impulse for planetary health in the age of the Anthropocene: a multi-study scale development and validation', *The Lancet Planetary Health*, 6(3), pp. e230–e242. Available at: https://doi.org/10.1016/S2542-5196(22)00004-3.

Berger, T. and Frey, B. (2016) *Digitalization, jobs, and convergence in Europe: strategies for closing the skills gap*, *European Commission - DG Internal Market, Industry, Entrepreneurship and SMEs*. Available at: http://www.oxfordmartin.ox.ac.uk/downloads/reports/SCALE_Digitalisation_Final.pdf.

Bertrand, M. (2011) 'New perspectives on gender', in *Handbook of Labor Economics*. Elsevier B.V., pp. 1543–1590. Available at: https://doi.org/10.1016/S0169-7218(11)02415-4.

Bertrand, M. and Duflo, E. (2016) 'Field Experiments on Discrimination', *NBER Working paper*, w22014. Available at: https://doi.org/10.3386/w22014.

Blair, P.Q.. and Deming, D. (2020) 'Structural Increases in Skill Demand after the Great Recession', *AEA Papers and Proceedings*, 110, pp. 362–365. Available at: https://doi.org/https://doi.org/10.1257/pandp.20201064.

Blau, F.D. and Kahn, L.M. (2017) 'The Gender Wage Gap: Extent, Trends, and Explanations', *Journal of Economic Literature*, 55(3), pp. 789–865. Available at: https://doi.org/10.1257/jel.20160995.

Boateng, G.O. *et al.* (2018) 'Best Practices for Developing and Validating Scales for Health, Social, and Behavioral Research: A Primer', *Frontiers in Public Health*, 6, p. 149. Available at: https://doi.org/10.3389/FPUBH.2018.00149.

Bode, E. *et al.* (2019) 'Worker Personality: Another Skill Bias Beyond Education in the Digital Age', *German Economic Review*, 20(4), pp. e254–e294. Available at: https://doi.org/10.2139/ssrn.2884733.

Borghans, L. *et al.* (2008) 'The Economics and Psychology of Personality Traits', *The Journal of Human Resources*, 43(4), pp. 972–1059. Available at: https://doi.org/https://doi.org/10.3368/jhr.43.4.972.

Borghans, L., Ter Weel, B. and Weinberg, B.A. (2006) ‘Interpersonal Styles and Labor Market Outcomes’, *United Nations MERIT Working Paper* [Preprint]. Available at: https://www.merit.unu.edu/publications/wppdf/2006/wp2006-045.pdf (Accessed: 11 April 2023).

Borghans, L., Ter Weel, B. and Weinberg, B.A. (2014) ‘People skills and the labor-market outcomes of underrepresented groups’, *ILR Review*, 67(2), pp. 287–334. Available at: https://doi.org/10.1177/001979391406700202.

Braakmann, N. (2009) ‘The Role of Psychological Traits for the Gender Gap in Full-Time Employment and Wages: Evidence from Germany’, *SOEP Paper*, 162. Available at: https://doi.org/https://dx.doi.org/10.2139/ssrn.1357346.

Braun, V. and Clarke, V. (2006) ‘Using thematic analysis in psychology’, *Qualitative Research in Psychology*, 3(2), pp. 77–101. Available at: https://doi.org/10.1191/1478088706qp063oa.

Brewer, M. (1991) ‘The social self: On being the same and different at the same time’, *Personality and Social Psychology Bulletin*, 17(5), pp. 475–482. Available at: https://doi.org/https://doi.org/10.1177/01461672911750.

Brynjolfsson, E., Mitchell, T. and Rock, D. (2018) ‘What Can Machines Learn and What Does It Mean for Occupations and the Economy?’, *American Economic Association*, 108, pp. 43–47. Available at: https://doi.org/10.1257/pandp.20181019.

Busic-Sontic, A., Czap, N. V. and Fuerst, F. (2017) ‘The role of personality traits in green decision-making’, *Journal of Economic Psychology*, 62, pp. 313–328. Available at: https://doi.org/10.1016/j.joep.2017.06.012.

Calanca, F. *et al.* (2019) ‘Responsible team players wanted: an analysis of soft skill requirements in job advertisements’, *EPJ Data Science*, 8(13). Available at: https://doi.org/10.1140/epjds/s13688-019-0190-z.

Campello, M., Kankanhalli, G. and Muthukrishnan, P. (2021) ‘Corporate Hiring under COVID-19: Financial Constraints and the Nature of New Jobs’, *Journal of Financial and Quantitative Analysis (JFQA), Forthcoming* [Preprint]. Available at: https://doi.org/10.2139/ssrn.3596655.

Carmeli, A., Reiter-Palmon, R. and Ziv, E. (2010) ‘Inclusive Leadership and Employee Involvement in Creative Tasks in the Workplace: The Mediating Role of Psychological Safety’, *Psychology Faculty Publications*, 30. Available at: https://digitalcommons.unomaha.edu/psychfacpub/30 (Accessed: 19 January 2023).

Carnevale, A., Jayasundera, T. and Repnikov, D. (2014) *Understanding Online Job Ads Data*, *Georgetown University Centre on Education and the Workforce*. Available at: https://cew.georgetown.edu/wp-content/uploads/2014/11/OCLM.Tech_.Web_.pdf.

Carpenter, S. (2018) ‘Ten Steps in Scale Development and Reporting: A Guide for Researchers’, *Communication Methods and Measures*, 12(1), pp. 25–44. Available at: https://doi.org/10.1080/19312458.2017.1396583.

Cerioli, M., Leotta, M. and Ricca, F. (2020) ‘What 5 Million Job Advertisements Tell Us about Testing: a Preliminary Empirical Investigation’, *Proceedings of the 35th Annual ACM Symposium on Applied Computing*, pp. 1586–1594. Available at: https://doi.org/https://doi.org/10.1145/3341105.3373961.

Chernoff, A.W. and Warman, C. (2020) ‘COVID-19 and Implications for Automation’, *NBER Working Paper Series*, w27249. Available at: https://doi.org/10.3386/w27249.

Clifton, J.D.W. (2020) ‘Managing validity versus reliability trade-offs in scale-building decisions’, *Psychological Methods*, 25(3), pp. 259–270. Available at: https://doi.org/10.1037/met0000236.

Cobb-Clark, D.A. (2015) ‘Locus of control and the labor market’, *IZA Journal of Labor Economics*, 4(3). Available at: https://doi.org/10.1186/s40172-014-0017-x.

Cobb-Clark, D.A. and Schurer, S. (2012) ‘The stability of big-five personality traits’, *Economics Letters*, 115, pp. 11–15. Available at: https://doi.org/https://doi.org/10.1016/j.econlet.2011.11.015.

Cobb-Clark, D.A. and Schurer, S. (2013) ‘Two economists’ musings on the stability of locus of control’, *Economic Journal*, 123(570). Available at: https://doi.org/10.1111/ecoj.12069.

Cobb-Clark, D.A. and Tan, M. (2011) ‘Noncognitive skills, occupational attainment, and relative wages’, *Labour Economics*, 18(1), pp. 1–13. Available at: https://doi.org/10.1016/j.labeco.2010.07.003.

Collischon, M. (2020) ‘The Returns to Personality Traits Across the Wage Distribution’, *LABOUR*, 34(1), pp. 48–79. Available at: https://doi.org/10.1111/labr.12165.

Cortes, G.M., Jaimovich, N. and Siu, H. (2018) ‘The “End of Men” and Rise of Women in the High-Skilled Labor Market’, *NBER Working Paper*, w24274. Available at: https://doi.org/10.3386/w24274.

Costa, P. and McCrae, R.R. (1992) ‘Four ways five factors are basic’, *Personality and Individual Differences*, 13(6), pp. 653–665. Available at: https://doi.org/10.1016/0191-8869(92)90236-I.

Credé, M. (2018) ‘What Shall We Do About Grit? A Critical Review of What We Know and What We Don’t Know’, *https://doi.org/10.3102/0013189X18801322*, 47(9), pp. 606–611. Available at: https://doi.org/10.3102/0013189X18801322.

Cronbach, L. (1951) ‘Coefficient alpha and the internal structure of tests’, *Psychometrika*, 16(3), pp. 297–334. Available at: https://doi.org/https://doi.org/10.1007/BF02310555.

Cross, R., Rebele, R. and Grant, A. (2016) ‘Collaborative overload’, *Harvard Business Review*, 2016(January-February). Available at: https://hbr.org/2016/01/collaborative-overload (Accessed: 12 April 2023).

Cubel, M. *et al.* (2014) ‘Do Personality Traits Affect Productivity? Evidence from the Lab’, *IZA Discussion Paper* [Preprint], (July). Available at: https://docs.iza.org/dp8308.pdf.

Deming, D. (2021) ‘The Growing Importance of Decision-Making on the Job’, *NBER Working paper series*, w28733. Available at: https://doi.org/10.2139/ssrn.3838499.

Deming, D. and Kahn, L.B. (2018) ‘Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals’, *Journal of Labor Economics*, 36(S1), pp. S337–S369. Available at: https://doi.org/https://doi.org/10.1086/694106.

Deming, D.J. (2017) ‘The Growing Importance of Social Skills in the Workplace’, *The Quarterly Journal of Economics*, 132(4), pp. 1593–1640. Available at: https://doi.org/https://doi.org/10.1093/qje/qjx022.

Deming, D.J. and Noray, K. (2020) ‘STEM careers and the changing skills requirements of work’, *The Quarterly Journal of Economics*, 135(4), pp. 1965–2005. Available at: https://doi.org/10.1093/qje/qjaa021.

Devlin, J. *et al.* (2019) ‘BERT: Pre-training of deep bidirectional transformers for language understanding’, *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 1(Mlm), pp. 4171–4186. Available at: https://deepsense.ai/wp-content/uploads/2023/03/1810.04805.pdf (Accessed: 12 April 2023).

Dingel, J.I. and Neiman, B. (2020) ‘How many jobs can be done at home?’, *Journal of Public Economics*, 189, p. 104235. Available at: https://doi.org/10.1016/j.jpubeco.2020.104235.

Dondi, M. *et al.* (2021) *Defining the skills citizens will need in the future world of work*, *McKinsey*. Available at: https://mck.co/3b1wULK.

Duckworth, A.L. *et al.* (2007) ‘Grit: Perseverance and Passion for Long-Term Goals’, *Journal of Personality and Social Psychology*, 92(6), pp. 1087–1101. Available at: https://doi.org/10.1037/0022-3514.92.6.1087.

Duckworth, A.L. *et al.* (2012) ‘Who does well in life? Conscientious adults excel in both objective and subjective success’, *Frontiers in Psychology*, 3(SEP), pp. 1–8. Available at: https://doi.org/10.3389/fpsyg.2012.00356.

Duckworth, A.L. and Quinn, P.D. (2009) ‘Development and validation of the short Grit Scale (Grit-S)’, *Journal of Personality Assessment*, 91(2), pp. 166–174. Available at: https://doi.org/10.1080/00223890802634290.

Eagly, A.H. and Sczesny, S. (2009) ‘Stereotypes about women, men, and leaders: Have times changed?’, in *The glass ceiling in the 21st century: Understanding barriers to gender equality*. American Psychological Association, pp. 21–47. Available at: https://doi.org/https://doi.org/10.1037/11863-002.

Edin, P.A. *et al.* (2022) ‘The Rising Return to Noncognitive Skill’, *American Economic Journal: Applied Economics*, 14(2), pp. 78–100. Available at: https://doi.org/10.1257/APP.20190199.

Edmondson, A.C. and Besieux, T. (2021) ‘Reflections: Voice and Silence in Workplace Conversations’, *Journal of Change Management*, 21(3). Available at: https://doi.org/10.1080/14697017.2021.1928910.

Faberman, J. and Kudlyak, M. (2016) ‘What does online job search tell us about the labor market?’, *Economic Perspectives*, 40(1), pp. 1–15. Available at: https://fraser.stlouisfed.org/files/docs/historical/frbchi/economicperspectives/frbchi_econper_2016n1.pdf.

Forsythe, E. *et al.* (2020) ‘Labor Demand in the time of COVID-19: Evidence from vacancy postings and UI claims’, *Nber Working Paper Series*, w27061. Available at: https://doi.org/10.3386/w27061.

Fortin, N.M., Bell, B. and Böhm, M. (2017) ‘Top earnings inequality and the gender pay gap: Canada, Sweden, and the United Kingdom’, *Labour Economics*, 47, pp. 107–123. Available at: https://doi.org/10.1016/j.labeco.2017.05.010.

Frey, C.B. and Osborne, M.A. (2017) ‘The future of employment: How susceptible are jobs to computerisation?’, *Technological Forecasting and Social Change*, 114, pp. 254–280. Available at: https://doi.org/10.1016/j.techfore.2016.08.019.

Fuller, J. *et al.* (2022) *The Emerging Degree Reset*, *White Paper, Burning Glass Institute*. Available at: https://www.hbs.edu/managing-the-future-of-work/Documents/research/emerging_degree_reset_020922.pdf.

Gensowski, M., Gørtz, M. and Schurer, S. (2021) ‘Inequality in personality over the life cycle’, *Journal of Economic Behavior and Organization*, 184, pp. 46–77. Available at: https://doi.org/10.1016/j.jebo.2021.01.018.

Gertler, P. *et al.* (2014) ‘Labor market returns to an early childhood stimulation intervention in Jamaica’, *Science*, 344(6187), pp. 998–1001. Available at: https://doi.org/10.1126/SCIENCE.1251178.

Ghislieri, C., Molino, M. and Cortese, C.G. (2018) ‘Work and Organizational Psychology Looks at the Fourth Industrial Revolution: How to Support Workers and Organizations?’, *Frontiers in Psychology*, 9(NOV), p. 2365. Available at: https://doi.org/10.3389/fpsyg.2018.02365.

Girotra, K., Terwiesch, C. and Ulrich, K.T. (2010) ‘Idea Generation and the Quality of the Best Idea’, *Management Science*, 56(4), pp. 591–605. Available at: https://doi.org/10.1287/mnsc.1090.1144.

Goldin, C. (2014) ‘A Grand Gender Convergence: Its Last Chapter’, *American Economic Review*, 104(4), pp. 1091–1119. Available at: https://doi.org/10.1257/aer.104.4.1091.

Goos, M. *et al.* (2019) ‘The impact of Technological innovation on the Future of Work’, *JRC Working Papers Series on Labour, Education and Technology*, No. 2019/03.

Griffin, B. and Hesketh, B. (2004) ‘Why openness to experience is not a good predictor of job performance’, *International Journal of Selection and Assessment*, 12(3), pp. 243–251. Available at: https://doi.org/10.1111/j.0965-075X.2004.278_1.x.

Gummer, T., Roßmann, J. and Silber, H. (2021) ‘Using Instructed Response Items as Attention Checks in Web Surveys: Properties and Implementation’, *Sociological Methods & Research*, 50(1), pp. 238–264. Available at: https://doi.org/10.1177/0049124118769083.

Gutman, L.M. and Schoon, I. (2013) *The impact of non-cognitive skills on outcomes for young people*, *The Institute of Education*. Available at: https://discovery.ucl.ac.uk/id/eprint/10125763/ (Accessed: 13 April 2023).

