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AI and Worker Well-being: Evidence from a Nationally Representative Study

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Abstract: Utilizing nationally representative cross-sectional and longitudinal data from Finland (2018–2023), we provide a population-level assessment of the relationship between AI and worker well-being. Contrary to international evidence suggesting a positive or an inverted U-shaped relationship, we find no systematic association between AI use intensity and job satisfaction. However, we do find that work engagement is higher among employees who are personally involved with AI, with the strongest association among intensive users for whom AI is an essential part of their work. Furthermore, technology-replacement fears have remained stable despite rapid AI advancement and do not predict subsequent labour market transitions. An interpretation is that Finland's high-trust institutional environment and robust social safety nets may effectively moderate the disruptive psychological and economic shocks typically associated with rapid technological change.

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Introduction

Since the launch of ChatGPT in November 2022, employers, citizens and academics have become increasingly aware of the potentially transformatory nature of Generative Artificial Intelligence (GenAI) given its capacity to automate job tasks across the whole skills distribution and, in doing so, fundamentally alter job content and the demand for labour. Today, around 80% of employees work in occupations where at least 10% of tasks are exposed to GenAI (Eloundou, et al., 2024). About 36% of occupations use AI for at least a quarter of their tasks but it is used most intensively in software development, writing, and analytical tasks (Handa, et al., 2025). GenAI is therefore already a significant factor in many knowledge-intensive occupations, and in roughly one third to one half of occupations its role is substantial or growing.

Most of the literature to date has focused on GenAI's impact on labour demand and the price of labour (wages) (see e.g. Drydakis, 2025, Schulz, et al., 2026). Even though the changes GenAI is ushering in have the potential to impact workers' wellbeing in several ways, comparatively little research has been undertaken regarding the effects of GenAI on job satisfaction and work engagement.

GenAI automates many routine and repetitive cognitive tasks, potentially narrowing the task content of some occupations as routines shift to AI. At the same time, the variety of jobs where AI supports human work increases: employees may focus on more creative, analytical, and interactive tasks, broadening work content and increasing cognitive demands. In principle, these AI-induced changes to job content may enhance workers' job satisfaction and work engagement. However, AI may also negatively impact workers' well-being where it is perceived as a threat to job security and in circumstances where it automates cognitively demanding high-skilled tasks. Moreover, Bailey (2022) suggests that emerging technologies at work may affect workers through multiple channels, including not only job displacement and algorithmic unfairness but also surveillance, new forms of managerial control, intensified performance measurement, and other changes in the organization of work. Since the theory suggests GenAI may have countervailing influences on job attitudes, the relationship merits careful empirical investigation.

More broadly, current debates on AI and the future of work often rest on competing one-sided narratives: one emphasizes complementarity, meaningful work, and improved job quality, while another stresses alienation, control, and displacement (Spencer, 2026). This suggests that the effects of AI on worker well-being are likely to be contingent rather than uniform, strengthening the case for direct empirical evidence on how AI relates to workers' experiences of their jobs.

Current research on the nexus between GenAI and job satisfaction relies on non-representative data, such as self-selected Glassdoor reviews (Schulz, et al., 2025, Chiong and Xie, 2024, Chen, et al., 2025), or surveys focused on specific worker groups (e.g. Bosek-Rak and Kaszyński, 2026, Filippelli, et al., 2026, Chuang, et al., 2025) where exposure is often inferred (based on, e.g., occupational descriptions rather than direct, individual-level usage). These studies indicate that GenAI's effects on job satisfaction are twofold and often nonlinear. Several international studies have found either a positive relationship or an inverted U-shaped relationship with moderate exposure increasing satisfaction but very high exposure reducing it (Chiong and Xie, 2024, Schulz, Bendig, Bräunche and Kindermann, 2025). Positive effects stem from reducing routine tasks and improving job content (Chen, Huang, Song and Tan, 2025), whereas negative effects arise from fears of replacement and skill obsolescence (Wu, et al., 2025).

To our knowledge, the only study using a representative sample is Wu, Yang, Yang, Su and Chen (2025), but it cannot measure AI use at the individual level and only captures data up to 2018 – before GenAI. Thus, GenAI's relationship with job satisfaction and work engagement has previously not been studied using representative samples.

We make three primary contributions to the literature on the economic and psychological impacts of AI. We are among the first to examine the association between AI, including GenAI, and job attitudes (satisfaction and engagement) with nationally representative data for wage earners – in our case for Finland. Second, we shift the analytical focus from inferred exposure to direct, individual-level measurement of AI usage and intensity. Third, we contribute a rare longitudinal perspective by tracking technology-replacement fears from a 2018 baseline through 2023 and linking these to subsequent labour market transitions. In doing so we find, contrary to most of the literature, that AI is not strongly associated with job satisfaction, nor with employees' expectations regarding employment and job quality. Nor do we find any relationship between employees' fear of being replaced by AI and subsequent labour market transitions. However, we do find that work engagement is higher among employees who are personally involved with AI, with the strongest association among intensive users for whom AI is an essential part of their work. We argue that one possible interpretation is that Finland's institutional environment may be related to these muted patterns.

Literature

Research on GenAI and job attitudes is still relatively new, with studies gradually uncovering how these technologies are shaping employees' experiences at work. Much of the early literature draws on large datasets, such as Glassdoor reviews, which provide broad insight into trends across industries and occupations. These studies, however, often infer AI exposure from occupational characteristics rather than measuring individual usage directly, making it difficult to capture the full nuance of how GenAI affects job satisfaction on a personal level. For example, Gimbel, et al. (2026) highlight substantial variance in GenAI exposure within occupations and over time, underscoring the limitations of such indirect measures.

Several key patterns have emerged from this literature. Schulz, Bendig, Bräunche and Kindermann (2025) found an inverted U-shaped relationship between firm-level AI adoption and employee job satisfaction: moderate adoption tends to boost satisfaction, while intensive adoption can lead to declines. Notably, research-driven organizations appear to tolerate higher levels of AI integration before negative effects set in. Similarly, Chiong and Xie (2024), analysing millions of Glassdoor reviews following the release of ChatGPT, observed that employees in occupations with moderate AI exposure reported the greatest improvements in job satisfaction, particularly in terms of compensation and changes to work tasks. In contrast, those in roles with low or high AI exposure saw fewer benefits, suggesting that the impact of generative AI is not uniform across the workforce.

Other studies have taken a more granular approach by constructing task-level AI exposure measures. For instance, Chen, Huang, Song and Tan (2025) combined Glassdoor reviews, patent data, and occupational task descriptions to demonstrate a generally positive association between AI exposure and job satisfaction. Their findings point to the value of AI augmentation—where AI supports rather than replaces human work—in enhancing wages and work–life balance.

Survey-based research provides additional context, focusing on psychological mechanisms such as technostress, team cohesion, and perceived fairness. Unlike studies using indirect measures, these surveys often ask directly about individual AI use. Wu, Yang, Yang, Su and Chen (2025), for example, used regional data from China’s Labour Force Dynamic Survey to reveal an inverted U-shape relationship: AI increases productivity and satisfaction up to a point, but concerns about job loss and skill obsolescence can erode these gains, especially among less-skilled workers. Importantly, perceived social fairness helps mitigate some of AI’s negative effects.

The impact of generative AI on psychological well-being also depends on workplace context. Chuang, Chiang and Lin (2025) found in Taiwan that AI-related efficiency can support engagement and satisfaction, whereas technostress is linked to exhaustion and work–family conflict. They also suggest that GenAI may alleviate technostress more effectively than traditional rule-based AI.Bosek-Rak and Kaszyński (2026) similarly showed that, among knowledge workers in Poland's financial sector, job satisfaction depends more on organizational support and leadership than on individual enthusiasm for AI. Filippelli, Popescu, Verteramo, Tani and Corvello (2026) found among Italian knowledge workers that generative AI is positively associated with emotional, social, and cognitive well-being, with team cohesion playing an important mediating role.

