Introduction

Contemporary societies are characterized by constant technological advancement, with Artificial Intelligence (AI) at the edge. despite the highest material well-being yielded by technology, concerns about its adverse effects have not diminished. A long-lasting concern about technology regards it is influence on human labor. It emerged from the early stage of machinery and automation of craftworks in the 16th century. When William Lee introduced his invention of the knitting machine for the first time in 1589, it was opposed by Queen Elizabeth I because of its impact on the work of hundreds of hand-knitting artisans with the fear of ending up in their mass joblessness. (Frey & Osborne, 2017).

The more technology advances and automates handwork, the more concern about mass unemployment becomes serious. Technological unemployment was the term Maynard Keynes used to predict the inevitable but temporary outcome of economizing the production process throughout the 1930s. He believed that technology, in the long run, creates more jobs, and under the scheme of the European welfare state, it can eventually lead to full employment (McGuinness et al., 2018).

٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫٫

Human work in the age of Artificial Intelligence

Despite the unprecedented prosperity that technology has brought to human life, its problematic relationship with human labor is undeniable. From the earliest stages of machinery and automation, machines have emerged as competitors to human work. As machines have increasingly taken over tasks previously performed by humans, concerns about the complete replacement of human workers have grown. Economists like John Maynard Keynes even considered technological unemployment an inevitable consequence of technological and economic growth, urging future societies to find alternative ways to distribute income and wealth beyond traditional work (Keynes, 1930).

As machines became more intelligent and equipped with computer systems, the debate over technological unemployment peaked in the 20th century. Early machines could execute simple, repetitive tasks in manufacturing, but computers could perform more complex tasks by following pre-determined instructions. Consequently, the risk of unemployment spread beyond manufacturing to include many office jobs and administrative tasks with clear instructions.

The emergence of Artificial Intelligence marked a significant leap in machine capabilities. AI-powered machines can mimic human intelligence, learning and making decisions based on experience using data or deductive reasoning. This means that even cognitive tasks are no longer exclusive to humans.

Along with waves of technological transformation, academics have conducted extensive research on how technology affects the workforce. Early critical approaches emphasized the degradation of labor. Neo-Marxists like Braverman argued that automation reduces human work to standard and routine tasks. Coupled with the dominance of Taylorist management in organizations, this reduction leads to a workforce devoid of skill and autonomy.

For a long time, the hypothesis of a deskilled workforce guided many labor studies. This hypothesis posits that the development of automation and computerization increasingly replaces human labor with machines and computers. In contrast, the neoliberal discourse offered a more optimistic view of the relationship between technological advances and labor skills. Historical evidence showed that, on average, the education level of the labor force has improved, and the number of employees in specialized jobs has increased. From this evidence, neoliberals concluded that the pattern of workforce changes is one of upscaling.

Meanwhile, another group of researchers identified a different pattern called skill polarization. Polarization refers to the simultaneous increase in both high-skilled and low-skilled labor, alongside a decrease in medium-skilled labor. This trend is mainly attributed to the skill-biased nature of technology. The development and use of advanced technologies in organizations increase the need for expert personnel while also maintaining a demand for human resources to perform low-skill tasks. In contrast, medium-skilled jobs, which involve standard and predetermined tasks, are increasingly assigned to machines and computers.

Researchers studying skill change patterns have made notable methodological contributions to measuring workforce skills. Initially, education level served as a proxy for skill, with an increase in the average education level of the workforce indicating upskilling. With the availability of administrative data on occupations, researchers could classify jobs into low-skill, middle-skill, and high-skill categories based on their task content. Changes in employment within these categories determine whether the workforce experiences upskilling, deskilling, or skill polarization. Later, job-level analysis was introduced to account for the variation in job skill requirements within the same occupation group.

Despite the valuable theoretical and empirical insights provided by this research strand, it often overlooks the unique features of artificial intelligence-based technologies, which differ from previous waves of automation and computerization. AI technologies, such as chatbots and GPT models, have become pervasive in today’s workplace, serving as ever-present assistants to workers regardless of their job or skill level. In manufacturing environments, collaborative robots, or cobots, work alongside humans in shared spaces. This complex relationship between workers and AI cannot be fully captured by displacement theories and requires a new framework to investigate the quality of coexistence between humans and machines.

In the coexistence discourse, humans and artificial intelligence possess unique characteristics. AI can learn quickly and perform complex tasks even with limited prior knowledge, relying on data and algorithms. Conversely, humans have unique skills such as creativity, initiative, emotional intelligence, communication, and persuasion that are beyond the capabilities of AI. Therefore, human and AI capabilities complement and augment each other. AI facilitates information acquisition and data analysis for humans, reducing calculation errors. Humans, in turn, monitor AI’s work processes, make results understandable and evaluable, and create spaces for AI’s continued development. This cooperative relationship, as described by Zirar and his colleagues (2023), is an endless cycle. Humans give up skills that AI is capable of performing and then acquire new ones. As AI masters these tasks and takes on more complex ones, it prompts humans to reskill and update themselves. This cycle is illustrated in Figure 1.

A diagram of a diagram of a worker

Description automatically generated

Figure 1. A cyclical perpetual race between worker and workplace AI

(Adopted from Zirar et al. 2023. Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda. Technovation 123, 7)

Shifting from a displacement perspective to a coexistence view allows researchers to investigate workforce skills within the workplace context. The connection between workers and AI depends on the specific AI-powered technologies integrated into the workplace (Krzywdzinski, 2017) and the upskilling opportunities organizational stakeholders provide (Alsos & Erik Dølvik, 2021). Consequently, workers in the same occupation or even under the same job title may have different opportunities to realize and enhance their skills. This shift in perspective underscores the importance of individual-level analysis in workforce studies. Today, nationwide surveys offer a rich source of data on the workforce. Many scholars utilize self-reported data from surveys to capture workers’ firsthand experiences with workplace technologies. (…)

As AI technologies rapidly integrate into workplaces, affecting employees across all skill levels, understanding how workers are prepared to collaborate constructively with AI becomes a critical research priority for contemporary societies. Through the lens of the coexistence framework, this thesis aims to examine the issue of workforce skills in the age of AI technologies and contribute valuable insights from Finland to this ongoing discussion.

Recognizing that data is the wealth of modern societies, this thesis utilizes pre-existing data from a highly reliable source: the Finnish Working Life Barometer produced by Statistics Finland. By applying rigorous methodologies and critical evaluation, this thesis also contributes to enriching the field of survey data analysis.

Research objectives and questions

Workplace technology advancements are accelerating, while historical concerns about the reduction of human involvement in the work process persist and have even intensified. Academic discussions, ranging from pessimistic accounts warning of the complete replacement of humans by machines, to optimistic views envisioning a prosperous future under technological advances, to realistic perspectives that see human-technology co-existence as the way forward, each has held theoretical dominance at different stages of technological evolution, shedding light on specific aspects of the problem.

Building upon existing research, this thesis aims to develop a robust methodology for measuring the actual utilization of workforce skills in contemporary Finnish workplaces. The next objective is to examine the changes in workforce skills over time providing a deeper understanding of the evolving nature of work in Finland. Finally, this study will explore disparities and inequalities in skill realization and development based on gender and age to identify potential biases and challenges within the Finnish workforce. Therefore the main research questions of this thesis are formulated as follows:

1. What is the most effective methodology for measuring workforce skills that capture the complexity of work in the age of AI workplace technologies?
2. How have Finnish workforce skills changed within the timeframe 2018 - 2022?
3. Are there significant disparities in workforce skills based on gender and age?