Hagger-Johnson, G. *et al.* (2012) 'School-related conscientiousness , alcohol drinking , and cigarette smoking in a representative sample of English school pupils', *British Journal of Health Psychology*, pp. 644–665. Available at: https://doi.org/10.1111/j.2044-8287.2011.02061.x.

Hair, J. *et al.* (2010) *Multivariate Data Analysis*. 7th edn.

Harrington, D. (2009) *Confirmatory Factor Analysis*, *Oxford University Press*.

Heckman, J. and Kautz, T. (2012) 'Hard evidence on soft skills', *Labour Economics*, 19(4), pp. 451–464. Available at: https://doi.org/10.1016/j.labeco.2012.05.014.

Heckman, J. and Kautz, T. (2013) 'Fostering and Measuring Skills: Interventions that improve character and cognition', *NBER Working Paper Series*, w19656. Available at: https://doi.org/10.3386/w19656.

Heckman, J., Stixrud, J. and Urzua, S. (2006) 'The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior', *Journal of Labor Economics*, 24(3), pp. 411–482. Available at: https://doi.org/10.1086/504455.

Heckman, J.J. *et al.* (2012) 'Web Appendix to Understanding the Mechanisms Through Which an Influential Early Childhood Program Boosted Adult Outcomes', *American Economic Review* [Preprint].

Heineck, G. (2011) 'Does it pay to be nice? Personality and Earnings in the United Kingdom', *Industrial and Labor Relations Review*, 64(5), pp. 1020–1038. Available at: https://doi.org/https://doi.org/10.1177/001979391106400509.

Heineck, G. and Anger, S. (2010) 'The returns to cognitive abilities and personality traits in Germany', *Labour Economics*, 17(3), pp. 535–546. Available at: https://doi.org/10.1016/j.labeco.2009.06.001.

Henrich, J., Heine, S.J. and Norenzayan, A. (2010) 'The weirdest people in the world?', *Behavioral and Brain Sciences*. Cambridge University Press, pp. 61–83. Available at: https://doi.org/10.1017/S0140525X0999152X.

Hershbein, B. and Kahn, L.B. (2018) 'Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings', *American Economic Review*, 108(7), pp. 1737–1772. Available at: https://doi.org/10.1257/aer.20161570.

Hoffman, M. and Tadelis, S. (2018) 'People Management Skills, Employee Attrition, and Manager Rewards: An Empirical Analysis', *Nber Working Paper Series*, w24360. Available at: https://doi.org/10.3386/w24360.

Hong, L. and Page, S.E. (2004) 'Groups of diverse problem solvers can outperform groups of high-ability problem solvers', *Proceedings of the National Academy of Sciences of the United States of America*, 101(46), pp. 16385–16389. Available at: https://doi.org/10.1073/pnas.0403723101.

Hoogendoorn, S. and Van Praag, M. (2012) ‘Ethnic Diversity and Team Performance: A Field Experiment’, *IZA Discussion Paper*, No. 6731. Available at: https://docs.iza.org/dp6731.pdf (Accessed: 13 January 2021).

Ibarra, H. and Hansen, M.T. (2011) ‘Are you a collaborative leader?’, *Harvard Business Review*, 3(July-August). Available at: https://hbr.org/2011/07/are-you-a-collaborative-leader (Accessed: 12 April 2023).

Institute for Social and Economic Research (2020) *Understanding Society Guidelines*. Available at: https://www.understandingsociety.ac.uk/documentation/mainstage/dataset-documentation/variable/big5a_dv (Accessed: 5 January 2020).

Jansen, W.S. *et al.* (2014) ‘Inclusion: Conceptualization and measurement’, *European Journal of Social Psychology*, 44(4), pp. 370–385. Available at: https://doi.org/10.1002/ejsp.2011.

John, K. and Thomsen, S.L. (2014) ‘Heterogeneous returns to personality: The role of occupational choice’, *Empirical Economics*, 47(2), pp. 553–592. Available at: https://doi.org/10.1007/s00181-013-0756-8.

John, O. and Srivastava, S. (1999) ‘The Big-Five Trait Taxonomy: History, Measurement, and Theoretical Perspectives’, in *Handbook of personality: Theory and research*, pp. 102–138.

Johnson, J.A. (1997) ‘Units of Analysis for the Description and Explanation of Personality’, *Handbook of Personality Psychology*, pp. 73–93. Available at: https://doi.org/10.1016/b978-012134645-4/50004-4.

Jollife, I.T. and Cadima, J. (2016) ‘Principal component analysis: a review and recent developments’, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2065). Available at: https://doi.org/10.1098/RSTA.2015.0202.

Josten, C. and Lordan, G. (2020) ‘Robots at Work: Automatable and non-automatable jobs’, in *Handbook of Labor, Human Resources and Population Economics*. Springer International Publishing, pp. 1–24. Available at: https://doi.org/10.1007/978-3-319-57365-6_10-1.

Josten, C. and Lordan, G. (2021) ‘The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic’, *LSE Public Policy Review*, 1(4), pp. 1–10. Available at: https://doi.org/10.31389/lseppr.31.

Josten, C. and Lordan, G. (2022) ‘Automation and the changing nature of work’, *PLOS ONE*, 17(5), p. e0266326. Available at: https://doi.org/10.1371/JOURNAL.PONE.0266326.

Judge, T.A., Heller, D. and Mount, M.K. (2002) ‘Five-Factor Model of Personality and Job Satisfaction: A Meta-Analysis’, *Journal of Applied Psychology*, 87(3), pp. 530–541. Available at: https://doi.org/10.1037/0021-9010.87.3.530.

Judge, T.A., Livingston, B.A. and Hurst, C. (2012) ‘Do nice guys-and gals-really finish last? The joint effects of sex and agreeableness on income’, *Journal of Personality and Social Psychology*, 102(2), pp. 390–407. Available at: https://doi.org/10.1037/a0026021.

Killingsworth, M.A., Kahneman, D. and Mellers, B. (2023) ‘Income and emotional well-being: A conflict resolved’, *Proceedings of the National Academy of Sciences of the United States of America*, 120(10). Available at: https://doi.org/10.1073/PNAS.2208661120.

Knudsen, E. *et al.* (2006) ‘Economic, Neurobiological and Behavioral Perspectives on Building America’s Future Workforce’, *NBER Working Paper Series*, w12298. Available at: https://doi.org/10.3386/w12298.

Kuhn, P. and Weinberger, C. (2005) ‘Leadership Skills and Wages’, *Journal of Labor Economics*, 23(3), pp. 395–436. Available at: https://doi.org/10.1086/430282.

Kung, F.Y.H., Kwok, N. and Brown, D.J. (2018) ‘Are Attention Check Questions a Threat to Scale Validity?’, *Applied Psychology*, 67(2), pp. 264–283. Available at: https://doi.org/10.1111/APPS.12108.

Kyriazos, T.A. and Stalikas, A. (2018) ‘Applied Psychometrics: The Steps of Scale Development and Standardization Process’, *Psychology*, 09(11), pp. 2531–2560. Available at: https://doi.org/10.4236/PSYCH.2018.911145.

Lee, S.Y. and Ohtake, F. (2018) ‘Is being agreeable a key to success or failure in the labor market?’, *Journal of the Japanese and International Economies*, 49(960), pp. 8–27. Available at: https://doi.org/10.1016/j.jjie.2018.01.003.

Lekfuangfu, W.N. *et al.* (2018) ‘Locus of Control and its Intergenerational Implications for Early Childhood Skill Formation’, *Economic Journal*, 128(608), pp. 298–329. Available at: https://doi.org/10.1111/ECOJ.12414.

Lewandowski, P. *et al.* (2019) ‘Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data’, *IZA Discussion Paper*, No. 12339. Available at: https://docs.iza.org/dp12339.pdf (Accessed: 9 July 2021).

Li, H., Chen, C. and Zhang, Z. (2021) ‘Are gender differences related to non-cognitive abilities? - Evidence from China’, *Journal of the Asia Pacific Economy*, pp. 1–20. Available at: https://doi.org/https://doi.org/10.1080/13547860.2021.1982483.

Lievens, F., De Corte, W. and Schollaert, E. (2008) ‘A Closer Look at the Frame-of-Reference Effect in Personality Scale Scores and Validity’, *Journal of Applied Psychology*, 93(2), pp. 268–279. Available at: https://doi.org/10.1037/0021-9010.93.2.268.

Lindqvist, E. and Vestman, R. (2011) ‘The labor market returns to cognitive and noncognitive ability: Evidence from the swedish enlistment’, *American Economic Journal: Applied Economics*, 3(1), pp. 101–128. Available at: https://doi.org/10.1257/app.3.1.101.

LinkUp (2022) *Job Market Data*.

Lordan, G. (2018) *Robots at work - A report on automatable and non-automatable employment shares in Europe*, *European Commission - Directorate-General for Employment, Social Affairs and Inclusion*. Available at: https://doi.org/10.2767/821645.

Lordan, G. (2021) ‘Automation and the changing nature of work: 2020 onwards’, *Working paper* [Preprint].

Lordan, G. and McGuire, A. (2019) 'Widening the High School Curriculum to Include Soft Skill Training: Impacts on Health, Behaviour, Emotional Wellbeing and Occupational Aspirations', *IZA Discussion Paper*, 12439. Available at: https://docs.iza.org/dp12439.pdf (Accessed: 13 April 2023).

Lordan, G. and Neumark, D. (2018) 'People versus machines: The impact of minimum wages on automatable jobs', *Labour Economics*, 52, pp. 40–53. Available at: https://doi.org/10.1016/j.labeco.2018.03.006.

Lordan, G. and Pischke, J.S. (2022a) 'Does Rosie Like Riveting? Male and Female Occupational Choices', *Economica*, 89(353), pp. 110–130. Available at: https://doi.org/10.1111/ecca.12390.

Lordan, G. and Pischke, J.S. (2022b) 'Does Rosie Like Riveting? Male and Female Occupational Choices - Appendix', *Economica*, 89(353), pp. 110–130. Available at: https://doi.org/10.1111/ecca.12390.

Lyons, E. (2017) 'Team Production in International Labor Markets: Experimental Evidence from the Field', *American Economic Journal: Applied Economics*, 9(3), pp. 70–104. Available at: https://doi.org/10.1257/app.20160179.

Maczulskij, T. and Viinikainen, J. (2018) 'Is personality related to permanent earnings? Evidence using a twin design', *Journal of Economic Psychology*, 64, pp. 116–129. Available at: https://doi.org/10.1016/j.joep.2018.01.001.

Manning, A. and Swaffield, J. (2008) 'The gender gap in early-career wage growth', *Economic Journal*, 118(530), pp. 983–1024. Available at: https://doi.org/10.1111/j.1468-0297.2008.02158.x.

Manyika, J. *et al.* (2017) *Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation*, *McKinsey Global Institute*. Available at: https://www.mckinsey.com/~/media/BAB489A30B724BECB5DEDC41E9BB9FAC.ashx.

Martin-Raugh, M.P., Williams, K.M. and Lentini, J. (2020) 'The Malleability of Workplace-Relevant Noncognitive Constructs: Empirical Evidence From 39 Meta-Analyses and Reviews', *ETS Research Report Series*, (1), pp. 1–25. Available at: https://doi.org/10.1002/ets2.12306.

Modestino, A.S., Shoag, D. and Balance, J. (2020) 'Upskilling: Do employers demand greater skill when workers are plentiful?', *Review of Economics and Statistics*, 102(4), pp. 793–805. Available at: https://doi.org/10.1162/rest_a_00835.

Mor Barak, M. *et al.* (2016) 'The Promise of Diversity Management for Climate of Inclusion: A State-of-the-Art Review and Meta-Analysis', *Human Service Organizations: Management, Leadership & Governance*, 40(4), pp. 305–333. Available at: https://doi.org/10.1080/23303131.2016.1138915.

Morgado, F.F.R. *et al.* (2017) 'Scale development: ten main limitations and recommendations to improve future research practices', *Psicologia: Reflexão e Crítica 2017 30:1*, 30(3), pp. 1–20. Available at: https://doi.org/10.1186/S41155-016-0057-1.

MSCI (2022) *MSCI World Index (USD)*. Available at: https://www.msci.com/documents/10199/178e6643-6ae6-47b9-82be-e1fc565ededb (Accessed: 12 January 2022).

Mueller, G. and Plug, E. (2006) 'Estimating the Effect of Personality on Male and Female Earnings', *Industrial and Labor Relations Review*, 60(1), pp. 3–22. Available at: https://doi.org/https://doi.org/10.1177/001979390606000101.

Nai, A. and Toros, E. (2020) 'The peculiar personality of strongmen: comparing the Big Five and Dark Triad traits of autocrats and non-autocrats', *Political Research Exchange*, 2(1), pp. 1–24. Available at: https://doi.org/10.1080/2474736x.2019.1707697.

Nandi, A. and Nicoletti, C. (2014) 'Explaining personality pay gaps in the UK', *Applied Economics*, 46(26), pp. 3131–3150. Available at: https://doi.org/10.1080/00036846.2014.922670.

Nembhard, I.M. and Edmondson, A.C. (2006) 'Making It Safe: The Effects of Leader Inclusiveness and Professional Status on Psychological Safety and Improvement Efforts in Health Care Teams', *Journal of Organizational Behavior*, 27(7), pp. 941–966. Available at: https://doi.org/10.1002/job.413.

Nishii, L.H. (2013) 'The Benefits of Climate for Inclusion for Gender-Diverse Groups', *Academy of Management Journal*, 50(6). Available at: https://doi.org/10.5465/amj.2009.0823.

Nishii, L.H. and Leroy, H. (2022) 'A Multi-Level Framework of Inclusive Leadership in Organizations', *Group and Organization Management*, 47(4), pp. 683–722. Available at: https://doi.org/https://doi.org/10.1177/10596011221111505.

Nishii, L.H. and Leroy, H.L. (2021) 'Inclusive leadership: Leaders as architects of inclusive workgroup climates', in J.P. B. M. Ferdman and R.E. Riggio (eds) *Inclusive leadership: Transforming diverse lives, workplaces, and societies*. Routledge/Taylor & Francis Group.

Norton, E.C., Wang, H. and Ai, C. (2004) 'Computing interaction effects and standard errors in logit and probit models', *The Stata Journal*, 4(2), pp. 154–167. Available at: www.jstor.org (Accessed: 7 June 2022).

Nyhus, E.K. and Pons, E. (2005) 'The effects of personality on earnings', *Journal of Economic Psychology*, 26(3), pp. 363–384. Available at: https://doi.org/10.1016/j.joep.2004.07.001.

OECD (2021) 'An Assessment of the Impact of COVID-19 on Job and Skills Demand Using Online Job Vacancy Data', *OECD*, (April), pp. 1–19. Available at: https://www.oecd.org/coronavirus/policy-responses/an-assessment-of-the-impact-of-covid-19-on-job-and-skills-demand-using-online-job-vacancy-data-20fff09e/ (Accessed: 12 April 2023).

Palan, S. and Schitter, C. (2018) 'Prolific.ac—A subject pool for online experiments', *Journal of Behavioral and Experimental Finance*, 17, pp. 22–27. Available at: https://doi.org/10.1016/J.JBEF.2017.12.004.

Peer, E. *et al.* (2017) 'Beyond the Turk: Alternative platforms for crowdsourcing behavioral research', *Journal of Experimental Social Psychology*, 70, pp. 153–163. Available at: https://doi.org/10.1016/J.JESP.2017.01.006.

