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White-Collar Automation: Adaptation, Compensation and the Politics of AI Exposure

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Research on the political consequences of workplace automation has focused primarily on blue-collar displacement, yet white-collar workers now face unprecedented exposure to artificial intelligence (AI). We examine a unique three-wave panel tracking a cohort of Swiss labor market entrants in administrative occupations as they experienced the widespread diffusion of large language models. Over this period, perceptions of digitalization at work change markedly: from largely unconcerned views to a strong focus on AI-driven automation. Most respondents remain confident and use AI frequently, yet rapid workplace change creates increasingly uncertain career prospects. This uncertainty fuels growing support for government intervention. Notably, policy demand among white-collar workers emphasizes adaptation: steering policies that buy workers time and investment policies that equip them with the skills to adjust. White-collar automation thus reshapes beliefs about the pace and governance of technological change, increasing demand for policies that actively manage digital transformation rather than buffer its consequences.

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Introduction

Technological change and automation have long been central to debates about economic inequality and political conflict. By reshaping the organization of work, altering skill demands and shifting economic risks, automation can influence political preferences, electoral behavior and support for government intervention (Autor et al. 2003; Acemoglu and Restrepo 2018; Thewissen and Rueda 2019; Gallego and Kurer 2022). A large literature links structural economic change to political backlash and the emergence of new political cleavages, highlighting how transformations in labor markets translate into political responses (e.g. Iversen and Soskice 2001; Rehm 2009; Colantone and Stanig 2018; Kurer 2020; Baccini and Weymouth 2021).

Recent advances in artificial intelligence (AI) and in particular the rapid diffusion of large language models (LLMs), have intensified these dynamics. Compared to earlier waves of automation that primarily targeted manual and routine production tasks, generative AI affects a wide range of cognitive, administrative and communicative activities that are central to many white-collar occupations (Brynjolfsson and McAfee 2014; Acemoglu and Restrepo 2020; Webb 2019; Felten et al. 2023; Eloundou et al. 2023; Handa et al. 2025). Automation hence increasingly reaches occupations that have traditionally been viewed as relatively protected. This shift not only accelerates the pace of technological change but also transforms its social relevance as labor market risks move further up the "skill ladder" (Gallego and Kurer 2022; Haslberger et al. 2023; Knotz et al. 2024).