Thesis structure

This thesis is organized into five chapters. The Introduction provides an overview of the research topic, highlights the research stance, and discusses the necessity and significance of the topic for contemporary societies and the field of Social Data Science (SDS). It also outlines the research questions and objectives. The LiteratureReview discusses existing theoretical insights and empirical findings that inform the chosen methodological approach for investigating the research topic. The Method and Data chapter explains the measurement instrument and the process of its development. It also details the data utilized in this research, including data preprocessing and weighting procedure, followed by a descriptive analysis of the variables of interest. The Results chapter presents the research findings corresponding to the core research questions. Finally, the Discussion and Conclusion chapter summarizes the key findings, discusses research limitations, and explores policy implications.

Theoretical background

Labor Process Theory

Tracing the contemporary debates on the impact of technology on human labor, Labor Process Theory (LPT) emerged as a prominent analytical framework in the 1970s (Jaros, 2000). This theory was popularized by Harry Braverman’s 1974 book Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century. In his influential book, Braverman examined the degradation of human labor tracing its roots in the logic of capitalism and Tayloristic organization of work (Knights & Willmott, 1990). He explained how breaking down complex work into simple repeatable individual tasks eroded the traditional notion of skill that used to be realized in craftwork. This fragmentation of work resulted in the appearance of a homogeneous working population whose labor was degraded to standardized, repetitious, and dexterous tasks. At the same time, technical knowledge was shifted away from labor and toward management which opened doors for managerial control of the labor process (Braverman, 1974). Braverman’s emphasis on the separation of management from labor due to advanced machinery operations and scientific organization of work enriched the stance of the technology’s deskilling impact on human labor.

Despite the dominance of degrading and deskilling arguments in the 1970s, empirical evidence appeared in the literature that showed an upward trend in workforce skills (Adler,2004). This body of empirical research discovered that the workforce skills have been upgraded over a longer term and in the aggregate. Digging into historical data revealed an evolution in the occupational distribution of the workforce with professional and technical occupations growing from 4% in 1900 to 16% in 2000. Some scholars cited the significant growth in the average education level of the workforce as an indicator of skill upgrading. Based on U.S. data, they reported that the population of high school graduates increased from 6% in 1900 to over 80% by the end of the century. Relying on these evidences, a considerable number of researchers, mostly among economists, concluded that technological advancement in a capitalistic context increases the demand for more skilled workers, suggesting that technology and human skills are complements rather than substitutes (Adler, 2004).

Expanding empirical research within Labor Process Theory revealed a third trend known as skill polarization. Unlike deskilling and upskilling arguments, which both identified unidirectional trends, researchers began to observe a binomial distribution of occupations. In this distribution, low-skilled and high-skilled occupations grew at the expense of disappearing middle-skilled occupations. The polarization argument gained prominence in the early 2000s when computer technology was evolving the work process. Due to its serious implications for wage gaps and societal inequality, numerous theoretical and empirical studies have delved into this phenomenon. Among the root causes of polarization, technological development stands out.

In their groundbreaking research, ‘The Skill Content of Recent Technological Change: An Empirical Exploration’ (2003), David H. Autor and his colleagues made significant contributions to understanding the impact of technology on human skills. Rather than relying on education or occupation as proxies for skill, they delved into the actual content of tasks performed by workers. Their central argument was that computer-powered technologies show a bias toward routine tasks. By routine tasks, they meant limited, well-defined tasks that can be turned into programmable rules such as organizing, storing, retrieving, and manipulating information. Accordingly, they anticipated that computers would replace workers engaged in routine tasks—whether manual or cognitive—while simultaneously complementing workers in nonroutine tasks. (Autor et.al, 2003).

Analyzing task content within occupation categories, they discovered that routine tasks have been most prevalent in middle-level occupations, such as clerical and administrative roles. Consequently, computer technologies tend to substitute middle-skilled workers. Meanwhile, the demand for high-skilled workers engaged in analytical and interactive tasks rapidly grows. Low-skilled workers performing dynamic manual tasks also remain in demand, as these tasks leave limited opportunities for codification. (Autor, et. all, 2003).

The concepts of deskilling, upskilling, and skill polarization captured significant interest and directed extensive empirical studies toward investigating trends in local labor markets. Beyond providing insightful knowledge about the workforce situation across different national contexts, this research strand also contributed to our understanding of how workforce skills can be effectively measured. The challenges related to skill measurement will be discussed subsequently.

Social Shaping of Technology

Another influential paradigm for understanding the relationship between technology and human work is the Social Shaping of Technology (SST) that emerged in the 1980s. SST challenges the technological determinism underpinning the Labor Process Theory and similar viewpoints.

In a deterministic view of technology, changes occur due to scientific innovations or internal technical logic, and these changes subsequently impact society in specific ways. However, the social shaping approach recognizes that technology is intertwined with society. It is not a neutral entity, and technological changes do not follow purely engineering logic. Instead, they are influenced by social circumstances and aligned with specific patterns of social relations. Therefore technological changes are not independent, autonomous forces that affect society from the outside. Rather, they are shaped by and within social contexts (MacKenzie & Wajcman, 1999).

In his important article New Connections: Social Studies of Science and Technology and Studies of Work (2006), Judy Wajcman discussed that studies of work have long been under the dominance of technological determinism which considers human labor as a passive factor merely reacting to ever-advancing technology. He argued that predictions of the future of work, whether optimistic accounts of upgrading or pessimistic accounts of degrading and polarizing trends, often overlook the potential role of social forces in revising the direction of technological advancements. Thus narrowing the possibilities for democratic engagement with technology. (Wajcman, 2006, p. 774)

In contrast, SST encourages viewing technology as a socio-technical entity that both shapes and is shaped by the existing social, cultural, and political patterns. Developing and deploying new technologies involves deciding among various technical alternatives. Social, political, and cultural factors play an important role in determining which options are adopted. Accordingly, the relationship between technology and work can not be captured through a snapshot view of technological evolution and its direct impact on human labor. Instead, it requires a more complex analysis of the coevolution of technology and the work environment consisting of individual workers, workplace relationships, culture, and management (Joyce, 2023, p.152).

This approach shifted the focus of studies of work from statistically predicting job loss toward understanding the everyday work practice at workplaces (Health, et.al., 2000). Everyday work practice is where newly adapted technologies intersect with long-lasting privilege patterns. Not all workers experience technology the same way; factors such as gender, age, and race influence how they are affected by technology. Moreover, everyday work practices are situated within an organizational setting. Practical organizational conduct, such as management methods, division of tasks, and forms of cooperation differentiate in the way workers interact with workplace technologies (Health, et.al., 2000).

The fruit of SST has been a substantial corpus of fieldwork and ethnographies investigating the coexistence of workers and technologies in a certain workplace and exploring how work and technologies mutually evolve during the work process. One classic example is the ethnographic study conducted by Health and Luff (1992) on Underground Line Control Rooms in London. Line Control Rooms are complex multimedia work environments equipped with advanced technologies including computer monitors, large displays, and various communication devices. Personnel in these rooms have distinct roles and act on a strict division of tasks, while simultaneously being aware of each other's tasks. In this context, technologies mediate collaborative work among personnel allowing them to make their activities visible, share necessary information with others, and coordinate their activities. The study emphasized the crucial role of technologies in creating a collaborative work environment where individuals have distinct obligations and skills, yet their work is highly interconnected. The findings also suggested that technology developers and designers should prioritize features that make the information public and exchangeable in an organizational setting (Health & Luff, 1992).

These types of workplace studies opened up opportunities for multidisciplinary collaboration between social scientists and computer scientists, informing designs and evaluation of technological innovations. Presently, the field of Human-Computer Interaction (HCI) takes the lead in conducting empirical studies in this domain.

Empirical background

Exploring the relationship between human labor and technology has raised enormous empirical studies whether quantitative research which tries to measure the impact of technologies on human skills and total employment or qualitative research with a focus on how workers experience and perceive technologies at work. This literature review is centered on the quantitative strand of research.