Pohlmeier, W. and Wichert, L. (2010) 'Female labor force participation and the big five', *ZEW Discussion Papers*, No. 10-003. Available at: https://madoc.bib.uni-mannheim.de/2827/1/dp10003.pdf (Accessed: 3 January 2020).

Rammstedt, B. and Beierlein, C. (2014) 'Can't we make it any shorter? The limits of personality assessment and ways to overcome them', *Journal of Individual Differences*, 35(4), pp. 212–220. Available at: https://doi.org/10.1027/1614-0001/a000141.

Randel, A.E. *et al.* (2018) 'Inclusive leadership: Realizing positive outcomes through belongingness and being valued for uniqueness', *Human Resource Management Review*, 28, pp. 190–203. Available at: https://doi.org/10.1016/j.hrmr.2017.07.002.

Roberson, Q. and Perry, J.L. (2022) 'Inclusive Leadership in Thought and Action: A Thematic Analysis', *Group & Organization Management*, 47(4), pp. 755–778. Available at: https://doi.org/10.1177/10596011211013161.

Roberson, Q.M. (2006) 'Disentangling the Meanings of Diversity and Inclusion in Organizations', *Group & Organization Management*, 31(2), pp. 212–236. Available at: https://doi.org/10.1177/1059601104273064.

Roberson, Q.M. (2019) 'Diversity in the Workplace: A Review, Synthesis, and Future Research Agenda', *Annual Review of Organizational Psychology and Organizational Behavior*, 6, pp. 69–88. Available at: https://doi.org/https://doi.org/10.1146/annurev-orgpsych-012218-015243.

Roberts, B.W., Caspi, A. and Moffitt, T.E. (2003) 'Work Experiences and Personality Development in Young Adulthood', *Journal of Personality and Social Psychology*, 84(3), pp. 582–593. Available at: https://doi.org/10.1037/0022-3514.84.3.582.

Roberts, B.W. and DelVecchio, W.F. (2000) 'The rank-order consistency of personality traits from childhood to old age: A quantitative review of longitudinal studies', *Psychological Bulletin*, 126(1), pp. 3–25. Available at: https://doi.org/10.1037/0033-2909.126.1.3.

Sadun, R. *et al.* (2022) 'The C-Suite Skills That Matter', *Harvard Business Review*. Available at: https://hbr.org/2022/07/the-c-suite-skills-that-matter-most.

Samek, L., Squicciarini, M. and Cammeraat, E. (2021) *The human capital behind AI*, *OECD Science, Technology and Innovation Policy Papers*.

Schmitt, D.P. *et al.* (2008) 'Why Can't a Man Be More Like a Woman? Sex Differences in Big Five Personality Traits Across 55 Cultures', *Journal of Personality and Social Psychology*, 94(1), pp. 168–182. Available at: https://doi.org/10.1037/0022-3514.94.1.168.

Schwab, K. (2015) 'The Fourth Industrial Revolution- What It Means and How to Respond', *Foreign Affairs*. Available at: https://www.foreignaffairs.com/world/fourth-industrial-revolution (Accessed: 12 April 2023).

Seong, J.Y. and Hong, D.S. (2013) ‘Gender diversity: How can we facilitate its positive effects on teams?’, *Social Behavior and Personality*, 41(3), pp. 497–507. Available at: https://doi.org/10.2224/sbp.2013.41.3.497.

Shore, L.M. *et al.* (2011) ‘Inclusion and Diversity in Work Groups: A Review and Model for Future Research’, *Journal of Management*, 37(4). Available at: https://doi.org/10.1177/0149206310385943.

Shore, L.M. and Chung, B.G. (2021) ‘Inclusive Leadership: How Leaders Sustain or Discourage Work Group Inclusion’, *Group and Organization Management*, 47(4). Available at: https://doi.org/10.1177/1059601121999580.

Shore, L.M., Cleveland, J.N. and Sanchez, D. (2018) ‘Inclusive workplaces: A review and model’, *Human Resource Management Review*, 28(2), pp. 176–189. Available at: https://doi.org/10.1016/j.hrmr.2017.07.003.

Sommers, S. (2006) ‘Diversity and Group Decision Making: Identifying Multiple Effects of Racial Composition on Jury Deliberations’, *Journal of Personality and Social Psychology*, 90(4). Available at: https://doi.org/10.1037/0022-3514.90.4.597.

Spurk, D. and Abele, A.E. (2011) ‘Who Earns More and Why? A Multiple Mediation Model from Personality to Salary’, *Journal of Business and Psychology*, 26, pp. 87–103. Available at: https://doi.org/10.1007/s10869-010-9184-3.

Squicciarini, M. and Nachtigall, H. (2021) ‘Demand for AI skills in jobs: Evidence from online job postings’, *OECD Science, Technology and Innovation Policy Papers*, 03. Available at: https://doi.org/10.1787/3ed32d94-en.

Stanton, J.M. *et al.* (2002) ‘Issues and strategies for reducing the length of self-report scales’, *Personnel Psychology*, 55(1), pp. 167–194. Available at: https://doi.org/10.1111/J.1744-6570.2002.TB00108.X.

Suhr, D. (2006) ‘Exploratory or confirmatory factor analysis?’, *Statistics and data analysis*, Paper 200-31. Available at: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=915520bdfde1423b0b73f7ed560c68e81678cda6 (Accessed: 12 April 2023).

Tabachnick, B. and Fidell, L. (2018) *Using Multivariate Statistics*. 7th edn. Pearson Education.

Thiel, H. and Thomsen, S.L. (2013) ‘Noncognitive skills in economics: Models, measurement, and empirical evidence’, *Research in Economics*, 67(2), pp. 189–214. Available at: https://doi.org/10.1016/j.rie.2013.03.002.

Tolan, S. *et al.* (2021) ‘Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks’, *Journal of Artificial Intelligence Research*, 71, pp. 191–236. Available at: https://doi.org/10.1613/jair.1.12647.

U.S. Department of Labor (2022) *Bureau of Labor Statistics*, *Occupational Employment Statistics*.

Uysal, S.D. and Pohlmeier, W. (2011) ‘Unemployment duration and personality’, *Journal of Economic Psychology*, 32(6), pp. 980–992. Available at: https://doi.org/10.1016/j.joep.2011.03.008.

Veli Korkmaz, A. *et al.* (2022) ‘About and beyond leading uniqueness and belongingness: A systematic review of inclusive leadership research’, *Human Resource Management Review*, p. 100894. Available at: https://doi.org/10.1016/J.HRMR.2022.100894.

Verma, A., Lamsal, K. and Verma, P. (2022) ‘An investigation of skill requirements in artificial intelligence and machine learning job advertisements’, *Industry and Higher Education*, 36(1), pp. 63–73. Available at: https://doi.org/10.1177/0950422221990990.

Viinikainen, J. *et al.* (2010) ‘Personality and Labour Market Income: Evidence from Longitudinal Data’, *LABOUR*, 24(2), pp. 201–220. Available at: https://doi.org/https://doi.org/10.1111/j.1467-9914.2010.00477.x.

Vivarelli, M. (2014) ‘Innovation, Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature’, *Journal of Economic Issues*, 48(1), pp. 123–154. Available at: https://doi.org/10.2753/JEI0021-3624480106.

Webb, M. (2019) ‘The Impact of Artificial Intelligence on the Labor Market’, *SSRN* [Preprint]. Available at: https://doi.org/https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3482150#:~:text=http%3A//dx.doi.org/10.2139/ssrn.3482150.

Weinberger, C. (2014) ‘The Increasing Complementarity between Cognitive and Social Skills’, *The Review of Economics and Statistics*, 96(5), pp. 849–861. Available at: https://doi.org/10.1162/REST_a_00449.

Wells, R., Ham, R. and Junankar, P.N. (Raja) (2016) ‘An examination of personality in occupational outcomes: antagonistic managers, careless workers and extraverted salespeople’, *Applied Economics*, 48(7), pp. 636–651. Available at: https://doi.org/10.1080/00036846.2015.1085636.

Zarifhonarvar, A. (2023) ‘Economics of ChatGPT: A Labor Market View on the Occupational Impact of Artificial Intelligence’, *SSRN* [Preprint]. Available at: https://doi.org/https://dx.doi.org/10.2139/ssrn.4350925.

Ziegler, L. (2021) ‘Skill Demand and Wages. Evidence from Linked Vacancy Data’, *IZA Discussion Paper Series*, No. 14511. Available at: https://doi.org/10.2139/ssrn.3879359.

Appendix A: The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic (Paper 1)

Published as:
Josten C, Lordan G. The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic. LSE Public Policy Review. 2021; 1(4): 5, pp. 1–10. DOI: https://doi.org/10.31389/lseppr.31

Josten C, Lordan G. The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic. *LSE Public Policy Review*. 2021; 1(4): 5, pp. 1–10. DOI: https://doi.org/10.31389/lseppr.31

RESEARCH

The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic

Cecily Josten and Grace Lordan
London School of Economics, UK
Corresponding author: Grace Lordan (g.lordan@lse.ac.uk)

The COVID-19 pandemic has brought with it a debate around which skills will be the most valuable in its aftermath. This study discusses the relevance of social skills in this debate and presents new evidence that shows its necessity. Specifically, we focus on knowledge workers and highlight that the importance of social skills was increasing pre-COVID-19 for these workers and that this importance has increased further during the pandemic, particularly for those in management roles. This study has also emphasised that we are at the beginning of the learning curve in understanding how social skills can be taught effectively to adults, and in particular knowledge workers. Establishing this evidence base is particularly important as governments around the world reconsider their skills agenda as a way to build up their economies post COVID-19.

Keywords: COVID-19; skills; social skills; knowledge workers; management

Introduction

The advent of the fourth industrial revolution[1] has brought with it a debate as to which skills will become redundant because of automation and which skills will remain in demand. The COVID-19 pandemic has increased the importance of this debate, with the UK government emphasising the necessity of providing skills that are valued by employers as a response to the COVID-19 pandemic. This study discusses the relevance of social skills in this debate. Specifically, we focus on knowledge workers and highlight that the importance of social skills was increasing pre-COVID-19 for these workers and that this importance has increased further during the pandemic, particularly for those in management roles.

Specifically, we

1) discuss the seminal work that highlights that those with social skills have better labour market outcomes pre COVID-19, and that there is an additional protection from job loss to automation for those that are high in both cognitive and social skills;
2) provide an overview of the evidence of the value to businesses for embracing social skills as key skills for knowledge workers, particularly during a pandemic;
3) present evidence that highlights that social skills may have increased their premium during the pandemic, and discuss why we expect this increased premium to prevail; and
4) discuss the emerging evidence on whether social skills can be taught effectively to individuals.

Defining Social Skills

The term "non-cognitive skills" has been frequently used in economics to study human capital [2]. Non-cognitive skills are an individual's "patterns of thought, feelings and behaviours" [3] and encapsulate a range of characteristics about a person that are not easily observable or calculable. Examples include personality traits, time preferences, and motivation [4]. Within this broad category of non-cognitive skills are social skills (or people skills) a subset of which more narrowly defines skills centred around human interaction [5]. Social skills in particular encompass the "ability to work with others" [4, 5] and include leadership, communication, and interpersonal skills more generally [6].

[1] The fourth industrial revolution describes the economic, social and political transition brought about by automation and new technologies (e.g. Internet of Things) in the 21st Century [1].

Social skills as a durable skill for knowledge workers: pre-COVID-19 assessment

The third industrial revolution shaped labour markets in developed countries, including the UK, to further increase the importance of cognitive skills [7]. It is worth emphasising that there is evidence that social skills are also of value to the labour market both directly and indirectly, as owed to their effects on an individual's education or motivation, for example. Borghans et al. [3] provide solid evidence of this in an analysis of individual-level longitudinal data from the US, the UK and Germany. The authors find that individuals who score high in people skills sort into occupations high on people-related tasks and end up having higher earnings in the long-term. Cortes et al. [8] also demonstrate the growing demand for social skills by analysing a database of newspaper job advertisements from 1980–2000 in the US, alongside information on job tasks and wages, finding that the demand for social skills has increased over the study period. This in turn explains their finding that the probability of females working in cognitive/high wage occupations has increased as compared to males as females score higher in social skills.

There is therefore a growing consensus that social skills are independently valuable in the labour market. Of more interest, there is evidence that suggests that there is a complementary interactive effect between cognitive skills and social skills in terms of improved labour market outcomes [6, 9]. Specifically, Weinberger [6] links adolescent skills data from two longitudinal studies of high school students from the US from 1972–1992 to adult outcomes. She finds that the earnings premiums for both cognitive and social skills have increased substantially across the two cohorts. That is, while both cognitive and social skills positively affect earnings, their joint importance and complementarity has increased over time. She verifies this conclusion further in an analysis that maps census data to job task measures.

There are a few points to emphasise from our discussion thus far. First, the evidence suggests that social skills can be labelled as durable skills, meaning that there is an expectation that they will be valuable despite changes to the labour market. Second, the complementary interactive effect between cognitive and social skills demonstrates that there are gains to knowledge workers acquiring social skills.

These conclusions align well with studies demonstrating that the demand and rewards for social skills have been increasing over the past decades [10, 5] and that they will likely continue to do so [11]. To consider this increasing trend of the importance, Deming [5] establishes a model for team production, where social skills are treated as an input that reduces coordination costs and makes teamwork more efficient. Drawing on data from the US National Longitudinal Survey of Youth (NLSY) from 1979 and1997, his paper then tested the assumptions of the team production model and verifies that cognitive and social skills are complementary. He also finds that there are positive returns to social skills in the labour market in terms of full-time employment status and wages, which have increased across the two cohorts studied. In a separate analysis he also demonstrates that, between 1980–2012, there was an increase in occupations that required high levels of social interaction by nearly 12 percentage points as a share of the U.S. labour force. In another study evaluating social skills in the labour market, Borghans et al. [3] also start with establishing a model that assumes that individuals differ in their level of people skills and that occupations differ in their requirements for such skills. The authors utilise individual-level longitudinal data from the US, Germany and the UK to test their model's assumptions. Overall, youth sociability is positively correlated with adult wages and affects sorting into adult occupations for which people tasks are important. Finally, in order to comment on trends of the future, Bode et al. [11] use data from the German Socioeconomic Panel (SOEP) to empirically test the impact of personality traits on working in an occupation that is susceptible to digitisation. They link their data with research that establishes which occupations are most susceptible to automation, finding that jobs which are filled by individuals who are open, less neurotic and less agreeable will be less susceptible to automation in the future.

Lordan [12] illustrates the increasing value of social skills most clearly in a quantitative analysis that relates job attributes to the probability that an individual's occupation will be automatable over the next decade. The novelty of her analysis is that it draws on a measure of automatable work constructed by Lordan and Josten [13] which takes into account the seismic change on the horizon with respect to jobs that face the risk of future automation by analysing patents. Essentially, Lordan and Josten create a classification that captures jobs that will be automatable over the next decade [13].

