Exposure to a job loss, care obligations and participation in training

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Contents

1. Introduction

Globalization and technological advancements have been substantially transforming labour markets across advanced economies. Before the widespread adoption of large language models and other forms of generative AI, labour market shifts were primarily driven by the diffusion of industrial robots and software tools, technologies that predominantly targeted routine tasks (Acemoglu and Restrepo, 2019; Webb, 2020). These earlier waves of automation contributed to a pronounced polarization of employment, marked by growth in both high-skilled, high-paying jobs and low-skilled, low-paying jobs, accompanied by a decline in middle-skill, routine occupations (Autor et al., 2006; Goos et al., 2009, 2014). This polarization operated through two key mechanisms: substitution and complementarity (Autor, 2015). On one hand, automation technologies substituted workers in carrying out routine job tasks, which involve standardized, repetitive procedures, that could be easily codified and executed by machines. On the other hand, they complemented human labour in performing non-routine cognitive and manual tasks that rely on tacit skills, such as creativity, problem-solving, and adaptability. These skills were difficult to codify and, until recent breakthroughs in generative AI, remained largely resistant to automation.

In this context, routine workers and their families have become particularly vulnerable, facing an elevated risk of job displacement. Before the advent of generative AI, studies estimated that between 9% and 47% of jobs in advanced economies were at risk of automation by digital technologies (Frey and Osborne, 2013; Arntz et al., 2016; Nedelkoska and Quintini, 2018). This risk is especially acute for workers in routine-intensive occupations, who not only experience heightened anxiety about automation-related job loss (Dekker et al., 2017), but are also more exposed to downward wage pressures and employment instability (Autor and Handel, 2013; Blien et al., 2013; Matysiak et al., 2024). Importantly, evidence suggests that women are somewhat more likely than men to be employed in jobs at high risk of automation, due to their overrepresentation in routine clerical and service roles (Arntz et al., 2016; Nedelkoska and Quintini, 2018; Brussevich et al., 2019), and their underrepresentation in analytical or managerial occupations (Matysiak et al., 2024). Combined with persistent gender inequalities in earnings and employment continuity—often stemming from disproportionate childcare responsibilities—this occupational distribution reinforces a cumulative pattern of disadvantage for women in the face of technological change.

For workers exposed to automation, participation in training represents a potentially transformative resilience strategy. Reskilling can help individuals transition out of routine-intensive roles that are susceptible to automation and into more secure, better-paying jobs (Zeyer-Gliozzo, 2020). Training, thus, has the potential to mitigate job displacement risks, boost earnings, and reduce future vulnerability to economic shocks.

However, access to training is highly unequal. Participation depends heavily on the availability of employer-sponsored programs, which account for 85% to 90% of all job-related training (Booth and Bryan, 2007; Heß et al., 2023). From an employer's perspective, training represents an investment, and firms may be more inclined to support workers whose skills are likely to be complemented by technology and who are expected to stay in the workforce long enough to generate returns on that investment. Routine workers—whose tasks are more likely to be substituted—therefore face a structural disadvantage in receiving employer-sponsored training. Similarly, employers may be less willing to invest in female employees, particularly mothers, based on assumptions that they are more likely to reduce working hours or temporarily exit the labour force due to caregiving responsibilities.

These constraints can also operate on the worker side. Mothers in particular may face practical barriers to engaging in training, even when it is offered, due to time poverty created by the dual burden of paid work and unpaid care. Research confirms that workers in automation-exposed occupations are significantly less likely to participate in training (Nedelkoska and Quintini, 2018; Ioannidou and Parma, 2021; Heß et al., 2023), as are women in general (Dämmrich et al., 2015; Vaculíková et al., 2020), and mothers in particular (Massing and Gauly, 2017; Stoilova et al., 2023 Lim et al., 2024; Zoch 2023; Zoch 2024; Lebert & Antal, 2016; Boll & Bublitz, 2018). To date, however, little research has directly examined how childcare responsibilities may exacerbate women's underparticipation in training when they are also concentrated in automation-exposed roles. Access to formal childcare may partially alleviate this constraint by freeing up time, but given that many working mothers already rely on childcare simply to sustain employment, its availability may offer limited additional benefit in enabling participation in training. As a result, women—especially mothers—may face a double disadvantage: they are both more exposed to automation and less able to access the key tool that could mitigate that risk.

This paper contributes to the literature on technological change and labour market inequality by investigating how exposure to automation influences participation in job-related training (Nedelkoska and Quintini, 2018 ; Ioannidou and Parma, 2021 ; Koster and Brunori, 2021 ; Heß et al., 2023), with a particular focus on gender and care responsibilities. While previous research has shown that workers in routine-intensive occupations—who are most exposed to automation—are also less likely to engage in training, the compounding disadvantage faced by women, and especially mothers, remains insufficiently understood. We extend this literature by examining whether being a woman, and mother in particular, further reduces the risk of training participation of workers exposed to automation. We also examine whether these associations vary across European countries and assess whether access to formal childcare helps mitigate these constraints and narrows the training participation gap between mothers and other groups. We make use of the EU Labour Force Survey and its Job Skills module conducted in 2022 in 26 European countries.

2. Background

Automation: Training Needs and Participation

Automation affects both routine and non-routine workers, although differently. Routine workers are vulnerable to displacement and downward wage pressure (Arntz et al., 2016; Frey and Osborne 2013; Nedelkoska and Quintini, 2018). In contrast, workers engaged in non-routine cognitive and manual tasks must adapt to evolving technologies that complement their work. Thus, automation has heightened the need for training across both occupational categories. Routine workers increasingly require reskilling to move into less automatable roles, while non-routine workers need ongoing upskilling to effectively manage emerging technologies.

The limited research available consistently finds that workers at risk of automation are less likely to participate in training activities. Nedelkoska and Quintini (2018) compared training participation among workers with varying levels of automation risk in a sample of 32 OECD countries. They found substantial differences in both overall training participation and time spent in training. Specifically, workers in fully automatable jobs (i.e. workers in jobs with a probability of automation of over 70%) are four times less likely to have participated in job-related training in the past year than those in non-automatable jobs. In terms of time spent in training, workers in automatable jobs spent 29 hours less annually than those in non-automatable jobs. This pattern appears consistent across different welfare regimes. Ioannidou and Parma (2021) examined training participation by automation risk and found that workers in high-risk occupations are less likely to engage in training across welfare regimes. However, the size of this gap in participation between low-risk and high-risk occupations varies by welfare regime: it is smaller in Southern and Scandinavian countries, but notably larger in Central-Eastern Europe.

Although these findings suggest that policy environments may influence disparities in training participation, direct evidence on their moderating role is limited. Koster and Brunori (2021) examined whether labor market policies moderate the link between automation risk and non-formal training participation, using EU-LFS data from 27 countries. They focused on three policy measures: active labor market policy (ALMP) spending, and the strictness of Employment Protection Legislation (EPL) for regular and temporary contracts. They found that workers at high automation risk were 2.4% less likely to attend training. However, ALMP spending and EPL did not moderate this gap, although both showed a direct positive effect on overall training participation. Thus, labor market policies appear to increase overall training participation, but do not reduce disparities by automation risk.

The persistent training gap appears to stem largely from employer-provided training. Heß et al. (2023) examined the relationship between exposure to robots and non-formal training participation among German workers. They found that workers in highly automated roles were 4% less likely to participate in firm-financed training, with no significant differences for partially or non-firm-financed training. Moreover, workers in highly automated roles were 13% less likely to receive time off and 10% less likely to receive financial support for training. The findings suggest that firms are less willing to invest in training employees they perceive as vulnerable to automation.

These studies have largely relied on occupation-level measures of automation risk, which assign a single risk score to entire occupations based on their typical task composition. Ioannidou and Parma (2021) used the average risk estimates per occupation developed by Nedelkoska and Quintini (2018), while Koster and Brunori (2021) drew on Frey and Osborne's (2017) U.S.-based estimates. Similarly, Heß et al. (2023) employed Webb's (2020) task-based exposure scores, also developed using U.S. data. These approaches assume that occupations are comparable across countries and that workers within the same occupation perform similar tasks. However, empirical studies suggest that these assumptions often do not hold, as there is cross-country variation and within-occupation task heterogeneity (Autor and Handel, 2013). As a result, such measures tend to overestimate the automatability of jobs (Arntz et al., 2016). To the best of our knowledge, Nedelkoska and Quintini (2018) is the only study that makes use of individual-level task data, which accounts for variation within occupations. Relying exclusively on occupation-level risk scores may lead to misclassification of individuals' actual exposure to automation, particularly when substantial differences exist between groups in the tasks they perform within the same occupation. This is particularly relevant when examining gender differences, as research shows that men and women often perform different tasks within the same occupations. For instance, Brussevich et al. (2019) found that across all occupations women have higher routine task intensity than men. This pattern stems from women being less likely to engage in abstract or manual tasks, while they are more likely to perform routine tasks. The size of this gender gap in routine intensity varies across regions, with larger differences in Eastern and Southern Europe and smaller ones in Scandinavian and Central European countries. In contrast, Matysiak et al. (2025) report no overall gender difference in routine tasks, but they find that women are more likely to perform social tasks and less likely to engage in manual tasks. Consequently, not accounting for differences between men and women within the same occupation can distort analyses of the relationship between automation risk and training behavior.