Workforce skill; measure and level of measurement

Most of the efforts of quantitative researchers have been devoted to measuring the workers' skills and linking them to the recent capabilities of ever-changing technologies. In this research tradition, human labor is viewed as a combination of skills and abilities put into a certain job (Felten, et.al., 2019). Thus ‘skill’ has been the central concept in these studies and a variety of strategies for measuring skill has been introduced. Primarily, years of schooling were considered the main builder of skill. The individuals with higher education level were known as the high-skill workers. However, education as a proxy for skill has been heavily criticized due to its static nature which neither diminishes due to lack of use nor enhances through work experience (Martinaitis, et.al. 2021). Additionally, the education people receive significantly varies in terms of content and quality (Esposto, 2008).

Autor and Handel (2013) added to this discussion by emphasizing the demand side of skills in the job market. They elaborated that the skills people use in their work depend on the tasks they are required to carry out. Thus the content of tasks determines the level of skill (Autor & Handel, 2013). This task-oriented approach found popularity as a strategy for measuring skill. The researchers using this approach, heavily relied on the dictionaries of occupations such as Occupational Information Network (O\*NET) that contain detailed descriptions of occupations in terms of their task content and skill requirements.

A pioneer empirical research within task framework was conducted by Autor, Levy, and Murnane (2003). Besides the novel implication of the task model, the additional value of this research was the categorization of tasks based on to what extent they are attributable to computerization. They distinguished four types of tasks: routine manual, non-routine manual, routine cognitive, and non-routine cognitive tasks consisting of analytical and interactive tasks, identifying routine tasks with precise and explicit rules potentially automatable by computers. Using the Dictionary of Occupational Titles (DOT) and occupational employment data (1970-1998), they found that the development of computer technologies has significantly increased the non-routine task input of occupations, and the trend in the US labor market has shifted in favor of educated workers involved in analytical and interactive tasks.

Another famous study in this stream is The Future of Employment: How Susceptible Are Jobs to Computerisation? (2013, 2016) conducted by Frey and Osborne. Unlike Autor et. al. (2003) who assumed that only routine tasks are codifiable and amenable to computerization, Frey and Osborne believe that recent developments in machine learning, robotics, and big data have extended computerization to a wide range of non-routine tasks. Alternative to routine and non-routine categorization of tasks, they suggested three types of tasks that are bottlenecks to computerization: Perception and Manipulation tasks, Creative Intelligence tasks, and Social Intelligence tasks. Using the O\*NET description of occupations they coded 702 occupations based on three bottlenecks and estimated the probability of computerization for each occupation. They input U.S. employment data (2o10) into their model and found out that 47% of U.S. total employment is at high risk of computerization.

This estimation raised concerns bout the future of work in the U.S. and inspired follow-up research. Arntz, Gregory, and Zierahn (2017) published a paper Revisiting the Risk of Automation wherein they made a valuable methodological contribution to this topic. They highlighted that Frey and Osborn's method overestimated the proportion of automatable jobs since it overlooked the variation of tasks within occupations and the adaptability of jobs to technological changes. They discussed that this heterogeneity can be captured by shifting from occupation-level analysis to job-level analysis which makes it possible to account for the worker competencies and workplace capacities when measuring the potential risk of job automation. Incorporating the workers' data from the Survey of Adult Skills (PIIAC) and accounting for worker’s characteristics and their tasks’ content, their estimation of automation risk in the US job market dropped to 9%.

Although their estimate deviated greatly from previous scenarios, Arntz and her colleagues' emphasis on the tasks and skills that workers employ in their jobs was groundbreaking. This approach situates human work within the organizational and social structure of the workplace allowing a deeper understanding of the dynamics involved in human-technology coexistence.

Another alternative approach to occupation-level analyses was presented by Zˇilvinas Martinaitis in his innovative work Measuring Skill in Europe (2013). He distinguished between the “potential to act” and “actually realized skills” (Martinaitis, 2013. 201). He suggested a new framework for measuring skills based on “how” workers do their tasks rather than “what” tasks their jobs contain. By taking the realized skill into account according to workers' self-reports, this framework allows to capture the interaction between individual qualities, job task requirements, and workplace potentials. To evaluate “how” tasks are performed, he proposed the Work Complexity Index which measures to what extent workers’ tasks are involved with Degree of Uncertainty, Level of Autonomy, and Continuous Skill-building.

Martinaitis implemented his proposed measure in an empirical cross-national study at the EU level (Martinaitis, et.al. 2021) using data from the European Working Condition Survey spanning time from 2005 to 2015. ‌The study revealed a significant difference in the workforce skills across European countries with the highest work complexity in Nordic countries. Investigating the skill distribution change over time (2005-2015), the findings demonstrated that the European labor markets witnessed the upskilling of the workforce in the aggregate, however, deskilling and skill polarization were observed in some countries.

Evidence on Finnish Workforce Skills

The Finnish labor market has been extensively explored by national and cross-national research (Asplund et al., 2011, Bockerman et al., 2019). Aligning with the methodological trends for skill measurement described in the last section, these studies have provided valuable insights into the changes in employment structure (macro-level) and the workers' situation (micro-level) under the influence of technological advancement.

Following the routinization hypothesis and task model of Autor, Levy, and Murnane (2003), Jari Vianiomäki (2014) monitored the changes in the Finnish private sector labor market for the period 1995-2008. He reported that the structure of employment in the private sector witnessed a decrease in the share of routine-intensive occupations while increasing the proportion of non-routine occupations (abstract and service work) signifying an upskilling trend within the sector. In addition, by examining the changes in wage distribution across occupations, he observed wage polarization at the private firm level over the specified time.

Replicating the method of Frey and Osborne (2013), Pajarinen and Rouvinen (2014) investigated the risk of computerization for employment in Finland. They discovered that approximately one-third of occupations are susceptible to computerization. This estimate was 10 percentage points lower than the corresponding estimate for the US (47%). However, similar to the US, occupations with low wages and low skill levels were found to be more vulnerable. Also, they found that service jobs will be relatively more secure compared to manufacturing jobs.

In a similar occupation-level analysis, based on the AI Occupational Impact measure proposed by Felten, Raj, and Seamans (2019) and PIIAC survey data, Georgieff and Hyee (2022) reported that occupations are highly exposed to AI in Northern European countries compared to eastern countries. Specifically, Finland obtained the higher average score of AI exposure across occupations (0.72) among the 23 countries that participated in this study.

Putting emphasis on the realized skill or skill-in-action (Martinaitis, 2013) rather than the potential skill requirement for occupations opens space for the contribution of “job quality” studies to the skill debate. This research tradition which gained special popularity in Finland due to its close association with workforce well-being, added to the literature by identifying the work conditions that allow or limit the realization of skills. Although job quality contains a variety of domains, Autonomy and Access to Training appear as two skill-specific domains, frequently used in empirical work.

In the Finnish context, Hartikainen et. al. (2010) evaluated the job quality of the workforce across European countries using self-report data from European Working Condition Survey (2005). Their results, with a focus on workforce skills, demonstrated that 60% of Finnish employees were involved in jobs with unforeseen and complex tasks requiring learning new things. However, Finnish employees reported lower work autonomy and discretion (51%) over their job tasks compared to other Nordic countries’ employees (60%).

Another research on Finnish workforce skills within the job quality framework was conducted by Mustosmäk, Oinas, and Antilas (2017). This study concerns the class and gendered inequalities in the workforce. In their trend analysis based on the Finnish Quality of Work Life survey data (1977–2013), they showed that Finnish blue-collar workers have seen improvements in their autonomy and opportunities for development, denoting the low risk of social class gap and polarization of job quality in the future. Regarding gender, their findings showed that the gender gap continued among blue-collar workers, while gradually disappearing for lower white-collar and upper white-collar women.