Lordan [12] focuses on three variables that are constructed based on data that describe the skills required to do a job along with the actual activities of the job. These three variables reasonably and accurately proxy work that involves using social skills, cognitive skills and physicality.[2,3] The author then, drawing on the EU Labour Force Survey data from 2013–2016, relates the classification of a job being automatable[4] to whether work involves 'social skills', 'cognitive skills' and 'physicality' as measured by these three variables. The author also considers the interaction between these three variables, which allows her to predict the usefulness of social skills, cognitive ability and physicality independently in terms of future employability, in addition to predicting the value of their interactions (i.e., the value of social skills combined with cognitive skills). A negative estimate implies that jobs that are high on a particular attribute are relatively safe from automation. That is, the author is able to speak about whether jobs that are high on cognitive skills, for example, are relatively safe from automation.

[2] We note that, in her work, Lordan [12] refers to these variables as people, brains and brawn respectively.
[3] Each variable is constructed to have a mean of 0 and standard deviation of 1.
[4] as defined by Lordan and Josten [13].

Table 1: The impact of social skills, cognitive skills and physicality on automation.

	EU LFS	UK – EU LFS
Social Skills	0.009***	0.006***
	(0.000)	(0.001)
Cognitive Ability	–0.070***	–0.100***
	(0.000)	(0.001)
Physicality	0.032***	0.007***
	(0.000)	(0.001)
Social Skills * Cognitive Skills	–0.002***	–0.005***
	(0.000)	(0.001)
Social Skills * Physicality	0.003***	–0.001***
	(0.000)	(0.000)
Cognitive Skills * Physicality	0.000***	–0.003***
	(0.000)	(0.001)
N	2,698,151	59575
R-squared	14%	13%

Data: EU Labor Force survey data from 2013–2016.

Notes: The stars of significance *, **, *** denote significance at the 10%, 5% and 1% levels, respectively. The table shows regression results from regressing a dummy representing whether a job is automatable (as defined by Lordan and Josten [13]) on the 'social skills', 'cognitive skills' and 'physicality' variables and their interactions.

The results for the EU and UK analyses are re-produced in **Table 1**. These estimates point clearly to the value of cognitive skills, strongly implying that jobs which require high level thinking will be safe from the impending wave of automation. In addition, for both the EU and the UK, the interaction between the 'social skills' and 'cognitive ability' attributes is negative and statistically significant. This signals that knowledge workers that also have high levels of social skills are even further insulated from automation. This complementarity is more pronounced in the UK as compared to the EU as a whole. Notably, evidence of the protective effect of social skills is only consistently revealed once there is an interaction with cognitive skills across both the UK and EU, suggesting that for jobs that do not also require a high level of cognitive skill, their value is less pronounced, if it exists at all. For our purposes, this emphasises clearly that, pre-COVID-19, the expectation was that social skills would continue to grow in value for knowledge workers.

The Value of Social Skills to Firms

The growing demand for social skills is, without a doubt, linked to the added value people high in these skills bring to firms. Deming and Kahn [9] provide evidence of this by analysing online job vacancies for a variety of professional services occupations in the US between 2010–2015. The authors focus on the financial returns of firms requiring certain social and cognitive skills in job adverts. They find that job adverts for cognitive and social skills positively predict firm performance, even after controlling for education and experience requirements and occupation and industry codes. Their finding is most prominent for firms that demand both cognitive and social skills, which highlights the increasing value of social skills in knowledge work.

At the individual level, productivity in adulthood has also been credibly linked to social and emotional skills in childhood. Knudsen et al. [14] review evidence from economics, developmental psychology and neurobiology and highlight that early experiences during childhood have a strong effect on children's development of cognitive and social skills. Such skills in turn affect important life outcomes such as educational attainment and wages.

Kuhn and Weinberger [15] test the impact of adolescent leadership skills on adult outcomes, drawing on three surveys of high school students in the US from 1960, 1972 and 1982 containing information on student test scores and leadership positions (e.g., acting as a team captain) as well as their labour market performance up to ten years after finishing high school. They find that students that fulfilled leadership positions during high school had significantly higher wages than those that did not. Gertler et al. [16] test the impact of an early childhood intervention fostering cognitive and socio-emotional skills on adult outcomes. They ran a randomised controlled experiment in Jamaica between 1986–1987, in which toddlers from disadvantaged backgrounds were provided with treatments that fostered their cognitive and socio-emotional skills. They found that the children that received the treatment had higher earnings at age 22 and that the treatment reduced later-life inequality. Their findings are even larger than those of similar programmes conducted in the US, indicating potentially larger rewards for early interventions in developing countries.

Edin et al. [17] studied the changing rewards for non-cognitive skills in Sweden between 1992–2013 using administrative data from the compulsory military draft that required men aged 18 or 19 to undergo tests on cognitive and non-cognitive skills. They find that the return in wages to non-cognitive skills doubled between 1992–2013 (from 7 to 14 percent for a one standard deviation increase in non-cognitive skills), and this growth was much larger than the return to cognitive skills. In an earlier study, Lindqvist and Vestman [18] compare non-cognitive to cognitive skills of Swedish men in the military also using the enlistment data, but matched with a representative sample of the Swedish population (LINDA). They find that non-cognitive skills matter more for earnings at the low end of the earnings distribution and are a stronger predictor of labour force participation than cognitive skills. They argue that the reason for this is that individuals with very low non-cognitive skills are more likely to be unemployed and that non-cognitive skills are more prevalent in individuals that earn higher wages.

This evidence shows that there is an intrinsic value in social skills that helps individuals to thrive in the long-run.

The Value of Social Skills During and After the Pandemic

The current value of social skills is reinforced by the evidence above that highlights that social skills are becoming increasingly valued in the labour market and the evidence that social skills are linked to firm success. A related question is: Has the value of social skills for knowledge workers increased during the COVID-19 pandemic?

During the COVID-19 pandemic, collaboration became particularly relevant, with effective group decision-making becoming more crucial in order for businesses and organisations to respond to the pandemic [19]. Intuitively, we may expect groups to be naturally superior in making decisions to individuals, but that is not always the case.

The theory behind the increased value of group decision making relies on groups being comprised of individuals with diverse perspectives,[5] and on all voices being heard in deliberations. The reality is that this does not always transpire. Empirical evidence on group performance is mixed and highlights that key judgemental biases can occur in groups which reduce innovation and productivity, for example, anchoring [22],[6] or the tendency of groups to ignore outside information more than individuals [23].

While collaborative decision making became essential during the pandemic, past research has also shown that deliberations, where each person around the table participates fully with their unique insights, often fail due to groupthink. Groupthink is the tendency of cohesive in-group members to find a consensus without critically appraising alternatives, which tends to lead to adverse or less innovative outcomes [24]. Sunstein [25] highlights two main reasons for why group collaboration fails. First, key information often remains privately held by some group member(s). Second, social pressure prevents group members from disclosing their information.

One way of addressing groupthink at the organisational level is by increasing diversity and inclusion efforts, such as through removing obstacles that hinder individuals from fully participating and contributing in group settings, or through fostering an individual's uniqueness in and sense of belonging to the organisation [26]. Managers, and indeed team members, with good social skills are likely required to secure this dynamic. This same dynamic is also invaluable for group deliberations that go beyond decision making, where the outcome desired requires creativity, innovation and the assessment of risk.

Inclusion at both the group and individual level is crucial for this dynamic to emerge. For example, Nishii [27] studies inclusive climate in a sample of employees at a large biomedical company, with specific attention to gender diversity. She finds that teams with an inclusive climate (i.e., a climate that fosters the integration and active participation of diverse employees) had lower levels of conflict and that inclusive climates reduce the potential negative effects of gender diversity on team conflict.[7] Similarly, in a study of work teams in South Korea, Seong and Hong [29] find that cooperative group norms (i.e., the importance placed on shared interests, etc.) moderated any negative effects of gender diversity on a self-reported team commitment. In a randomised experiment, Weidmann and Deming [30] test whether individuals that they label 'team players' can contribute to a team's performance. They find that team players with distinct contributions increase the team's outcome in problem-solving tasks. In this study, team players were not significantly different to other team members with respect to IQ, age, gender, ethnicity or personality traits, allowing them to attribute the effects found entirely to being a team player.

Working Together Virtually

The value of social skills for the management of knowledge workers goes beyond the avoidance of groupthink and encompasses the value inclusive cultures provide. For the majority of knowledge workers -an estimated 62% in the UK[8]- the COVID-19 lockdown meant that they spent the majority of their time working from home. This posed two challenges for managers of knowledge workers. First, they had to figure out how to get teams to function cohesively

[5] Diversity has been shown to positively impact group outcomes and reduce group biases, see for example [20 and 21].

[6] Anchoring is the provision of initial information that then determines and can bias decision-making. For example, when participants of a study were asked to estimate the percentage of African countries in the United Nations, those that received a low anchor (i.e., 10%) estimated a lower percentage than those participants that received a high anchor (i.e., 65%) [22].

[7] In a review of the evidence on the impact of gender diversity on group outcomes, Azmat and Petrongolo [28] find mixed results. One study they cite, for example, finds that gender quotas in Norway reduced a company's operating profits and stock prices, a finding that is attributed to women being less experienced and women being also less willing to lay off staff.

[8] This estimate is derived using the COVID-19 waves from the Understanding Society restricted to knowledge workers (i.e., ISCO-88 three-digit codes of below 400) comparing individuals who indicate to always work from home or often as compared to those who indicate to only sometimes or never work from home.

while ensuring that members could work productively in a more individual environment. Second, they had to manage team members sensitively, taking into account the fact that some workers would be subject to more negative effects than others. For example, it has been highlighted that on average, working married women bore more of the mental health burden than their working male spouses [31, 32]. In line with this, evidence from the UK Household Longitudinal Survey (UKHLS) COVID-19 module shows that while mental health overall declined sharply during the lockdown, this reduction was twice as large for women than it was for men [33]. Further evidence by Adams-Prassl et al. [34] again supports the argument that women suffered greater mental health declines during the pandemic. Using real-time survey data from the US and exploiting the variation in timing of the stay-at-home orders in the US, Adams-Prassl et al. document that the large mental health burden caused by the pandemic is borne entirely by women [34]. However, the mechanisms through which the lockdown measures negatively affect women are unclear and cannot be explained solely by increased financial worries nor by increased childcare responsibilities.

To manage effectively during a pandemic, the managers of knowledge workers therefore need substantial social skills. Such a conclusion was also drawn from a qualitative piece of research that we conducted in order to better understand the actions that managers can take in order to create more inclusive cultures. There, we engaged 35 of London's most senior leaders in virtual listening interviews right after the UK government announced its first lockdown. These leaders came from 16 major companies and comprised of CEOs and other executive committee members (5), non-executive board (2), income generators at managing director level+ or equivalent (15), senior HR (5) and senior non-HR functions (first line of defence, technology, risk and audit) (8). The companies represented were: Aberdeen Standard Capital, Alliance Bernstein, Allianz Global Investors, Citi, CIBC, Goldman Sachs, HSBC, ING, J.P. Morgan, Mustard Seed, NatWest, Rathbones, Refinitiv, Standard Chartered, Starling Bank and UBS. The following two questions were sent to the leaders that participated in an email with an option to provide responses in writing (21 received) or via a 45 minute video conference (14 received):[9]

1. When thinking of inclusivity when all team members are working at home, can you identify one best practice that you will definitely be using to manage your team?
2. When thinking of inclusivity when all team members are working at home, can you identify the biggest challenge or obstacle you expect to face with respect to keeping your team engaged in their daily tasks?

Once the email responses were received and the virtual interviews completed, we conducted a thematic analysis. This is the ideal approach as we were essentially trying to identify the people's beliefs and knowledge from a set of interview data.[10] **Table 2** summarises the themes that emerged regarding the obstacles virtual inclusion faces, and also the themes that emerged around actions that can be taken to overcome them.[11] Notably, twenty of the thirty actions identified to respond to identified obstacles undoubtedly require managers with high levels of social skills to execute them effectively (we delineate these from other actions in **Table 2** with the italic font for ease of reference).

Table 2 illustrates the importance of managers with high social skills for the effective running of organisations during the COVID-19 pandemic. Of course, the context to **Table 2** concerns a state of the world where the majority of professional workers are working at home, (and this likely increased the need for managers with such social skills). The question to be answered is whether this will still be the case post-pandemic. Our expectation is that this "new" normal will leverage some of the positive changes to work that were introduced to allow workers to continue to work safely during the pandemic. For example, we expect one such change to be a move towards hybrid working for professional workers. In such a setting, some workers will work on site, others will work from home. In some instances, this will mean having a rotating attendance of employees on-site, while in others the nature of the job may mean that it is entirely off-site (or on-site). Either way, a move towards hybrid working, where some employees communicate face to face and others online, poses similar challenges for inclusivity to those posed in **Table 2**, imply in that managers with good social skills will maintain their importance post-pandemic.

Our conclusion that hybrid working will prevail post-COVID-19 is shared by Barrero et al. [36] who surveyed 15,000 working-age Americans between May and October 2020 in six waves, asking them whether they work from home and what their employers' attitudes are towards working from home. Overall, they find that employers estimate that employees will spend 22% of paid days at home as compared to 5% before the pandemic. Barrero et al. [36] also set out five reasons explaining why working from home will stick: First, there is reduced stigma with regard to productivity at the home office; second, the experience of the pandemic has shown employers and employees that working from home actually works; third, recent investment in work from home equipment has made working from home less costly; fourth, survey respondents think they will persistently fear proximity to others (e.g., on the subway), which indicates some demand for distanced working; and fifth, technical innovation is increasing and will make connecting remotely easier. This paper also estimates that employees will be 2.4% more productive in a post-pandemic world working from home based on self-assessed productivity estimates.

---

[9] We note that we did not find significant differences in the themes identified with the responses received via email or in a virtual meeting.

[10] The advantage of this approach is that it allows flexibility in approaching large interview data sets. The drawback is that we risk missed nuances as it is largely subjective. To overcome this two researchers worked independently on determining the themes, and came together ex post to discuss the findings.

[11] We note that a more complete overview of the obstacles identified and actions that can be taken can be found in Lordan [35].

Table 2: Obstacles to virtual inclusion and the actions to overcome them.

