ETLA Working Papers | 135 27.1.2026

AI Has Not Impacted the Youth Labor Market in Finland

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Suggested citation:
Kauhanen, Antti & Rouvinen, Petri (27.1.2026). "AI Has Not Impacted the Youth Labor Market in Finland". ETLA Working Papers No 135. https://pub.etla.fi/ETLA-Working-Papers-135.pdf

Abstract

We examine the impact of generative AI on the youth labor market in Finland by replicating the key analyses of Brynjolfsson et al. (2025) with comprehensive population-level data. Contrary to the US findings, we find no systematic displacement effects linked to AI exposure among youth in Finland. Employment trends reflect demographic shifts rather than AI-driven changes, with early career groups showing modest declines and senior workers experiencing growth. Wage trajectories show no persistent differences across AI exposure levels. These results suggest that Finland's labor market is resilient to immediate AI-induced disruptions in entry-level roles, likely because of structural and policy factors.

Tiivistelmä

Tekoäly ei ole vaikuttanut nuorten työmarkkina-asemaan Suomessa

Tutkimme generatiivisen tekoälyn vaikutusta nuorten työmarkkinoihin Suomessa toistamalla Brynjolfssonin ym. (2025) Yhdysvaltoja koskevat keskeiset analyysit kattavilla koko väestöä koskevilla aineistoilla. Yhdysvaltojen tuloksista poiketen emme Suomessa havaitse systemaattisia tekoälyaltistukseen liittyviä syrjäyttämisvaikutuksia nuorten työntekijöiden keskuudessa. Eri ikäryhmien työllisyyskehitys poikkeaa toisistaan, mutta erot eivät selity altistumisella tekoälylle: uran alkuvaiheen ryhmien työllisyyskehitys osoittaa vain lievää laskua, kun taas vanhemmilla työntekijöillä työllisyys on kasvanut. Palkkakehityksessä ei ole eroja tekoälyaltistumisen suhteen. Tulokset viittaavat siihen, että Suomen työmarkkinoilla tekoäly ei ole vaikuttanut työllisyyteen työuran alkuvaiheen tehtävissä; ero Yhdysvaltoihin selittynee rakenteellisilla ja institutionaalisilla tekijöillä.

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KTT **Antti Kauhanen** on Elinkeinoelämän tutkimuslaitoksen tutkimusjohtaja ja työelämäprofessori Aalto-yliopistossa.

Ph.D. (Econ.) **Petri Rouvinen** on Elinkeinoelämän tutkimuslaitoksen tutkimusneuvonantaja ja Suomen itsenäisyyden juhlarahaston Sitran vanhempi neuvonantaja.

Acknowledgements: This working paper is part of Etla's Cartagena project kindly supported by Business Finland. The authors are grateful to Pekka Vanhala for research assistance.

Artificial intelligence has been used to support human work in the production of this working paper in accordance with Etla's ethical guidelines (version 26.1.2026, see https://www.etla.fi/en/ai-ethics/).

Kiitokset: Työpaperi on osa Business Finlandin tukemaa Cartagena-hanketta. Kiitämme Pekka Vanhalaa tutkimusavusta.

Tämän työpaperin työstämisessä on hyödynnetty tekoälyä ihmistyön tukena Etlan eettisen ohjeiston mukaisesti (versio 26.1.2026, ks. https://www.etla.fi/ai-etiikka).

Keywords: Generative artificial intelligence, Technological change, Employment, Wages, Occupations

Asiasanat: Generatiivinen tekoäly, Teknologinen muutos, Työllisyys, Palkat, Ammatit

JEL: E24, J21, O33

Introduction

Many recent empirical studies have shown that generative AI affects disproportionately entry-level work (Brynjolfsson et al. 2025, Klein Teeselink 2025, Lichtinger and Hosseini Maasoum 2025, Liu et al. 2025) and these findings have also attracted a lot of interest among general public.

A key study in this vein is Brynjolfsson et al. (2025), which analyzes high-frequency ADP payroll data and finds that early career workers (ages 22-25) in AI-exposed occupations experienced a 16% relative employment decline since late 2022 (i.e., since the launch of ChatGPT), while experienced workers remained unaffected. These effects are driven by applications where AI *automates* rather than *augments* labor.

Storm et al. (2025) find that in Germany, while there are no meaningful displacement effects on average, there is notable skill heterogeneity: "expert" workers with deep domain knowledge realize gains, while "non-experts" (often including juniors) face higher displacement risk.

Other studies focus on firm-level outcomes instead of occupation-level outcomes. Klein Teeselink (2025) shows that a one standard deviation increase in LLM exposure is associated with a 0.4% reduction in junior positions, whereas senior roles show negligible changes. Highly exposed firms significantly reduced technical and creative job listings.

Lichtinger and Hosseini Maasoum (2025) identify GenAI-adopting firms through "integrator" job postings. They find that adoption leads to a 9-10% decline in junior employment relative to non-adopting firms, while senior employment remains unchanged. This decline is driven by slower hiring rather than layoffs, suggesting that firms are preemptively closing the bottom rungs of the career ladder.

There is evidence that generative AI affects not only the hiring patterns of firms but also the job search patterns of young employees. Goller et al. (2025) utilize a difference-in-discontinuity approach to examine the Swiss apprenticeship market following the launch of ChatGPT. They find a substantial decline in the intensity of vacancy searches among young people, particularly for occupations requiring high cognitive and language skills. While the total number of signed contracts did not immediately fall, the quality of the applicant pool decreased for highly exposed roles, such as commercial employees. This suggests that high-ability youth proactively avoid career paths perceived as being vulnerable to AI-driven automation.