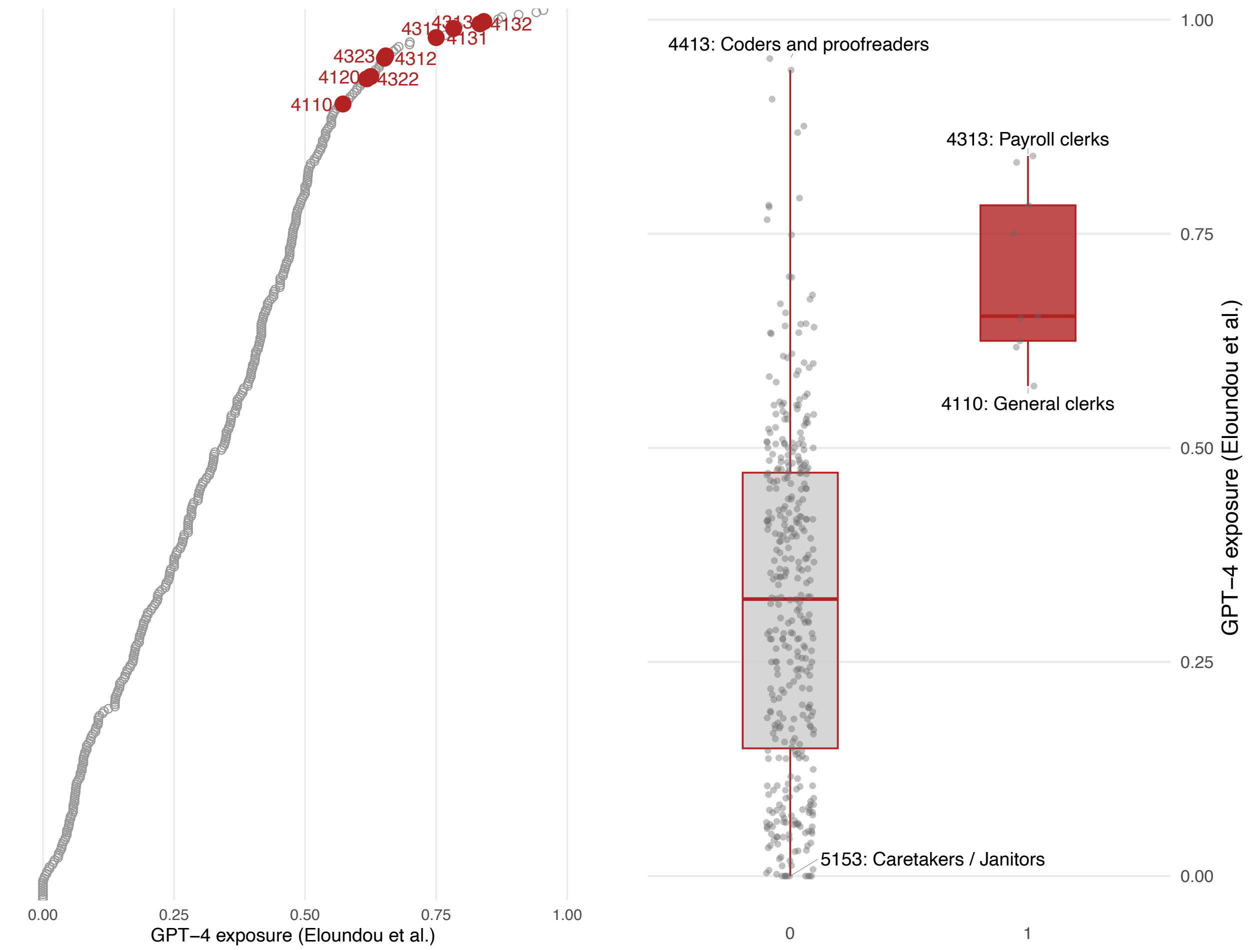
Despite this development, research on the political consequences of automation has – sometimes explicitly but more often implicitly – focused mainly on manufacturing and blue-collar displacement dominated by routine manual tasks. Much of the existing literature examines how exposure to routine task intensity, job loss and local economic change shapes political attitudes and electoral behavior, often focusing on settings associated with deindustrialization and employment decline (Autor et al. 2013; Rodríguez-Pose 2018; Colantone and Stanig 2018; Broz et al. 2021; Baccini and Weymouth 2021). While these accounts have generated important insights into political backlash, they anchor political responses to automation in experiences of displacement and income loss. Far less is known about how white-collar workers respond politically to automation, even though office-based work has long included a broad variety of (cognitive) routine tasks and is now even more directly affected by AI-driven automation.

This paper argues that white-collar automation generates a distinctive political response. While factory closures and job displacement remain a recurring feature in parts of the blue-collar economy, technological change in white-collar settings is more likely to be experienced as continuous transformation of everyday work. Workers face uncertainty about future skill requirements and their ability to keep up with accelerating change.

This raises a central question: what kind of policy response addresses concerns rooted in uncertainty about the pace and direction technological change? Following Bürgisser (2023), we distinguish between three types of policy responses according to their intended goal. *Compensation* policies provide a financial safety net for workers who lose their jobs because of technological change. *Investment* policies prepare workers to adapt through education, retraining and support for labor market transitions. *Steering* policies seek to influence the pace and direction of technological change by shaping the incentives under which firms adopt new technologies. We argue that the political challenge posed by white collar automation is less about insuring against immediate labor market risks and more about supporting and enabling adaptation. *Adaptation* therefore combines support for steering policies that allow affected workers to gain time amid rapid workplace change and investment policies that equip them with the skills needed to adjust to technological change. Consequently, compensation policies are expected to receive comparatively less support.