More broadly, Jia, et al. (2025) identify four channels through which GenAI may shape job attitudes—resource, stress, cognitive, and motivation—highlighting both potential benefits and risks. Dewie, et al. (2022), Korzynski, et al. (2026),Liu and Li (2025), Manresa, et al. (2024), and Vuong (2026) likewise suggest that AI can support performance and engagement, but as Liu and Li (2025) show, it may also lead to feelings of alienation if core tasks are heavily automated. Braganza, et al. (2021) further argue that while strong psychological contracts usually support engagement, AI may weaken this relationship and increase alienation.

There is broad consensus across studies that AI can have both positive and negative impacts on job attitudes. Three themes emerge.

The first theme to emerge is the nonlinearity in GenAI effects. Many studies (Schulz, Bendig, Bräunche and Kindermann, 2025, Chiong and Xie, 2024, Wu, Yang, Yang, Su and Chen, 2025) show that satisfaction does not increase linearly with AI use: too little exposure yields few benefits; too much exposure – especially in low-skill or routine knowledge work – can decrease satisfaction due to job insecurity and overload. Second, increased job satisfaction is strongly linked to AI removing "boring and repetitive" tasks, allowing employees to focus on more challenging and creative aspects of work (Schulz, Bendig, Bräunche and Kindermann, 2025, Chen, Huang, Song and Tan, 2025). Negative impacts on the other hand are due to fear of AI replacing humans (Chiong and Xie, 2024) or if AI leads to alienation (Braganza, Chen, Canhoto and Sap, 2021, Liu and Li, 2025). Third, studies emphasize the role of organizational context and social environment showing that technology alone does not determine outcomes. Evidence from large companies around the world (Korzynski, Protsiuk, Tursunbayeva, Papa and De Cremer, 2026), Poland (Bosek-Rak and Kaszyński, 2026), Italy (Filippelli, Popescu, Verteramo, Tani and Corvello, 2026), and Taiwan (Chuang, Chiang and Lin, 2025) emphasizes that leadership, team cohesion, and change management are essential for turning AI into a resource rather than a stressor. These results are similar to what has been found earlier in studies concerning computer use (Minardi, et al., 2023).

Data

The 2023 Quality of Work Life Survey (QWLS) conducted by Statistics Finland is a large, nationally representative survey examining the working conditions of wage earners. It is the ninth iteration of a study series that began in 1977. The survey provides comprehensive information on the quality of Finnish working life, including physical and psychological workload, opportunities for influence, working hours, and the reconciliation of work and family life. The 2023 data were collected for the first time through an online survey, whereas all previous rounds had been conducted via face-to-face interviews. The sample was drawn from respondents to Statistics Finland's Labour Force Survey, and it is representative of the entire Finnish wage-earning population across occupations and industries. The response rate was 71%, and the dataset includes 5,742 respondents. All results presented below use sampling weights to ensure that the data reflect the structure of the target population despite group-specific differences in response rates. The QWLS data is matched to Statistics Finland's FOLK basic data base for the years 2010-2023, which contains individual demographics and data on employment and earnings. We use FOLK to measure some control variables, such as education and work history.

In the final section, we also use the 2018 wave of the QWLS. The 2018 survey was conducted through face-to-face interviews and includes 4,110 respondents, with a response rate of 67%. Weights are also applied in the analyses utilizing the 2018 data. The 2018 QWLS is also linked to FOLK basic module, which makes it possible to follow the individuals who participated in QWLS over time. We utilize this matching in the final section.

Measures of AI use

Our key measure of AI use is based on the following question: Does your workplace use technology based on artificial intelligence, such as chatbots, virtual assistants, speech recognition, machine vision, machine translation or data analysis based on machine learning? Responses are pre-coded where 1 = Yes, and I am personally involved with it, 2 = Yes, but I am not involved with it in my work, and 3 = No. This measure is a wide measure of AI, which includes also GenAI.

For those answering Yes, we measure the intensity of AI use with the follow-up question: How well do the following statements describe your own work? Utilisation of artificial intelligence is an essential part of my work. This variable is measured on a 4-point scale ranging from totally true to totally untrue.

Dependent variables

We have two measures of wellbeing at work. The first is a traditional measure of job satisfaction and is based on the question "How satisfied are you with your current job?". This is measured on a 5-point

Likert scale ranging from very unsatisfied to very satisfied. Higher values indicate better job satisfaction.

The second is a measure of work engagement and builds on the measure used in Hakanen, et al. (2021). It measures work engagement using three items with 4-point response scales (Totally true to Totally untrue), the items being “I am enthusiastic about my work", “I feel happy when I am deep in my work”, and “At my job, I feel strong and vigorous”. This standardized scale has a Cronbach's alpha is 0.79. Higher values indicate better work engagement. A similar measure of work engagement based on three variables (UWES-3) has been shown to be a valid measure of work engagement by Schaufeli, et al. (2017). Hakanen, Rouvinen and Ylhäinen (2021) show that the particular version that we also use is highly correlated with UWES-3.

These two variables capture different facets of employee well-being. For example, Macey and Schneider (2008) suggest that job satisfaction refers to contentment and a general sense of well-being (typically a more settled state with relatively moderate emotional activation), while work engagement denotes an energized, high-activation state characterized by vigour, enthusiasm, and investment in one’s work.

In the final section, we examine the relationship between concerns regarding technological replacement of work contributions and subsequent occupational changes, transitions from employment to education, or shifts from employment to unemployment. All transitions are assessed utilizing FOLK. Occupational change is defined by variation in occupational codes between years *t* and *t-1*. The transition from employment to education is identified as a change in primary activity from employed to student between years *t* and *t-1*. Transitions from employment to unemployment are measured by a change in main activity from employed to unemployed or being outside the labour force.

Control variables

In the regressions with control variables, the following variables are included (they originate from QWLS unless indicated). Our explanatory variables are gender (male/female), age (five categories), occupation (ten categories, FOLK), education level (six categories, FOLK), field of education (twelve categories, FOLK), supervisory duties (dummy)[1], temporary work contract(dummy)[2], self-assessed

[1] This is based on the question “Do your tasks involve supervision of the work of others or delegation of tasks to other employees?” with responses coded 1 = Yes 0 = No.
[2] This based on question “What kind of employment contract do you have? 0=A permanent employment contract, 1= A fixed-term employment contract.

health (5-point Likert scale ranging from good to poor)[3], remote work (dummy)[4], industry (seventeen categories), employer's sector (five categories) and region (four categories).

In robustness analyses we additionally control for individual work history. Longer-term work history is measured by average employment months and taxable earnings in 2010-2022. Short-term work history is measured by annual employment months and earnings in 2018-2022. The inclusion of these variables is motivated by studies of high-involvement management and job satisfaction (Böckerman, et al., 2012) and job design and job satisfaction (Böckerman, et al., 2017), in which the authors argue that controlling for respondents' work histories is important because workers do not sort randomly into different types of jobs, and that failing to account for this sorting can bias estimated relationships between job attributes and outcomes. Higher-ability workers with stronger wage and employment histories are more likely to enter favourable or advanced job roles, and estimates change notably once these histories are included. Including work-history controls therefore helps ensure that any observed association between AI use and job satisfaction is not simply driven by pre-existing differences in worker quality or stability.

Table A 1 in the Appendix shows summary statistics for the dependent variables and the control variables.

Methods and model specifications

We use linear regression analysis for the most part when we study the association between AI use and job satisfaction and employee engagement. First, we present models without control variables and then add the control variables discussed above. Even though we use a rich set of controls, these variables do not eliminate selection on unobservables. We discuss this further in the section Robustness checks. Linear regression models are appropriate even though the job satisfaction variable is an ordinal one. It gives a good understanding of the marginal effects of AI use on job satisfaction (Angrist and Pischke, 2009). We calculate robust standard errors.