Virtual Inclusion: Obstacles and Actions	
Obstacles to Virtual Inclusion	**Actions to overcome obstacles**
1. Problem: Physical distance can lead to an employee's psychological distance from their firm	**1. Action:** Humanise interactions with colleagues. – *by leveraging video technology (e.g., virtual coffee breaks, socials, etc.) or having a buddy system that connects colleagues.* **2. Action:** *Actively seeking feedback.* – *makes colleagues realize they are being listened to despite physical distance.* **3. Action:** *Open the virtual door.* – *by keeping a video conference line open for the same time period each day for anyone to drop in.*
2. Problem: Presenteeism may be replaced by virtual presenteeism due to constant availability (e.g. instant messaging etc.)	**1. Action:** Rethink attitudes to working at home. – by creating a system that allows for individual differences in concentration style, while still maintaining some core hours for virtual team gatherings. **2. Action:** Have daily set times free of digital disruptions. **3. Action:** Opt-out of being green online – as that signals to team members that it is OK to a take time out from being virtually present.
3. Problem: Communication may be difficult due to information overload	**1. Action:** *Give certainty.* – *by having the CEO describing knock-on effects that COVID-19 is having on the business as that prevents employees seeking out information to deal with their uncertainty.* **2. Action:** *Make salient what is important.* – *managers should provide clarity to team members on what tasks are pressing, and identify tasks that can be dropped or put on ice.* **3. Action:** *Pay attention to messenger effects and framing.* – *To improve effective communication, firms can devote time to understanding how best to frame their desired message, and who the ideal messenger should be at any one occasion.*
4. Problem: In-groups increase the risk of tunnel vision	**1. Action:** *Make salient that diverse perspectives add value.* **2. Action:** *Identify weak ties to bridge information silos.* – *By ensuring that information diffuses effectively within organisations.* **3. Action:** Audit who gets what and why. – To make sure that no one is missing out on opportunities and to prevent favoritism
5. Problem: Virtual groupthink (i.e., the tendency to favour conformity as team)	**1. Action:** *Intervene to ensure that all voices are heard (also via chats).* **2. Action:** *Discourage an over-focus on shared information.* – *By separating brainstorming sessions from sessions where decisions are made.* **3. Action:** *Embrace dissent.* – *Instead of forcing consensus that encourages groupthink.*
6. Problem: Unfamiliar context and uncertainty regarding Covid-19	**1. Action:** *Fundamental attribution error.* – *whereby an outcome is viewed as a reflection of the person rather than simply the situation they are in.* **2. Action:** *Celebrate small wins.* **3. Action:** *Re-focus your attention.* – *Which serves to minimise the likelihood of the affect heuristic, a mental shortcut that causes decisions and reactions to happen quickly when emotional that are not necessarily in the firms or an individual's best interests.*
7. Problem: Work is now home	**1. Action:** A designated work space. **2. Action:** Maximise home work spaces. – Increase information on how to best work at home (e.g., by going for walks to increase productivity). **3. Action:** *Discuss what works with respect to work space.*

(Contd.)

Virtual Inclusion: Obstacles and Actions

Obstacles to Virtual Inclusion	Actions to overcome obstacles
8. Problem: Maintaining motivation when becoming de-motivated	**1. Action:** *Identify meaning at work.* – *As when a goal is identified as meaningful, individuals put much more effort into fulfilling it.* **2. Action:** *Link meaning to own skills and abilities.* – *By highlighting for team members, the specific skill the employee is brought out to the firm that is unique to them.* **3. Action:** *Use narrative or visuals to illustrate meaning.* – *By bringing the stakeholders of a firm's outputs closer to employees.*
9. Problem: Beware of illusory correlation	**1. Action:** Confidence is not competence or ability. **2. Action:** Quality over quantity. – Rather than focusing on virtual presenteeism as a correlation for ability, measure a person based on their output. **3. Action:** *Don't log every ball that gets dropped* – *By ensuring that an employee's future career success is not unforgivingly linked to performance during the COVID-19 response period.*
10. Problem: Re-start with inclusion	**1. Action:** *Stay connected to customers and clients.* **2. Action:** *Speak to a different type of shareholder, client and customer.* – *As being seen as a leader in the COVID-19 response, to the inclusion of all persons, puts the good values of the firm in the spotlight.* **3. Action:** Create post COVID-19 priorities.

Source: Lordan, G. (2020): Virtual Inclusion in The City, Report.

Bartik et al. [37] also document evidence that working from home is likely to increase post-pandemic, while emphasising that this mode of working will suit certain jobs and industries more than others. Their work surveys leaders of small businesses as well as business economists in the US. They find that the industries that can move to remote work more smoothly have a better educated and higher paid workforce, who are less affected by productivity losses resulting from switching to remote work. In another study, Bick et al. [38] similarly find that the characteristics of those working from home differed substantially across different socioeconomic groups and industries when analysing data from a large US survey. They found that those that switched to working from home during the pandemic were predominantly educated, white and high earners before the pandemic. These two papers underline our conjecture that knowledge workers are more likely to work from home post-pandemic, and, together with evidence presented earlier in this section emphasises the need for these workers, and particularly their managers, to have or to acquire high levels of social skills.

Can we teach social skills to adults?

As highlighted above, social skills are increasingly important for knowledge workers. This importance has been shaped and accelerated by the third and fourth industrial revolutions, and the COVID-19 pandemic. It is therefore increasingly important for knowledge workers to acquire social skills, and in turn, raises the question as to whether it is possible for knowledge workers to be taught such skills. It is worth emphasising that while teaching soft skills has been shown to be particularly effective at young ages [14], soft skills have also been shown to be malleable across the entire lifespan (and to be more malleable than cognitive skills) [2]. Here we focus on the evidence that relates to adults, but it is worth highlighting now the seminal papers that relate to the transfer of social skills to young children [16, 39] and adolescents [40]. This literature suggests that there is good evidence that we can change soft skills, including social skills for both children and adolescents. However, we know little about what the most effective curricula are, and indeed studies that follow participants over years (rather than months or days), such as Heckman and Kautz [39] and Lordan and McGuire [40] are too rare, meaning there is still a lot to learn about adaptation.

Turning to adults, we would summarise that this body of literature establishes a clear link between social skills programmes in some contexts, in addition to pointing to individual differences in the effects these programmes have on labour market outcomes. For example, in a randomised experiment in Colombia, Barrera-Osorio et al. [41] test the impact of teaching social skills as part of a vocational training on the participants' future job outcomes. The participants that are assigned to vocational training courses are randomly assigned to different trainings that vary in the technical and social skills taught. Social skills training was provided by social workers and included fostering self-esteem, work ethic, organisational skills, inter-personal skills and communication skills. The technical skills taught differed by course but included, for example, security and surveillance services, cashiers, or cooking assistant skills. Overall, the courses lasted between 4 and 10 weeks for 5 to 8 hours a day. The authors find that being allocated to a vocational training programme has an overall positive effect on labour market outcomes. Initially, individuals allocated to a programme that was intense in technical skills performed better than those in programmes fostering social skills with regard to employment probability and wages. After 6 to 12 months, however, individuals from the social skills trainings caught up and were slightly more successful in maintaining their jobs.

In contrast, Groh et al. [42] find no significant employment effects of a soft skills programme provided to female community college graduates. In their study, female community college graduates were randomly allocated into soft skills training that lasted for 45 hours in total and the treatment and control groups were then interviewed again 6, 14 and 27 months after training to test the impact of the programme on employment outcomes. The training included training in communication, business writing, team building, team work skills, time management, positive thinking and how to use the learnt skills in business situations and career advice. The authors were surprised that they did not find statistically significant effects but believed that the relatively short length of the course could be insufficient to effectively impact soft skills (we are sceptical as it is more likely that people revert to old styles of thinking over time, implying that any effects found are likely to diminish. We expect the training was simply not effective).

Conversely, a study by Acevedo et al. [43] points to individual differences in labour market effects following soft skill training. The authors ran a randomised field experiment to test the impact of including soft skills into a vocational training course for youths in the Dominican Republic on skill development and labour market outcomes. They randomly assigned two interventions to participants. The first was vocational training with soft skills training and an internship. The second one was soft skills only training with an internship. Soft skills training included 75 hours of training in self-esteem, communication skills, conflict resolution, life planning, time management, teamwork, decision-making, hygiene and health, and coaching on risky behaviours. They find positive short-term effects of both training interventions for women, but not men.

These three studies illustrate neatly for both children and adolescents trends and deficiencies in the literature on transferring social skills to adults overall. First, the evidence is mixed on how different programmes impact labour market outcomes, and there is evidence of individual differences in impacts. Second, there is a paucity of evidence that considers the transfer of social skills to knowledge workers in a randomised framework that allows causal inference. This is a major deficiency given the gains to these workers to acquiring these skills, and the fact that employers of knowledge workers typically provide a variety of trainings in soft skills already. The latter suggests that employers are providing trainings with no idea of whether they are effective, despite having the opportunity to do so. Last, we are not yet at a place where we can cross compare studies and learn what is the best curriculum and approach for the transfer of social skills, as the majority of studies consider newly created programmes whose rationale for included content is often not clear. To move this agenda forward, it would be beneficial for studies of this kind to include detailed notes on the modules that are taught along with a mapping of the rationale for their inclusion.

Conclusions

Our work has emphasised that the value of social skills was increasing for knowledge workers pre-COVID-19. We have provided new evidence that illustrates that their premium has increased during the pandemic for these workers, and that this acceleration is unlikely to reverse when the pandemic response ends and we enter a new normal. The fact that COVID-19 has changed the labour market trajectory to speed up trends that were already occurring is unsurprising. This is a typical reaction to large macro-economic shocks. For example, following the Great Recession, there was a persistent shift in firms' demand away from low skills in routine-task occupations that lead to an overall upskilling of the workforce and a depreciation of low skills [44].

While the value of social skills is clear, particularly for knowledge workers, this study has also emphasised that we are at the beginning of the learning curve in understanding how social skills can be taught effectively to adults and, in particular, knowledge workers. As we move forward and the value of these skills continues to rise, we hope that programmes established to upskill workers in this regard will be assessed in a framework that is robust enough to establish causal inference, and detailed enough to allow cross curriculum comparisons. This is particularly important as governments around the world, including the UK, reconsider their skills agenda as a way to build their economies post COVID-19.

Competing Interests

The authors have no competing interests to declare.

Publisher's Note

This paper underwent peer review using the Cross-Publisher COVID-19 Rapid Review Initiative.

References

1. **Schwab K.** The fourth industrial revolution; 2017.
2. **Almlund M,** et al. Personality Psychology and Economics. *NBER Working Paper Series*; 2011. DOI: https://doi.org/10.3386/w16822
3. **Borghans L, Duckworth A,** et al. The Economics and Psychology of Personality Traits. *The Journal of Human Resources*, 43(May 2006). 2014; 972–1059. DOI: https://doi.org/10.3368/jhr.43.4.972

4. **Heckman JJ.** Schools, skills, and synapses. *Economic Inquiry*. 2008; 46(3): 289–324. DOI: https://doi.org/10.1111/j.1465-7295.2008.00163.x
5. **Deming DJ.** The Growing Importance of Digital Skills in the Workplace. *Quarterly Journal of Economics*, 132(October). 2017; 1593–1640. DOI: https://doi.org/10.1093/qje/qjx022
6. **Weinberger C.** The Increasing Complementarity between Cognitive and Social Skills. *The Review of Economics and Statistics*. 2014; 96(5). DOI: https://doi.org/10.1162/REST_a_00449
7. **Autor DH, Levy F, Murnane RJ.** The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics*. 2013; 118(4): 1279–1333. DOI: https://doi.org/10.1162/003355303322552801
8. **Cortes GM, Jaimovich N, Siu H.** The "End of Men" and Rise of Women in the High-Skilled Labor Market. *NBER Working Paper*; 2018. DOI: https://doi.org/10.3386/w24274
9. **Deming D, Kahn L.** Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals. *NBER Working Paper Series*. Cambridge, MA; 2010.
10. **Borghans L, Weel BT, Weinberg BA.** People skills and the labor-market outcomes of underrepresented groups. *ILR Review*. 2014; 67(2): 287–334. DOI: https://doi.org/10.1177/001979391406700202
11. **Bode E,** et al. Worker Personality: Another Skill Bias Beyond Education in the Digital Age. *SSRN Electronic Journal*. 2017; 20(4). DOI: https://doi.org/10.2139/ssrn.2884733
12. **Lordan G.** Automation and the changing nature of work: 2020 onwards. London School of Economics; 2021.
13. **Josten C, Lordan G.** Robots at Work: Automatable and Non-automatable Jobs, in Handbook of Labor, Human Resources and Population Economics. Springer International Publishing. 2020; pp. 1–24. DOI: https://doi.org/10.1007/978-3-319-57365-6_10-1
14. **Knudsen E,** et al. Economic, Neurobiological and Behavioral Perspectives on Building America's Future Workforce. *NBER Working Paper Series*. Cambridge, MA; 2006. DOI: https://doi.org/10.3386/w12298
15. **Kuhn P, Weinberger C.** Leadership Skills and Wages. *Journal of Labor Economics*. 2005; 23(3): 395–436. DOI: https://doi.org/10.1086/430282
16. **Gertler P,** et al. Labor market returns to an early childhood stimulation intervention in Jamaica. Science. *American Association for the Advancement of Science*. 2014; 344(6187): 998–1001. DOI: https://doi.org/10.1126/science.1251178
17. **Edin P-A,** et al. The Rising Return to Non-Cognitive Skill. *IZA Discussion Paper*; 2017.
18. **Lindqvist E, Vestman R.** The labor market returns to cognitive and noncognitive ability: Evidence from the Swedish enlistment. *American Economic Journal: Applied Economics*. 2011; 3(1): 101–128. DOI: https://doi.org/10.1257/app.3.1.101
19. **Rutter H, Wolpert M, Greenhalgh T.** Managing uncertainty in the covid-19 era. *The BMJ*. BMJ Publishing Group; 2020. DOI: https://doi.org/10.1136/bmj.m3349
20. **Hoogendoorn S, Oosterbeek H, van Praag M.** The Impact of Gender Diversity on the Performance of Business Teams: Evidence from a Field Experiment. *Management Science*. 2013; 59. DOI: https://doi.org/10.1287/mnsc.1120.1674
21. **Hoogendoorn S, Van Praag M.** Ethnic Diversity and Team Performance: A Field Experiment. *IZA Discussion Paper*; 2012. DOI: https://doi.org/10.2139/ssrn.2105284
22. **de Wilde TRW, Ten Velden FS, De Dreu CKW.** The anchoring-bias in groups. *Journal of Experimental Social Psychology*. Academic Press Inc. 2018; 76: 116–126. DOI: https://doi.org/10.1016/j.jesp.2018.02.001
23. **Minson JA, Mueller JS.** The cost of collaboration: Why joint decision making exacerbates rejection of outside information. *Psychological Science*. SAGE Publications Inc. 2012; 23(3): 219–224. DOI: https://doi.org/10.1177/0956797611429132
24. **Irving J.** Victims of groupthink: A psychological study of foreign-policy decisions and fiascoes. Houghton Mifflin; 1972.
25. **Sunstein CR.** Group judgments: Statistical means, deliberation, and information markets. *New York University Law Review*. 2005; 80(3): 962–1049.
26. **Shore LM,** et al. Inclusion and Diversity in Work Groups: A Review and Model for Future Research. *Journal of Management*. 2011; 37. DOI: https://doi.org/10.1177/0149206310385943
27. **Nishii LH.** The Benefits of Climate for Inclusion for Gender-Diverse Groups. *Academy of Management Journal*. 2013; 50(6). DOI: https://doi.org/10.5465/amj.2009.0823
28. **Azmat G, Petrongolo B.** Gender and the labor market: What have we learned from field and lab experiments? *Labour Economics*. Elsevier, 2014; 30: 32–40. DOI: https://doi.org/10.1016/j.labeco.2014.06.005
29. **Seong JY, Hong DS.** Gender diversity: How can we facilitate its positive effects on teams? *Social Behavior and Personality*. 2013; 41(3): 497–507. DOI: https://doi.org/10.2224/sbp.2013.41.3.497
30. **Weidmann B, Deming D.** Team Players: How Social Skills Improve Group Performance. *NBER Working Paper.* Cambridge, MA; 2020. DOI: https://doi.org/10.3386/w27071
31. **Andrew A,** et al. The gendered division of paid and domestic work under lockdown. *IZA Discussion Paper*. 2020; 1(39): 109–138.
32. **Sevilla A, Smith S.** Baby steps: the gender division of childcare during the COVID-19 pandemic. *Oxford Review of Economic Policy*. Oxford University Press. 2020; 36: S169–S186. DOI: https://doi.org/10.1093/oxrep/graa027