Gender and Training Participation

The prevailing theoretical frameworks suggest that women are generally less likely than men to participate in training. The neoclassical theory of labour supply (Becker, 1981) emphasizes gender differences in the incentives to invest in training, particularly within the context of traditional gender norms. It argues that women often anticipate career interruptions due to childbearing and caregiving responsibilities (Dieckhoff and Steiber, 2009). As a result, women may perceive lower long-term returns on investment in training, making them less inclined to pursue such opportunities.

Contrasting this perspective, discrimination theories (Becker, 1957; Phelps, 1972) focus on employers' biased practices that disadvantage women in access to training opportunities. These theories suggest that employers may be reluctant to invest in training women either due to personal prejudices (taste-based discrimination) (Becker, 1957) or based on assumptions about women's future labour market behavior (statistical discrimination) (Phelps, 1972). For example, employers may anticipate that women will experience career interruptions due to childbirth and caregiving responsibilities, or they may be uncertain whether women will return to the same company after maternity leave. This perceived risk can lead employers to allocate fewer training resources to female employees, reinforcing gender disparities in skill development and career advancement.

However, these theoretical perspectives do not consider individual differences. The impact of these mechanisms may vary significantly by educational attainment and position in the labour market. First, the assumptions of extended career interruptions and a primary focus on unpaid caregiving are less applicable to highly educated women. Research shows that they are more likely to return to work relatively quickly after childbirth (Wallace and Saurel-Cubizolles, 2013; Eriksson et al., 2022). Additionally, highly educated women may be perceived as more career-oriented and committed to continuous employment (Steinber et al., 2015), which can reduce the likelihood of employer discrimination. Second, at the time of the quickly changing demand for skills due to rapid technological transformation the nature of the tasks performed in a job, particularly the degree of routine intensity, can further shape employers' training decisions. In high-skilled, non-routine jobs that require analytical thinking, problem-solving, or firm-specific knowledge, employers are more likely to anticipate high returns from training and may be less concerned about potential career interruptions. In contrast, in low-skilled, routine-intensive jobs, where tasks are easily standardized and workers more easily replaceable, employers may see lower value in training and be more inclined to favor male employees, if they perceive women as more likely to experience work interruptions. It is, thus, likely that the gender gap in training in favour of men among routine workers is larger than among nonroutine workers.

Empirical studies report mixed findings regarding gender gaps in training participation. While some studies find a gender gap in favour of men (Dieckhoff & Steiber, 2010), other studies find a gap in favour of women (Massing & Gauly, 2017). These divergent results likely reflect differences in the type of training and individual characteristics. Studies that distinguish between type of training consistently find that men are more likely to participate in employer-sponsored training, whereas women are more frequently involved in non-employer-sponsored or self-financed training (Vaculíková et al., 2020; Dämmrich et al., 2015; Kalenda et al., 2024; Stoilova et al., 2023). Additionally, the gender gap in training varies by education level. Although there is a gap in favour of men among those without a degree, among highly educated, women participate more in training compared to men (Vaculíková, 2020). However, the literature lacks studies examining how the risk of automation affects gender gaps in training participation.

Childcare and Training Participation

Family responsibilities, in particular childcare, can pose a barrier to participation in training programs. This might be especially true for mothers, who often shoulder a larger share of housework and childcare responsibilities (Garcia-Mainar et al., 2011; Craig and Mullan, 2011; Argyrous and Rahman, 2017). Indeed, women are considerably more likely to not undertake training due to family responsibilities (Massing and Gauly, 2017; Stoilova et al., 2023). Additionally, research shows that for women, childbirth (Lim et al., 2024; Zoch 2023; Zoch 2024) and the presence of pre-school-aged children (Lebert & Antal, 2016; Massing & Gauly, 2017; Boll & Bublitz, 2018) are linked with lower probabilities of participating in training activities. In contrast, these factors do not appear to negatively affect fathers. Studies find that fathers' participation in training is either not significantly different from that of men without children (Zoch, 2023), or is even higher (Lebert & Antal, 2016; Dieckhoff & Steiber, 2011).

These barriers may be especially pronounced for mothers in jobs at risk of automation. Since women in routine-intensive roles already receive less employer-sponsored training, those with young children may also struggle to participate in self-financed or voluntary training due to time and financial constraints. As a result, mothers in high-automation-risk jobs may be doubly disadvantaged, by being both less likely to receive employer-provided training and less able to pursue it independently. In contrast, men in similar jobs are unlikely to experience reduced training participation based on parenthood, as fathers' engagement in training appears largely unaffected by childcare responsibilities. In other words, childcare responsibilities may further widen the gender gap in training in favour of men among routine workers and contribute to the accumulation of disadvantages of female routine workers. While existing research documents the gendered impact of family responsibilities on training participation, little is known about how these dynamics interact with automation risk.

Given these challenges, childcare can support mothers' participation in job-related training by helping them balance work and family responsibilities. For mothers with young children, access to childcare has been shown to reduce employment interruptions and increase working hours, which in turn facilitates engagement in training upon returning to work (Zoch, 2024). However, since working mothers likely already use formal childcare to maintain employment and opening hours of formal childcare facilities are fairly rigid, its availability may have a limited additional effect on increasing training participation.

3. Methodology

Data and sample

We make use of the EU-Labour Force Survey (EU-LFS) together with the ad hoc module 'Job skills' conducted in 2022. As a result, the data captures the labour market conditions before the rapid spread of generative AI and the resulting changes in labour demand. EU-LFS is a household survey conducted quarterly in all EU countries, 4 candidate countries, and 3 European Free Trade Association countries. It provides detailed data on the employment of all household members aged 15 or above. In addition to the main survey, since 1999 Eurostat has recommended conducting EU-LFS ad hoc modules on a sample of workers participating in the main survey. The ad hoc modules include questions on specific topics concerning the labour market. The 2022 module provides detailed information on the task content of jobs, allowing us to estimate the automation risk at job-level.

In our study, we focus on countries that provide data on household composition (e.g. the age of the youngest child). This leaves us with 26 out of 29 countries participating in the 2022 module[1]. We then apply a series of sample restrictions. First, we retained only employed respondents who participated in the 2022 'Job Skills' module, resulting in 181.571 women and 200.181 men. Second, we restricted the sample to individuals aged 25 to 59, yielding 150.433 women and 161.864 men. Finally, we dropped observations with missing values on any key variables—including task measures, training participation and relevant control variables—resulting in a final sample of 136.198 women and 142.752 men. The sample distribution by country is presented in Table A.1 in the Appendix.

Table 1. Sample Size Following Restrictions

Sample restrictions	Women	Men
Employed workers participating in the module	181.571	200.181
Aged 25-59	150.433	161.864
Interest variables available	136.198	142.752

[1] We exclude Switzerland, Sweden, and the Netherlands, which do not provide data on household composition.

Measures

Exposure to automation

The literature on exposure to automation is dominated by two approaches to estimating the risk of automation. The first approach, developed by Autor and Dorn (2013), estimates the extent to which the content of occupations is dominated by routine tasks. Their routine task intensity index (RTI) quantifies the prevalence of routine tasks within an occupation by combining information on routine, manual, and abstract tasks. It is calculated by subtracting the prevalence of manual and abstract tasks from the prevalence of routine tasks. Thus, the RTI captures the degree to which an occupation depends on tasks that can be codified and are, therefore, more susceptible to automation, with higher values indicating a greater reliance on routine activities. The second approach, developed by Frey and Osborne (2017), estimates the susceptibility of occupations to automation. Their automation risk index combines expert evaluations of the automatability of 70 occupations with nine task content variables that describe the levels of perception and manipulation, creativity, and social intelligence required to perform each occupation. Specifically, they used these task content variables as predictors for the experts' assessments of an occupation's susceptibility to automation. After validating their approach, they extended the model to estimate the probability of computerization for all occupations. The resulting index ranges from zero to one, indicating the estimated risk of automation for each occupation. Both approaches rely on data from the Occupational Information Network (O*NET) for information on the task content of occupations. This dataset provides standardized information on the tasks, skills, and work activities associated with U.S. occupations (SOC codes), based on surveys of workers and experts. The main drawback of both approaches is the assumption that workers within the same occupation perform similar tasks, which is not supported by empirical evidence (Autor and Handel, 2013). Given that men and women in similar occupations perform considerably different tasks (Brussevich et al., 2019; Matysiak et al., 2024), measuring exposure to automation at occupation level can hide important gender differences.