How does the current study utilize and add to the existing literature?

(Need more content on the priority of WCI)

Reviewing the theoretical and empirical literature, it is evident that the field has benefited from extensive multidisciplinary analyses and still has remained appealing to further exploration due to the ever-evolving technologies and dynamic world of work.

Labor Process Theory and the spectrum of empirical research inspired by this theory have dominantly produced the most hypotheses and methodological innovations for measuring the impact of technologies on human labor. In this section, we introduced some of the proposed measures and indices for evaluating workforce skills and discussed how these measures gradually evolved from analyzing the potential effect of technology on occupations to capturing the materialized effect of workplace technologies on workers.

In earlier studies, human labor was viewed as a passive entity at high risk of being displaced by technology. Compatible with the insight from the Social Shaping of Technology discourse, the more recent studies view human skills and technologies situated in the workplace. In this approach, workers' skills and their job tasks change alongside technological progress as the technology is developed and adapted according to the workers' and organizations’ needs. Furthermore, by shifting the level of measurement from the occupation level to the worker level, more nuanced and subjective analyses of the workforce skills and capturing heterogeneities among workers have been possible.

This thesis contributes to the literature by deploying and developing the Work Complexity Index (WCI) proposed by Martinaitis (2013, 2021)\_a skill measurement strategy concentrated on how tasks are performed by workers at the workplace\_ and producing the most recent evidence on Finnish workforce skills using the Finnish Working Life Barometer data (2018-2022).

Method and Data

Work Complexity Index

The Work Complexity Index (WCI), proposed by Martinaitis (2013), is a measure for assessing workforce skills that is concerned with “how” workers perform their job tasks. WCI consists of three dimensions: Degree of Uncertainty, Level of Autonomy, and Continuous Skill-building. The index \_a value in the range of 0-1\_ is calculated by the sum of the average scores in all three dimensions for each worker. A larger value of WCI indicates a job involves more complexity which protects the job holder from the risk of skill erosion and consequently job loss.

In this study, the worker-level data comes from the Finnish Working Life Barometer (FWLB), a national repeated cross-sectional survey. FWLB is chosen due to its high quality, the most updated data on the workforce in Finland, and also its availability to the public. Additionally, FWLB provides annual data allowing us to monitor the changes in work complexity over time. For this trend analysis, aggregate work complexity is obtained from the average of individuals' work complexity scores for each year.

Although nationwide surveys are extensively beneficial for workforce studies, they have a number of limitations. First and foremost, they are pre-generated data which means researchers face an existing set of variables that are not primarily collected for the purpose of their research. Therefore, utilizing these survey data to address specific research questions might involve trade-offs in selecting and including variables.

Another limitation, specifically related to repeated cross-sectional surveys, is that different rounds of surveys might adapt different modes of data collection or include different sets of variables. This inconsistency causes serious restrictions for trend analysts as they might encounter with absence of a certain variable in some rounds of the survey, forcing them to exclude that variable from the entire analysis. Changing data collection mode also makes different rounds of surveys incomparable due to different weighting systems and their potential biases for estimation. These issues are addressed and discussed in expert forums, however, no solution is found to be offered to data analysts who deal with such challenges while having limited access to auxiliary information to fix them.

Keeping these limitations in mind, I generated a pool of variables, included in the last five rounds of FWLB (2018 – 2022), that pertained to the quality of performing tasks by the workers. Among existing variables, two sets of variables perfectly corresponded to two dimensions of WCI: Level of Autonomy and Continuous Skill-building, however, no variable is found in the dataset corresponding to the third dimension of WCI, Degree of Uncertainty. On the other hand, the dataset contains an interesting variable asking workers about the collaborative nature of their tasks that explicitly reflects the complexity of their work.

According to the organizational management discussions (Leonardi et al., 2013, Kane, 2017, Benbya et al., 2020, Baptistaa et al.,2020), collaborative work is known as an indicator of complex work design in computer-mediated work environments. These articles highlight that Information and Communication Technologies (ICT), widely adopted in today’s workplaces, have facilitated real-time information sharing, connected individual tasks, and created a more interdependent workflow where the output of one task comes as the input of other tasks. This interdependency requires coordination, process thinking, and effective communication from workers to ensure a cohesive outcome.

In addition to approaches that emphasize the material ICT-related facilities underpinning collaborative work, it is heavily discussed that collaboration or teamwork requires social skills such as social perceptiveness, negotiation, persuasion, and assisting and caring for others (Frey & Osborne, 2016), which are skills that are very difficult for machines to replicate. So it can be concluded that workers engaged in collaborative work, requiring human edge skills, are more immune to the risk of automation.

Relying on these theoretical supports, Collaborative Work can be accounted as a dimension of work complexity, however, deciding about the inclusion of a new dimension in the construct of WCI requires examining its correlation with other dimensions. Before delving into the statistical examination, I overview the hypothesized construct of WCI, and the FWLB variables corresponding to each dimension of the WCI, summarized in Table 1.

Table 1

As summarised in Table 1, the hypothesized WCI model is composed of three dimensions and a total of nine items.

**Level of autonomy**: employees with autonomy over their job content, methods, and pace generally encounter higher job complexity. Conversely, those who follow clear instructions, standardized procedures, and predetermined timelines experience lower work complexity. In this account, a higher level of autonomy requires higher experience, knowledge, curiosity for the task domain, a dare of trial and error, and problem-solving skills in case of unexpected challenges.

Within the FWLB, variables K11a\_1 and K11a\_2 measure the individuals’ autonomy at work by asking about their influence on their task’ content and pace. Variable K11a\_3 also asks about the individuals’ influence on the allocation of tasks between people which indicates the autonomy over the entire work design, structuring, and organizing tasks, mostly done by the managers.

**Continuous skill-building**: work complexity tends to be higher for workers engaged in tasks demanding continuous skill development and knowledge updates. These people are better equipped to adapt to emerging technologies in the workplace. Especially, in the era of machine learning and artificial intelligence, it is crucial for workers to maintain their professional relevance to be able to understand, monitor, and oversee the machine's performance (Levels et al., 2019).

Within the FWLB, variables K21b\_1, K52a, K52b, and K52c ask participants whether they have been trained under supervision or independently over the past 12 months.

**Collaborative work**: Workers whose work is defined in a complex network of tasks, requiring constant sharing of information and progression with others, evaluating their own and others’ tasks to decide about the next steps, and applying strong communication and persuasion skills experience higher work complexity. In contrast, individual work involves less interdependency, unpredictability, and multidisciplinary approaches thus less complex work.

One can say task interdependency and working in close connection with others decreases individual autonomy and freedom at work. A classic work by Kiggundu (1981) points out a subtle difference between task interdependence and autonomy. While autonomy involves responsibility for outcomes of personal work, task interdependence involves responsibility for the outcomes of other tasks and the entire work as a collective product. With this explanation autonomy and task interdependency act in two distinct levels, the former on the individual level, the latter on the collective level. The data also shows a positive correlation between two dimensions which aligns with this theoretical expectation.

Two variables within the FWLB measure aspects of collaborative work. Variable K48 directly asks if the worker uses electronic workspaces in their work allowing them to chat, share information, and collaborate virtually. Variable K43a asks respondents how often they have worked remotely in the last 12 months. FWLB data indicates a positive correlation between telework and the use of electronic workspaces. It is expected that telework became feasible and popular after its technological infrastructure emerged and was widely adopted in the workplaces. Today, collaborative tools and platforms allow people to maintain collaborative work without the need to be physically present at work. Therefore it is reasonable to posit that telework serves as an indirect indicator of collaborative work. A higher frequency of remote work likely corresponds to a greater probability of utilizing digital workspaces, which directly measures the extent of collaborative work.