33. **Etheridge B, Spantig L.** The Gender Gap in Mental Well-Being During the Covid-19 Outbreak: Evidence from the UK. *ISER Working paper series*; 2020.
34. **Adams-Prassl A,** et al. The Impact of the Coronavirus Lockdown on Mental Health: Evidence from the US. *Cambridge Working Papers in Economics*; 2020.
35. **Lordan G.** Virtual Inclusion in The City; 2020.
36. **Barrero JM, Bloom N, Davis SJ.** Why Working From Home Will Stick. *BFI Working Paper*; 2020. DOI: https://doi.org/10.31235/osf.io/wfdbe
37. **Bartik A,** et al. What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys. *NBER Working Paper Series*. Cambridge, MA; 2020. DOI: https://doi.org/10.3386/w27422
38. **Bick A, Blandin A, Mertens K.** Work from Home After the COVID-19 Outbreak. *Federal Reserve Bank of Dallas, Working Papers*; 2020. DOI: https://doi.org/10.24149/wp2017r1
39. **Heckman J, Kautz T.** Fostering and Measuring Skills: Interventions that improve character and cognition. *NBER Working Paper Series*; 2013. DOI: https://doi.org/10.3386/w19656
40. **Lordan G, McGuire A.** Widening the High School Curriculum to Include Soft Skill Training: Impacts on Health, Behaviour, Emotional Wellbeing and Occupational Aspirations. *IZA Discussion Paper*, (12439); 2019.
41. **Barrera-Osorio F, Kugler A, Silliman M.** Hard and Soft Skills in Vocational Training: Experimental Evidence from Colombia. *NBER Working Paper*; 2020. DOI: https://doi.org/10.3386/w27548
42. **Groh M,** et al. The impact of soft skills training on female youth employment: evidence from a randomized experiment in Jordan. *IZA Journal of Labor and Development*. 2016; 5(1): 9. Springer Open. DOI: https://doi.org/10.1186/s40175-016-0055-9
43. **Acevedo P,** et al. Living up to expectations: How job training made women better off and men worse off. *NBER Working Paper Series*; 2017. DOI: https://doi.org/10.3386/w23264
44. **Hershbein B, Kahn LB.** Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review*. 2018; 108(7): 1737–1772. DOI: https://doi.org/10.1257/aer.20161570

How to cite this article: Josten C, Lordan G. The Accelerated Value of Social Skills in Knowledge Work and the COVID-19 Pandemic. *LSE Public Policy Review*. 2021; 1(4): 5, pp. 1–10. DOI: https://doi.org/10.31389/lseppr.31

Submitted: 01 February 2021 **Accepted:** 25 March 2021 **Published:** 03 May 2021

Appendix B: Automation and the changing nature of work (Paper 2)

Published as:
Josten C, Lordan G (2022) Automation and the changing nature of work. PLoS ONE 17(5): e0266326. https://doi.org/10.1371/journal. pone.0266326

PLOS ONE

RESEARCH ARTICLE

Automation and the changing nature of work

Cecily Josten, Grace Lordan *

Department of Psychological and Behavioural Science, The London School of Economics and Political Science, London, United Kingdom

* g.lordan@lse.ac.uk

Abstract

This study identifies the job attributes, and in particular skills and abilities, which predict the likelihood a job is recently automatable drawing on the Josten and Lordan (2020) classification of automatability, EU labour force survey data and a machine learning regression approach. We find that skills and abilities which relate to non-linear abstract thinking are those that are the safest from automation. We also find that jobs that require 'people' engagement interacted with 'brains' are also less likely to be automated. The skills that are required for these jobs include soft skills. Finally, we find that jobs that require physically making objects or physicality more generally are most likely to be automated unless they involve interaction with 'brains' and/or 'people'.

Citation: Josten C, Lordan G (2022) Automation and the changing nature of work. PLoS ONE 17(5): e0266326. https://doi.org/10.1371/journal.pone.0266326

Editor: Ahmed Mancy Mosa, Al Mansour University College-Baghdad-Iraq, IRAQ

Received: January 7, 2021

Accepted: March 20, 2022

Published: May 5, 2022

Data Availability Statement: The data used in this study are third party data. The data can be accessed at: https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey. Details of how to apply for these data can be found at: https://ec.europa.eu/eurostat/documents/203647/771732/How_to_apply_for_microdata_access.pdf. Users who wish to use the data need to provide a project description, rationale, and a data dictionary of variables that they need to get access. The authors confirm that they did not have any special access privileges that others would not have.

1. Introduction

Research on the automation and the future of work has brought with it a range of research contributions, which seek to determine which occupations will be lost to automation. For example, Frey and Osborne [1] estimate the susceptibility of occupations to computerization and find that 47% of US occupations are at risk of automation, and point to service jobs as being susceptible to automation. Many other contributions in the automation literature rely on defining automatable work through measures of the tasks associated with a particular occupation rather than the occupation overall to get a more nuanced understanding of the impact of automation on employment [2–4]. One of the most prominent is owed to Autor and Dorn [5] and Autor et al. [6] who define a job as automatable if it is high in routine task-intensity. Specifically, routine task-intensity is defined based on how high a job ranks on routine content, and how low it ranks on abstract and manual content. Information on the routine, abstract and manual task content of each respective occupation comes from the US *Dictionary of Occupation Titles* where incumbents are asked to grade their occupation with respect to particular attributes. A job is then defined as automatable if it is in the top third of the distribution of routine task-intensity. This measure of automatable work has followed the big movements in the occupation distribution accurately over the last decades–namely the hollowing out of the middle of the occupational distribution [7]. To this end the types of occupations available have become more polarized, with the majority of occupations falling into high and low skill categories, and mid skill jobs disappearing in numbers [8].

Funding: The authors received no specific funding for this work.

Competing interests: The authors have declared that no competing interests exist.

Further, Arntz et al. [2] estimate the risk of automation for 21 OECD countries also using a task-based approach. They argue that other studies using an occupation rather than a task-based approach such as Frey and Osborne [1] overestimate the risk of automation, partly due to the fact that cross-country variation is not taken into account other than through differences in occupation structure. They highlight that technical possibilities of automation do not equate to actual automation because that may be hindered by legal or ethical obstacles. They find that overall only 9% of jobs are automatable. Similarly, Nedelkoska and Quintini [9] also study automation of jobs in OECD countries using the Survey of Adult Skills (PIAAC). They focus on very detailed occupational categories and the tasks therein and find that 14% of jobs in OECD countries are at high risk of being automated and 32% have a probability of being automated of 50% to 70%. Gregory et al. [4] emphasize that while routine occupations have been replaced between 1999 and 2010, product demand has also increased as a result of routine-replacing technological change leading to a net employment growth. Also focusing on routine-task intensity, Lewandowski et al. [3] focus on cross-country differences in the level of routineness in occupations. They find lower levels of routineness in high-skill occupations in countries with a higher GDP per capita. They also find correlations between computer use, higher education and higher literacy skills in a given country with routine task intensity.

While much of the automation literature relies on past employment data, the rapid progress on robotics, artificial intelligence (AI) and automation technologies has also motivated predicting automation developments in the near future [10, 11]. The importance of this exercise is bellied in Lordan [12] and Lordan and Neumark [13] who suggest that new jobs are now being automated; particularly jobs traditionally at the bottom of the occupation distribution. Further, advances in AI and in particular machine learning will likely affect at least some tasks in most occupations and will hence also disrupt jobs at the top of the income distribution [14].

Concretely, Webb [8] studies the impact of automation on occupational tasks and matches information on job tasks to patents issued for robots, software and AI to identify which tasks can be automated by different technologies to derive an exposure to automation score. He uses Google patents data, the O*NET database of occupations and tasks and US census data. O*NET is a database of occupations and tasks published by the US Department of Labor that provides detailed descriptions of a large number of occupations and has been used frequently in the literature studying the impact of automation and technical innovation on employment [5, 6, 8, 15]. He first analyzes the impact of his 'exposure to automation score on employment using historical data on robots and software patents and job descriptions and then repeats this exercise using patents on AI to predict future employment effects. AI is studied with respect to future developments as it is a relatively new phenomenon as compared to software and robotic innovations. While innovation on robots and software has mainly affected low skill and low wage occupations in the past, he finds that AI is increasingly predicted to disrupt high-skill occupations. Building on this work, Tolan et al. [16] link research intensity in AI to abilities required for specific job tasks using European survey data, O*NET data and AI benchmarking platforms. They find that jobs that were originally classified as non-automatable are increasingly affected by automation such as medical doctors. They find that abilities particularly affected by automation are abilities for idea creation while people abilities are less affected.

Lordan and Josten's [10] study is also forward-looking and takes the occupations classified by Autor and Dorn (2013) as given while reclassifying the remaining occupations as automatable depending on the number of patents recently available for each specific occupation thereby also predicting which jobs will be automated in the near future. They try to capture the most recent wave of automation by using patent developments in artificial intelligence, robots and automation more broadly as a proxy for technology that will be on the market shortly. If for any given occupation the authors find a large number of patents and find that successful patent pilots have been covered by the media, this occupation is classified as being on track to become automatable. A full list of the occupations classified as automatable by Lordan and Josten [10] can be found in S1 Table. This study builds on and uses the classification by Lordan and Josten [10] to analyze which job attributes and requirements predict the likelihood that a job is reclassified as automatable under their new definition. It thereby speaks to the literature on the automatability of tasks, skills and abilities.

In particular we use the automatability indicator by Lordan and Josten [10] matched with employment data from the European Labor Force Survey (EU-LFS) and with data on the skills and abilities required on the job from O*NET. The EU-LFS covers employment statistics of households from EU member countries, Switzerland, Sweden and the UK quarterly. We then regress the automatability indicator on the skills and abilities respectively to analyze which skills and which abilities required in different occupations are susceptible to automation. This is then further linked to work by Lordan and Pischke [17] who capture the 'people', 'brains' and 'brawn' content of occupations with different risks of being automated; i.e. the extent to which an occupation involves people interaction, cognitive thinking skills or physicality respectively.

Identifying future job requirements by occupations is crucial to be able to quantify changes in demand for skills and abilities resulting from automation [18]. First, this information is relevant to policymakers and companies interested in the future of work. In particular, it informs on the skills and abilities required of workers in the near future as well as the activities they will likely be engaged in. Second, these findings further help conversations surrounding the re-organization of education and other development activities to ensure the stock and flow of the relevant skills for the 4th industrial revolution. The returns to education are constantly increasing with the rise in technological progress with specific skills such as digital and non-cognitive skills becoming particularly important [19]. Third, this information also helps to gain a more nuanced understanding of the exact aspects of the occupations at risk of automation and hence addresses criticism by Arntz et al. [20], among others, who find that focusing on the automatability of occupations rather than job tasks overstates the risk of automation and omits important aspects of the automation developments.

2. Data

Job level abilities and skills proxies

To capture the abilities and skills required by occupations at the three-digit occupation level we draw on O*NET version 15. O*NET is an occupational database by the US Department of Labor that narrowly defines occupations with respect to the tasks and activities and the skills and abilities required on the job. This database has been used frequently in the automation literature both in the US and the UK [2, 3, 5, 16]. The difference in task content of occupations in the US versus the UK has been shown to be small, further justifying using this resource to classify occupation attributes using UK data [3, 21].

Specifically, O*NET offers 80 distinct items in the abilities classification. The first column of Table 2 lists each of these items and column (2) provides a brief description of the item. The third column of Table 2 documents the secondary category a specific ability is in, while column (4) provides an overall category. In addition to abilities, O*NET offers 40 distinct items in the skills classification. Again the first column of Table 3 lists each of these items and column (2) provides a brief description each item. The third column documents the secondary category a specific ability is in, while column (4) provides an overall category. Given the large number of abilities (80) and skills (40) items, the secondary and overall category in columns (3) and (4) from Tables 2 and 3 will be utilized respectively for the interpretation of the analysis.

EU LFS and Lordan and Josten

Our analysis relies on data from Lordan and Josten [10] who match data from the European Labour Force Survey (EU-LFS) between 2013–2016 to their automation classification. The EU-LFS is conducted across all Member States of the European Union, Iceland, Norway, Switzerland and the United Kingdom and consists of quarterly collected household data on employment. We include all countries that have data in the years we analyze, in addition to 3-digit occupation codes. A full list of the countries we include can be found in Table 1.

Lordan and Josten [10] match their definition of recently automatable jobs based on patents at the 3-digit code occupation level to the EU-LFS using crosswalks provided by Lordan and Pischke [17]. To derive the automation classification, Lordan and Josten [10] revise 216 occupations that have been classified as non-automatable by Autor and Dorn [6] and search for the occupation name together with either the term "robot", "automation", or "artificial intelligence" in Google patents and then also in Google News. Depending on the number of patents and/or news articles, an occupation is then classified as either fully automatable, polarized automatable (i.e. partially automatable) or non-automatable.

Table 1 shows the shares of automatable employment (i.e. polarized and fully automatable) by EU-LFS country. We first note that the Lordan and Josten [10] classifications suggest that a large share of jobs in every country is recently automatable. Specifically, Finland is the country that has the lowest share of jobs that are classified as recently automatable (approximately 21%). For the remaining Scandinavian countries (Norway, Sweden and Denmark), Table 1

Table 1. Lordan and Josten (2020) shares of employment in 2013–2016 by country.

	Recently Automatable
Austria	0.516
Belgium	0.443
Croatia	0.565
Cyprus	0.512
Czech Republic	0.516
Denmark	0.370
Estonia	0.458
Finland	0.207
France	0.478
Germany	0.474
Greece	0.574
Hungary	0.544
Iceland	0.374
Ireland	0.481
Italy	0.508
Latvia	0.525
Lithuania	0.527
Luxembourg	0.442
Netherlands	0.374
Norway	0.363
Portugal	0.485
Spain	0.474
Sweden	0.378
Slovakia	0.513
UK	0.405

https://doi.org/10.1371/journal.pone.0266326.t001

suggests that about 37% of the jobs are automatable, similar to the shares for the Netherlands and Iceland. In contrast, for Croatia, Czech Republic, Italy and Latvia more than 50% of the jobs are recently automatable. Overall, Table 1 highlights that there is large variation in the share of occupations that can be automated across EU-LFS countries.

3. Methodology

The main analysis in this work relies on EU-LFS data. Our main analysis relies on an indicator variable that is equal to 1 if an occupation is newly automatable under the Lordan and Josten [10] classification and 0 otherwise. Jobs that are denoted as automatable by Author and Dorn [5] are excluded from the analysis given that these jobs were classified as automatable based on O*NET occupation attributes (i.e. routine, manual and abstract tasks), so they mechanically relate to the O*NET attributes. In addition, this exclusion allows us to clarify the differences in skills and abilities between non-automatable jobs and newly automatable jobs. If these jobs were included this delineation would not be possible.