In estimating exposure to automation, we build on the approach developed by Autor and Dorn (2013), which is commonly used in the literature (e.g. Lewandowski et al., 2022; Górka et al., 2017). The main advantage of our measures is the use of individual-level information on task content of jobs. This allows us to account for the heterogeneity of tasks workers perform within occupations. To this end we draw on the EU-LFS 'Job Skills' module, which provides information on the time workers spend in performing various tasks in their jobs. In building the RTI index, first we identified a set of tasks that mirror the tasks employed by Autor and Dorn (2013) in building the RTI index. The selected items are summarized in Table 1, while Table A.2 in the Appendix provides detailed information on variable coding. We construct four separate task-content indices: cognitive-analytical, cognitive-interactive, manual, and routine. The cognitive-analytical measure captures time spent reading manuals and technical documents, as well as performing relatively complex calculations. The cognitive-interactive measure reflects time spent interacting with people within the same company, interacting with external contacts, and advising, training, or teaching others. Manual task content is based on the amount of time spent on physically demanding tasks and tasks requiring fine motor skills, such as finger dexterity. Finally, the routine task index captures the degree of task repetitiveness, the extent to which tasks are governed by strict procedural rules, and the level of autonomy workers report over both the content and the order of their tasks. The autonomy variables are inversely coded so that higher values indicate lower autonomy, consistent with greater task routineness. All indices are coded such that higher values indicate a greater intensity in the respective task domain.

Table 2. Task Items Included in the Task Content Measures

Task content	Task items (Time Spent or Degree of…)
Cognitive analytical	Reading manuals and technical documents
	Doing relatively complex calculations
Cognitive interactive	Interacting with people from the same company
	Interacting with people from outside the company
	advising, training or teaching other people
Manual	doing hard physical work
	tasks involving finger dexterity
Routine	Repetitiveness of tasks
	Tasks precisely described by strict procedures
	Autonomy on content of tasks (inversely coded)
	Autonomy on order of tasks (inversely coded)

The task measures were computed using the full sample of respondents with complete data on task and occupation, without imposing additional restrictions. To construct the final task content measures, we first standardized each task item by subtracting the mean and dividing by the standard deviation of the entire EU sample. We then summed the relevant standardized items to form composite measures for the four task dimensions: cognitive analytical, cognitive interactive, manual, and routine. These composite measures were then standardized again using the entire EU sample. Based on these standardized task measures, we followed the approach of Lewandowski et al. (2022), which builds on Autor and Dorn (2013), to construct a synthetic measure of Relative Routine Task Intensity (RTI), defined as:

$$RTI = ln\,(routine) \; - ln\,(\frac{cog_{analytical}+cog_{interactive}}{2}),$$

where routine is the routine task measure, while $cog_{analytical}$ and $cog_{interactive}$ are the cognitive analytical and cognitive interactive tasks measures[2] .The RTI captures the relative intensity of routine tasks compared to cognitive tasks, with higher values indicating a greater reliance on routine tasks, which are at risk of being substituted by automation technologies. The RTI is also standardized using the entire EU sample mean and standard deviation. Consequently, the final task content scores are expressed in standard deviation units relative to the EU average, where higher values indicate a higher routine intensity.

[2] Following Lewandowski et al. (2022) to avoid nonpositive values in the logarithm, for each task, the lowest score in the sample is added to the scores of all individuals, plus 0.1.

In order to assess the implications of using job-level versus occupation-level task data, we compared the task content measures and the RTI index computed from individual-level EU-LFS data with equivalent measures constructed using occupation-level information from the U.S.-based ONET database. For this purpose, we merged the EU-LFS with ONET using 3-digit ISCO[3] occupation codes and computed the ONET-based task content measures in a manner analogous to our EU-LFS-based measures. The resulting task measures from the two sources are moderately to strongly correlated. Figures A.1 to A.5 in the Appendix display the comparisons between EU-LFS and ONET task content measures and RTI across the 3-digit ISCO occupations. The y-axis represents the average value of each respective task measure and RTI index, while the x-axis represents the 3-digit ISCO code of occupations. The figures show that while the overall patterns are similar across the two sources, there are differences in the magnitude of task scores. The O*NET-based measures generally assign higher values to cognitive tasks, particularly in professional and managerial occupations, and manual tasks, particularly workers in trades and machine operation roles. In contrast, the scores for routine tasks and RTI index are more closely aligned across the two measures. Overall, the two sources are similar, as indicated by the correlation coefficients between EU-LFS-based and O*NET-based task scores: 0.759 for cognitive analytical, 0.697 for cognitive interactive, 0.762 for manual, and 0.714 for routine tasks. The RTI index also exhibits a relatively strong correlation of 0.690.

Based on the values of the estimated RTI index derived from the EU-LFS data, we classify workers into two groups within each country: those in high-RTI occupations (at or above the country-specific 75th percentile) and those in low-RTI occupations (below the 75th percentile). This country-relative classification is used in the subsequent analyses to estimate the effect of exposure to automation on job-related training participation.

Training participation

We measure training participation using a self-reported indicator of participation in job-related non-formal education or training within the last 12 months. Specifically, the variable is coded as 1 for respondents who reported participating in at least one job-related non-formal training activity, and 0 otherwise.

Moderating variables

We consider several factors that may moderate the relationship between automation risk and training participation. To capture potential gender differences in how individuals respond to automation risk, we include a binary indicator for sex. We also account for family responsibilities that may constrain individuals' ability to engage in training, focusing generally on the presence of children and on the presence of young children (aged 0 to 3) in the household.

For those with young children, we examine the moderating role of childcare availability. Specifically, we use Eurostat data on the proportion of children aged 0 to 3 enrolled in formal childcare. We distinguish between two measures based on the number of hours children spend in care: 1–29 hours per week and 30 hours or more[4]. We rely on childcare enrollment as a proxy for availability, as it is a widely used indicator in the literature (Wood et al., 2016; Wood and Neels, 2019; Matysiak et al., 2024).

[3] For observations where occupation data was available only at the 1-digit ISCO level, we assigned the average O*NET task values across all 3-digit occupations nested within the corresponding 1-digit category.
[4] For Norway, data on childcare for 2022 is not available. To address this gap, we estimated the 2022 value using linear interpolation based on the available data from 2015–2020 and 2023–2024.

Control variables

To account for individual and job-related factors that may influence participation in training, we include a range of control variables. At the individual level, we control for educational attainment, distinguishing between low, medium, and high education based on ISCED classification. We also include age groups (25–29, 30–34, 35–39, 40–44, 45–49, 50–54, and 55–59), as training participation may vary across life stages. General health status is controlled for using five categories (very good, good, fair, bad, and very bad), as poor health may hinder engagement in training activities. In addition, we account for family structure by including whether the respondent lives with a partner and the number of children under the age of 14, both of which may affect time availability and household responsibilities.

Regarding job characteristics, we include an indicator for employment status (full-time vs. part-time) and firm size, categorized as small (1–49 employees), medium (50–249), and large (250+), since training opportunities tend to be more available in larger firms (Aisa et al., 2016). Lastly, we include industry fixed-effects at the NACE 1-digit level and country fixed-effects.

Estimation strategy

We estimate linear probability models to examine the relationship between automation risk and training participation. Linear probability models are preferred over logistic models in this context because they yield coefficients that are comparable to those from logistic regression, while being easier to interpret (Adolfsson et al., 2022).

To examine the compounding disadvantage of exposure to automation, gender, and parenthood, our analytical strategy proceeds in four steps. First, we compare workers in occupations with low-RTI and high-RTI on their likelihood of participating in job-related training. Second, to assess the potential cumulative disadvantage of exposure to automation and gender, we include an interaction term between RTI and gender. This allows us to test whether women in high-RTI occupations are disproportionately less likely to participate in training compared to their male counterparts. Third, we further extend this analysis by incorporating parenthood, estimating a three-way interaction between RTI, gender, and parental status. This enables us to examine whether mothers in particular face an additional disadvantage in accessing training when exposed to automation. We estimate these models both on the pooled sample and separately by country group[5]. This disaggregation is motivated by prior research showing that gender gaps in training and the influence of caregiving responsibilities vary across welfare regimes. Gender disparities in training tend to be narrower in Nordic countries, where institutional support for work–family reconciliation is strong, and more pronounced in Southern

[5] Countries were grouped as follows: (1) Nordic: Denmark, Norway, Finland; (2) Southern: Italy, Greece, Spain, Portugal, Cyprus, Malta. (3) Central-Eastern: Czech Republic, Slovakia, Poland, Hungary, Romania, Bulgaria, Slovenia, Estonia, Lithuania, Latvia, Croatia, Luxembourg; (4) Continental: Austria, Belgium, France, Germany. These groupings reflect broad welfare regime typologies commonly used in comparative policy research. Ireland, the sole Anglo-Saxon country in the data, was excluded from group analyses due to a low number of observations, which limited its statistical reliability.

and Central-Eastern European countries, where traditional norms and limited support structures persist (Dämmrich et al., 2015; Dieckhoff & Steiber, 2010).