In the next section when we analyse the incidence of AI use, we estimate an ordered logit model, since in that case we are interested in the predicted probabilities. These cannot be calculated correctly with linear models.

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[3] This is based on the question "In your opinion, how is your health nowadays?",

[4] This is based on question "Do you do remote work/telework?" 1 I do at present, 0 "No, but I have done before" and "No, I do not do".

Use of AI

Table 1 shows that most wage earners do not yet encounter AI at their workplace: 71% report that AI is not used at all at their workplace. About one fifth (19%) state that AI is used at the workplace but that they themselves do not work with it, whereas only around 9% use AI in their own job. Overall, the direct use of AI in everyday work is still relatively rare. Only 1.7% of respondents say that it is 'totally true' that AI is essential to their work, while 4% find it somewhat true. In contrast, 3.8% see it as somewhat untrue, and 0.7% say it's totally untrue. Thus, it appears that very few workers regard AI as central to their jobs. As a result, it may be difficult to find links between employee well-being and AI use due to limited statistical power.

Table 1: Use of AI at the workplace in Finland.

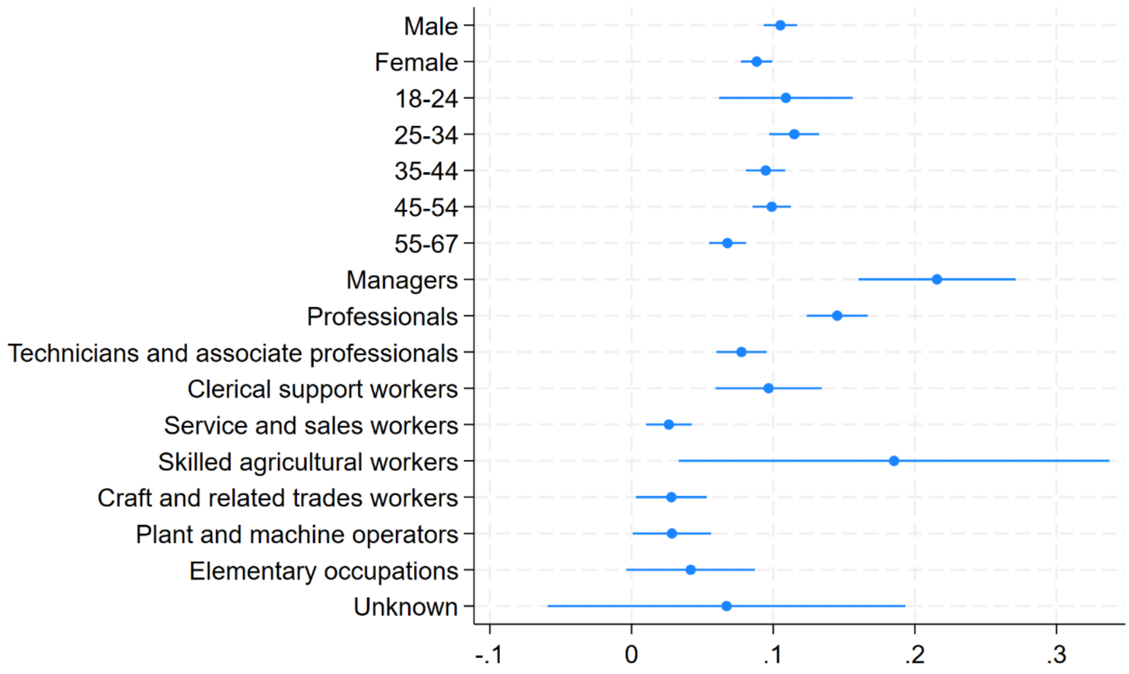
	N	Percent
Use of AI at the workplace		
Yes, and I am personally involved with it	585	9.33
Yes, but I am not involved with it in my work	1224	19.24
No	3904	71.43
Total	5713	100
AI essential part of work		
Totally true	99	1.73
True to some extent	229	4.01
Untrue to some extent	216	3.78
Totally untrue	41	0.72
I do not use AI	5128	89.76
Total	5713	100
Fear of not learning to use new technology well enough		
Yes	1058	16.53
No	4641	83.47
Total	5699	100
Threat of work input being replaced with technology in the near future		
Yes	454	8.60
No	5279	92.08
Total	5733	100
Digitalization or robotization have contributed to the change in the number of employees		
Yes	102	4.16
No	2450	96.00
Total	2552	100

Source: Quality of Work Life Survey 2023, the authors' calculations.

Table 1 also indicates that technology-related anxieties and perceived employment effects are present but far from dominant. Around 16.5% of respondents report a fear of not learning to use new technology well enough, while the large majority (83.5%) do not share this concern. Similarly, only 8.6% perceive a threat that their work input will be replaced by technology in the near future, compared with 92.1% who do not. Consistent with these relatively low levels of perceived disruption, just 4.2% report that digitalization or robotization has contributed to a change in the number of employees at their workplace, whereas 96.0% report no such impact. This item has fewer observations because only respondents reporting a change in employee numbers were asked this question. Overall, the descriptive evidence suggests that, in 2023, most Finnish wage earners neither anticipate imminent technological replacement nor observe substantial technology-driven staffing changes.

To examine differences in AI use across groups, we estimated a multinomial logistic regression model where the dependent variable corresponds to the question on AI use shown in Table 1. Using this model, we calculated predicted probabilities for distinct groups regarding whether AI is used at the workplace and whether the respondent personally works with it. The predicted probabilities are calculated using observed values of the explanatory variables for each individual. Figures 1 and 2 show the results for personal use of AI at work. The figures are based on the same model, but the results are divided to two figures for clarity.

Figure 1: Differences in AI use between groups.

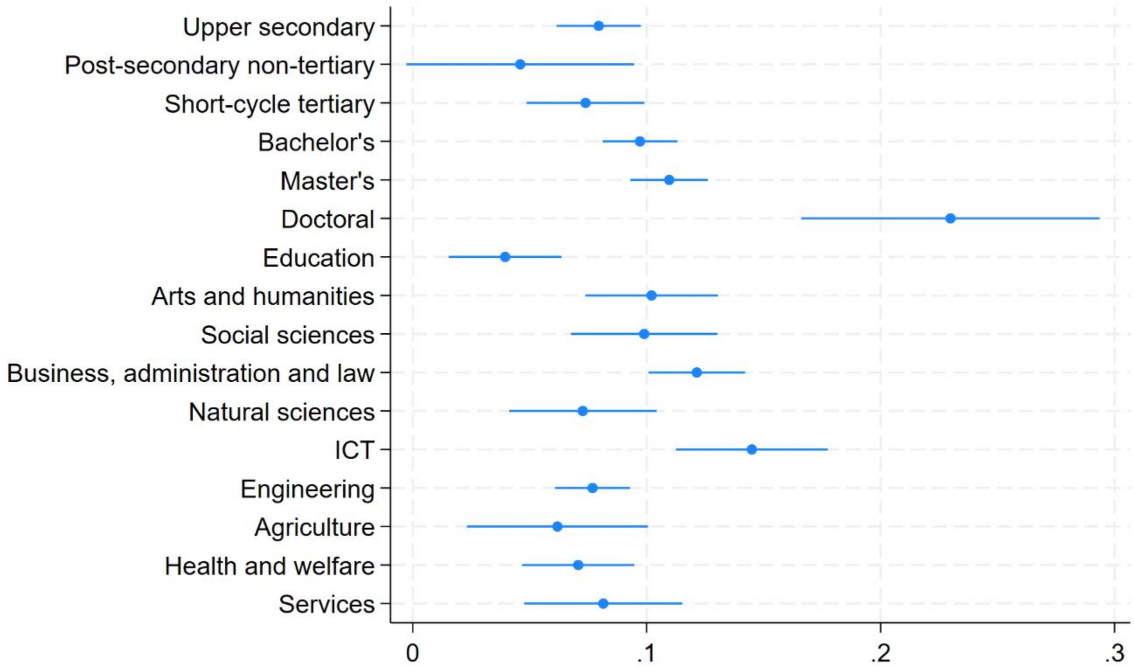


Source: Quality of Work Life Survey 2023, the authors' calculations.