In addition to empirical evidence, there are also good theoretical grounds to expect larger impacts of generative AI on entry-level positions compared to more senior positions. Ide (2025) develops a theoretical model focusing on the transmission of tacit knowledge—the practical, experiential skills critical for professional success. The paper argues that, as AI enables senior workers to perform tasks independently, it reduces the demand for "novice" labor, thereby eroding the entry-level opportunities necessary for the next generation to acquire expertise. This disruption creates an intergenerational trade-off: short-run productivity gains for seniors are achieved at the cost of slower long-run growth owing to a less-skilled future workforce.

However, not all studies find that young or entry-level workers are more affected by generative AI. Humlum and Vestergaard (2025) provide a rigorous empirical counter-narrative to claims of imminent AI-driven disruption in the youth labor market by analyzing representative adoption data linked to comprehensive administrative records in Denmark. They focus on 11 occupations that are highly exposed to generative AI. Utilizing a difference-in-differences framework, they estimate precise null effects on earnings and hours worked for early career positions during the two years following the launch of ChatGPT. While this study replicates the aggregate decline in early career employment within AI-exposed occupations documented by Brynjolfsson et al. (2025), the authors' analysis shows that this downward trend is **not** driven by the actual adoption of AI chatbots at the workplace level.

Given the diverging results in the literature, we replicate the key analyses of Brynjolfsson et al. (2025) using population-level data from Finland. Similarly, we use high-frequency wage data and AI exposure indices developed by Eloundou et al. (2024) and Handa et al. (2025) and follow their analyses as closely as possible.

Our key difference to Brynjolfsson et al. (2025) is that we use **population-level** data concerning **Finland**, whereas they use payroll data covering only a part of the US economy.

Data

The main dataset used in this study is the Incomes Register at Statistics Finland, a national database maintained by the Finnish Tax Authority. It contains information on wages, pensions, and benefits. Information on wages is available as of January 2019. Owing to their nature, these data are accurate, reliable, and essentially complete. The data are released for research purposes at a monthly frequency, and the final data point used in this study is September 2025. To maintain comparability with Brynjolfsson et al. (2025), we focus only on private sector employers.

The data contain occupation codes at the four-digit level. The occupational classification TK-10 is a national version of the ISCO classification. We match these data with the AI exposure measures of Eloundou et al. (2024) and Handa et al. (2025). Below, we summarize these exposure measures and how we map the occupational classification used in these measures to the Finnish data.

The AI exposure index developed by Eloundou et al. (2024) provides a structured way to estimate how large language models (LLMs) might affect work tasks and occupations. It uses O*NET task data and defines exposure as the ability of an LLM or LLM-powered system to reduce task completion time by at least 50% while maintaining comparable quality. This index distinguishes between tasks exposed through LLMs alone (E1) and those requiring additional domain-specific software (E2). Three composite measures are reported: E1 (LLMs only), E1 + 0.5×E2 (partial integration of complementary tools), and E1 + E2 (full integration). As Brynjolfsson et al. (2025), we use the partial integration measure rated by GPT-4. To map the Eloundou et al. (2024) measure to the TK-10 classification, we converted the data defined for the US Standard Occupational Classification (SOC) to the International Standard Classification of Occupations (ISCO-08 – with virtually one-to-one correspondence to TK-10). In the US data provided by Eloundou et al. (2024), there are 923 SOC occupations. The number of occupations drops to 410 with mapping to the Finnish classification. Nevertheless, our data covers practically all Finnish workers (99.3%) with a valid occupation code at the 4-digit level in Finland in 2021. On average, the data using this exposure measure contains 1.29 million people per month.

The AI exposure index developed by Handa et al. (2025) introduces a framework for mapping real-world AI usage to occupational tasks using the O*NET database. Instead of theoretically predicting exposure, the index measures actual adoption by analyzing millions of Claude.ai conversations and classifying them into task categories. Tasks are linked to occupations, enabling aggregation at the occupational level. The index also distinguishes between automation (AI performing tasks with minimal human input) and augmentation (AI assisting humans collaboratively). In the Handa et al. (2025) classification, there were 749 O*NET-SOC occupation codes. We converted the data to the ISCO-08 classification in three steps: 1) O*NET 2019 to SOC 2018, 2) SOC 2018 to SOC 2010, and 3) SOC 2010 to ISCO-08. The number of occupations drops to 296 after mapping to the ISCO-08 classification, but our data nevertheless covers 79.2% of Finnish workers with a valid occupation code at the 4-digit level in 2021. On average, the data using this exposure contains 1.07 million people per month. The difference in the number of observations compared to Eloundou et al. (2024) is due to the lower coverage of occupations.

The key difference between the two measures is that Eloundou et al. (2024) estimate *the potential capability* of LLMs to affect tasks under ideal conditions, producing exposure scores for all occupations—even those not yet using AI—while Handa et al. (2025) measure *actual usage* in practice, revealing where AI is currently integrated and how (automation vs. augmentation).

Results

Use of AI in Finland

Table 1 shows that in Finland in 2024, 20% of the employed had used generative AI at work, and this number has risen to 37% in 2025. In the whole population, including those not in employment, the use of generative AI has increased from 23% of respondents to 41% from 2024 to 2025. Men use generative AI more than women do, although the difference has diminished since 2024. Employed persons are more likely than average respondents to use generative AI.

Table 1 Adoption of Generative AI in Finland: Share of respondents using AI tools in the past three months by employment status and gender.