We study these dynamics among labor market entrants in white-collar occupations, a group that is particularly informative for understanding the current wave of automation. Recent research on the labor market implications of generative AI characterizes workers in highly exposed entry-level occupations as "canaries in the coal mine" (Brynjolfsson et al. 2025) because they are the first to experience the (adverse) consequences of new technology. Figure 1 illustrates this exposure by situating office-work jobs within the full distribution of LLM exposure across all occupations.[1] The figure shows that the office occupations studied here rank at the very top of the distribution, which

[1] We rely on the task-based measure developed by Eloundou et al. (2023), which was applied to the a European occupational classification by Klaeui and Siegenthaler (2025).



(a) AI Exposure by ISCO-4d Occupation **(b)** AI Exposure by Occupational Group

Figure 1: Task-Based GenAI Exposure among Clerical and Administrative Occupations

clearly underscores the exceptionally pronounced exposure to recent advances in generative AI among our respondents.

Our empirical analysis is based on a unique original panel survey designed specifically to study white-collar automation. We follow a full cohort of apprentices in Switzerland who completed vocational training that prepares them for a wide range of white-collar jobs in offices and administration. We first interviewed them in November 2021, approximately half a year before graduation. A second wave was fielded after their labor market entry in fall 2022. By coincidence, this second wave was completed just before the public launch of ChatGPT on November 30, 2022. We run a third wave in summer 2025, after the widespread adoption of LLM-based tools. This unique data collection offers several key advantages: The sample is highly homogeneous, operates within a common institutional context and allows us to trace within-individual change over time. This is precisely the type of evidence that is rarely available but crucial for distinguishing between stable individual differences and genuine responses to technological change. Our analysis focuses exclusively on within-occupation dynamics rather than cross-occupational comparisons and thus circumvents some of the core empirical issues related to confounding driven by occupational self-selection.[2]

Descriptively, we document a clear and striking shift in how respondents perceive digitalization at work. Open-ended responses and quantitative measures show a move from generic and largely unconcerned descriptions in 2021 to a strong focus on AI-driven automation in 2025. Importantly, this shift is accompanied by ambivalent to largely positive evaluations of AI use. Clearly, among our white-collar workers, imminent technology-induced job loss is not a widespread concern. Most respondents report intensive use of AI tools and tend to view them as an opportunity rather than a risk. However, the perceived pace of workplace change is a source of concern and implies increasingly uncertain occupational prospects.

Politically, these perceptions translate into rising support for government intervention across several policy domains. Uncertainty appears to generate demand for intervention almost across the board, but the overall structure of policy demand points to adaptation rather than compensation. Demand for both investment and steering increases with the wider diffusion of generative AI. Within-individual analyses show that increases in perceived automation risk translate primarily into greater support for greater support for slowing the pace of digitalization, whereas support for investment that help workers adapt through education and training rises more broadly and largely independently of individual risk updating. These findings distinguish our results from narrow risk-insurance accounts and align more closely with arguments emphasizing pre-distribution and institutional steering (Rodrik and Sabel 2019; Rodrik and Stantcheva 2021; Gallego et al. 2022; Bürgisser 2023; Gallego and Kuo 2026).

Taken together, our findings have broader implications for research, policy and politics. From a research perspective, our most important substantive contribution is the specific focus on white-collar automation, which enriches and extends previous findings from cross-occupation samples

[2]The data underlying this article will be made available in the Harvard Dataverse upon publication.

that tend to emphasize a demand for passive transfers and ex post compensation (Kurer and Häusermann 2022; Busemeyer and Tober 2023). Empirically, our analysis underscores the limits of cross-sectional analyses in this domain and highlight the value of panel designs for identifying how political preferences respond to technological change. From a policy perspective, they suggest a shift in focus away from compensation toward steering and investment. This shift in policy demand is particularly relevant at a time when debates about the governance and regulation of AI have become increasingly salient (Gallego et al. 2026).