Finally, to explore the potential moderating role of formal childcare availability, we adopt a two-step approach. First, we restrict the sample to women and estimate an interaction between RTI and the presence of young children (aged 0 to 3), to assess how motherhood affects training participation across occupational contexts. Second, we further narrow the sample to mothers with young children and estimate an interaction between RTI and the number of hours of formal childcare available. The second analysis is conducted using a multilevel linear probability model to account for country-level clustering.

4. Results

Descriptive statistics

Table 3 presents the descriptive statistics for the women and men in our sample. A larger share of women have a high level of education (45.1%) compared to men (33.2%), while men have higher proportions in medium (50.3% vs. 43.5%) and low education levels (11.4% vs. 11.3%). Employment patterns also differ, with 79.3% of women working full-time compared to 94.9% of men. The average number of children and the presence of young children (aged 0–3) are similar across genders, while differences in firm size distribution and general health status are small. In terms of training participation, men and women report relatively similar rates, with 28.4% of women and 24.9% of men having attended non-formal job-related training in the last 12 months.

Table 3. Sample and descriptive statistics

Variable	Category	Women		Men	
		Mean	SD	Mean	SD
Education	Low	0.114	0.318	0.166	0.372
	Medium	0.435	0.496	0.503	0.500
	High	0.451	0.498	0.332	0.471
Age group	25–29	0.085	0.279	0.091	0.288
	30–34	0.110	0.313	0.115	0.319
	35–39	0.133	0.339	0.133	0.340
	40–44	0.158	0.365	0.156	0.362
	45–49	0.174	0.379	0.170	0.376
	50–54	0.178	0.383	0.173	0.379
	55–59	0.162	0.368	0.161	0.368
General health	Very good	0.325	0.469	0.348	0.476
	Good	0.529	0.499	0.528	0.499
	Fair	0.122	0.327	0.106	0.308
	Bad	0.020	0.141	0.016	0.125
	Very bad	0.003	0.055	0.003	0.053
Partner	Yes	0.668	0.471	0.676	0.468
Number of children		0.555	0.846	0.569	0.886

Employment status	Full-time	0.793	0.405	0.949	0.219
Firm size	1–49 employees	0.630	0.483	0.621	0.485
	50–249 employees	0.214	0.410	0.209	0.407
	>250 employees	0.152	0.359	0.166	0.372
Child aged 0–3	Yes	0.097	0.296	0.114	0.318
EU-LFS RTI	High	0.222	0.415	0.263	0.440
Training	Yes	0.284	0.451	0.249	0.433
Number of observations		136.007		142.564	

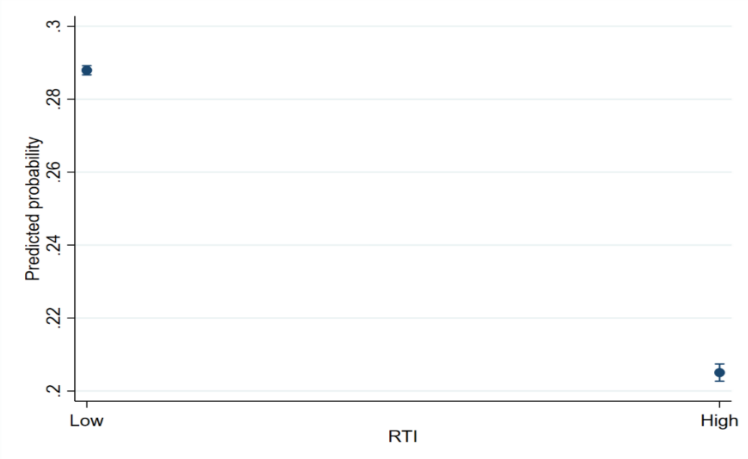
Exposure to Automation

We start by presenting differences in job-related training participation between workers employed in jobs highly exposed to automation (high-RTI jobs, RTI at or above the country-specific 75th percentile) and workers employed in jobs with low to moderate exposure to automation (low-RTI; RTI below the country-specific 75th percentile).

The main results are shown in Figure 1, while detailed regression estimates can be found in Appendix Table A3. The figure presents the probability of participating in training predicted based on our models for workers in low-RTI and high-RTI jobs. We use 83% confidence intervals as they are better suited for illustrating whether the differences between predicted probabilities are statistically significant than 95% confidence intervals. Namely, it was demonstrated that non-overlapping 83% CIs indicate a statistical difference between two probabilities at 0.05 significance level (Austin and Hux 2003).

We find that workers in low-RTI jobs have a significantly higher likelihood of participating in training (≈ 29%) compared to those in high-RTI jobs (≈ 21%). This represents a gap of approximately 8 percentage points in training participation between the two groups.

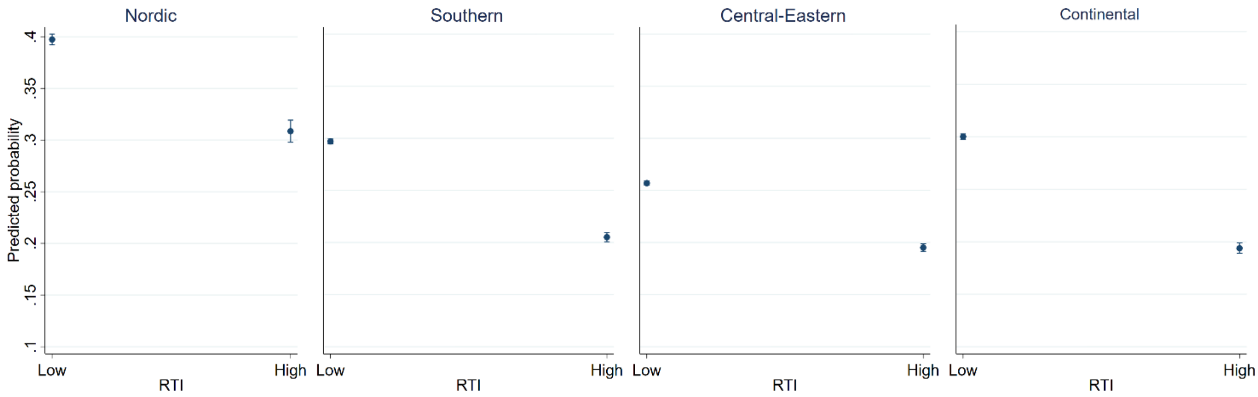
Figure 1. Predicted Probability of Training Participation by RTI



Note: Predicted probability of participating in training by RTI (83% CI), based on pooled data including control variables and country fixed effects.

The size of the training gap appears to vary substantially across country groups. These results are presented in Figure 2, with the full regression models reported in Appendix Table A3. Among low-RTI workers, participation is highest in the Nordic countries (40%), followed by Southern (30%), Continental (30%), and Central-Eastern European countries (26%). For high-RTI workers, participation is also highest in the Nordic group (31%), while it is lower in the Central-Eastern (20%), Southern (21%), and the Continental group (19%). The resulting training gaps between low-RTI and high-RTI workers are widest in the Continental countries (a 11 percentage point difference), followed by the Nordic group (9 points) and Southern Europe (9 points), and are smallest in Central and Eastern Europe (6 points). In other words, workers in Nordic and Continental countries are most likely to participate in training, but they are also heavily punished for working in highly automatable jobs when it comes to training. In contrast, workers in Central-Eastern Europe are less likely to participate in training, but the differences between those most and less exposed to automation are less pronounced.

Figure 2. Predicted Probability of Training Participation by RTI across Country Groups



Note: Predicted probability of participating in training by RTI (83% CI), based on pooled data including control variables and country fixed effects.

Exposure to Automation and Gender

Next, we examine gender differences in participation in training depending on the risk of exposure to automation, in order to assess whether the reduction in the probability of participating in training observed for workers in highly automatable jobs is stronger for women than men. In other words, we examine whether the difficulties with accessing training compound for certain groups of workers. The main results are presented in Figure 3, while the full regression models are reported in Appendix Table A.4.