	Employed, work use	Employed, all use	Male	Female	Overall
2024	20	29	28	19	23
2025	37	53	43	39	41

Source: Suomen virallinen tilasto (SVT) (2025)

The numbers for work use for the employed are similar to those reported for other countries. A large-scale US survey from mid-2025 indicates that LLM adoption at work among adults reached 46% but fell to 36% by December 2025 (Hartley et al. 2025). Another survey shows that in late 2024, approximately 40% of the US population between ages 18 and 64 reported using generative AI, with 23% using it for work weekly and 9% using it daily (Bick et al. 2024). For Germany, survey evidence suggests that 45% to 62% of German workers use AI tools (Arntz et al. 2025), and for Denmark, Humlum and Vestergaard (2025) report that approximately 40% of workers have used chatbots for work in the absence of employer initiatives, while 6% use them daily. In workplaces where use is explicitly encouraged, adoption rates in Denmark rise to 75%, with daily use increasing to 11%.

Overall employment pattern

Understanding the overall employment trend is essential for interpreting subsequent figures regarding career stage and AI exposure. A long-run view provides the baseline context against which any post-2022 changes can be assessed. Without this perspective, short-term fluctuations might be misattributed to technological factors rather than broader economic cycles or demographic shifts. By first examining aggregate employment dynamics, we can distinguish structural patterns, such as recovery from economic downturns or aging workforce effects from AI-related disruptions. This foundation ensures that later analyses of headcounts and wage trajectories by exposure level are interpreted within the correct macroeconomic and labor market context. In all the following figures, a vertical line shows October 2022, depicting the last month before the launch of ChatGPT. All figures end in September 2025.

Figure 1 illustrates the overall employment patterns in the Finnish Labor Force Survey over time, showing a relatively stable upward trend in employment rates with minor cyclical fluctuations. It can be seen from the figure that employment has gradually increased from around 69–70% in the early 2010s to approximately 76–78% by 2025, despite temporary dips during economic downturns and the COVID-19 period.

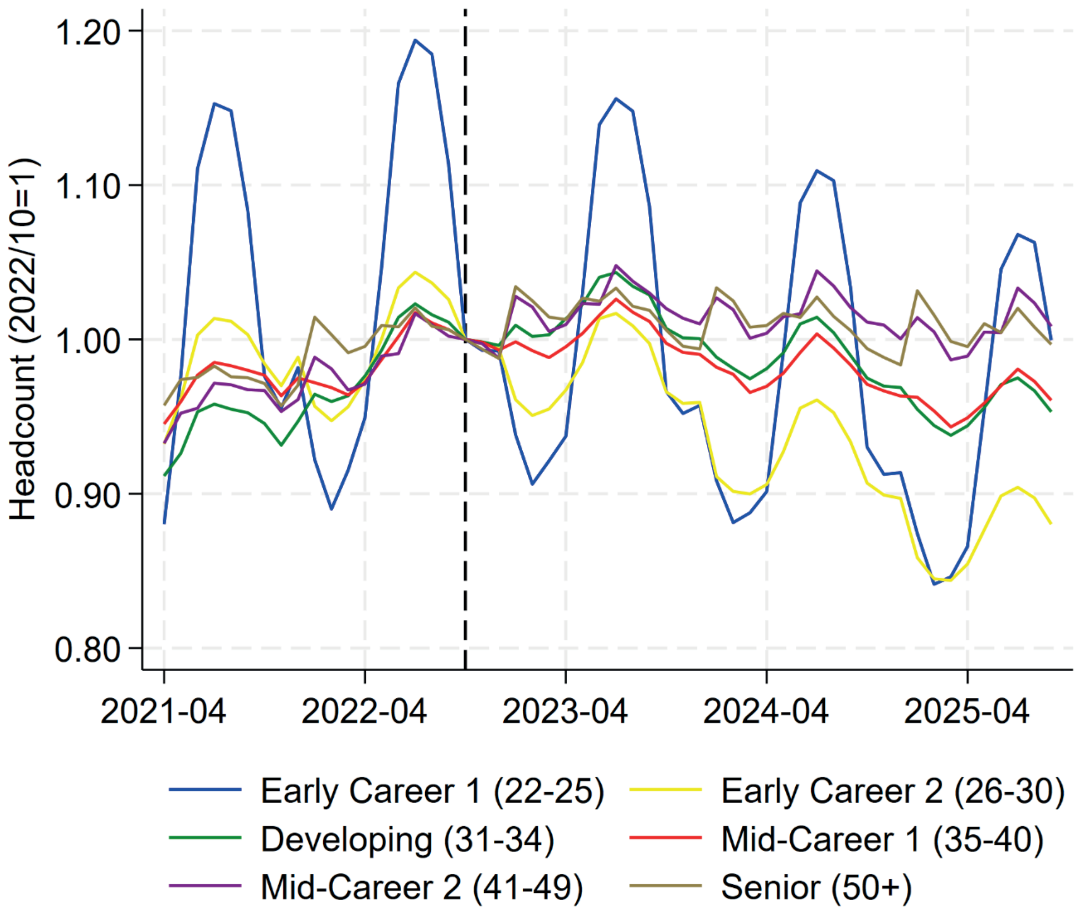
Figure 1 Monthly Employment Rate in Finland: Long-run trends and cyclical fluctuations based on Labor Force Survey data.

Source: Statistics Finland, Labor Force Survey. Employment rate for 20-64-year-olds.

