Contemporary societies are experiencing the fastest technological advancements. While yielding the most material well-being, causes the biggest concern about human work. mass unemployment has been a long-lasting concern associated with technology since the Elizabeth…But today it is finding broader aspects. Machines can do much more than repetitive handwork. Today, autonomous technologies that utilize artificial intelligence, are able to take over cognitive tasks. They can be trained to simulate the decision-making process in humans and perform complex tasks. However, the experts believe this is not artificial intelligence yet. The impact of recent AI-powered technologies has expanded to even human cognitive ability to perform cognitive abilities that have been simulated and executable for machines.

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 exhibited 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 a purely engineering logic. Instead, they are influenced by social circumstances, designed to create certain opportunities while closing others, 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.

-----------------Suitability to computarization----------------

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. Aligning with the methodological trend 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).

Three dimensions should be defined

Write in Bullet points form

WCI strategy focal points: realized skills at work, subjective evaluation, how to perform tasks

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 expactation.

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 created 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 described sample distribution over gender, age, and occupational groups represents the true population distribution, I incorporate weight into work 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.

Table 5 indicates the quantification of the dimensional changes over the years, in addition to the share of each dimension in overall work complexity which is obtained as follows:

Formula

Table 5

A screen shot of numbers

Description automatically generated



Table 5 presents the average overall work complexity and dimension averages for each year. Among all dimensions, Collaborative Work exhibits the largest deviation in averages over the years. Specifically, the smallest average for collaborative work (0.357) was obtained for 2018, while the largest average (0.505) was obtained for 2021.

The table also highlights that Continuous Skill-building contributes the most to the overall Work Complexity average, accounting for 33.87% of the changes. Following closely, the Level of Autonomy represents 33.35% of the Work Complexity variations. Collaborative Work has the least impact, contributing 32.73% to changes in work complexity.

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. Table 6 summarizes the differences in average work complexity and three dimensions for each group.

Table 6

A screenshot of a computer code

Description automatically generated

A screenshot of a computer screen

Description automatically generated

According to Table 6, the work complexity is lower in women than men on average. Looking at dimensions, while women have experienced lower autonomy and collaborative work in their jobs, they have spent continuous skill-building compared to men.

For this task, I used data from 2021 and 2022. As documented by the FWLB, these two datasets are directly comparable due to their similar data collection mode and weighting system, thus perfectly reliable for population estimation. The included weight (tb\_paino) in these datasets is derived from a large set of auxiliary variables: gender, age groups, education level, major regions, socioeconomic status, and wage decile.

Table 6 indicates the differences in mean and standard deviation for gender and age groups.

Mean and sd?

Significant relationship? Regression

Diagnosis

Discussion: the importance of design and features in technology

subjectivity/locality/social relations (gender, class, …)

importance of revaluation and redefining human participation in work/augmentation

promotes a passive attitude to technological change. It focuses our minds on how to adapt to technological change, not on how to shape it. I

Empowered subjects

Output: individual-level workforce analysis + changes over years + changes across groups

Technology and human labor, class conflict, under control of capital logic and scientific management: degrading

Empirical research /historical data analysis revealed different trends

Deterministic view

Sociotechnical view: leave room for empowering workers and redesigning the technological objects/

participatory design of work/Participatory design of technology

situate their work within the existing body of knowledge in the field

to provide context and justification for their research

identifies research gaps, and how the research being done will add to current knowledge.

Literatures:

Universal:

Finland: theoretical articles (discussion)

* understanding work in the age of information, Passi Pyoria
* the information society and the welfare state, Castells & Himanen
* Coordinated economy, state-led social partnership skill systems (Mustosmaki)/institutional setting can mitigate the risk of technological transformations.

Finland: empirical articles

* quality of working life (job quality: Hartikainen 2010) under the labor market transformations including technological changes
* This time may be a little different” – exploring the Finnish view on the future of work, Pulkka 2018
* Vianiomaki 2014, polarization in Finland
* Computerization Threatens One-Third of Finnish Employment, Pajarinen & Rouvinen 2014
* Does ICT Usage Erode Routine Occupations at the Firm Level? Bockerman 2019
* Mustosmäki, Oinas, and Anttila (2017) Abating inequalities? Job quality at the
* intersection of class and gender in Finland 1977–2013.

اونایی که نگاه یونیورسال و کلان دارند با داده های کلان کار می کنند و به مگاترندها می رسند: اقتصاد کار

اونایی که فاکتورهای متنوع تر و در سطح فردی رو لحاظ می کنند: اجتماعی

با وجود دشواری اندازه گیری مقوله متفییری مثل اسکیل پز/شهش های خوبی انجام شده تا این را تعریف و قابل اندازه گیری کنند

workers need to both learn to work effectively with the new technology and to adapt to a changing task composition that puts more emphasis on tasks that AI cannot yet perform. Such adaptation is costly and the cost will depend on worker characteristics. / Artificial Intelligence and Employment: New Cross-Country Evidence

Conclusion: The skill index is based on workers’ subjective evaluations of their job requirements (Hartikainen 2010)

Mknma

Discussion: three dimensions have implications for social inequality: source of inequality. Unequal access to training, hierarchical power structure, and discrimination based on gender, nationality, and language, in collaborative work.