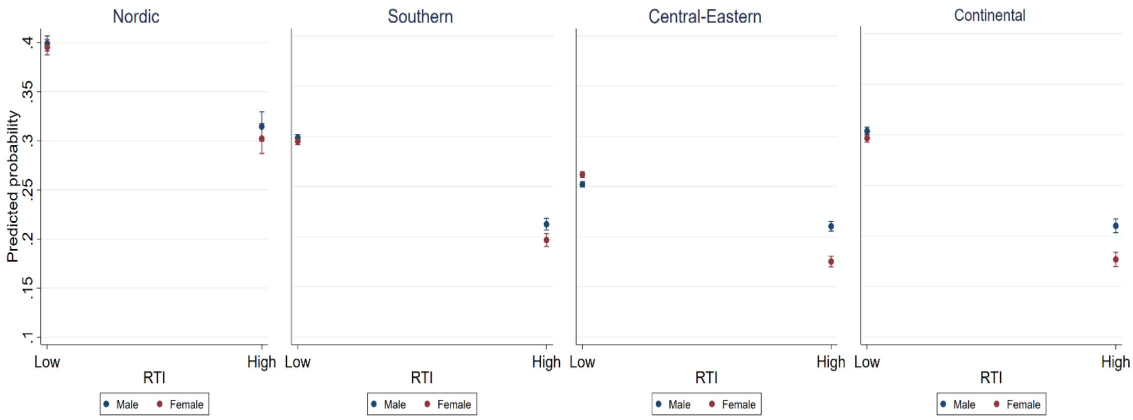
The findings show that among men, those in high-RTI jobs have a predicted training participation rate of 21.7%, compared to 28.7% for men in low-RTI jobs —a gap of approximately 7 percentage points. Among women, the gap is wider and amounts to 9.8 pp. Namely, women in jobs with low-RTI face the same likelihood of participating in training as men, but women in highly automatable jobs are less likely to participate in training than men in similar jobs (this probability amounts 19.1% for women).

Figure 3. Predicted Probability of Training Participation by RTI and Gender

Note: Predicted probability of participating in training by RTI and gender (83% CI), based on pooled data including control variables and country fixed effects.

Figure 4 presents the same analysis disaggregated by country group (see Appendix Table A.4 for full models). Across all country groups, both men and women in high-RTI jobs participate in training at lower rates than their counterparts in low-RTI jobs. Among low-RTI workers, men and women show very similar participation rates, with no notable gender differences. However, gender gaps emerge among high-RTI workers in several regions. The largest gap is observed in Central-Eastern Europe, where women's participation is 17.5% compared to 21.0% for men—a difference of 3.5 percentage points. In Continental Europe, the gap is slightly smaller at 3.3 points (17.7% for women vs. 21.0% for men), and in Southern Europe it is 1.5 points (19.7% vs. 21.2%). By contrast, in the Nordic countries, participation rates among high-RTI workers are similar for men and women (30.2% vs. 31.5%), and the difference is not statistically significant. In other words, in all country groups the probability of participating in training declines for women and men as the exposure to automation increases. This decline is steeper for women than for men in Central-Eastern and Continental countries, a bit steeper in Southern Europe and similar for both genders in Nordic Europe .

Figure 4. Predicted Probability of Training Participation by RTI and Gender across Country Groups



Note: Predicted probability of participating in training by RTI and gender (83% CI), based on pooled data including control variables and country fixed effects.

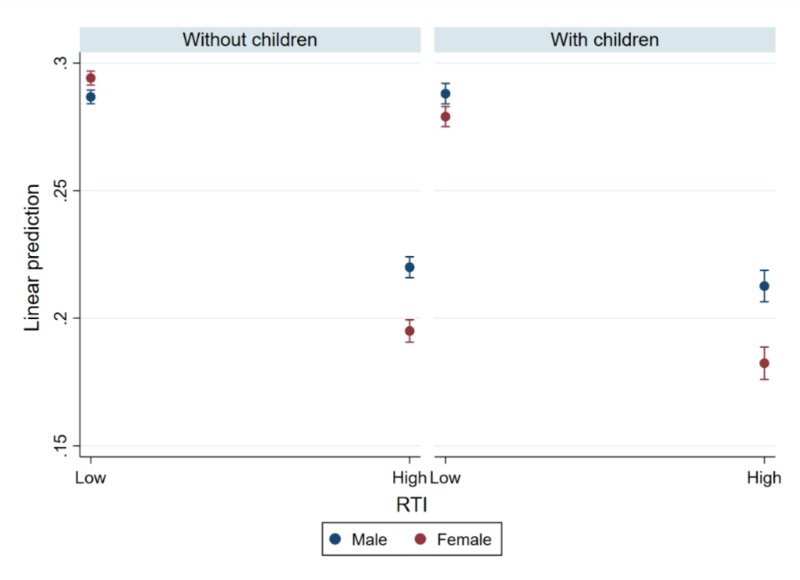
Exposure to Automation , Gender and Parenthood

We expand the analysis by incorporating parenthood status to assess whether women's lower access to training in automatable jobs is partly explained by childcare responsibilities. Figure 5 (full models in Appendix Table A.5) shows that for men, parenthood makes little difference: participation rates remain almost identical between those with and without children. In low-RTI jobs, childless men have a predicted participation rate of 28.7%, nearly matching fathers, at 28.8%. In high-RTI jobs the participation in training is reduced, but this reduction is similar for men withouth children and fathers. Namely, 22% of men withouth children and 21.3% of fathers in highly automatable jobs participate in training.

Conversly, motherhood reduces participation in traing, but it does so regardless of job automation risk. For women, however, parenthood is associated with a clear disadvantage. Mothers are less likely than women withouth children to engage in training in both in low-RTI and high-RTI jobs. In low-RTI jobs, 29.4% of women withouth children participate in training compared to 27.9% of mothers, while in high-RTI jobs, the rates fall to 19.5% and 18.2%.

When we compare across gender and job type, a pattern of cumulative disadvantage emerges. Working in a highly automatable job lowers training participation for all workers, but women consistently have lower rates than men—and mothers lowest of all. Nearly 30% of women and men withouth children working in less automatable jobs participate in training, yet the rate drops to just 19.5% for women withouth children in highly automatable jobs, and further to 18.2% for mothers. For men in the same high-RTI jobs, participation is higher—22.0% for men withouth children and 21.3% for fathers. This pattern shows how disadvantages compound: being in an automatable job reduces training opportunities, but being a woman—and especially a mother—exacerbates that reduction even further.

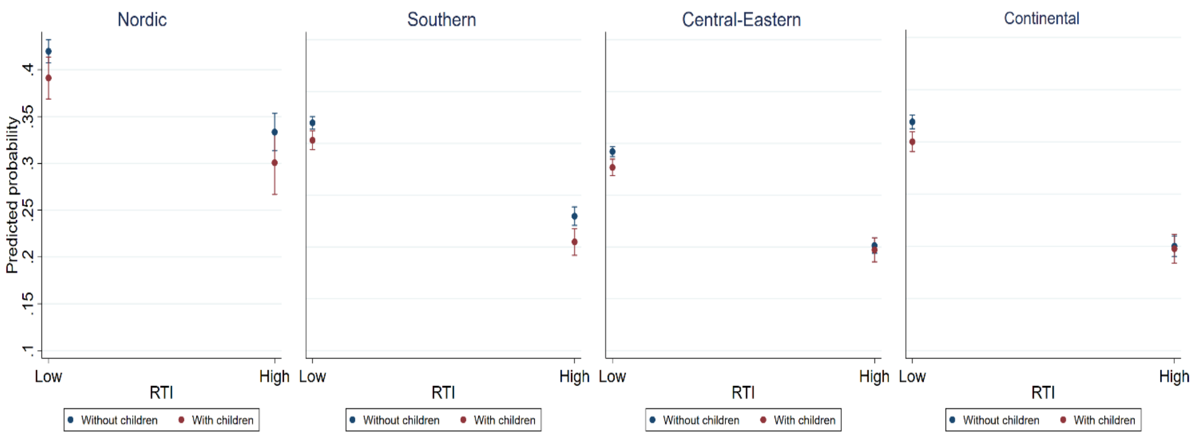
Figure 5. Predicted Probability of Training Participation by RTI, Gender and Parenthood Status



Note: Predicted probability of participating in training by RTI, gender and parenthood status (83% CI), based on pooled data including control variables and country fixed effects.

Given that significant parenthood-related differences emerged only among women, Figure 6 focuses on the gender gap in training participation among women, disaggregated by country group (full models including men are provided in Appendix Table A.5). In low-RTI jobs, women without children are significantly more likely to participate in training than mothers, with the largest gaps observed in the Nordic countries (42.0% vs. 39.1%) and Southern Europe (32.0% vs. 30.3%). In high-RTI jobs the motherhood gap is less pronounced across all country groups. We found a statistically significant difference of 2.5 percentage points between childless women and mothers only in Southern Europe (22.9% vs. 20.5%). In Central-Eastern Europe (20.1% vs. 19.7%), Continental Europe (20.0% vs. 19.8%), and the Nordic countries (33.0% vs. 30.0%), the differences are not statistically significant.