Figure 1 shows differences in the probability of using AI across demographic and occupational groups. Gender differences are small, but younger groups have a slightly higher probability of using AI at work compared to those aged 55 or older. The largest differences relate to occupations: managers, professionals, and associate professionals stand out as groups with a high probability of AI use, whereas workers in service, sales, construction, process, and transport occupations – as well as other manual occupations – have a considerably lower probability. Overall, the figure illustrates that AI adoption in Finland is advancing unevenly and is concentrated in knowledge-intensive expert occupations.

Figure 2 shows that the predicted probability of AI use varies clearly by educational level and education specialism. Individuals with doctoral-level education have the highest predicted probability, followed by those with higher and lower tertiary degrees. Among fields of education, ICT stands out with a higher probability of AI use compared to other fields. In contrast, the education field of pedagogy shows little AI use. Overall, the figure illustrates that AI in Finland is concentrated especially among the highly educated and in knowledge-intensive fields.

Figure 2: Differences in AI use by education.



Source: Quality of Work Life Survey 2023, the authors' calculations.

AI and Employee Well-Being

In this section, we examine whether exposure to AI at work is associated with employees' well-being. We focus on two outcomes—job satisfaction and work engagement—and begin with descriptive models without covariates before turning to specifications that adjust for worker, job, and workplace characteristics. Tables 2 and 3 report the corresponding regression estimates.

Table 2: The association between AI use and Employee well-being, no control variables

	Job satisfaction		Work Engagement	
Does your workplace use AI-based technologies?				
Yes, and I am personally involved with it	0.134 ***		0.217 ***	
	(0.044)		(0.040)	
Yes, but I am not involved with it in my work	0.098 ***		0.121 ***	
	(0.029)		(0.029)	
AI essential part of work				
Totally true		0.179 *		0.399 ***
		(0.109)		(0.095)
True to some extent		0.094		0.180 ***
		(0.069)		(0.058)
Untrue to some extent		0.076		0.107 *
		(0.066)		(0.062)
Totally untrue		0.216 *		0.135
		(0.128)		(0.145)
Number of observations	5710	5710	5711	5711
*** p<.01, ** p<.05, * p<.1				

Note. Table shows coefficients and robust standard errors from OLS estimation. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table 2 shows that, the absence of controls, employees in AI-using workplaces report higher job satisfaction and work engagement than those in workplaces without AI. Both those who are direct users of AI and employees who do not use it directly, but are in a workplace where it is used, report higher well-being, with coefficients of 0.134 and 0.098 for job satisfaction, and 0.217 and 0.121 for work engagement (all p<.01). Among AI users, those who say AI is essential to their work show even higher scores (job satisfaction 0.179, work engagement 0.399), while partial users also have increased work engagement (0.180). The descriptive regressions indicate a positive correlation between AI exposure—especially intensive use—and employee well-being, which is examined further in Table 3.

Table 3: AI use and Employee Well-Being, with control variables

	Job satisfaction			Work Engagement		
Does your workplace use AI-based technologies?						
Yes, and I am personally involved with it	0.053			0.103	**	
	(0.045)			(0.043)		
Yes, but I am not involved with it in my work	0.026			0.036		
	(0.031)			(0.031)		
AI essential part of work						
Totally true		0.138	*		0.311	***
		(0.081)			(0.093)	
True to some extent		0.022			0.084	
		(0.068)			(0.058)	
Untrue to some extent		-0.000			0.001	
		(0.064)			(0.059)	
Totally untrue		0.146			0.075	
		(0.141)			(0.162)	
Number of observations	5369	5369		5371	5371	

*** p<.01, ** p<.05, * p<.1

Note. Table shows coefficients and robust standard errors from OLS estimation. All columns include the following control variables: gender, age, occupation, supervisory duties, fixed-term employment relationship, remote work, level of education, field of education, self-assessed health status, industry, geographical area and employer's sector. Full estimation results are shown in Table A1. Job satisfaction is measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied", 4 "Quite satisfied", 3 "Difficult to say", 2 "Rather unsatisfied", 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work", "I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table 3 shows that once a rich set of background characteristics is controlled for, the positive associations between AI exposure and well-being become substantially weaker (full estimation results are shown in Table A 2 in the Appendix). This result is not due to different sample composition: estimating the model in Table 2 for the sample used in Table 3 leads to qualitatively similar results. For job satisfaction, neither working in an AI-using workplace (whether personally involved: 0.053; or not involved: 0.026) nor reporting higher AI intensity (coefficients ranging from −0.000 to 0.146 across the intensity categories) is statistically indistinguishable from zero and also the magnitudes are small compared to the standard deviation of the job satisfaction variable (0.84). This of course does not definitively prove that there is no association; it could also result from a lack of sufficient statistical power. By contrast, for work engagement, respondents who are personally involved with AI report higher engagement (0.103, p<.05). In addition, the work-engagement association is strongest among those reporting that AI is totally true to be an essential part of their work (0.311, p<.01), whereas other intensity categories are small and not statistically significant. The strength of these associations is relatively modest. As indicated in Table A1, the standard deviation of work engagement is 0.86; accordingly, these associations represent 12% (0.103/0.86) and 36% (0.311/0.86) of one standard deviation, respectively. Overall, Table 3 indicates that the raw positive correlations in Table 2 are largely explained by compositional differences across workers and jobs, with the clearest remaining relationship being between intensive, hands-on AI use and higher work engagement.

These results differ somewhat from parts of the international literature, which often reports either a positive relationship or an inverted U-shaped relationship between AI exposure and job satisfaction based on non-representative sources such as Glassdoor reviews (Chiong and Xie 2024; Schulz et al. 2025) or indirect measures of exposure (Chen et al. 2025). It appears that, in this nationally representative sample for Finland, who adopts AI and in which jobs it is used account for much of the raw correlation between AI and job satisfaction (as in Table 2), leaving little residual association once these compositional factors are controlled for (Table 3). Finland's high-trust institutional environment and extensive social safety nets may also dampen both the upside (large productivity-driven improvements in job quality) and the downside (technostress and replacement anxiety), yielding comparatively muted average effects in the early stages of adoption.

AI and technology-related fears

As previous research has shown, the arrival of GenAI in workplaces can also generate various technology-related fears. Table 4 examines whether technology-related concerns vary with the intensity of AI use (full estimation results are shown in Table A 3 in the Appendix). Overall, there is little evidence that more intensive AI use is associated with greater fear of not learning new technology: the estimated coefficients are close to zero and statistically insignificant for most intensity categories. Those who do not use AI at all report less fear of not learning new technologies, however, the magnitude is modest, only 23% of standard deviation[5]. In contrast, perceived employment effects are more clearly linked to intensive use: respondents who report that AI is an essential part of their work are more likely to report that digitalization/robotization has contributed to changes in the number of employees at their workplace. Here the magnitude is also larger, being about 63% of standard deviation[6]. Finally, perceived replacement risk shows that compared to those who do not use AI at all, the persons answering that AI is to some extent an essential part of their work perceive a slightly higher near-term replacement threat, but again the magnitude is modest, being 0.24 standard deviations[7]. Taken together, the results suggest that intensive AI use is not systematically related to skills-related

[5] Table 1 shows that 16.5% have responded positively to this binary question. Thus, the standard deviation of the variable is sqrt(0.165*(1-0.165)) =0.37.
[6] Similar calculations to footnote 5 show that the standard deviation is 0.19.
[7] Similar calculations to footnote 7 show that the standard deviation is 0.27.

anxiety, but it is associated with reports of technology-driven staffing change and, for some groups, heightened perceptions of replacement risk.