To ensure that the three dimensions of WCI all correlate in the same direction and consistently measure the Work Complexity, I performed a correlation test between each pair of dimensions. Table 2 shows that the correlation coefficients in all cases are positive and significant, indicating that all dimensions consistently measure work complexity in the same direction. Also, the small coefficients ensure that each dimension measures a distinct aspect of Work Complexity.

Table 2

Construct reliability and validity: Factor Analysis

To examine the validity of the hypothesized WCI model, I utilize the Factor Analysis method. First, I employ Explanatory Factor Analysis (EFA) to explore how selected variables (observed variables in the data) relate to a set of unobserved latent variables (Vehkalahti & Everitt, 2019) and evaluate their factor loadings. Then I run Confirmatory Factor Analysis (CFA) to evaluate how well the hypothesized WCI model fits the data. Before everything else, I split the data into train and test sets. The train set containing 70% of the data is intended to be used for EFA, and the test set with 30% of the data is kept for CFA.

Exploratory Factor Analysis

I ran EFA with Maximum Likelihood (ML) as an estimator, oblique rotation method, and number of factors set at 3. The output indicates that Variable K11a\_1, K11a\_2, and K11a\_3 relate to a common factor (ML3) which I named ‘Level of Autonomy’. Variable K11a\_1 (influence on own job tasks) has the highest factor loading of 0.8, while two other variables K11a\_2 (influence on own job pace) and K11a\_c (allocation of tasks between others) have factor loading of 0.6 and 0.5 respectively.

Among four variables grouped under factor ML2, K52b (training independently) has the highest factor loading of 0.7. K52c (training by online materials) has the next highest factor loading of 0.6. Variables K52a (training under supervision) and K21b\_1 (paid training) have factor loading of 0.4 similarly. I named this factor ‘Continuous Skill-building’.

Corresponding variables to the factor ML3 are K48 (using digital workspace) and K43a (telework) with factor loadings of 0.9 and 0.4 respectively. I named this factor ‘Collaborative Work’.

Looking at communality values, K48 (using digital workspace) has the highest commonality among the variables. 68% of K48’s variance is explained by factors all together. The next highest communality value is obtained for K11a\_1 (influence on own job tasks) with 67.6% of its variability being explainable by all factors. It means that these two variables are well fit within the factors structure. In contrast, K52a and K21b\_1 have the lowest communality values of 0.13 and 0.17 respectively which means they are weakly explainable by all factors combined. Factor loading and communality values are summarized in Table 3.

Confirmatory factor analysis

After ensuring the WCI model is structurally reliable and substantially meaningful, I began fitting the model to the FWLB data to test its validity. Traditionally, we looked at a chi-square statistic to assess the fitness of a model. In this case, the chi-square value is 179.171 with 24 degrees of freedom. The corresponding p-value is 0.000, indicating strong evidence against the null hypothesis (perfect model fit) and suggesting a poor fit between the WCI model and the data.

In the CFA, a non-significant chi-square p-value does not necessarily mean the construct is invalid. Other fit indices play roles in judgment about the goodness of a model (Vehkalahti & Everitt, 2019). In this test, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are respectively 0.958 and 0.937 which suggest a perfect fit. Two other indices RMSEA with a value of 0.050 and confidence interval of 0.044, 0.057 and SRMR with a value of 0.032 also support the model's fitness and thus validity of the WCI construct.

Finnish Working Life Barometer

The data for this study has been obtained from the Finnish Working Life Barometer (FWLB) spanning time from 2018 to 2022. FWLB is an annual survey which is carried out by Statistics Finland, on the assignment of the Ministry of Economic Affairs and Employment, to monitor the work conditions of wage earners. This barometer is the longest time series in Finland that covers almost 30 years starting from 1992 (“Statistics Finland,” Retrieved on July 22, 2024).

The target population of FWLB is employed wage earners aged 18-64 who regularly work at least 10 hours a week. The sample of the survey is drawn from respondents to Statistics Finland’s Labour Force Survey. The sample of the Labour Force Survey itself is drawn from Statistics Finland’s population database, which is based on the Central Population Register. While the Labour Force Survey microdata is not publicly available, the FWLB microdata is annually released through the Finnish Social Science Data Archive, making it an ideal source for research on the workforce.

This study utilizes data from the last five rounds of the FWLS covering 2018 to 2022. The reason for choosing this period is the availability of variables of interest in these rounds of data. As mentioned before, one challenge of using repeated surveys is that data producers have to revise the content of variables as well as ways of asking them from respondents to maintain the quality of the survey. These refinements are mostly done at the expense of losing consistency and comparability between different rounds of the survey which is troublesome for researchers who are interested in analyzing the changes in opinions or behaviors over time.

In addition to variables, the data collection mode has changed since 2021. Previously, the data was collected through telephone interviews only from Finnish speakers. Two last rounds of FWLB (2021 and 2022) use a combined method: telephone interview and online form. Since the online form was available in Finnish, Swedish, and English languages, the target population of the survey became larger. As alarmed by the data producer, this change in the population coverage creates estimation bias in comparative studies.

I take these limitations on board and try to extract insight from this valuable source of data while taking the mentioned source of bias into account when interpreting the results.

Data Preprocessing

As the FWLB data for each year has been published separately, the first step is integrating and harmonizing five data sets. For this purpose, a set of variables contributing to the work complexity measure were extracted, renamed, scaled to 0-1, and recoded in some cases so that all variables measure the work complexity in the same direction with the smallest value denoting the least work complexity and vice versa. The size of 2018, 2019, 2020, 2021, and 2022 data sets were respectively 1650, 1555, 1647, 1899, and 1862 records. After harmonizing variables and combining data sets, the final integrated data was obtained containing 8613 records and 12??? variables including background and WCI-related variables. This process was carried out using R software.

Missing data

The integrated data contains a minimal number of missing responses in WCI-related variables, 100 cases in total. Among background variables, missing responses were observed only in the “Occupation” variable with 91 NAs. Dealing with the missing values primarily requires knowing the reason for missing responses. Reviewing the FWLB’s documentation, I found no explanation of the missing data mechanism. However, visualization can provide insight into the pattern of missing values in the sample and suggest an approach to deal with them. Figure 2 shows the amount of missingness per variable and in combination of variables.

Figure 2

Figure 2 shows that the sample has 8441 complete cases with no missing values. There are 90 rows with missing values only in Occupation and 81 rows with missing values in the combinations of WCI-related variables. I adopted two different strategies for dealing with missing values. For the Occupation variable, I replaced NA with “Unknown”, a pre-defined category in the Statistics Finland Classification of Occupations 2010, coded as ‘99’ in the FWLB. As a result, the complete cases of the sample increased to 8531 records.

For WCI-related variables, I assumed that the data is missing completely at random (MCAR) and I adopted the “available-case analysis” approach since first, the amount of missing data is relatively small (100 cases). Second, by available-case analysis, I can utilize the most available information in the data (Vehkalahti & Everitt, 2019), especially if there is such a pattern that specific people do not tend to respond to specific questions. In this case, the work complexity calculation might be biased toward the people who are more open to giving information, those probably with higher socio-economic status. Available-case analysis has its drawbacks, for example, it can lead to different sample sizes for different calculations. While acknowledging the potential limitations of available-case analysis, I opt for this approach to maximize the utilization of available data. To implement this approach, I set ‘na.rm=TRUE’ for all calculations in R.

Descriptive analysis

This section outlines the demographic profile of the survey participants. Descriptive statistics of key background variables including Age, Gender, and Occupation are presented to provide essential context for interpreting the research results.

Table 4

As summarised in Table 4, the sample includes 8613 participants, with 4463 (51.82%) females and 4150 (48.18%) males. As is common in social surveys, the female participants have a higher sound in this sample.