Figure 2 shows headcount trends across career stages from April 2021 to September 2025, indexed to October 2022 as the baseline, using the Incomes registry data. Early career groups (ages 22–30; as compared to Brynjolfsson et al., 2025, at times we set the upper bound to 30 rather than 25, as Finns tend to be older upon entering the labor market after graduation[i]) experienced a modest decline after 2022, stabilizing below the baseline by 2025, indicating a slight contraction among younger cohorts. This is most notable for 26-to 30-year-olds. The developing stage (31–34) remained largely unchanged, while mid-career groups (35–49) saw slight growth, trending above the baseline. The most notable increase occurred among senior employees (50+ years), whose headcount rose significantly, reaching nearly 20% above baseline by 2025.

Overall, the data suggest a demographic shift toward older and mid-career workers, with early career representation declining slightly over the period. We want to understand whether this decline is linked to exposure to generative AI.

Figure 2 Headcount Trends by Career Stage: Early career cohorts decline slightly post-2022, while senior workers show sustained growth.

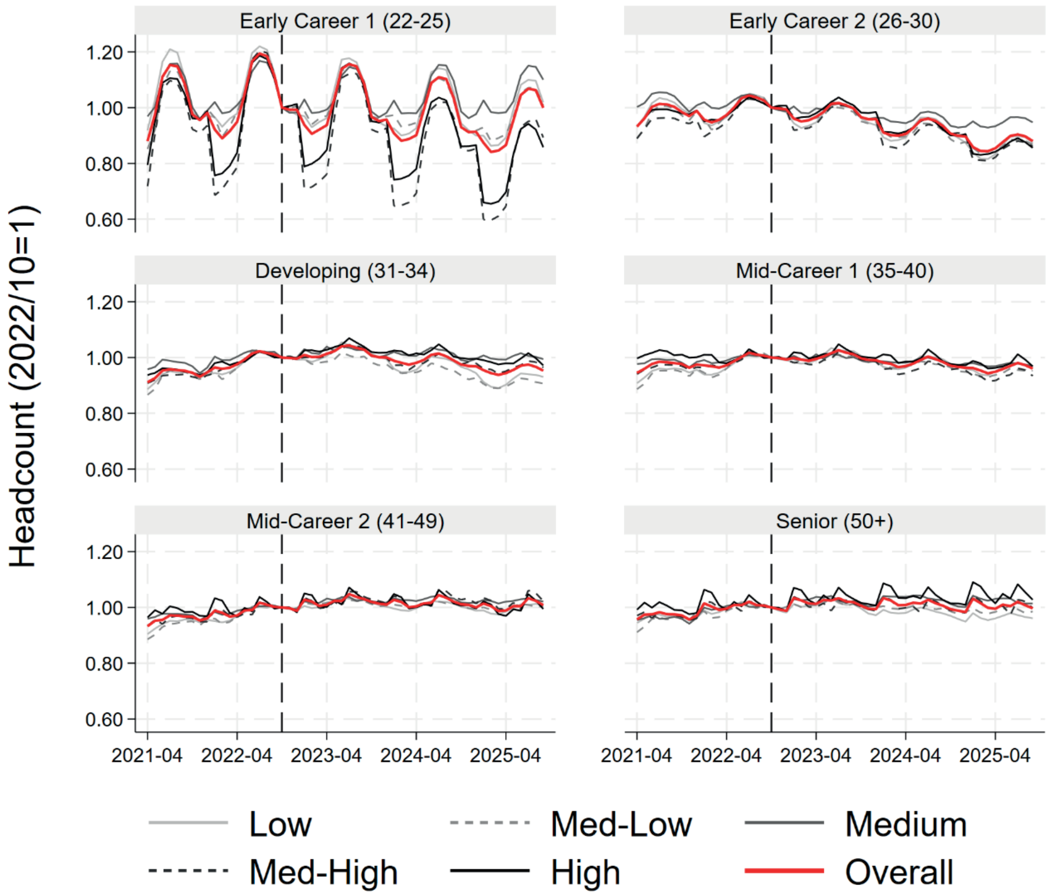


Source: The authors' calculations. October 2022 indexed to 1.00.

AI Exposure and employment

The following figures plot headcounts (October 2022, indexed to 1.00) by career stage and AI exposure. Figure 3 uses the exposure measure of Eloundou et al. (2024). If exposure to AI drives the decline in early career employment, we should see stronger declines in more highly exposed occupations. In the figures, occupations are classified into exposure quantiles (Low, Medium-Low, Medium, Medium-High, and High).

Figure 3 Employment Dynamics by Career Stage and AI Exposure (Eloundou et al. index): Headcount trajectories remain broadly similar across exposure bands.