Table 4: AI use intensity and technology-related fears

	Fear of not learning to use new technology well enough		Digitalization or robotization have contributed to the change in the number of employees		Threat of work input becoming replaced with technology in the near future	
AI essential part of work						
Totally true	0.007		0.124	**	0.060	
	(0.044)		(0.050)		(0.043)	
True to some extent	-0.003		0.039		0.064	**
	(0.028)		(0.025)		(0.029)	
Untrue to some extent	0.000		0.041		0.031	
	(0.029)		(0.028)		(0.026)	
Totally untrue	-0.085	**	-0.004		0.009	
	(0.035)		(0.031)		(0.049)	
Number of observations	5334		2378		5365	

*** p<.01, ** p<.05, * p<.1

Table shows coefficients and robust standard errors from OLS estimation. All columns include the following control variables: gender, age, occupation, supervisory duties, fixed-term employment relationship, remote work, level of education, field of education, self-assessed health status, industry, geographical area and employer's sector. Full estimation results are shown in Table A2. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table A 4 in the Appendix reports OLS regressions (with the same controls as Table 3) but interacts *AI use at the workplace* with the technology-related perceptions to see how these relate to job satisfaction and work engagement.

Across the three “fear/impact” blocks studied above, the main pattern is that the negative associations are concentrated among respondents who report the fear/concern, regardless of whether their workplace uses AI. For *fear of not learning to use new technology well enough*, it is those in non-AI workplaces who also report this fear who have significantly lower job satisfaction and work engagement than any other group of workers. Those who say they do perceive a *threat that work input will be replaced* have lower job satisfaction than other workers, regardless of whether they or their colleagues use AI. When it comes to work engagement, the result is a little different: it is those who perceive a threat but are in a workplace where colleagues only use AI who tend to report the lowest work engagement. For both job satisfaction and work engagement it is those who are personally using GenAI but see no threat who report the highest well-being.

By contrast, for *digitalization/robotization contributing to changes in employee numbers*, the coefficients are more mixed: there are positive associations with work engagement in some groups (e.g., AI users who are personally involved but report "no" change still show higher engagement; and AI users not involved who report "yes" change show higher engagement, while job satisfaction effects are generally imprecise with one positive exception for personally involved AI users reporting change. This column has fewer observations because only respondents reporting a change in employee numbers were asked this question.

Technology fears have remained stable

Technological fears have remained very stable despite the technological transformation. Table 2 presents responses to the question about whether one's own work contribution might be replaced by technology, based on the 2018 and 2023 Quality of Work Life Surveys.

Table 5: Responses on whether one's own work contribution might be replaced by technology.

	2018	2023
Threat: Own work input replaced with technology		
No	92.1	92.2
Yes	7.9	7.8
Observations	3781	5733

Source: Quality of Work Life Survey 2018 and 2023

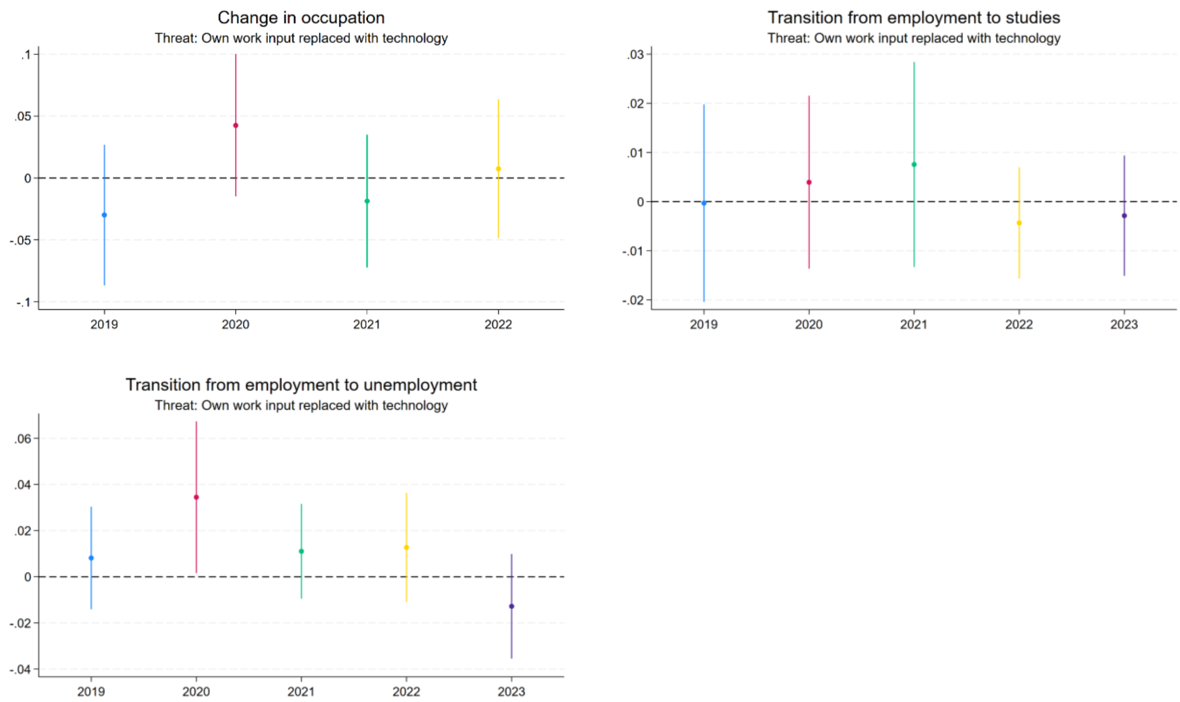
The table shows that the fear of one's work contribution being replaced by technology has remained almost unchanged between 2018 and 2023. Concretely, the share of respondents answering "yes" was 7.9% in 2018 and 7.8% in 2023[8]. This suggests that the acceleration of technological development has not manifested as an increase in workers' fear of being replaced.

Figure 3 follows individuals over time who participated in the 2018 Quality of Work Life Survey. The aim is to determine whether people who feared that their work contribution might be replaced by technology were more likely than others to change occupations, enter education, or become unemployed between 2019 and 2023. The figures present results from a regression model in which the

[8] In the 2023 wave, the answers can be broken down by AI use. The results show that 15.5% of those who use AI in their work experience the threat of their work input being replaced with technology, and the corresponding figures are 13.0% who do not use themselves, but AI is used at their workplace, and 5.4% for those who work in workplaces where AI is not used.

outcomes are occupation change, transition from employment to education, or transition from employment to unemployment. The key explanatory variable is the technology-replacement fear shown in Table 5. The other explanatory variables are the same as in the other analyses, but we also include the persons history of the outcome variable from the years 2010-2017. So, for example, in the regression concerning occupation change, the number of occupation changes in the years 2010-2017 is controlled for. All other explanatory variables are measured in 2018.

Figure 3 Fear of being replaced by technology in 2018 are not reflected in subsequent labour market transitions



Source: Quality of Work Life Survey 2023, the authors' calculations.

Based on Figures 3, technology fears do not appear to lead to exceptional labour market transitions, even though some employees experience uncertainty about the prospect that their work will be replaced by technology. The figures tracking respondents from the 2018 survey in 2019–2023 show that fear of job replacement does not systematically predict occupation changes, transitions from employment to study, or transitions from employment to unemployment. The only exception concerns the COVID19 year 2020 for unemployment. Taken together, the figures indicate that, although concern about technological impacts exists, it does not materialize as a higher likelihood of changes in labour market status; career trajectories appear to progress similarly regardless of a person's initial technology fear.