The participants range in age from 18 to 65 with a mean age of 44. Following the common practice in social research, I turned the numeric age variable into a categorical variable with 5 levels. Employees aged 45-54 consist of 26.24% of participants. The next large group aged between 55 to 65 with 25.08%. 2099 of participants (24.37%) belonged to age group 35-44. The fourth group in size is people aged 25-34 which consists of 19.39% of the participants. Young employees aged 18-24 are the smallest group in the sample with 4.92% of the participants.

The survey has collected the occupation of participants based on the Statistics Finland Classification of Occupations 2010 at one digit level. Participants are placed in 9 occupation groups. Professionals are the largest group represented in this sample with 32%. Technicians and associate professionals are the second largest group with 22.10% of the total. These two groups consist of more than half of our sample population (54.21%). The third group in size is Service and sales workers with 15.65% of the total sample. Craft and related trades workers are the fourth largest group with 8.65%, followed by the Plant, machine operators, and assemblers with 6.65%. The last 10% of the sample population are employed in Clerical support, Elementary occupations, Management, Agricultural, forestry, and fishery occupations, and Army with respectively 5.93%, 4.92%, 2.90%, 0.72%, and 0.39% of the total sample population.

In conclusion, we face a sample of employees in which women, middle-aged, and professionals will have the largest share in the analyses. This distribution, depicted in Figure 3, has significant implications for the average work complexity obtained from this sample.

Figure 3

(Bar plot: each bar shows an occupation, each bar is divided into 5 age groups, and the plot is grouped by gender)

Weighting data

To ensure the sample distribution over gender, age, and occupational groups represents the true population distribution, I incorporate weight into analyses. The FWLB itself has included the weight variable ‘tb\_paino’ in each year's dataset to correspond the data to its target population and reduce the non-response bias. However, since the FWLB data collection mode and subsequently, its weighting system has changed since 2021, incorporating the existing weight into comparative analyses is not a proper practice. As an alternative, I created post-stratification weights for each year’s dataset by using a set of auxiliary variables.

Given the theoretical expectation and the availability of register data, I use ‘Occupation’ and ‘Gender’ as auxiliary information. Statistics Finland’s Employment database provides data on the joint distribution of the population by gender and occupational groups, exclusively for wage earners and separately by year which is ideal for calculating post-stratification weight. Accordingly, I calculated the weight coefficient for all 22 strata obtained from a combination of Gender with two categories and Occupation with 11 categories:

Formula

Where “wps” is the post-stratified weight. “si” is each stratum from 22 strata. “Nsi” is the count of wage earners in each stratum in the population and “nsi” is the count of wage earners in each stratum in the sample. N is the total wage earners in the population.

Results

Work complexity changes over time

Addressing the first research question, I developed a skill measurement tool called the Work Complexity Index (WCI) that captures workers’ subjective evaluations of the skills they apply in their job tasks. The WCI is based on Martinaitis’s (2013) theory and was further expanded using data from the Finnish Working Life Barometer spanning the years 2018 to 2022.

Using the WCI tool and FWLB data, I address the second research question by calculating work complexity (mean of three equally weighted dimensions) at the individual worker level and analyzing its changes over the years. To ensure the results reflect the Finnish population, I used weighted data (own calculated weight). The average work complexity for each year is depicted in Figure 4.

Figure 4

A graph with a line and numbers

Description automatically generated

The line plot (Figure 4) illustrates an upward trend in average work complexity during the study timeline (2018-2022). Starting in 2018, we observe a gradual increase in average work complexity from 0.423 to 0.425 in 2019. Subsequently, there was a significant growth in average work complexity in 2020, reaching 0.447. The upward trend continued, peaking at 0.46 in 2021, followed by a slight decrease to 0.45 in 2022. Despite the decline between 2021 and 2022, the average work complexity at the end of the timeline remains higher than in all previous years, except for 2021.

The most substantial increase occurred between 2019 and 2020, continuing into 2021. This sudden surge may be linked to the profound impact of the COVID-19 pandemic on the world of work. The pandemic reshaped how workers performed their job tasks. Strict social distancing rules necessitated a shift to remote work, leading organizations to adopt digital collaboration tools and enhance Collaborative Work (dimension 3). Furthermore, lockdowns provided individuals with more time to self-educate and upgrade their knowledge and skills through online materials, courses, and webinars which contributed to Skill-building (dimension2). Moreover, in the absence of stable circumstances, workers encountered more transformations and unpredictability at work, which enabled them to exercise greater discretion and autonomy over their jobs (dimension1). These changes can explain the significant growth in work complexity during the pandemic. However, to validate this, I will examine changes within each work complexity dimension separately in the following section.

Overall, the average work complexity of the Finnish workforce has increased, implying that employees, as a whole, have become more empowered as technology continues to evolve year by year. Another significant finding is that work complexity experienced substantial growth during the coronavirus pandemic. It is reasonable to assert that the global pandemic accelerated the upward trend in work complexity between 2019 and 2021. While the post-pandemic world still benefits from the fundamental changes that necessitated a more complex approach to work, the growth of work complexity has since slowed down. These findings align with the upgrading and upskilling hypothesis advocated by many scholars reviewed earlier. However, the downward trend observed in 2022 challenges optimistic views regarding the future of human work. This issue will be further investigated.

Deconstructing work complexity; dimensional changes over time

In this section, I deconstruct the work complexity into its constituents in order to investigate the contribution of each dimension to the overall work complexity average. Figure 5 visually presents the changes within each dimension over time.

Figure 5

A graph of different colored lines

Description automatically generated

As depicted in Figure 5, not all dimensions have changed in the same way over time. Collaborative Work experienced the most pronounced increase over the study period. From 2018 to 2021, it followed an upward trajectory, with steeper growth in 2021. Since 2022, it has begun to decline steadily.

It is worth mentioning that Collaborative Work has been measured by two variables: frequency of telework and use of electronic workspace which both became widespread during the pandemic time. So, this sharp upward slope from 2020 to 2021 and the gentle downward slope from 2021 to 2022 are expected to be a result of the pandemic situation. The interesting point is that collaborative work, with the mediation of digital technology that facilitated telework, has been already growing in pre-pandemic years as is evident from 2018 to 2019.

Continuous Skill-building shows the most fluctuations over this period. While the pattern from 2018 to 2019 is decreasing, it changes to an upward trend from 2019 to 2020. From 2020 to the last year of the timeframe, Continuous Skill building saw a decline, with a steeper slope in 2020-2021 and a slower slope in 2021-2022. Concentrating on the beginning and end of the timeline, we realized that workers’ access to training and skill development opportunities has declined which can be a red flag for the Finnish workforce.

Level of Autonomy demonstrates a decreasing trend from 2018 to 2020 denoting that the workers were experiencing less control over their jobs year by year, howe the changes were very small. Since 2020, the Level of autonomy has seen a growing trend at a relatively high pace.

If considering 2020-2021 as the peak of the pandemic, it is evident that the Finnish workers experienced a higher level of autonomy while fewer training and skill development opportunities during this time.

The figure clearly shows that the sharp fluctuations within dimensions have moderated, as reflected in the Work Complexity line, which represents the average of the three dimensions. Without delving into each dimension, analyzing work complexity remains incomplete as it is missing the nuances inherent to each dimension, each with its unique dynamics.

Show means in the plot!

Disparities in work complexity across demographic groups

This section addresses the third research question by identifying how work complexity and its dimensions differ by gender and age groups. The result from this subgroup analysis provides insight into the nature of inequalities in work conditions which result in different vulnerabilities to technological transformations.

For this task, I used integrated data with 8613 observations regardless of year. The calculated weight is not incorporated into this subgroup analysis since it was calculated based on annual register data, thus only beneficial for studying work complexity changes over the years.