The implications for welfare coalition building are *a priori* ambiguous. On the one hand, the specific policy priorities among white-collar workers documented in this paper may be read as a potential obstacle to building large, unified – and thus politically influential – coalitions for government action. If blue and white-collar workers experience automation in systematically different ways and demand different forms of intervention, the expansion of automation into white-collar work may fragment political responses across occupational groups. On the other hand, the growing exposure of white-collar workers to AI may create a new and politically influential constituency for adaptation-oriented policies. As automation expands into occupations that have historically been relatively insulated from technological change, an increasingly large share of the workforce may come to demand investment and steering policies that facilitate adjustment. Importantly, this need not require blue-collar workers to adopt identical policy priorities. If they, at least passively, support adaptation alongside compensation, the growing mobilization of white-collar workers may be sufficient to place adaptation-oriented responses at the center of the political agenda. As we show below, our findings are more consistent with this latter perspective.

Theory

Automation Risk and Demand for Government Support

A central political economy framework linking structural economic change to political outcomes is the risk–insurance model (Iversen and Soskice 2001; Moene and Wallerstein 2001; Cusack et al.

2006; Rehm 2009). In this perspective, exposure to labor market risks generates demand for government intervention as a form of social insurance against uncertain future labor market and income trajectories. Individuals are assumed to evaluate policies not only in terms of current material self-interest, but also with regard to their capacity to insure against prospective job or wage loss. As labor markets become more volatile due to technological change, this framework predicts rising support for compensation policies that buffer workers against the adverse consequences of labor market disruption.

Much of the contemporary empirical literature on technological change operationalizes labor market risk through exposure to automation, most prominently via measures of routine task intensity (RTI). Building explicitly on the insurance component of redistribution preferences, Thewissen and Rueda (2019) argue that occupations characterized by a high share of routine tasks face elevated risks of automation and thus greater income insecurity. Individuals in such occupations are therefore more likely to favor redistribution as insurance against automation-induced job loss. Later research largely confirms this main idea. Across many studies, workers who face a higher risk of automation – whether this risk is measured objectively using occupational characteristics or subjectively based on people's own perceptions – are more likely to support government redistribution. In particular, they tend to favor passive labor market policies, such as unemployment benefits, social assistance and direct income transfers, which provide financial protection against potential job loss (for detailed reviews, see Gallego and Kurer 2022; Weisstanner 2023). These findings align closely with the risk–insurance model: when individuals anticipate job displacement or income losses, they tend to favor policies that provide immediate and reliable compensation.

At the same time, the welfare state is not only about income protection but also about the "creation, mobilization and preservation of skills and human capital" through social investment (Garritzmann et al. 2022). The aim of these policies is to prepare, support and equip individuals in ways to cope with structural economic changes and reduce future risks of income and job loss (Morel et al. 2012; Bonoli 2013; Hemerijck 2013). While social investment policies can theoretically function as a form of insurance, their benefits typically materialize in the long term rather than providing immediate relief (Busemeyer and Sahm 2022). For individuals facing an imminent risk of job loss, investment-oriented policies may thus appear less attractive than direct income protection. This interpretation is supported by Busemeyer and Tober (2023), who show that workers at risk of displacement tend to prefer tangible and reliable forms of compensation over investment policies whose returns are uncertain and contingent on successful integration into the labor market.

An alternative future-oriented strategy to cope with structural change is associated with support for steering policies that slow down change or constrain the reach of technological innovation at work. Rather than relying on ex-post compensation, at-risk individuals seek to gain time for adaptation in order to keep up with rapidly changing requirements. Such policies can include stricter regulation of technology adoption in the workplace, requirements for worker approval and tax-based incentives or disincentives that influence firms' technology adoption decisions (Bürgisser 2023). Rather than preventing technological change altogether, these policies aim to manage its pace so that workers, firms and institutions have more time to adjust. Several studies suggest that such steering responses may find fertile ground among workers who feel highly exposed to technological change (Gallego et al. 2022; Kuo et al. 2024; Busemeyer et al. 2023; Bicchi et al. 2025; Gallego and Kuo 2026). Although aggregate public support for policies that slow the pace of technological change is overall lower than for compensation and investment, among those most exposed to technological risk, support for steering policies is the most preferred policy response (Gallego et al. 2022).