Figure 6. Predicted Probability of Training Participation Among Women by RTI and Parenthood Status across Country Groups

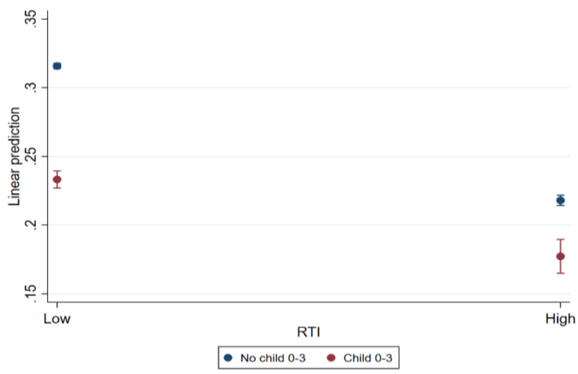


Note: Predicted probability of participating in training by RTI, gender and parenthood status (83% CI), based on pooled data including control variables and country fixed effects.

Childcare Availability

Motherhood reduces participation in training particularly strongly among women with young children, aged 0-3 (see Figure 7). This effect is particularly strong among women in jobs with low-RTI. In these jobs, women without young children (without children or with older children) have a significantly higher predicted probability of participating in training (31.6%) compared to mothers with young children (23.3%)—a gap of over 8 percentage points. The probability of participating in training is substantially lower for women in highly automatable jobs. This difference is also large among women without young children, for whom the probability of training participation declines to 21.8%. Nonetheless, the probability of participating in training is the lowest among mothers with young children (aged 0-3) and amounts to 17.7%. Thus, mothers with young children in highly automatable jobs are particularly disadvantaged in terms of training participation.

Figure 7. Predicted Probability of Training Participation by RTI and Presence of Young Children



Note: Predicted probability of participating in training by RTI and presence of young children aged 0 to 3 (83% CI), based on pooled data including control variables and country fixed effects.

We next examined whether childcare availability helps mothers of young children participate in training, espescially if they are in a particular need of training because they work in highly automatable jobs. To this end, we estimate multilevel linear probability models with childcare availability as an additional covariate which is introduced in an interaction with job type. We assess childcare avaiability with enrolment in childcare for 1–29 hours per week (Model 1) and 30 hours or more per week (Model 2). The results indicate a positive effect of formal childcare availability on training participation, which is statistically significant when we consider enrolment in childcare for 30 hours or more per week but not the part-time enrolment (Model 2). This finding allignes with our expectations, as participating in training, in addition to working for pay, may require childcare for more than 30 hours per week. Specifically, for each percentage point increase in the rate of mothers using formal childcare for 30+ hours weekly, the probability of training participation increases by 0.4 percentage points. However, this positive effect is reduced by 0.2 percentage points for mothers in high-RTI jobs. This means that the benefit of formal childcare on training is notably smaller for mothers working in routine-intensive jobs than among mothers in jobs less exposed to automation.

Table 4. Interaction Effects of RTI and Childcare Availability among Mothers with Young Children

Variable	**Model 1**	**Model 2**
	Coef. (SE)	**Coef. (SE)**
Constant	0.084 (0.049)	0.030 (0.050)
High-RTI	-0.023 (0.017)	-0.023 (0.019)
Childcare (0-29 h/week)	0.006 (0.003)	
Childcare (≥ 30 h/week)		0.004** (0.001)
High-RTI * Childcare (0-29 h/week)	-0.004 ** (0.001)	
High-RTI * Childcare (≥ 30 h/week)		-0.002** (0.001)
Controls	Yes	Yes
No obs.	13.154	13.154
No. groups	26	26

5. Conclusions

Training is increasingly recognised as a core resilience strategy for workers facing the disruptive effects of technological change. A large body of research demonstrates that automation erodes or eliminates routine jobs, fundamentally reshaping the demand for skills (Autor et al., 2006; Acemoglu & Restrepo, 2019). For workers whose roles are most exposed, reskilling is essential to safeguard employability, transition into less automatable occupations, and maintain economic security. This is not only a matter of individual adjustment, but a pressing social and policy challenge: without widespread opportunities for retraining, technological innovation risks deepening inequalities, marginalising vulnerable groups, and undermining the adaptability of Europe's labour force. Against this backdrop, our study investigates a central question: are the workers most exposed to automation receiving the training they need to remain resilient—and if not, who is being left behind? We focus particularly on the intersection of automation risk, gender, and parenthood, and examine whether access to childcare mitigates the barriers to training faced by workers with childcare obligations. We are interested in this particular group since childcare obligations may constitute an important barrier in undertaking training, further reducing the labour market perspectives of workers exposed to automation.

Building on earlier literature, we examined how likely workers in highly automatable jobs are to participate in training compared to those in low-RTI jobs and how this likelihood further depends on gender and parenthood. To this end, we used rich individual-level data from the 2022 EU Labour Force Survey and its Job Skills module, covering 26 European countries. This approach enabled us to assess automation risk at the job level, to capture gender and parenthood effects, and to analyse variation across European regions (country groups).

Our analysis confirmed that **workers who need training most are the least likely to receive it**. Across Europe, the estimated probability of participating in job-related training is **21%** for workers in highly automatable (high-RTI) jobs, compared to **29%** for those in less automatable jobs—an **8 percentage point gap**. This pattern is evident in every country group, but varies in magnitude: it is most pronounced in Continental countries (11 points) and least pronounced in Central-Eastern Europe (6 points).

Gender compounds this disadvantage. Women and men in low-RTI jobs have similar estimated probabilities of participating in training (around 29%), but in highly automatable roles, women's predicted participation drops to 19.1%, compared with 21.7% for men.

Motherhood adds another dimension. Mothers are consistently less likely to participate in training than women withouth children, regardless of whether they work in high-RTI or low-RTI job. In low-RTI jobs, the predicted probability of participating in training is 29.4% for women without children and 27.9% for mothers; in high-RTI jobs, these probabilities fall to 19.5% and 18.2%, respectively. Importantly, the “motherhood gap” does not widen in automatable jobs—but because mothers already start from a lower baseline, the combination of **job automatability, gender, and parenthood** produces a pattern of **cumulative disadvantage**. Each factor—being in an automatable job, being a woman, and being a mother—further reduces the likelihood of training participation. This accumulation has critical implications: **the workers most urgently in need of upskilling to navigate technological disruption—mothers in automatable jobs—are those least likely to access it.**

Our cross-country analysis provides further nuance. In the Nordic countries, estimated training participation is highest overall—40% for low-RTI jobs and 31% for high-RTI jobs—with virtually no gender gap in automatable roles, likely reflecting more supportive institutional frameworks. In contrast, in Central-Eastern and Continental Europe, women in high-RTI jobs face the steepest declines, with predicted participation among mothers falling below 20%.

We also investigated whether childcare provision mitigates these barriers. Full-time childcare availability (30+ hours per week) slightly increases mothers’ training participation, but its effect is weaker for those in highly automatable jobs. A possible explanation for this finding is that many working mothers already rely on formal childcare simply to sustain employment; additional training requires further time that current childcare arrangements do not cover. Most formal childcare operates during standard working hours, while training often requires time in evenings or weekends—precisely when childcare is unavailable.

These findings carry **important policy lessons**. Employers have little incentives to invest in training workers in automatable jobs—especially women and mothers—because they perceive low returns or possible future attrition. However, without targeted reskilling efforts, these groups are at greater risk of job displacement, and European member states risk underutilizing valuable human capital and missing the opportunities offered by technological progress. Public policy intervention is thus needed:

- **Government financed targeted training programmes** should be designed for workers in automatable jobs, with a special focus on women and parents.
- **Extension of childcare support beyond standard hours may be needed** to cover the “second shift” of evening and weekend training.
- **Public funding is essential**, because employers alone will not provide training to those they perceive as “at risk.”

Although our data precede the large-scale diffusion of large language models, the urgency of these findings has only grown. The rise of generative AI may intensify the pace of skill obsolescence, widening training needs across the workforce. Without targeted intervention, we risk leaving behind those who most need help to adapt.

In conclusion, our study suggests that Europe faces a clear policy challange: **to ensure that those most exposed to automation—particularly mothers in routine-intensive jobs—can access the training they need.** Failure to address these compounded disadvantages will deepen social inequality, reduce labour force participation, and prevent Europe from fully benefiting from technological progress.

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Appendix

Table A.1. Sample Size by Country

Country	Women	Men
AT	7097	7251
BE	6690	6925
BG	4962	5192
CY	2406	2261
CZ	6479	7040
DE	9399	10311
DK	3181	2978
EE	2435	2263
EL	3446	4331
ES	11806	12079
FI	3369	3501
FR	11060	10572
HR	1398	1426
HU	5792	6182
IE	2362	2266
IT	14900	17778
LT	2758	2170
LU	1643	1720
LV	1559	1325
MT	1732	2206
NO	3155	3309
PL	9211	8639
PT	4937	4531
RO	8311	10246
SI	3206	3359
SK	2713	2703

Table A.2. Items and Coding Used to Construct Task Content

Task content	Task items	Measure
Cognitive	Time spent on reading manuals and technical documents	1 = None of the working time; 5 = All or most of the working time.
	Time spent on doing relatively complex calculations	1 = None of the working time; 5 = All or most of the working time.
	Time spent on interacting with people from the same company	1 = None of the working time; 5 = All or most of the working time.
	Time spent on interacting with people from outside the company	1 = None of the working time; 5 = All or most of the working time.
	Time spent on advising, training or teaching other people	1 = None of the working time; 5 = All or most of the working time.
Routine	Repetitiveness of tasks	1 = To no extent; 5 = To a very large extent.
	Tasks precisely described by strict procedures	1 = To no extent; 5 = To a very large extent.
	Degree of autonomy on content of tasks	1 = High (11, 21, 31) 2 = Medium (12, 22, 32) 3 = Low (13, 23, 33)
	Degree of autonomy on order of tasks	1 = High (11, 12, 13) 2 = Medium (21, 22, 23) 3 = Low (31, 32, 33)
Manual	Time spent on doing hard physical work	1 = None of the working time; 5 = All or most of the working time.
	Time spent on tasks involving finger dexterity	1 = None of the working time; 5 = All or most of the working time.