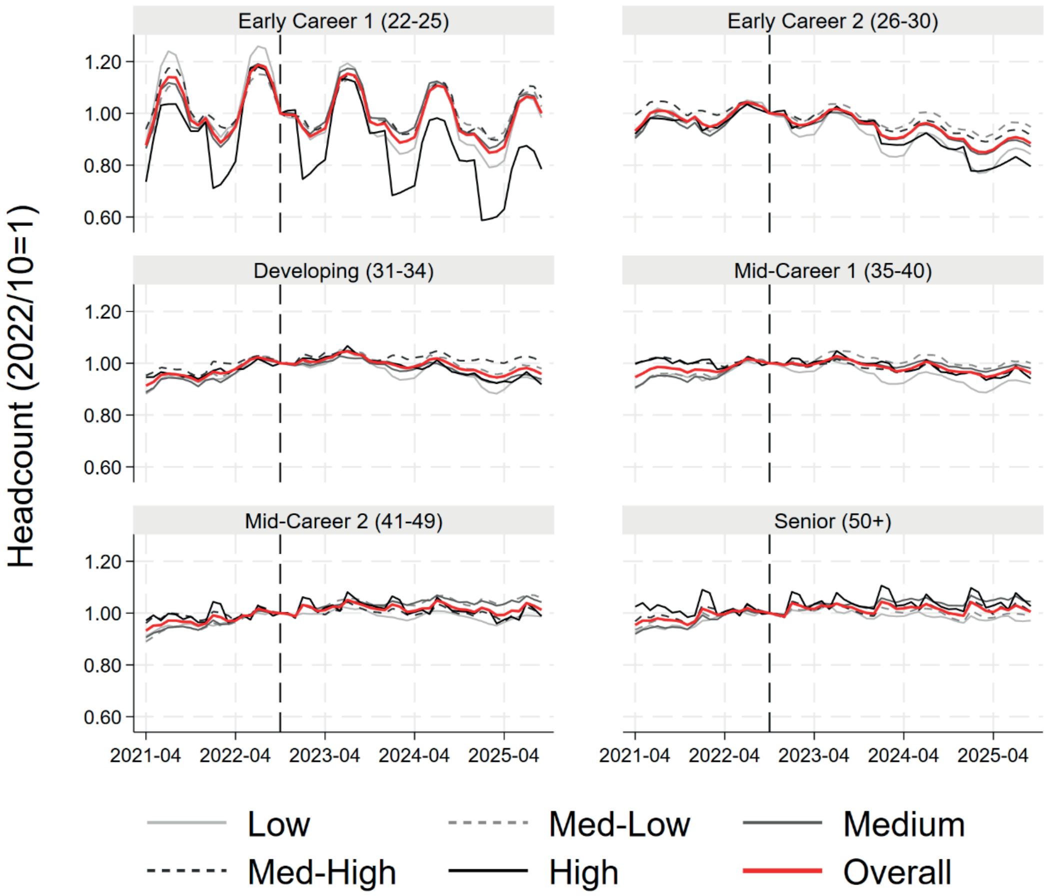


Source: The authors' calculations. October 2022 indexed to 1.00.

In Figure 3, early career workers show the weakest dynamics: ages 22–25 display pronounced seasonality around the baseline, while ages 26–30 trend slightly downward after 2023. Developing (31–34) and midcareer groups (35–49) remain broadly stable, with a mild uptick toward the end of the period, and seniors (50+) rise modestly above the baseline. Across all panels, the AI exposure bands (low to high) largely co-move with small gaps and no persistent divergence, indicating that changes in headcount are driven more by career stage than by differential AI exposure. For example, the employment of 26–30-year-olds declined similarly in the high- and low-exposure groups.

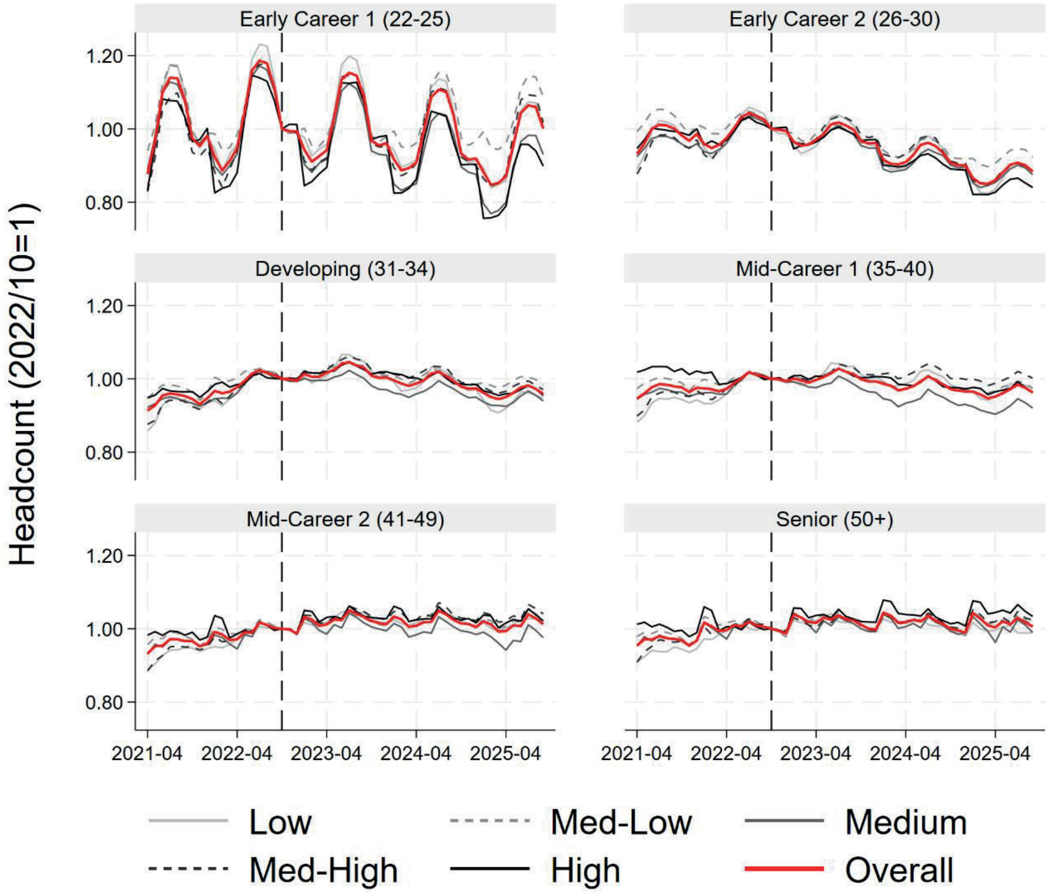
Figure 4–6 show a similar analysis using the Handa et al. (2025) "Claude" exposure classification. Figure 4 uses the overall index, whereas Figures 5 and 6 use the automation and augmentation indices, respectively.