We proceed by regressing the indicator variable on each set of job attributes and skills respectively as provided by O*NET. We control for differences across country with a set of country fixed effects and for differences across time with a set of year fixed effects. We have two main sets of regressions. The first set regresses the automation indicator variable on the 80 ability domains and the second regresses it on the 40 skills domains. We apply Lasso regression analysis, a shrinkage and a variable selection method for linear regression models. This approach is chosen as we wish to reduce the dimensionality of the abilities and skills variables under consideration. The goal of a Lasso regression is to obtain the subset of predictors that minimizes prediction error for a quantitative response variable. The Lasso does this by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward zero. Variables with a regression coefficient equal to zero after the shrinkage process are excluded from the model. That is, these variables do not explain variation in the propensity for a job to be recently automatable and will be shown with a value of zero in the results tables. The remaining variables with a positive sign are those that describe the core skills and abilities that are most likely to become redundant because of the most recent wave of automation. In contrast, the remaining variables with a negative sign describe the core skills and abilities that are most likely to become more valuable. All non-zero variables are significant at the 1% significance level.

When estimating the Lasso for the abilities attributes we include 60 abilities attributes, in addition to country and year fixed effects. Country fixed effects control for location specific factors that are time invariant. Given the small time window we do not expect that time varying factors will distort our results.

4. Results

Abilities

The results from the pooled country analysis for abilities are documented in Table 2. We first note that the regression considering abilities explains 97% of the variation in the Lordan and Josten [10] automation indicator. That is, we can explain almost all of the variation in the indicator variable with these measures of ability. Second, if we take column (3) and column (4) there is no single secondary or overall ability category that persistently has negative or positive signs. Rather, within each of these categories there are abilities that are becoming less important and others that are becoming more important. For example, arm-hand steadiness is a fine manipulative psychomotor ability (e.g. the ability to keep your hand and arm steady while moving your arm) that is highly unlikely to be automated given the estimates. In contrast,

Table 2. Abilities estimates.

(1)	(2)	(3)	(4)	(5)
ONET Item	**Description**	**Secondary category**	**Overall category**	**Coefficient**
Arm-Hand Steadiness	The ability to keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.	Fine manipulative abilities	Psychomotor abilities	-3.587
Auditory Attention	The ability to focus on a single source of sound in the presence of other distracting sounds.	Auditory and speech abilities	Sensory Abilities	0.000
Category Flexibility	The ability to generate or use different sets of rules for combining or grouping things in different ways.	Idea Generation and Reasoning Abilities	Cognitive Abilities	-2.381
Control Precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.	Control Movement Abilities	Psychomotor Abilities	1.663
Deductive Reasoning	The ability to apply general rules to specific problems to produce answers that make sense.	Idea Generation and Reasoning Abilities	Cognitive Abilities	-4.904
Depth Perception	The ability to judge which of several objects is closer or farther away from you, or to judge the distance between you and an object.	Visual Abilities	Sensory Abilities	0.558
Dynamic Flexibility	The ability to quickly and repeatedly bend, stretch, twist, or reach out with your body, arms, and/or legs.	Flexibility, Balance and Coordination	Physical Abilities	2.784
Dynamic Strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.	Physical Strength	Physical Abilities	-0.256
{2,3Explosive Strength	The ability to use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object.	Physical Strength	Physical Abilities	0.555
Extent Flexibility	The ability to bend, stretch, twist, or reach with your body, arms, and/or legs.	Flexibility, balance and coordination	Physical Abilities	-2.347
Far Vision	The ability to see details at a distance.	Visual Abilities	Sensory Abilities	-2.219
Finger Dexterity	The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.	Fine manipulative abilities	Psychomotor abilities	2.169
Flexibility of Closure	The ability to identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.	Perceptual Abilities	Cognitive abilities	0.000
Fluency of ideas	The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).	Ideas generation and reasoning abilities	Cognitive abilities	-2.830
Glare sensitivity	The ability to see objects in the presence of glare or bright lighting.	Visual abilities	Sensory abilities	-3.635
Gross Body Co-ordination	The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.	Flexibility, Balance and Coordination	Physical Abilities	0.266
Gross Body Equilibrium	The ability to keep or regain your body balance or stay upright when in an unstable position.	Flexibility, Balance and Coordination	Physical Abilities	0.000
Hearing Sensitivity	The ability to detect or tell the differences between sounds that vary in pitch and loudness.	Auditory and Speech abilities	Sensory Abilities	-1.139
Inductive Reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).	Idea Generation and Reasoning Abilities	Cognitive Abilities	0.000
Information Ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g., patterns of numbers, letters, words, pictures, mathematical operations).	Idea Generation and Reasoning Abilities	Cognitive Abilities	0.000
Manual Dexterity	The ability to quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.	Fine Manipulative Abilities	Psychomotor Abilities	0.000
Math Reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.	Quantitative Abilities	Cognitive Abilities	1.253
Memorization	Abilities related to the recall of available information.	Quantitative Abilities	Cognitive Abilities	0.000
Multi Limb Co-ordination	The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.	Control movement abilities	Psychomotor Abilities	1.604
Near Vision	The ability to see details at close range (within a few feet of the observer).	Near Vision	Visual Abilities	0.000
Night Vision	The ability to see under low light conditions.	Near Vision	Visual Abilities	3.025
Number Facility	The ability to add, subtract, multiply, or divide quickly and correctly.	Quantitative Abilities	Cognitive Abilities	-1.817

(*Continued*)

Table 2. (Continued)

(1)	(2)	(3)	(4)	(5)
ONET Item	**Description**	**Secondary category**	**Overall category**	**Coefficient**
Oral Comprehension	The ability to listen to and understand information and ideas presented through spoken words and sentences.	Verbal Abilities	Cognitive Abilities	0.000
Oral Expression	The ability to communicate information and ideas in speaking so others will understand.	Verbal Abilities	Cognitive Abilities	4.378
Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.	Idea generation and Reasoning Abilities	Cognitive Abilities	0.000
Perceptual Speed	The ability to quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object.	Perceptual Abilities	Cognitive Abilities	-4.204
Perceptual Vision	The ability to see objects or movement of objects to one's side when the eyes are looking ahead.	Visual Abilities	Sensory Abilities	0.713
Problem Sensitivity	The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing there is a problem.	Idea generation and Reasoning Abilities	Cognitive Abilities	2.190
Rate Control	The ability to time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.	Control Movement Abilities	Psychomotor Abilities	3.112
Reaction Time	The ability to quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears.	Reaction Time and Speed Abilities	Psychomotor Abilities	2.509
Response Orientation	The ability to choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.	Control Movement Abilities	Psychomotor Abilities	-4.984
Selective Attention	The ability to concentrate on a task over a period of time without being distracted.	Attentiveness	Cognitive Abilities	-0.963
Sound Localisation	The ability to tell the direction from which a sound originated.	Auditory and Speech Abilities	Sensory Abilities	-1.685
Spatial Orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.	Spatial Abilities	Cognitive Abilities	1.051
Speech Clarity	The ability to speak clearly so others can understand you.	Auditory and Speech Abilities	Sensory Abilities	0.000
Speech Recognition	The ability to identify and understand the speech of another person.	Auditory and Speech Abilities	Sensory Abilities	-2.099
Speed of Closure	The ability to quickly make sense of, combine, and organize information into meaningful patterns.	Perceptual Abilities	Cognitive Abilities	5.164
Speed of Limb Movement	The ability to quickly move the arms and legs.	Reaction Time and Speed Abilities	Psychomotor Abilities	-1.118
Stamina	The ability to exert yourself physically over long periods of time without getting winded or out of breath.	Endurance	Physical Abilities	0.557
Static Strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.	Physical Strength Abilities	Physical Abilities	0.679
Time Sharing	The ability to shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources).	Attentiveness	Cognitive Abilities	2.796
Trunk Strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without 'giving out' or fatiguing.	Physical Strength Abilities	Physical Abilities	0.000
Visual Color Discrimination	The ability to match or detect differences between colors, including shades of color and brightness.	Visual Abilities	Sensory Abilities	4.322
Visualisation	The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.	Spatial Abilities	Cognitive Abilities	-0.752
Wrist-Finger Speed	The ability to make fast, simple, repeated movements of the fingers, hands, and wrists.	Reaction Time and Speed Abilities	Psychomotor Abilities	-1.251
Written Comprehension	The ability to read and understand information and ideas presented in writing.	Verbal Abilities	Cognitive Abilities	0.000
Written Expression	The ability to communicate information and ideas in writing so others will understand.	Verbal Abilities	Cognitive Abilities	-0.295
R Squared = 0.97				2701297

https://doi.org/10.1371/journal.pone.0266326.t002

finger dexterity which is also a fine manipulative psychomotor ability (i.e. the ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects) is likely to be automated. Similarly, fluency of ideas is an idea generation and reasoning ability which relates to the ability to come up with a number of ideas about a topic (i.e. the number of ideas is important, not their quality, correctness, or creativity) which is highly unlikely to be automated. In contrast, problem sensitivity (i.e. recognizing that there is a problem but not solving the problem) in the same category is highly likely to be automated.

Although it may seem counter-intuitive that within the same ability category there are pairs of abilities that are both automatable and non-automatable, the description of each item (see column (2) Table 2) highlights a logical theme. In general, an ability is automatable if it entails an underlying action that is repeatable or follows some logic. For example, control precision relies on adjusting controls quickly and repeatedly. The repetitive nature of this ability implies it is easily codifiable and machines have a comparative advantage in speed of execution. In contrast, speech recognition, which involves understanding spoken language, is unlikely to be automated. This finding is intuitive as it is difficult to predict what someone will say unless it entails common conversations such as those in telephone customer care. For example, customer care in banking now frequently utilize artificial intelligence to direct calls or provide bank balances but it is human operators that deal with complaints and other issues.

The overall conclusion from studying Table 2 is that jobs that are high on 'brains' (i.e. involve abstract thinking) are far less likely to be automated. In this case, 'brains' is short-hand for thinking and can involve reacting to other individuals (e.g. in caring or teaching professions), performing a service (e.g. as mechanic or fine dining waiter) or engaging in agile or creative thinking (e.g. in a leadership or knowledge worker role). Occupations that are predicted to be automated are low on 'brains' and high in routine contents. The abilities analysis is hence largely in line with the work by Author and Dorn [6] who predict that jobs that involve routine tasks will be automated. However, given that in this analysis we only focus on the occupations classified as non-automatable by Author and Dorn [6] it further reiterates that automation has continued to make progress automating jobs that are high in routine content.

Skills

The results from the pooled country analysis for skills are documented in Table 3. This regression explains 84% of the variation in the Lordan and Josten [10] automation indicator. Analyzing columns (3) and (4) of Table 3, the results are consistent with the analysis of abilities in that there is again no secondary or overall skills category that has a persistent negative or positive effect on the automation indicator. In addition and also consistent with the abilities analysis, there is a pattern which suggests that 'brains' (i.e. thinking and reacting) is becoming more important while on the job as compared to routine work.

For example, within the overall category of basic skills (see column 4), the O*NET item active learning is a skill that is more likely to be automated. This is consistent with machines being able to process a large amount of information quickly. However, the O*NET items critical thinking and monitoring of performance, which essentially involve using information that is available to pass judgement and make decisions, are less likely to be automated. Within cross functional skills, skills that center around identifying potential problems, setting rules and gathering information are most likely to be automated (for example the O*NET items of time management, operation monitoring, system evaluation and management of human resources). In contrast, those skills that require manual actions (e.g. equipment maintenance),

Table 3. Skills estimates.

(1)	(2)	(3)	(4)	(5)
ONET Item	**Description**	**Secondary category**	**Overall category**	**Coefficient**
Active Learning	Understanding the implications of new information for both current and future problem-solving and decision-making.	Process	Basic Skills	1.630
Active Listening	Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.	Content	Basic Skills	0.608
Complex Problem Solving	Identifying complex problems and reviewing related information to develop and evaluate options and implement solutions.	Complex Problem Solving	Cross Functional Skills	-0.580
Coordination	Adjusting actions in relation to others' actions.	Social Skills	Cross Functional Skills	-6.025
Critical Thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.	Process	Basic Skills	-3.233
Equipment Maintenance	Performing routine maintenance on equipment and determining when and what kind of maintenance is needed.	Technical Skills	Cross Functional Skills	-0.504
Equipment Selection	Determining the kind of tools and equipment needed to do a job.	Technical Skills	Cross Functional Skills	0.000
Installation	Installing equipment, machines, wiring, or programs to meet specifications.	Technical Skills	Cross Functional Skills	0.540
Instructing	Teaching others how to do something.	Social Skills	Cross Functional Skills	-2.752
Judgement and Decision Making	Considering the relative costs and benefits of potential actions to choose the most appropriate one.	Systems Skills	Cross Functional Skills	2.775
Learning Strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.	Systems Skills	Cross Functional Skills	0.000
Management of Financial Resources	Determining how money will be spent to get the work done, and accounting for these expenditures.	Resource Management Skills	Cross functional Skills	0.000
Management of Material Resources	Obtaining and seeing to the appropriate use of equipment, facilities, and materials needed to do certain work.	Resource Management Skills	Cross functional Skills	-1.262
Management of Personnel Resources	Motivating, developing, and directing people as they work, identifying the best people for the job.	Resource Management Skills	Cross functional Skills	2.264
Mathematics	Using mathematics to solve problems.	Content	Basic Skills	0.000
Monitoring	Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.	Process	Basic Skills	-4.676
Negotiation	Bringing others together and trying to reconcile differences.	Social Skills	Cross functional Skills	1.967
Operation Monitoring	Watching gauges, dials, or other indicators to make sure a machine is working properly.	Technical Skills	Cross Functional Skills	1.831
Operation and Control	Controlling operations of equipment or systems.	Technical Skills	Cross Functional Skills	0.000
Operations Analysis	Analyzing needs and product requirements to create a design.	Technical Skills	Cross Functional Skills	-1.091
Persuasion	Persuading others to change their minds or behavior.	Social Skills	Cross functional Skills	-0.827
Programming	Writing computer programs for various purposes.	Technical Skills	Cross functional Skills	0.000
Quality Control Analysis	Conducting tests and inspections of products, services, or processes to evaluate quality or performance.	Technical Skills	Cross functional Skills	0.000
Reading Comprehension	Understanding written sentences and paragraphs in work related documents.	Content	Basic Skills	-2.474
Repairing	Repairing machines or systems using the needed tools.	Technical Skills	Cross Functional Skills	-0.935
Science	Using scientific rules and methods to solve problems.	Content	Basic Skills	1.044
Service Orientation	Actively looking for ways to help people.	Social Skills	Cross Functional Skills	-0.854

(*Continued*)

Table 3. (Continued)

(1)	(2)	(3)	(4)	(5)
ONET Item	**Description**	**Secondary category**	**Overall category**	**Coefficient**
Social Perceptiveness	Being aware of others' reactions and understanding why they react as they do.	Social Skills	Cross Functional Skills	0.000
Speaking	Talking to others to convey information effectively.	Content	Basic Skills	1.235
System Analysis	Determining how a system should work and how changes in conditions, operations, and the environment will affect outcomes.	Systems Skills	Cross Functional Skills	-2.530
System Evaluation	Identifying measures or indicators of system performance and the actions needed to improve or correct performance, relative to the goals of the system.	Systems Skills	Cross Functional Skills	4.365
Technology Design	Generating or adapting equipment and technology to serve user needs.	Technical Skills	Cross Functional Skills	-2.203
Time Management	Managing one's own time and the time of others.	Resource Management Skills	Cross Functional Skills	4.214
Troubleshooting	Determining causes of operating errors and deciding what to do about it.	Technical Skills	Cross Functional Skills	0.000
Writing	Communicating effectively in writing as appropriate for the needs of the audience.	Content	Basic Skills	1.686
R squared = 0.84			N =	2701297

https://doi.org/10.1371/journal.pone.0266326.t003

communicating information (for example instructing), leadership (e.g. persuasion) and knowledge work (e.g. systems analysis and technology design) are less likely to be automated.