Table 6

A screenshot of a computer code

Description automatically generated

Based on Table 6, work complexity tends to be lower for women compared to men on average. When examining specific dimensions, women report lower autonomy (0.404) and collaborative work (0.429) in their jobs. However, they invest more time in continuous skill-building (0.462) compared to men. Among the three dimensions, women achieve higher scores in continuous skill-building but notably lower scores in autonomy. In contrast, men with higher overall work complexity experience notably higher autonomy (0.484) at work, while their lowest score relates to skill-building (0.437).

To examine whether gender-based differences in work complexity and each dimension are statistically significant, I performed two-sample t-tests for gender groups. The null hypothesis is that there is no difference in the population mean of the two gender groups. The alternative hypothesis is that the population mean of the two gender groups is different.

Prior to running the test, t-test assumptions were checked. Among t-test assumptions, the independence of the observations is met as the observations are selected through random sampling. The normality of the groups’ distributions was checked using histograms and the Shapiro–Wilk test. The homogeneity of variances was examined by performing Levenes’s test. Based on the assumption check results, I chose the appropriate test and displayed the outcomes in Table 7.

Table 7

A table that has three columns for assumptions (normality, homogeneity of variances, independence of observations), one column for test’ name, and one column for p-values.

Based on Table 7, the resultant p-values from standard t-tests and Welch’s t-test are all significant, indicating that men and women have different average scores in work complexity and three dimensions in the population.

Table 8

A screenshot of a computer screen

Description automatically generated

Regarding work complexity disparities across age groups, it is evident from Table 8 that workers in the first and last age groups 18-25 and 55-66 see the lowest work complexity with a similar score of 0.401. This result becomes sensible when delving into dimensional analysis. Younger workers do less collaborative work in the sense that it is defined/intended in this study. They are at the beginning of their career path and probably more engaged in service jobs requiring presence at a certain location (less telework) and executing well-defined tasks independent from others (less task interdependency). Older workers are also less involved in collaborative work, in addition to continuous skill-building which is reasonably linked to their declining cognitive abilities and low motivation for learning new things in the years leading up to retirement.

The data suggests that the highest work complexity occurs within the age group of 35-45, closely followed by the 25-35 age group. Workers aged 25-35 achieve the highest score for continuous skill-building (0.505) among all groups, while those aged 35-45 excel in collaborative work and then in continuous skill-building. These two age groups show lower vulnerability to ever-changing technologies. Their accumulated knowledge, ability to rapidly update their skills, and credibility in managing tasks—both their own and others’—enable them to effectively act in a work environment where humans and machines coexist and complement each other.

The significance of mean differences based on age group was tested using ANOVA and Welch's ANOVA. In ANOVA tests the null hypothesis is that there is no difference in the population means of the five age groups. The alternative hypothesis is that at least one age group's mean is different from other age groups.

As displayed in Table 9, while differences in population mean of age groups in overall work complexity, skill-building, and collaborative work are statistically significant (i.e. at least one group has a different average score than other groups), the differences among age groups based on autonomy is not found statistically significant.

In summary, the subgroup analysis indicates that women and middle-aged individuals (aged 55-66) face heightened vulnerability to adverse effects from technological changes. Among the factors contributing to work complexity, women face challenges due to lower perceived autonomy in their jobs, while middle-aged workers struggle with limited capacity to update and develop skills compared to their younger counterparts. Given Finland’s aging population, it is expected that the growth in the middle-aged population poses a higher risk to the workforce in the country. Addressing this risk should be a central focus of labor policies.

Discussion and Conclusion

This thesis is centered on two primary objectives. First, it develops a robust measurement tool that aligns with the theoretical stance of this research. This tool is based on a thorough examination of methodologies employed in prior studies.

Challenging deterministic perspectives on technology’s impact on human work, this thesis posits a coevolutionary relationship between technological advances and human skills. This coevolution occurs in the workplace context and is shaped by the social, organizational, and managerial characteristics of the workplace. Therefore, macro-level analyses that attempt to predict job obsolescence and worker displacement fail to capture the dynamic coexistence of humans and technology in a work environment.

Instead, this thesis examines the actual skills utilized by employees in the workplace to gain a nuanced understanding of worker-technology interaction. To achieve this, the Work Complexity Index (WCI) was utilized and further developed using data from the Finnish Working Life Barometer (FWLB). The WCI is constructed from three dimensions: Level of Autonomy, Continuos Skill-building, and Collaborative Working all of which have strong theoretical support within the field. The validity and reliability of the index were assessed using the Factor Analysis method. This tool not only allows for a subjective analysis of workforce skills through self-reports but highlights the disparities among workers in their abilities to function effectively in a technology-rich environment.

The second objective of this thesis is to provide insights into the Finnish workforce skills using the WCI tool and FWLB data. The empirical findings of the thesis are summarized as follows.

**Finding 1** Finnish employees experienced an increase in work complexity from 2018 to 2021, indicating an upskilling trend. However, this trend slightly declined from 2021 to 2022, the final year of the study. This finding aligns with previous research using different skill measurement strategies. Martinaitis (2013) and Martinaitis et al. (2021), using a structurally different Work Complexity Index, reported that Finland, along with other Nordic countries, achieved the highest workforce skill scores in Europe in 2010. However, they did not observe a clearly pronounced upskilling trend in Finland when examining data from 2005 to 2015. Other research, which considered wage as a measure of skill, also recognized an upward trend in the share of employment in high-wage occupations, implying upskilling of the Finnish workforce over time (Asplund et al., 2011; Alsos & Erik Dølvik, 2021).

**Finding 2**: Assessing work complexity without dimensional analysis is insufficient and potentially misleading. As depicted in Figure 4, while work complexity has been steadily increasing, the levels of autonomy and continuous skill-building have shown fluctuations. In contrast, collaborative work has seen a dramatic increase, suggesting that it significantly contributes to changes in overall work complexity.

The COVID-19 pandemic, a major event during the study period, particularly influenced collaborative work. Despite the critical economic and employment impacts of the pandemic, this thesis highlights its influence on employees’ work complexity. The pandemic necessitated temporary telework and accelerated the integration of communication technologies into workflows, a trend that persists in the post-pandemic era, as shown in Figure 4. Previous research (???) emphasizes that teamwork, coordination, communication skills, and digital literacy are essential in human-technology interaction, and the pandemic accelerated upskilling in these areas.

Another important insight from the dimensional analysis is the decline in continuous skill-building over the years, with a slight increase in 2020. This downward trend aligns with the most recent FWLB 2023 data. According to the Ministry of Economic Affairs and Employment, employee participation in workplace training (measured by variable K21b\_1) has remained at 40% since 2021, the lowest level recorded since FWLB began tracking workplace training in 2001 (Lyly-Yrjänäinen, 2024).

Finnish workers have reported an improved level of autonomy since 2020, which is a promising development that aligns with/deviates from…

**Finding 3**: Gender and age significantly influence the work complexity of employees. Women and workers aged 55-65 have lower work complexity scores compared to their counterparts. Although women invest more in skill-building, they perceive notably lower autonomy over their work compared to men and also score lower in collaborative work. This finding is partially supported by Mustosmäki et al., (2017). Analyzing data from the Finnish Quality of Work Life survey (1977–2013), they discovered that women, in general, had less influence over their work and fewer opportunities for on-the-job training and development. However, by 2013, this gender gap in skill development opportunities had been eliminated among upper-white-collar women.