Figure 4 Headcount Trends by Career Stage under Alternative AI Exposure Measures (the Claude Index, Overall): No systematic divergence by exposure intensity.



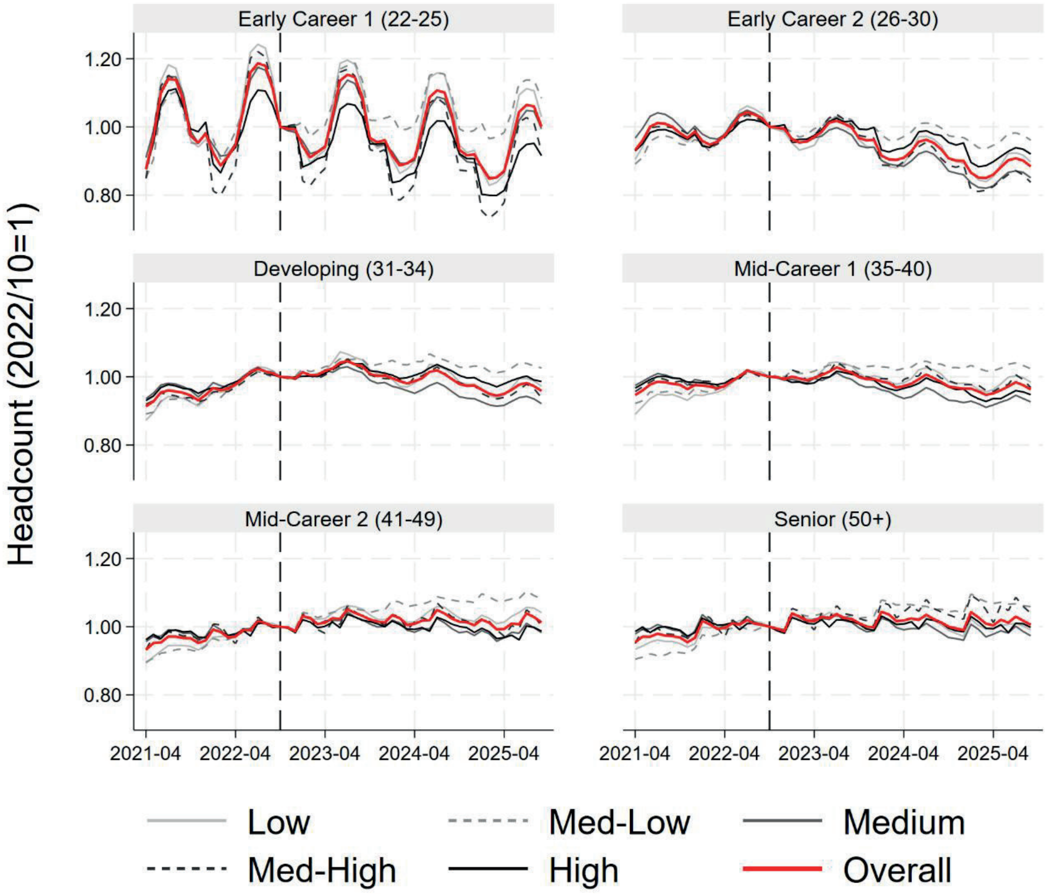
Source: The authors' calculations. October 2022 indexed to 1.00.

Figure 5 Headcount Trends by Career Stage under Alternative AI Exposure Measures (the Claude Index, Automation): No systematic divergence by exposure intensity.



Source: The authors' calculations. October 2022 indexed to 1.00.

Figure 6 Headcount Trends by Career Stage under Alternative AI Exposure Measures (the Claude Index, Augmentation): No systematic divergence by exposure intensity.



Source: The authors' calculations. October 2022 indexed to 1.00.

Across all three "Claude" AI exposure measures—overall, automation, and augmentation—the headcount trajectories are driven more by career stage than by exposure intensity: early career groups (22–30) dip or hover around the baseline after 2022 (with the 22–25 cohort showing notable seasonality and 26–30 trending slightly downward), midcareer workers remain broadly stable with a mild uptick, and seniors (50+) rise the most, reaching close to 20% above the baseline by 2025. Within each panel, the exposure bands (low, medium low, medium, medium high, high, and overall) largely co-move with only small gaps and no persistent divergence; therefore, the automation and augmentation views closely mirror the overall measure rather than revealing systematic differences by AI exposure.

AI Exposure and employment, conditioning on firm-level shocks

To rule out the possibility that industry- or firm-level shocks correlated with AI exposure and age drive their results, Brynjolfsson et al. (2025) estimate regression models controlling for a rich set of fixed effects designed to capture such shocks. We follow their analysis by estimating the following poisson regression

$$log\left(E\left[y_{f,q,t}\right]\right) = \sum_{q'\neq 1}\sum_{j\neq -1}\gamma_{q',j}1\{t=j\}1\{q'=q\} + \alpha_{f,q} + \beta_{f,t} + \varepsilon_{f,q,t}$$

Where f indexes firms, q indexes exposure quantiles, and t indexes months, with $t = -1$ being the reference category (October 2022). The outcome variable is employment in f, q, t. We estimate this model separately for each age group as a Poisson regression due to the zero counts in the outcome variable using the methods developed in Correia et al. (2020). We cluster the standard errors by firm. As in Brynjolfsson et al. (2025), we impose the following sample restrictions: firms have to hire at least 10 employees within each age group in each month and cumulatively over the observation period, firms have to employ at least 100 employees in all quantiles (i.e., on average, about two employees per quantile each month).