Robustness checks

The first robustness check considers a richer model for job satisfaction. Here we include additional control variables, which prior research has shown to be important determinants of job satisfaction. These are opportunities for development at work (e.g., Morrison, et al., 2005), social relations in the workplace (e.g. Repetti and Cosmas, 1991), and supervisor support (e.g. Wood, 2008). The opportunity for development at work is measured with a direct question (B40).

Social relations are constructed as a standardized scale based on the following Likert-scale statements: 'In our work community there is an atmosphere where work-related problems and mistakes can be openly addressed,' 'I often feel a sense of community and togetherness in my work,' 'In our work community, supervisors and employees work together in good spirit,' and 'I receive appreciation for my work from other members of the work community or from customers.'

Supervisor support is constructed as a standardized scale based on the following Likert-scale statements: 'My supervisor supports and encourages me,' 'My supervisor communicates openly about workplace matters,' 'My supervisor trusts their employees,' 'My supervisor encourages employees to learn and develop in their work,' 'My supervisor knows my work tasks well enough,' 'My supervisor gives sufficient feedback on how I have performed at work,' 'My supervisor distributes responsibilities to employees in a reasonable way,' and 'My supervisor treats different genders equally.'

Table A 5 in the Appendix shows that the results are a little weaker than in Table 3, but the association between intensive AI use and higher work engagement is still seen.

The second robustness check considers work history of the respondents. We measure work history by the average of work months and earnings in 2010–2022 (long-term measure) and the annual work months and earnings in 2018–2022 (short term measure). These variables are measured using Statistics Finland's FOLK database, which has been linked to the QWLS. Comparison of Table A6 in the Appendix and Table 3 shows that the results are similar whether the work history is controlled for or not.

Table A7 demonstrates that using ordered logit to estimate job satisfaction yields results consistent with Table 3. Marginal effects for the top two outcomes are reported, and comparisons confirm similarity to Table 3.

Conclusion

We use a nationally representative dataset for Finland, which provides a unique institutional environment to assess the relationship. Finland is a high-skill, high-trust environment with highly unionized and structured labour markets and extensive social safety nets. These structural characteristics may function as a buffer, potentially dampening ”technostress” and replacement fears, while fostering organizational environments that prioritize human–AI complementarity over substitution.

We provide one of the first representative, population-level assessments of how AI adoption relates to job satisfaction and technology-related fears. Utilizing the 2023 Quality of Work Life Survey, we find little evidence of a systematic relationship between AI use (or its reported intensity) and job satisfaction once worker, job, and workplace characteristics are accounted for. The positive raw correlations observed in simple models are largely explained by compositional differences in who works in AI-using workplaces and in which jobs AI is deployed. In contrast, we do find a more consistent positive association for work engagement: employees who are personally involved with AI report higher engagement, and the association is strongest among those for whom AI is an essential part of their work.

We also find no evidence of a broad-based increase in technology-related anxiety associated with AI use. Contrary to narratives of a technological revolution, our longitudinal analysis suggests a high degree of stability in employee sentiment. The share of workers fearing technology-driven job loss remained unchanged between 2018 and 2023. Furthermore, tracking respondents from 2018 show that initial technology fears do not systematically predict changes in occupation, transitions to education, or unemployment.

Our findings stand in contrast to previous international evidence, which typically documents either a positive or an inverted U-shaped relationship between AI exposure and satisfaction. We argue that this divergence is driven by two primary factors. First, Finland’s high-trust, high-skill environment may serve as a moderator. Second, self-selected samples such as Glassdoor may inadvertently lead to emphasize either enthusiasts or highly exposed/impacted.

Our findings also speak to a broader debate on technology and work in which AI is often portrayed as either uniformly beneficial or uniformly harmful (Spencer, 2026). Instead, the Finnish evidence suggests a more conditional pattern: AI use as such is not systematically associated with job satisfaction, but direct and especially intensive involvement with AI is linked to higher work engagement. This points to the importance of how AI is embedded in work rather than AI exposure alone.

Overall, these results imply that the effects of AI on Finnish employees are currently muted. As AI becomes more deeply embedded in daily workflows, its implications for job design and worker well-being may evolve.

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Appendix

Table A 1 Summary Statistics

N	5,742
How satisfied are you with your current job?	
Very unsatisfied	66 (1.1%)
Rather unsatisfied	377 (6.6%)
Difficult to say	544 (9.5%)
Quite satisfied	3,266 (56.9%)
Very satisfied	1,486 (25.9%)
Work Engagement (scale)	-0.02 (0.86)
Does your workplace use AI-based technologies?	
Yes, and I am personally involved with it	533 (9.3%)
Yes, but I am not involved with it in my work	1,099 (19.2%)
No	4,080 (71.4%)
AI essential part of work	
Totally true	98 (1.7%)
True to some extent	207 (3.6%)
Untrue to some extent	186 (3.3%)
Totally untrue	42 (0.7%)
I do not use AI	5,178 (90.7%)
Gender	
Male	2,826 (49.2%)
Female	2,917 (50.8%)
Age	
18-24	516 (9.0%)
25-34	1,329 (23.1%)
35-44	1,427 (24.9%)
45-54	1,257 (21.9%)
55-67	1,214 (21.1%)
Occupation	
Managers	155 (2.7%)
Professionals	1,664 (29.0%)
Technicians and associate professionals	1,212 (21.1%)
Clerical support workers	309 (5.4%)
Service and sales workers	1,041 (18.1%)
Skilled agricultural workers	37 (0.6%)
Craft and related trades workers	572 (10.0%)
Plant and machine operators	411 (7.2%)
Elementary occupations	320 (5.6%)
Unknown	20 (0.3%)
Supervisory duties	
No	3,896 (68.1%)
Yes	1,828 (31.9%)
Employment relationship	
Valid until further notice	4,998 (87.3%)
Fixed term	729 (12.7%)

Remote work	
No	3,719 (64.8%)
Yes	2,019 (35.2%)
Level of education	
Upper secondary	2,478 (47.2%)
Post-secondary non-tertiary	116 (2.2%)
Short-cycle tertiary	376 (7.2%)
Bachelor's	1,108 (21.1%)
Master's	1,061 (20.2%)
Doctoral	106 (2.0%)
Field of education	
Generic	431 (8.2%)
Education	141 (2.7%)
Arts and humanities	276 (5.3%)
Social sciences	177 (3.4%)
Business, administration and law	873 (16.7%)
Natural sciences	116 (2.2%)
ICT	311 (5.9%)
Engineering	1,312 (25.0%)
Agriculture	145 (2.8%)
Health and welfare	933 (17.8%)
Services	528 (10.1%)
Self-assessed health	
Good	1,815 (32.0%)
Fairly good	2,496 (44.0%)
Average	1,134 (20.0%)
Quite poor	192 (3.4%)
Poor	30 (0.5%)

Note. Table shows frequencies (percentages) for categorical variables and mean and standard deviation for continuous variables. Source: Quality of Work Life Survey 2023.