Among age groups, employees aged 55-65 have lower work complexity due to significantly lower scores in continuous learning and collaborative work, making them more susceptible to skill erosion. On a macro level, the increasing population of older workers who struggle to keep pace with technological transformations accelerates the adoption of labor-saving technology. Other studies explain this process differently. For instance, Moreno-Galbis and Sopraseuth (2014) argue that an aging population increases demand for personal services, leading to growth in low-paid care jobs. Asemoglu and Restrepo (2021) suggest that an aging society provides greater opportunities for technology adoption due to a shortage of middle-aged workers who can perform manual production tasks, resulting in machines taking on more physically demanding tasks. Despite differing arguments and methodologies, this thesis confirms the potential of an aging workforce to hasten the substitution of human labor with machines.

Testing the significance of differences in the mean work complexity across gender and age groups, the t-test revealed that the differences are all statistically significant, except for the level of autonomy among age groups. The data suggests that workers aged 35-44, followed by those aged 25-34 have the highest autonomy over their work, while the youngest and the oldest workers similarly share the lowest job autonomy.

While the t-test cannot pinpoint the exact groups with insignificant differences, it is commonly believed that older age, often associated with greater work experience, leads to higher autonomy and discretion at work. The thesis findings challenge this common perception, potentially due to the unique nature of technology-rich workplaces which can rapidly obsolete the current skills and necessitate reskilling. In such dynamic environments, it is probable that workers with lower reskilling capabilities feel less empowered in their tasks and have less influence on the whole work process regardless of their work experience.

Contribution to Methodology, SDS, and Policy

This thesis contributes to the study of worker-technology interaction by developing WCI, a skill measurement methodology capable of providing a nuanced understanding of this interplay. Despite significant advancements in skill measurement, WCI remains relevant due to the evolving skill demands of AI technologies.

In the field of Social Data Science, particularly Survey Data Analysis, this research addresses the challenge of maintaining the relevance of repeated cross-sectional surveys. It highlights the difficulty of updating survey content to reflect new topics and variables while preserving data comparability across different survey rounds. This thesis encountered challenges in utilizing variables of interest, as some were excluded from certain survey rounds, complicating the tracking of changes over time. Additionally, changes in data collection mode since 2021 have hindered direct comparisons of different rounds of the survey. This thesis underscores the limitations that such inconsistencies impose on longitudinal studies in social sciences.

Finally, this research informs workforce and employment policies by systematically studying working conditions in a national context and providing reliable insights into areas and demographic groups requiring increased policy attention. Based on these findings, Finnish workplaces should prioritize offering more skill development opportunities and incentivizing employee participation. Upskilling and reskilling initiatives are essential for safeguarding the workforce from the adverse consequences of technology, ensuring inclusivity and accessibility for all workers, particularly women and older individuals. To achieve this, organizations should focus on upskilling existing employees and reallocating tasks to bridge skill gaps, rather than relying on external recruitment when introducing new technology (Sadun, 2023)

Thesis limitations and future directions

One significant limitation of this study is subject to using pre-existing data. While the Finnish Working Life Barometer is a valuable data source for researching the national workforce, it lacks certain variables that could enhance the construct of the Work Complexity Index developed and used in this thesis. Although the current construct of WCI is both theoretically and statistically validated, the literature suggests additional dimensions that contribute to the complexity of work, especially in the context of AI technologies. Incorporating these missing variables could result in a more sophisticated and multidimensional WCI. Consequently, the constructing the WCI, based on available data, may be overly subjective and its validity could be questioned.

Another limitation stems from to the reduction of Collaborative Work to solely material aspects. Collaborative Work is intended to measure tasks’ interdependence which is an indicator of complex work design. Electronic workplace and communication platforms are merely infrastructure necessary for implementing this work design but they do not garantee the realization of tasks’ interdependence within a specific workplace. Therefore, the true essence of collaborative work cannot be fully captured only through material devices. Ultimatley, the absence of relevant variables in FWLB to adequately measure collaborative work resulted in oversimplified findings.

Lastly, this thesis faced a limitation due to restricted access to important background information on survey participants, particularly wage and education level. These variables are theorized to be proxies for skills and are methodologically utilized as criteria to assess the validity and estimation power of multi-dimensional skill measurement strategies such as WCI. (Martinaitis, et.al. 2021). The dataset used in this study does not permit further exploration of the index validity in relation to these factors.

Future research could expand the scope of the WCI using diverse data sources and employing it in predictive models to investigate various hypotheses related to workforce skills. Also, the WCI could be utilized in comparative studies of workforce skills across countries, examining cross-national differences and linking them to different economic, political and social institutions.

Another avenue for research is qualitative exploration of how workers perceive their relationship with workplace technologies within specific industries or organizations. These case studies can identify the most pressing and promising areas within worker-technology interactions. These newly discovered domains can inform and enrich quantitative metrics used in workforce skill analyses.

Conclusion

Recent technological advancements, particularly in artificial intelligence, have intensified debates about the future of the workforce. This topic has been extensively studied across various theoretical and methodological frameworks. This thesis contributes to this discussion by adopting a theoretical perspective that views humans and technology as collaborative partners in a shared workplace, mutually enhancing each other.

Compatible with this perspective, a strategy for evaluating workforce skills was employed. The Work Complexity Index (WCI), initially introduced by Martinaitis (2013), was further developed and expanded in scope to serve as a skill measurement tool for this study. Data for this thesis were provided by the Finnish Working Life Barometer (2018-2022) produced by Statistics Finland.

The findings of this thesis generally indicate an increase in work complexity among the Finnish workforce from 2018 to 2021, followed by a decline in 2021-2022. Dimensional analysis reveals that collaborative work has primarily contributed to the overall growth in work complexity. Finnish workers' autonomy decreased from 2018 to 2020 but has since improved. Additionally, Finnish workers' skill-building has fluctuated, with a significant decline since 2020.

These findings should be interpreted cautiously due to the limitations of the applied measurement tool. The construction of the WCI was heavily reliant on the available variables in FWLB data. Future research can further refine the index to incorporate additional dimensions related to the complexity of the work in today’s workplace. Qualitative case studies can also significantly contribute to this body of research by exploring emerging domains of complexity involved in workers-technology collaboration.

Abstract

**Problem**: The widespread adoption of AI technologies in workplaces, from cobots in manufacturing environments to a variety of AI-powered tools in office settings, has significantly altered our perception of the human-technology relationship. Displacement theories that view technology as merely substituting humans overlook the current reality of human-technology coexistence and collaboration in contemporary workplaces. This dynamic interplay between humans and technology in the workplace requires further exploration.

**Objectives**: This thesis aims to investigate how workers’ skills in Finland have evolved over time, enabling or hindering their ability to effectively function in technology-rich contemporary workplaces. Additionally, this study seeks to examine disparities in workforce skills based on gender and age to identify potential inequalities embedded within the Finnish work environment.

**Method:** To evaluate workforce skills, the Work Complexity Index (WCI) was adapted and further developed using data from the Finnish Working Life Barometer (FWLB) and the factor analysis method. The WCI comprises three dimensions: Level of Autonomy, Continuous Skill-building, and Collaborative Work, serving as a measure of workforce skill. By analyzing worker-level FWLB data from 2018-2022, this study tracked changes in workforce skills and examined disparities across gender and age groups.

**Results:** The thesis results demonstrated an upward trend in work complexity in Finland over the study period, with a slight decline observed from 2021 to 2022. Dimensional analysis revealed varying trends: while collaborative work increased over time, continuous skill-building and the level of autonomy experienced considerable fluctuations. Subgroup analysis also revealed interesting insights: women, despite investing more in skill-building, perceived lower autonomy compared to men. Additionally, workers aged 55-66 reported significantly lower levels of skill development and collaborative work, placing them at a higher risk of skill erosion.

**Conclusion**: This study provided valuable insight into workforce skills in Finland, highlighting both pressing and promising areas in worker-technology interaction. These findings also offer important implications for technology adoption and workforce policies.