In the following event-study graph, we plot the coefficients $\gamma_{q,t}$, which show how employment in a given quantile has developed over time compared to the lowest exposure quantile, conditional on the two high-dimensional fixed effects. The fixed effects $\alpha_{f,q}$ capture shocks specific to an exposure quantile in a given firm and fixed effects $\beta_{f,t}$ capture shocks specific to firms affecting all quantiles similarly.

In Figure 7, if anything, employment has **increased** in more exposed quantiles compared to the least exposed quantile in the early career groups. In other age groups, the changes over time are even smaller.

Figure 7 : Employment Dynamics by AI Exposure Quantile, Conditional on Firm-Level Fixed Effects

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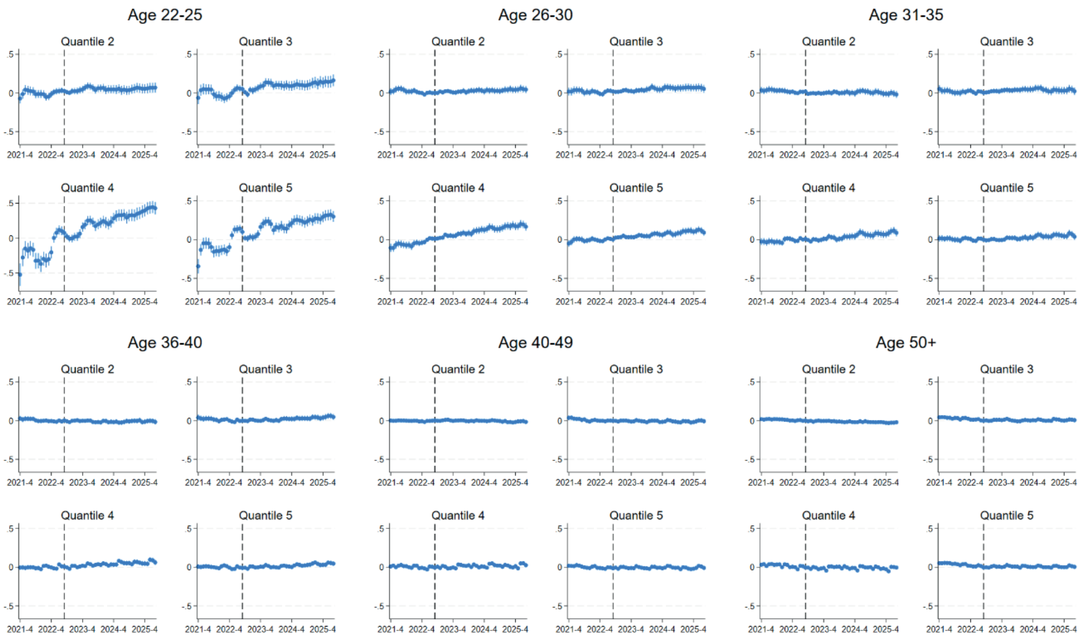
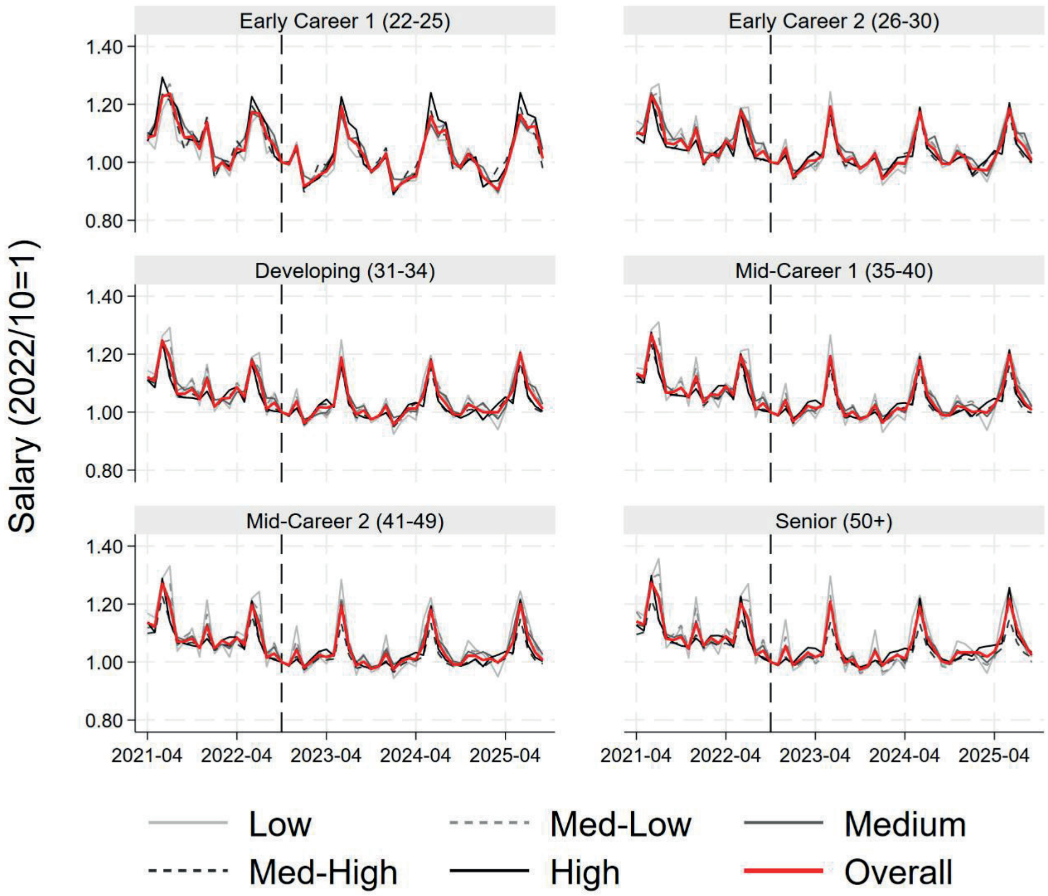


Source: The authors' calculations. October 2022, as the reference, is normalized to 0.