A second notable pattern emerges if we reconsider Table 3. In general, the skills that require active interactions with people (i.e. implying that there is at least a two-way dialogue where an employee is reacting to the other person(s)) are not automatable. In essence, these jobs are an interaction between 'brains' and 'people' skills. In Table 3, these include coordination, instructing, monitoring and persuasion. This observation seems to suggest that jobs that involve 'people' interacted with 'brains' skills are also less likely to be automated.

Conclusion from the skills and abilities analysis

From the estimates documented in Tables 2 and 3 we make the following three conclusions:

1. We can explain almost all of the variation in the jobs that are newly defined as automatable by Lordan and Josten [10] using the O*NET items of abilities or skills.

2. Jobs that require 'brains' (i.e. abstract and non-linear thinking) are far less likely to be automated as compared to jobs which require linear and codifiable thinking skills and abilities. At the top of the income distribution, jobs that require non-linear thinking may need critical thinking, decision-making and creativity. Elsewhere in the income distribution these jobs require skills that have been traditionally delivered in apprenticeships, from mechanics and carpenters to florists and hairdressers.

3. Jobs that require 'people' engagement interacted with 'brains' are also less likely to be automated. These jobs include management across all levels, coordinators of all types, teachers, carer and medical practitioners (including nursing). The skills and abilities that are required for these jobs include soft skills. The value of these skills in terms of adult outcomes has become a topic of recent writings in economics (for example Heckman and Kautz (2013) [22]; Kautz et al., (2014) [23] and Lordan and McGuire (2019) [24]) and has been recently noted specifically as skills that will be needed in the advent of the Fourth Industrial Revolution [12, 25].

Activities

To summarize further the conclusions described in conclusions 2. and 3. from the skills and abilities analysis (i.e. that jobs which require 'brains' and 'people' interacted with 'brains' are those that are the least likely to be automated) we consider a third analysis on work activities and context of a person's occupation. This third analysis is a replication of Table 3 in Lordan and Josten [10]. We later go further than Lordan and Josten [10] and present these estimates separately for each country in our dataset to allow for cross country comparisons.

To replicate their work we first follow Lordan and Pischke [17] and create three factors that represent the 'people' 'brains' and 'brawn' content in each three-digit code occupation. That is:

1. 'People' is a variable, which distils the information from many domains in activities and context that relate to having interactions with people on a day-to-day basis.
2. 'Brains' is a variable which distils the information from many domains in activities and context that relate to abstract thinking.
3. 'Brawn' is a variable which distils the information from many domains in activities and context that relate to interacting physically with objects, including making them on a daily basis.

We then regress our dummy representing whether a job is automatable on the 'people', 'brains' and 'brawn' variables (using ordinary least squares (OLS)). Consistent with Lordan and Josten [10]) we also interact the three variables with each other, implying we also include in our regression people*brains, people*brawn and brains*brawn. We again control for fixed country differences and yearly differences in the regression. The results from this analysis are documented in Table 4.

Turning to Table 4, we can explain 42% of the variation in our automatable employment indicator with the three latent factors. The size and significance of the negative coefficient on the 'brain' factor strongly implies that jobs which require thinking are those that are safe from the most recent wave of automation. In addition, the interaction between the 'people' and 'brains' factors is negative and significant. This highlights that jobs which require thinking and

Table 4. 'People', 'brains' and 'brawn' estimates.

Variable	Marginal effect
People	0.009***
	(0.000)
Brains	-0.070***
	(0.000)
Brawn	0.032***
	(0.000)
People * Brains	-0.002***
	(0.000)
People* Brawn	0.003***
	(0.000)
Brains* Brawn	0.000***
	(0.000)
N	2,698,151
R squared	42%

Notes *, **, *** denotes significance at the 10%, 5% and 1% levels respectively.

https://doi.org/10.1371/journal.pone.0266326.t004

social interactions are safer in the most recent wave of automation as compared to those that simply involve people interactions (as evidenced by the positive and significant coefficient on the 'people' factor). We note that the estimates in Table 4 imply that jobs that are high on 'brawn' content are those that are most likely to be automated in the most recent wave of automation. These jobs include making objects and physically lifting items. Overall, these conclusions align well with those that came from the abilities and skills analyses in Tables 2 and 3 respectively as they highlight the importance of abstract thinking and the combination of abstract thinking and people skills.

Country-level analysis

The S1 Appendix contains the estimates from Table 2 through 4 by country including all EU-LFS countries as depicted in Table 1. The differences across these estimates is driven only by differences in the occupation distribution for each country, while the classification of whether a job is recently automatable is fixed across time and country. We note that the separate analyses of skills and abilities for each country allows us to draw similar conclusions to the pooled country estimates in Tables 2 and 3. That is, the abilities and skills that are becoming more important relate to the ability and skill to use 'brains' for abstract, strategic and creative thinking and the ability and skill to use 'brains' interacted with 'people'.

The 'people', 'brains' and 'brawn' categories allow us to summarize the differences and commonalities across countries most succinctly. These are:

1. For all countries, jobs that are high on 'brains' are least likely to be automated in the most recent wave of automation.
2. For many countries the 'people' coefficient is also negative and significant, implying that jobs that are 'people' facing are relatively safe from automation, regardless of their interaction with 'brains'. These countries are: Austria, Belgium, Cyprus, Czech Republic, Denmark, Germany, Estonia, Spain, France, Ireland, the Netherlands, Norway, Sweden.
3. For almost all countries there is a negative and significant relationship between the potential for automation and the 'people' and 'brains' interaction. The exceptions are Cyprus, Estonia, Ireland, Norway, Sweden and the UK. We note that for Estonia, Ireland, Norway and Sweden both the 'people' and 'brains' effects are independently negative and significant, highlighting that 'people' jobs in general are unlikely to disappear significantly. For Cyprus and the UK, the estimates suggest that 'brains' are the most important skills and abilities to develop given the current distribution of jobs.
4. In general, the brawn effect is positive and significant, implying that jobs that are high on 'brawn' content are at risk from automation. The exception of countries where this effect is negative are Cyprus, Czech Republic and Estonia.
5. The interaction effect between 'people' and 'brawn' is in general positive, significant but small in magnitude for just over half the countries in our study. In contrast, it is negative and significant but small in magnitude for: Finland, France, Hungary, Ireland, Iceland, Latvia, Norway, Sweden, Slovakia and the UK. The difference seems to be driven by a relatively large number of jobs in these countries in the low end of the income distribution that require physical lifting and people (for example, cleaning and caring).
6. The interaction effect between 'brains' and 'brawn' is in general negative, significant but small in magnitude. There are only three exceptions. These are: Cyprus, Czech Republic and Ireland.

5. Conclusion

This study identifies the job attributes which predict the likelihood that a job is recently automatable. In particular, it looks at the i) abilities and ii) skills required on the job and how they link to automatability. A third analysis (iii) considers the 'people', 'brains' and 'brawn' content of an occupation, i.e. the extent to which an occupation involves people interactions, abstract thinking and physicality respectively. The three analyses are also done on a country level to see how the impact of automatability on the labour market differs across countries.

Overall, we find that skills and abilities which relate to non-linear abstract thinking, which we term 'brains', are those that are the safest from automation. We also find that jobs that require 'people' engagement interacted with 'brains' are also less likely to be automated. The skills and abilities that are required for these jobs include soft skills. Finally, we find that jobs that require physicality (e.g. creating objects manually) are most likely to be automated unless they involve interaction with 'brains' and/or 'people'.

These findings are in line with the literature on the growing importance of cognitive and social skills for the future of work. In particular, Deming [25] finds that the interaction between cognitive and social skills has seen greater wage and employment growth, which is comparable to our finding of the importance of 'brains' alongside 'people' skills and abilities. It also matches findings of studies that link skills endowments or demand for skills to labour market outcomes and find that social and cognitive skills are increasingly rewarded and that there is a complementarity across those two dimension [26, 27].

Information and knowledge on future job requirements by occupations and by country is essential when trying to predict the demand for skills and abilities and activities going forward. It is important knowledge for policymakers and companies who can adapt policies and organizational settings regarding the future of work accordingly and ensure that individuals are prepared for current developments and what is yet to come. In particular, it informs conversations surrounding the re-organization of education and other development activities to ensure that the stock and flow of skills are ready for the Fourth Industrial Revolution. The returns to education are constantly increasing with the rise in technological progress with specific skills such as digital and non-cognitive skills becoming particularly important [19]. And this information also helps to gain a more nuanced understanding of the exact aspects of the occupations at risk of automation rather than just predicting automation overall and hence extends previous work. While we summarize our findings at the 'people', 'brains' and 'brawn' level, we still show and have briefly discussed the results by each O*NET abilities and skills item, which is informative to the reader interested in specific aspects of occupations and their automatability.

The differences in effects found at the country level likely reflect the fact that the structure of jobs and skills within country differ, coupled with each country being on a different trajectory with respect to automation. In addition, the policies that can protect jobs from automation also differ within country. A better understanding of such within country policies, coupled with their interaction with the labour market is an area for future research.

Supporting information

S1 Table. Occupations classified by Josten and Lordan (2020) as automatable.
(DOCX)

S1 Appendix. Individual country analysis.
(DOCX)

Author Contributions

Conceptualization: Cecily Josten, Grace Lordan.

Data curation: Grace Lordan.

Formal analysis: Grace Lordan.

Funding acquisition: Grace Lordan.

Investigation: Grace Lordan.

Methodology: Grace Lordan.

Project administration: Grace Lordan.

Resources: Grace Lordan.

Software: Grace Lordan.

Supervision: Grace Lordan.

Validation: Grace Lordan.

Visualization: Grace Lordan.

Writing – original draft: Grace Lordan.

Writing – review & editing: Cecily Josten, Grace Lordan.

References

1. Frey CB, Osborne MA. The future of employment: how susceptible are jobs to computerization? Technol Forecast Soc Change. 2013;1–72.
2. Arntz M, Gregory T, Zierahn U. The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis Working Papers No. 189 The Risk of Automation for Jobs in OECD Countries A COMPARATIVE ANALYSIS. OECD Soc Employment, Migr Work Pap. 2016;(May):0_1.
3. Lewandowski P, Park A, Hardy W, Yang D. Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data. IZA Discuss Pap [Internet]. 2019 [cited 2021 Jul 9]; Available from: www.iza.org
4. Gregory T, Salomons A, Zierahn U. Racing With or Against the Machine? Evidence from Europe. IZA Discuss Pap. 2019;
5. Autor D, Dorn D. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. Am Econ Rev. 2013; 103(5):1553–97.
6. Autor DH, Dorn D, Hanson GH. Untangling Trade and Technology: Evidence from Local Labour Markets. Econ J. 2015; 125(584):621–46.
7. Acemoglu D, Restrepo P. Tasks, automation, and the rise in US wage inequality. NBER Work Pap [Internet]. 2021;No. 28920. Available from: http://www.nber.org/papers/w28920
8. Webb M. The Impact of Artificial Intelligence on the Labor Market. SSRN. 2019;
9. Nedelkoska L, Quintini G. Automation, skills use and training (OECD Working Paper). OECD Soc Employment, Migr Work Pap [Internet]. 2018;(202):1–125. Available from: https://doi.org/10.1787/2e2f4eea-en
10. Josten C, Lordan G. Robots at Work: Automatable and Non-automatable Jobs. In: Handbook of Labor, Human Resources and Population Economics. Springer International Publishing; 2020. p. 1–24.
11. Innovation Vivarelli M., Employment and Skills in Advanced and Developing Countries: A Survey of Economic Literature. J Econ Issues [Internet]. 2014 [cited 2019 Nov 14]; 48(1):123–54. Available from: https://www.tandfonline.com/action/journalInformation?journalCode=mjei20
12. Lordan G. Robots at work—A report on automatable and non-automatable employment shares in Europe. Eur Comm—Dir Employment, Soc Aff Incl. 2018;
13. Lordan G, Neumark D. People versus machines: The impact of minimum wages on automatable jobs. Labour Econ. 2018 Jun 1; 52:40–53.

14. Brynjolfsson E, Mitchell T, Rock D. What Can Machines Learn and What Does It Mean for Occupations and the Economy? Am Econ Assoc. 2018; 108:43–7.

15. Frey CB, Osborne MA. The future of employment: How susceptible are jobs to computerisation? Technol Forecast Soc Change. 2017 Jan 1; 114:254–80.

16. Tolan S, Pesole A, Martínez-Plumed F, Fernández-Macías E, Hernández-Orallo J, Gómez E. Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks. J Artif Intell Res. 2021; 71:191–236.

17. Lordan G, Pischke J-S. Does Rosie like riveting? Male and female occupational choices. NBER Work Pap [Internet]. 2016 [cited 2019 Nov 27]; Available from: http://www.nber.org/data-appendix/w22495

18. Djumalieva J, Lima A, Sleeman C. Classifying Occupations According to Their Skill Requirements in Job Advertisements. ESCoE Discuss Pap [Internet]. 2018 [cited 2021 Jul 5]; Available from: www.escoe.ac.uk.

19. Goos M, Arntz M, Zierahn U, Gregory T, Carretero Gómez S, González Vázquez I, et al. The impact of Technological innovation on the Future of Work. JRC Work Pap Ser Labour, Educ Technol [Internet]. 2019 [cited 2021 Jul 5]; Available from: https://ec.europa.eu/jrc

20. Arntz M, Gregory T, Zierahn U. Revisiting the risk of automation. Econ Lett. 2017 Oct 1; 159:157–60.

21. Fernández-Macías E, Hurley J, Bisello M. What do Europeans do at work?: A task-based analysis: European Jobs Monitor 2016. Publ Off Eur Union [Internet]. 2016 [cited 2021 Jul 9]; Available from: www.eurofound.europa.eu

22. Heckman J, Kautz T. Fostering and Measuring Skills: Interventions that improve character and cognition. Nber Work Pap Ser. 2013;

23. Kautz T, Heckman JJ, Diris R, Weel B ter, Borghans L. Fostering and Measuring Skills: Improving Cognitive and Non-Cognitive Skills to Promote Lifetime Success. Natl Bur Econ Res [Internet]. 2014 Dec 15 [cited 2021 Jul 12]; Available from: https://www.nber.org/papers/w20749

24. Lordan G, McGuire A. Widening the High School Curriculum to Include Soft Skill Training: Impacts on Health, Behaviour, Emotional Wellbeing and Occupational Aspirations. IZA Discuss Pap. 2019; (12439).

25. Deming DJ. The Growing Importance of Digital Skills in the Workplace. Q J Econ. 2017; 132(October):1593–640.

26. Deming D, Kahn LB. Skill Requirements across Firms and Labor Markets: Evidence from Job Postings for Professionals. J Labor Econ. 2018; 36(S1).

27. Weinberger C. The Increasing Complementarity between Cognitive and Social Skills. Rev Econ Stat [Internet]. 2014 [cited 2021 Jan 20]; 96(5). Available from: http://www.mitpressjournals.org/doi/abs/10.1162/REST_a_00449