Table A 2 AI use and Employee Well-Being, with control variables, full table

	Job satisfaction				Work Engagement			
Does your workplace use AI-based technologies?								
Yes, and I am personally involved with it	0.053				0.103	**		
	(0.045)				(0.043)			
Yes, but I am not involved with it in my work	0.026				0.036			
	(0.031)				(0.031)			
AI essential part of work								
Totally true			0.138	*			0.311	***
			(0.081)				(0.093)	
True to some extent			0.022				0.084	
			(0.068)				(0.058)	
Untrue to some extent			-0.000				0.001	
			(0.064)				(0.059)	
Totally untrue			0.146				0.075	
			(0.141)				(0.162)	
Gender								
Female	-0.019		-0.019		0.041		0.041	
	(0.031)		(0.031)		(0.031)		(0.031)	
Age								
25-34	-0.022		-0.019		0.002		0.007	
	(0.065)		(0.065)		(0.067)		(0.067)	
35-44	0.061		0.062		0.094		0.098	
	(0.064)		(0.064)		(0.065)		(0.065)	
45-54	0.108	*	0.112	*	0.136	**	0.143	**
	(0.064)		(0.064)		(0.065)		(0.065)	
55-67	0.161	**	0.164	**	0.130	**	0.136	**
	(0.064)		(0.064)		(0.065)		(0.065)	
Occupation								
Professionals	-0.106	*	-0.108	*	-0.138	**	-0.140	**
	(0.063)		(0.063)		(0.056)		(0.056)	
Technicians and associate professionals	-0.172	**	-0.174	**	-0.187	***	-0.189	***
	(0.068)		(0.068)		(0.062)		(0.062)	
Clerical support workers	-0.236	***	-0.237	***	-0.291	***	-0.294	***
	(0.088)		(0.088)		(0.083)		(0.083)	
Service and sales workers	-0.172	**	-0.175	**	-0.203	***	-0.210	***
	(0.078)		(0.078)		(0.073)		(0.073)	
Skilled agricultural workers	-0.289		-0.300		-0.243		-0.251	
	(0.192)		(0.192)		(0.213)		(0.213)	
Craft and related trades workers	-0.166	*	-0.170	**	-0.205	**	-0.213	***
	(0.086)		(0.085)		(0.082)		(0.082)	
Plant and machine operators	-0.226	**	-0.231	**	-0.450	***	-0.460	***
	(0.096)		(0.096)		(0.089)		(0.089)	

Elementary occupations	-0.230	**	-0.236	**	-0.330	***	-0.339	***
	(0.101)		(0.100)		(0.100)		(0.100)	
Unknown	0.049		0.052		0.021		0.027	
	(0.185)		(0.186)		(0.182)		(0.183)	
Supervisory duties								
Yes	0.042		0.041		0.108	***	0.107	***
	(0.027)		(0.027)		(0.026)		(0.026)	
Employment relationship								
Fixed term	0.060		0.060		0.127	***	0.127	***
	(0.041)		(0.041)		(0.040)		(0.040)	
Remote work								
Yes	0.070	**	0.074	**	0.063	*	0.068	**
	(0.032)		(0.032)		(0.033)		(0.032)	
Level of education								
Post-secondary non-tertiary	0.106		0.104		0.066		0.062	
	(0.082)		(0.082)		(0.087)		(0.086)	
Short-cycle tertiary	-0.079	*	-0.079	*	-0.038		-0.038	
	(0.047)		(0.047)		(0.046)		(0.046)	
Bachelor's	-0.113	***	-0.111	***	-0.111	***	-0.111	***
	(0.040)		(0.040)		(0.041)		(0.041)	
Master's	-0.172	***	-0.169	***	-0.150	***	-0.148	***
	(0.046)		(0.047)		(0.047)		(0.047)	
Doctoral	-0.135		-0.133		-0.174	**	-0.177	**
	(0.089)		(0.089)		(0.079)		(0.078)	
Field of education								
Education	0.175	*	0.170	*	0.269	***	0.263	***
	(0.093)		(0.093)		(0.093)		(0.093)	
Services	0.124		0.122		0.133	*	0.129	*
	(0.076)		(0.076)		(0.077)		(0.077)	
Arts and humanities	0.029		0.029		0.048		0.050	
	(0.086)		(0.086)		(0.084)		(0.084)	
Social sciences	0.161	*	0.160	*	0.181	**	0.180	**
	(0.088)		(0.088)		(0.090)		(0.090)	
Business, administration and law	0.127	*	0.125	*	0.091		0.090	
	(0.067)		(0.067)		(0.067)		(0.067)	
Natural sciences	0.264	***	0.264	***	0.228	***	0.228	***
	(0.094)		(0.094)		(0.088)		(0.088)	
ICT	0.151	*	0.148	*	0.177	**	0.172	**
	(0.084)		(0.083)		(0.077)		(0.077)	
Engineering	0.087		0.085		0.096		0.092	
	(0.065)		(0.065)		(0.065)		(0.066)	
Agriculture	0.171	*	0.167		0.155		0.148	
	(0.104)		(0.104)		(0.097)		(0.097)	
Health and welfare	0.175	**	0.175	**	0.191	**	0.191	**
	(0.074)		(0.074)		(0.076)		(0.076)	
Unknown	1.008	***	0.970	***	0.553		0.557	
	(0.271)		(0.300)		(0.450)		(0.444)	
Self-assessed health								

Fairly good	-0.203	***	-0.202	***	-0.302	***	-0.299	***
	(0.027)		(0.027)		(0.026)		(0.027)	
Average	-0.540	***	-0.540	***	-0.701	***	-0.700	***
	(0.037)		(0.037)		(0.036)		(0.036)	
Quite poor	-0.840	***	-0.840	***	-1.023	***	-1.019	***
	(0.092)		(0.092)		(0.090)		(0.090)	
Poor	-0.811	***	-0.814	***	-1.418	***	-1.424	***
	(0.256)		(0.256)		(0.238)		(0.238)	
Number of observations	5369		5369		5371		5371	

*** p<.01, ** p<.05, * p<.1

Table shows coefficients and robust standard errors from OLS estimation. Additional control variables not shown in the table are industry, geographical area and employer's sector. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table A 3 AI use intensity and technology-related fears, full table

	Fear of not learning to use new technology well enough		Digitalization or robotization have contributed to the change in the number of employees		Threat of work input becoming replaced with technology in the near future	
AI essential part of work						
Totally true	0.007		0.124	**	0.060	
	(0.044)		(0.050)		(0.043)	
True to some extent	-0.003		0.039		0.064	**
	(0.028)		(0.025)		(0.029)	
Untrue to some extent	0.000		0.041		0.031	
	(0.029)		(0.028)		(0.026)	
Totally untrue	-0.085	**	-0.004		0.009	
	(0.035)		(0.031)		(0.049)	
Gender						
Female	0.040	***	-0.004		0.003	
	(0.012)		(0.010)		(0.010)	
Age						
25-34	0.011		0.042	***	0.016	
	(0.021)		(0.012)		(0.019)	
35-44	0.050	**	0.041	***	0.010	
	(0.021)		(0.013)		(0.018)	
45-54	0.108	***	0.047	***	0.001	
	(0.022)		(0.013)		(0.018)	
55-67	0.161	***	0.034	***	-0.010	
	(0.022)		(0.013)		(0.018)	
Occupation						
Professionals	0.040		0.015		0.050	***
	(0.027)		(0.026)		(0.016)	
Technicians and associate professionals	0.038		0.013		0.057	***
	(0.029)		(0.029)		(0.018)	
Clerical support workers	0.036		0.041		0.122	***
	(0.036)		(0.038)		(0.030)	
Service and sales workers	0.029		0.024		0.031	
	(0.033)		(0.033)		(0.021)	
Skilled agricultural workers	0.069		0.063		0.105	*
	(0.091)		(0.095)		(0.057)	
Craft and related trades workers	0.027		-0.007		0.013	
	(0.037)		(0.035)		(0.023)	
Plant and machine operators	0.013		0.018		0.014	
	(0.039)		(0.040)		(0.022)	
Elementary occupations	0.006		0.029		0.032	
	(0.038)		(0.041)		(0.027)	