AI Exposure and earnings

While the previous section showed no systematic employment divergence across exposure groups, the following analysis examines whether similar patterns emerge in salary trends. The earnings concept used in the following graph is total earnings, which includes all taxable earnings from employment relationships.

Figure 8 Salary Trends by AI Exposure Level and Age Group (Indexed to Oct 2022): No persistent wage premium or penalty across exposure bands.



Source: The authors' calculations. October 2022 indexed to 1.00.

In Figure 8, across all six age groups, salary trends for different AI exposure levels, ranging from low to high, move in close alignment with the overall measure (red line), tracking the group cluster and showing no persistent premium or penalty for higher exposure. Seasonal fluctuations are evident throughout the period, with pronounced peaks and troughs that occur simultaneously across exposure bands. The largest peaks are due to vacation pay, which is typically paid in June. These fluctuations are most noticeable among early career cohorts (ages 22–30), while senior workers (50+) exhibit the highest seasonal peaks. Relative to the October 2022 baseline (indexed to 1.00), salaries remain near the baseline after 2022, with only short-lived deviations and no structural divergence by AI exposure level.

Discussion

Our results regarding Finland contrast sharply with recent US findings.

Using payroll data, Brynjolfsson et al. (2025) document substantial employment declines for early career workers (ages 22–25) in AI-exposed occupations—roughly 15–16 log points relative to less-exposed groups—while older cohorts remain stable or grow. These effects are concentrated in the roles where AI automates tasks, not those where it augments work, and persist after controlling for firm-level shocks. The wage trends show little divergence, suggesting short-run stickiness.

In Finland, by contrast, headcount trajectories across AI exposure bands largely co-move, with no persistent gaps: early career groups dip modestly, mid-career groups remain flat, and senior workers rise nearly 20% above the baseline by 2025. Salary indices cluster tightly across exposure levels, with only synchronized seasonal fluctuations. Overall, **Finnish evidence points to demographic rather than exposure-driven shifts**, whereas US data indicate early signs of exposure-linked displacement among young workers.

In contrast to the US results, Humlum and Vestergaard (2025) document precise null effects of chatbot adoption on earnings, hours, and workplace employment in Denmark, including early career jobs. While aggregate data replicate the US pattern of declining junior roles in exposed occupations, their difference-in-differences analysis shows that these declines are not driven by firms adopting AI chatbots. Instead, the main adjustment margin is occupational mobility: adopters are more likely to switch occupations, but without net changes in pay or hours. Taken together, **Finnish and Danish studies point to limited short-run disruption for young workers**.

One potential reason for the different results between Finland and the U.S. is differences in **employment protection** legislation (EPL). According to the OECD (2020, p. 186) Employment Protection Legislation Index, employment protection is the weakest in the US, while Finland is close to the OECD average. These institutional differences may influence how firms adopt generative AI. The low-EPL environment of the U.S. allows firms to rapidly "fire and hire" to acquire new AI-related skills, possibly leading to higher labor volatility and faster reallocation. In Finland, stricter protections mean that firms might be more likely to adjust their workforce through hiring freezes and voluntary attrition, or by investing in the retraining of incumbent workers to handle AI-augmented tasks. However, Denmark is also among the countries with low regulatory protection, and the Danish results do not imply restructuring similar to the US.

Conclusion

This study investigates the impact of generative AI on the youth labor market in Finland by replicating the key analyses of Brynjolfsson et al. (2025) using comprehensive population-level data and AI exposure indices. Contrary to findings from the U.S., where early career workers in AI-exposed occupations experienced significant employment declines, **our analysis reveals no systematic displacement effects linked to AI exposure among young Finnish workers**. Employment trends are primarily shaped by career stage demographics rather than differential AI exposure, with early career groups showing only modest declines, mid-career groups remaining stable, and senior workers experiencing notable growth. Similarly, wage trajectories exhibit no persistent premiums or penalties across AI exposure levels, highlighting the absence of structural wage impacts attributable to AI integration.

Our findings align with recent Danish evidence from Humlum and Vestergaard (2025), which also reports limited short-run disruption for early career positions despite aggregate employment shifts.

Overall, the Finnish labor market appears resilient to immediate generative AI-driven displacement among youth, suggesting that concerns over rapid automation-induced job losses in entry-level roles may be mitigated by structural and policy factors.

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[i] For example, compared to U.S. where over 90% of entrants to bachelor's programmes start right after completing secondary education, in Finland only 20% do (OECD 2019, Box B4.1.). The average age of new entrants to higher education is in Finland among the highest in OECD countries (OECD 2019, Table B.4.2).

Elinkeinoelämän tutkimuslaitos

ETLA Economic Research

ISSN-L 2323-2420
ISSN 2323-2420 (print)
ISSN 2323-2439 (pdf)

Publisher: Etlatieto Oy

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