Table A.3. Estimated Effects of RTI on Training Participation

Variable	Pooled model	Nordic	Southern	Central-Eastern	Continental
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
High-RTI (*ref: Low*)	-0.082*** (0.002)	-0.089*** (0.002)	-0.092*** (0.004)	–0.062 *** (0.003)	–0.106 *** (0.004)
Education (*ref: Low*)					
Medium	0.053*** (0.003)	0.045*** (0.013)	0.060*** (0.004)	0.022 *** (0.005)	0.055 *** (0.006)
High	0.140*** (0.003)	0.096*** (0.014)	0.153*** (0.004)	0.110 *** (0.005)	0.145 *** (0.006)
Age Group (*ref: 25-29*)					
30-34	-0.005 (0.004)	-0.017 (0.014)	-0.010 (0.007)	–0.010 (0.006)	0.009 (0.007)
35-39	0.001 (0.004)	0.001 (0.004)	-0.003 (0.007)	–0.004 (0.006)	0.014 * (0.007)
40-44	0.010*** (0.003)	0.009 (0.014)	0.015** (0.007)	0.000 (0.005)	0.021 ** (0.007)
45-49	0.011*** (0.003)	-0.009 (0.013)	0.021*** (0.007)	–0.002 (0.005)	0.024 *** (0.007)
50-54	0.003 (0.003)	-0.001 (0.013)	0.021*** (0.007)	–0.016 ** (0.005)	0.009 (0.007)
55-59	-0.008 (0.003)	-0.011 (0.013)	0.012 (0.007)	–0.021 *** (0.006)	–0.018 ** (0.007)
General Health (*ref: Very good*)					
Good	-0.006** (0.002)	-0.005 (0.008)	-0.004 (0.003)	–0.019 *** (0.003)	0.009 ** (0.004)
Fair	-0.004 (0.003)	-0.011 (0.011)	-0.005 (0.005)	–0.008 (0.005)	0.001 (0.005)
Bad	-0.037*** (0.006)	-0.055*** (0.021)	-0.042*** (0.012)	–0.031 *** (0.011)	–0.030 ** (0.011)
Very bad	-0.061*** (0.015)	-0.087 (0.057)	-0.096*** (0.034)	–0.026 (0.023)	–0.087 ** (0.029)
Partner	0.001 (0.002)	0.017* (0.008)	-0.003 (0.003)	0.002 (0.003)	0.001 (0.004)
Number of children	0.003* (0.001)	0.001 (0.004)	0.007** (0.002)	0.000 (0.002)	0.000 (0.002)
Employment (*ref: Full-time*)					
Part-time	-0.036*** (0.003)	-0.080*** (0.010)	-0.043*** (0.005)	–0.022 *** (0.006)	–0.026 *** (0.004)

Firm Size (ref: *<50 emp)*					
50–249 emp	0.052*** (0.002)	0.028*** (0.008)	0.075*** (0.004)	0.059 *** (0.003)	0.027 *** (0.004)
≥250 emp	0.068*** (0.002)	0.056*** (0.010)	0.102*** (0.005)	0.071 *** (0.004)	0.048 *** (0.004)
Constant	0.188*** (0.006)	0.250*** (0.029)	0.081*** (0.011)	–0.068 *** (0.009)	0.210 *** (0.014)
Industry FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1342	0.068	0.139	0.179	0.085
Observations	278.571	19.493	82.413	102.732	69,305

Table A.4. Estimated Effects of RTI and Gender on Training Participation

Variable	**Pooled model**	**Nordic**	**Southern**	**Central-Eastern**	**Continental**
	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**
High-RTI (*ref: Low*)	-0.070 *** (0.003)	-0.085 *** (0.012)	-0.086 *** (0.005)	-0.042*** (0.004)	-0.094 *** (0.006)
Gender (*ref: Male*)	0.001 (0.002)	-0.004 (0.008)	-0.003 (0.004)	0.010 ** (0.003)	-0.007 (0.004)
High-RTI * Female	-0.028 (0.004) ***	-0.008 (0.017)	-0.012 (0.007)	-0.045 *** (0.006)	-0.026 ** (0.008)
Constant	0.185 *** (0.006)	0.249 *** (0.029)	0.080 *** (0.011)	-0.073 *** (0.009)	0.210 *** (0.014)
Industry FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.1344	0.068	0.139	0.179	0.085
Observations	278.571	19.493	82.413	102.732	69.305

Table A.5. Estimated Effects of RTI, Gender and Parenthood Status on Training Participation

Variable	**Pooled model**	**Nordic**	**Southern**	**Central-Eastern**	**Continental**
	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**
High-RTI (*ref: Low*)	-0.067 *** (0.003)	-0.102 *** (0.014)	-0.082 (0.006) ***	-0.035 *** (0.005)	-0.091 *** (0.007)
Gender (*ref: Male*)	0.007 ** (0.002)	-0.008 (0.010)	-0.002 (0.004)	0.021 *** (0.004)	0.001 (0.005)
Parent (*ref: Without children*)	0.001 (0.004)	-0.036 * (0.018)	-0.007 (0.008)	0.013 * (0.006)	0.001 (0.008)
High-RTI * Female	-0.032 *** (0.005)	0.011 (0.019)	-0.013 (0.009)	-0.055 *** (0.007)	-0.034 *** (0.010)
With children * Female	-0.016 *** (0.004)	0.014 (0.016)	-0.011 (0.010)	-0.019 * (0.008)	-0.006 (0.011)
High-RTI * With children	-0.009 (0.005)	0.065 * (0.026)	-0.005 (0.007)	-0.032 *** (0.006)	-0.021 ** (0.008)
High-RTI * Female * With children	0.011 (0.008)	-0.070 (0.038)	0.001 (0.014)	0.029 * (0.012)	0.020 (0.016)
Constant	0.182*** (0.006)	0.254 *** (0.029)	0.078 *** (0.011)	-0.078 *** (0.009)	0.206 *** (0.015)
Industry FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.134	0.068	0.139	0.179	0.085
Observations	278.571	19.493	82.413	102.732	69.305