Unknown	-0.081		0.081		0.094	
	(0.055)		(0.106)		(0.089)	
Supervisory duties						
Yes	-0.010		-0.015	*	-0.029	***
	(0.011)		(0.009)		(0.008)	
Employment relationship						
Fixed term	-0.023		-0.016		0.002	
	(0.016)		(0.010)		(0.013)	
Remote work						
Yes	0.007		-0.004		0.036	***
	(0.014)		(0.011)		(0.011)	
Level of education						
Post-secondary non-tertiary	-0.053		-0.009		-0.044	**
	(0.035)		(0.021)		(0.019)	
Short-cycle tertiary	0.055	**	0.040	**	0.020	
	(0.024)		(0.020)		(0.017)	
Bachelor's	0.034	**	0.005		-0.006	
	(0.016)		(0.014)		(0.015)	
Master's	0.016		0.019		-0.019	
	(0.020)		(0.019)		(0.017)	
Doctoral	-0.025		-0.033		-0.007	
	(0.037)		(0.020)		(0.033)	
Field of education						
Education	-0.045		-0.007		-0.036	
	(0.038)		(0.031)		(0.026)	
Services	-0.021		-0.045	**	-0.016	
	(0.025)		(0.021)		(0.021)	
Arts and humanities	0.019		-0.029		0.038	
	(0.031)		(0.024)		(0.029)	
Social sciences	0.001		0.037		0.010	
	(0.035)		(0.041)		(0.030)	
Business, administration and law	-0.031		-0.005		0.040	*
	(0.024)		(0.024)		(0.023)	
Natural sciences	0.010		-0.036		-0.049	*
	(0.042)		(0.028)		(0.028)	
ICT	0.043		-0.037		0.012	
	(0.032)		(0.026)		(0.028)	
Engineering	-0.004		-0.013		-0.021	
	(0.022)		(0.021)		(0.020)	
Agriculture	-0.017		0.014		-0.042	*
	(0.037)		(0.037)		(0.025)	
Health and welfare	-0.006		-0.018		-0.036	
	(0.027)		(0.024)		(0.022)	
Unknown	-0.134	***			-0.077	
	(0.044)				(0.053)	
Self-assessed health						
Fairly good	0.050	***	-0.004		0.028	***
	(0.011)		(0.010)		(0.008)	

Average	0.111	***	-0.009		0.044	***
	(0.015)		(0.012)		(0.012)	
Quite poor	0.165	***	0.016		0.052	**
	(0.034)		(0.023)		(0.026)	
Poor	0.280	**	-0.027	*	0.167	*
	(0.117)		(0.014)		(0.090)	
Number of observations	5334		2378		5365	

*** p<.01, ** p<.05, * p<.1

Table shows coefficients and robust standard errors from OLS estimation. All columns include the following control variables: gender, age, occupation, supervisory duties, fixed-term employment relationship, remote work, level of education, field of education, self-assessed health status, industry, geographical area and employer's sector. Full estimation results are shown in Table A2. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table A 4 AI and Employee Welk-Being: Interactions with Technology Fear Variables

	Job satisfaction		Work engagement	
Does your workplace use AI-based technologies? # Fear of not learning to use new technology well enough				
Yes, and I am personally involved with it # No	0.058		0.116 **	
	(0.049)		(0.046)	
Yes, and I am personally involved with it # Yes	-0.097		-0.087	
	(0.094)		(0.092)	
Yes, but I am not involved with it in my work # No	0.027		0.038	
	(0.034)		(0.035)	
Yes, but I am not involved with it in my work # Yes	-0.069		-0.082	
	(0.060)		(0.053)	
No # Yes	-0.119 ***		-0.153 ***	
	(0.040)		(0.038)	
Does your workplace use AI-based technologies? # Threat of work input becoming replaced with technology in the near future				
Yes, and I am personally involved with it # No		0.083 *		0.138 ***
		(0.046)		(0.046)
Yes, and I am personally involved with it # Yes		-0.203 *		-0.121
		(0.114)		(0.081)
Yes, but I am not involved with it in my work # No		0.045		0.060 *
		(0.032)		(0.032)
Yes, but I am not involved with it in my work # Yes		-0.242 ***		-0.189 **
		(0.085)		(0.075)
No # Yes		-0.175 **		-0.078
		(0.071)		(0.070)
Does your workplace use AI-based technologies? # Digitalization or robotization have contributed to the change in the number of employees				

Yes, and I am personally involved with it # No			0.044			0.154 **
			(0.071)			(0.066)
Yes, and I am personally involved with it # Yes			0.290 **			0.041
			(0.131)			(0.170)
Yes, but I am not involved with it in my work # No			0.077			0.048
			(0.048)			(0.047)
Yes, but I am not involved with it in my work # Yes			-0.049			0.301 **
			(0.157)			(0.128)
No # Yes			-0.151			0.028
			(0.185)			(0.165)
Number of observations	5331	5362	2377	5334	5365	2378

*** p<.01, ** p<.05, * p<.1

Table shows coefficients and robust standard errors from OLS estimation. Additional control variables not shown in the table are industry, geographical area and employer's sector. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table A 5 AI use and Employee Well-Being, with work controls for development possibilities, social relations, and supervisor support

	Job satisfaction		Work Engagement		
Does your workplace use AI-based technologies?					
Yes, and I am personally involved with it	-0.040		-0.002		
	(0.038)		(0.037)		
Yes, but I am not involved with it in my work	0.016		-0.010		
	(0.027)		(0.027)		
AI essential part of work					
Totally true		0.015		0.163	**
		(0.063)		(0.080)	
True to some extent		-0.056		0.005	
		(0.056)		(0.049)	
Untrue to some extent		-0.055		-0.063	
		(0.055)		(0.052)	
Totally untrue		0.062		-0.024	
		(0.132)		(0.139)	
Number of observations	5293	5293	5296	5296	

*** p<.01, ** p<.05, * p<.1

Table shows coefficients and robust standard errors from OLS estimation. These models contain controls for development at work, social relations in the workplace, and supervisor support. All columns include the following control variables: gender, age, occupation, supervisory duties, fixed-term employment relationship, remote work, level of education, field of education, self-assessed health status, industry, geographical area and employer's sector. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".

Table A 6 AI use and Employee Well-Being, with work history controls

	Job satisfaction		Work Engagement	
Does your workplace use AI-based technologies?				
Yes, and I am personally involved with it	0.048		0.084 *	
	(0.046)		(0.043)	
Yes, but I am not involved with it in my work	0.041		0.033	
	(0.031)		(0.031)	
AI essential part of work				
Totally true		0.151		0.286 ***
		(0.093)		(0.093)
True to some extent		0.033		0.073
		(0.066)		(0.061)
Untrue to some extent		-0.019		0.008
		(0.067)		(0.059)
Totally untrue		0.052		-0.004
		(0.128)		(0.155)
Number of observations	4842	4842	4844	4844

*** p<.01, ** p<.05, * p<.1

Table shows coefficients and robust standard errors from OLS estimation. These models contain controls for work history. Longer-term work history is measured as average work months and taxable earnings per year in 2010-2022. Short-term work history is measured by the number of work months and taxable earnings in the years 2018-2022. All columns include the following control variables: gender, age, occupation, supervisory duties, fixed-term employment relationship, remote work, level of education, field of education, self-assessed health status, industry, geographical area and employer's sector. Full estimation results are shown in Table A1. Job satisfaction in measured as the answer to the question "How satisfied are you with your current job?" with answer possibilities 5 "Very satisfied" 4 "Quite satisfied" 3" Difficult to say" 2 "Rather unsatisfied" 1 "Very unsatisfied". The measure of work engagement is similar to the measure used by Hakanen et al. (2021) and it measures work engagement using three items measured on a 4-point scale (totally true to totally untrue), the items being "I am enthusiastic about my work"," I feel happy when I am deep in my work", and "At my job, I feel strong and vigorous".