Figure A.1. EU-LFS vs. O*NET: Cognitive Analytical Tasks

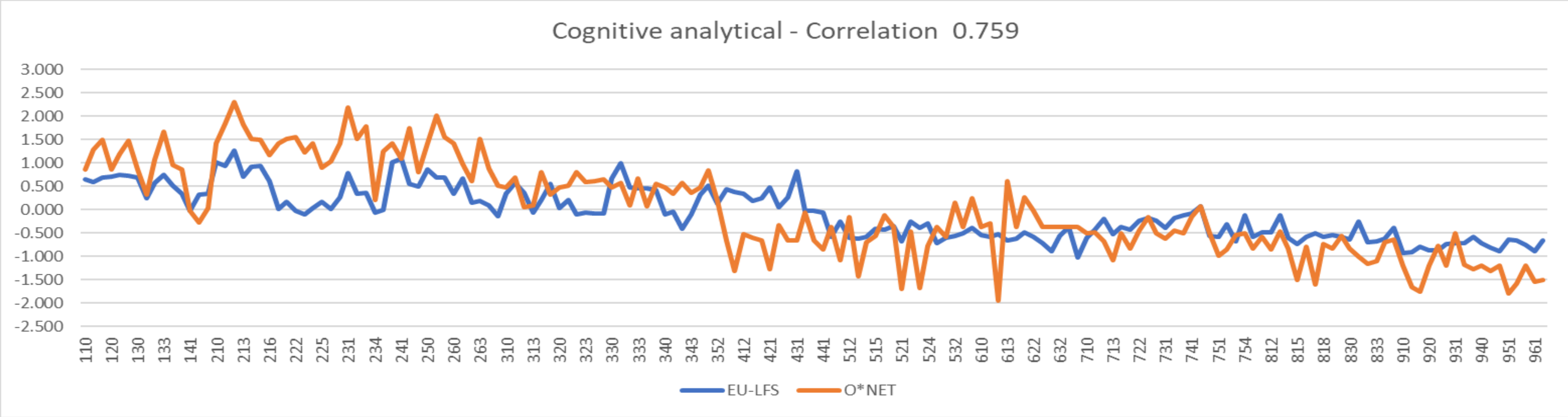


Figure A.2. EU-LFS vs. O*NET: Cognitive Interactive Tasks

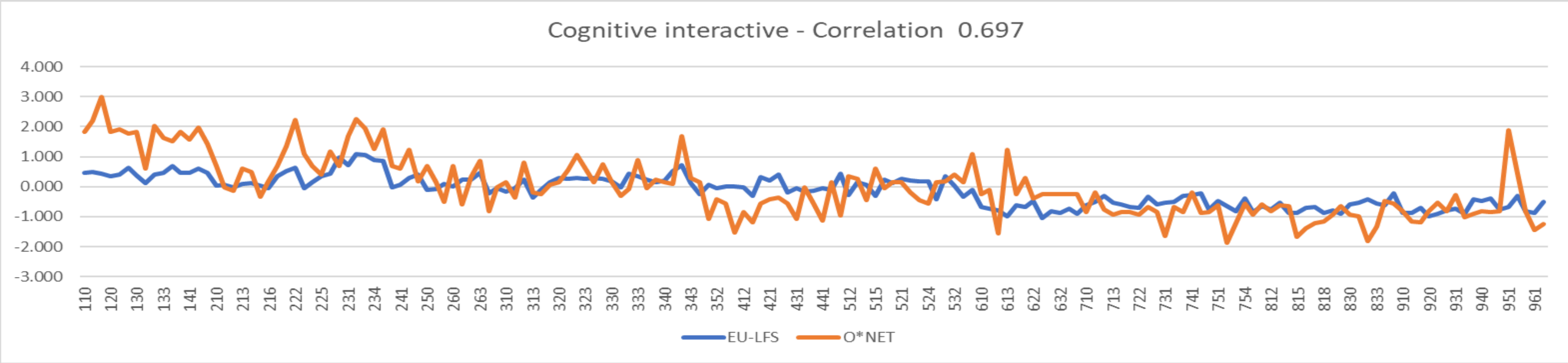


Figure A.3. EU-LFS vs. O*NET: Manual Tasks

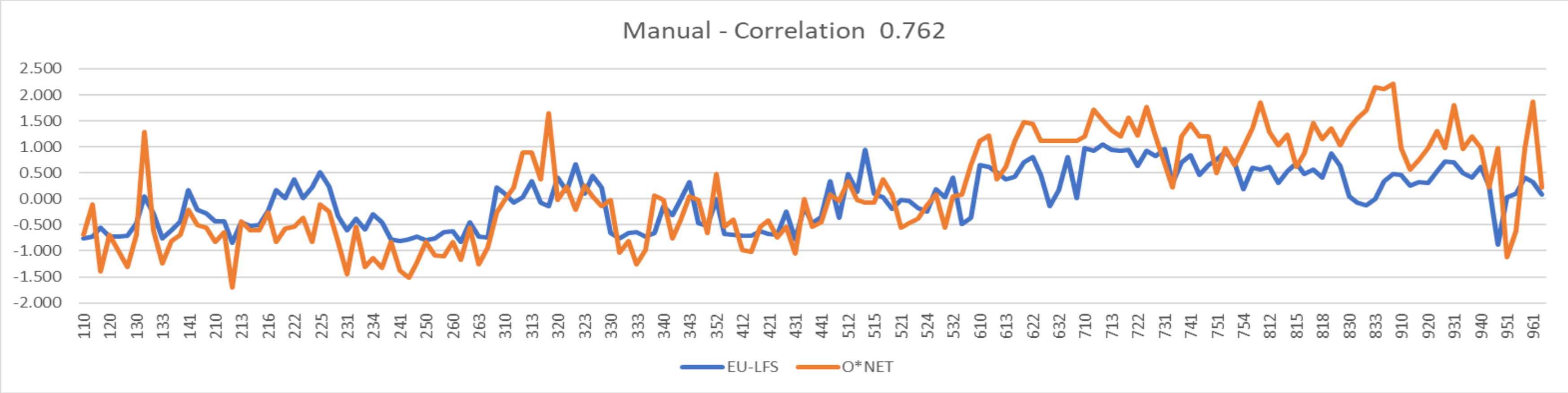


Figure A.4. EU-LFS vs. O*NET: Routine Tasks

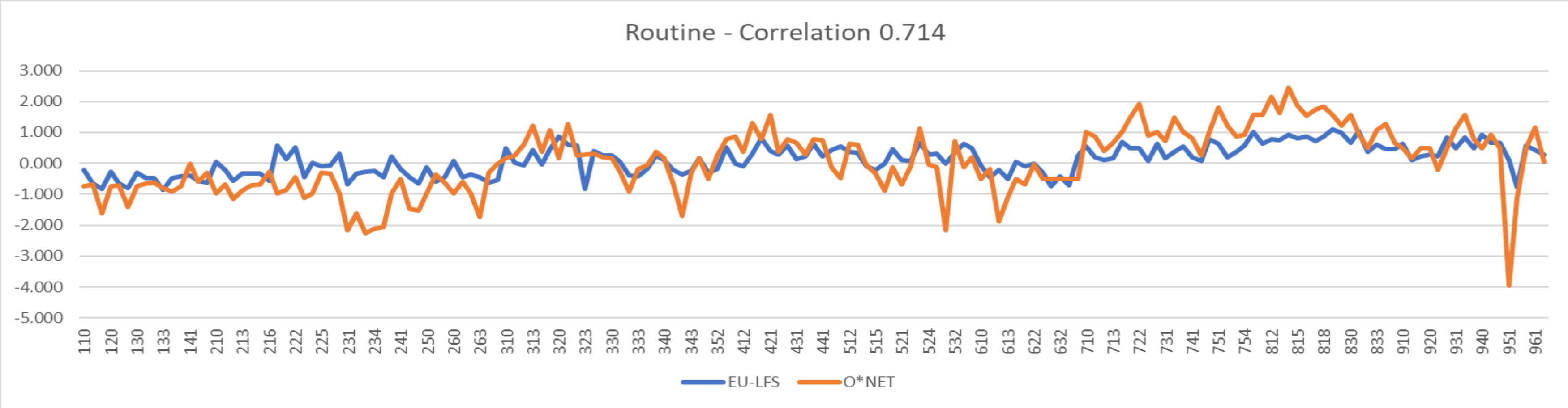
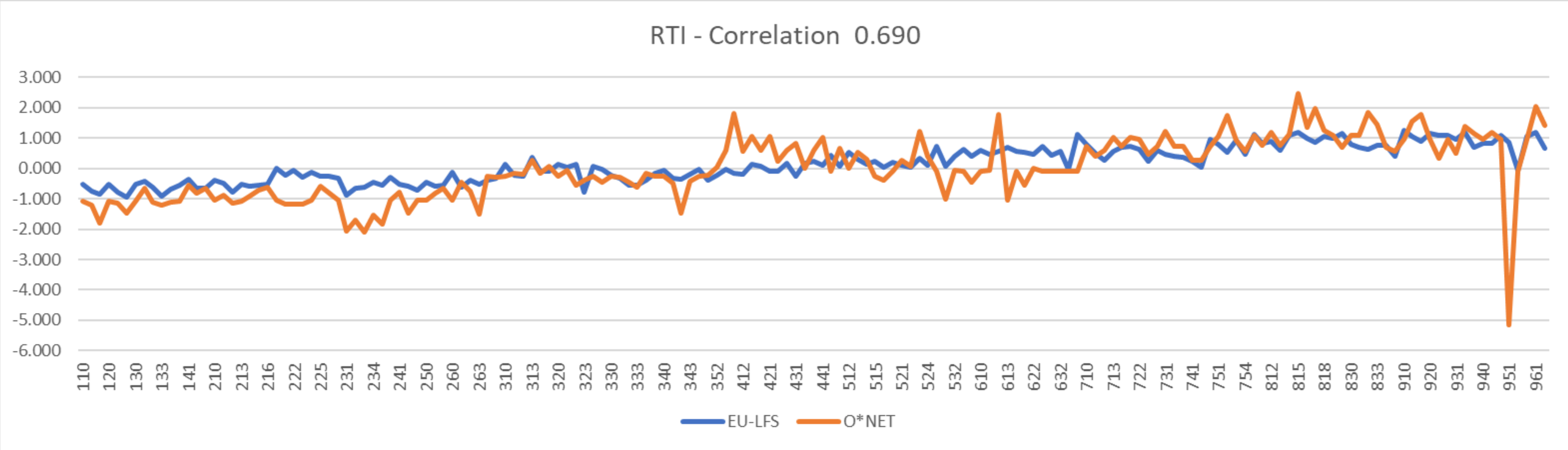


Figure A.5. EU-LFS vs. O*NET: RTI



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