Taken together, these findings suggest that technological risk does not necessarily generate a uniform political response. While much of the literature emphasizes demand for compensation, other work points to support for investment or steering policies. One possible explanation is that different measures of technological exposure capture distinct types of work and occupational groups, leading to systematically different experiences of risk and, consequently, different policy preferences.

Emerging Evidence on the Political Implications of AI Exposure

Recent advances in artificial intelligence provide a useful setting to examine how differences in the experience of technological risk translate into policy preferences. Because AI affects different task domains and occupational groups than earlier waves of automation, it may generate distinct forms of perceived risk and, consequently, different patterns of policy demand.

A small but growing literature has begun to examine how exposure to AI affects risk perceptions and political preferences. One strand of this research largely mirrors findings from earlier waves of technological change. Heinrich and Witko (2025) show that individuals in AI-exposed occupations express stronger support for steering policies governing AI and welfare spending. In a similar vein, Knotz (2025) argues that technological vulnerability has spread to higher-educated workers and shows that greater subjective AI-related risk among this group reduces support for investment policies while increasing demand for compensation. Complementing this perspective, Knotz et al. (2024), drawing on survey data from 25 countries, show that many highly educated workers, particularly those in finance and IT, perceive substantial risks of being replaced by AI. Finally, Grant et al. (2025) offer evidence that both objective and subjective AI exposure predict support for steering policies that regulate AI in Britain.

At the same time, emerging research suggests that the political consequences of AI exposure extend beyond a simple risk–insurance logic. One line of work argues that AI can shape policy preferences through sociotropic concerns rather than egotropic risk assessments: experimental evidence shows that exposure to AI increases support for active labor market policies even without raising perceived personal labor market risk (Haslberger et al. 2025). A second perspective emphasizes expectations about opportunity and productivity. Rather than viewing AI primarily as a source of displacement, workers may anticipate that it complements rather than substitutes their skills, raising productivity and expanding career opportunities (Weisstanner et al. 2026). At the individual level, such expectations can translate into more optimistic assessments of future earnings and employment prospects and, consequently, weaker demand for redistribution (Lall 2025). By contrast, another contribution to this special issue argues that exposure may generate an expectations shock, particularly among highly educated workers whose anticipated career trajectories are disrupted by rapid technological change. Rather than immediate fears of job loss, AI erodes expected returns to education and career investments, fostering perceptions of economic unfairness and political realignment (Inglese 2026).

Overall, the emerging and rapidly evolving literature on AI exposure and policy preferences remains fragmented. A central reason for this fragmentation is that existing studies rely on heterogeneous measures of exposure and varying research designs studying different populations. Many analyses use short-term experimental treatments – often centered on tools such as ChatGPT – that are only loosely connected to respondents' actual work environments. As a result, it is often unclear whether observed responses reflect perceived personal labor market risks, broader societal concerns or evaluations of AI as a general-purpose technology. Moreover, few studies systematically link objective exposure to evolving perceptions of workplace vulnerability or focus on occupational groups that are most directly affected by AI. This makes it difficult to assess how AI reshapes risk perceptions relative to earlier waves of technological change and how these perceptions translate into policy demand.

The Political Response to White-Collar Automation

White-collar clerical and administrative occupations deserve particular attention because they are doubly affected by the two major waves of technology-induced labor market disruption. The first stems from their longstanding concentration of routine tasks. Seminal work on computerization and automation highlighted that routine task intensity (RTI) is not confined to industrial production but is widespread in office, clerical and secretarial work as well (Autor et al. 2003). Subsequent studies showed that these occupations are, on average, just as exposed to traditional forms of routine task automation as blue-collar process, plant and machine operators (Goos et al. 2014). Reflecting this vulnerability, routine-intensive occupations have faced some of the most pronounced employment and wage declines in recent decades, with sales and office or administrative jobs particularly affected alongside production work (Acemoglu and Autor 2011).

The second wave, driven by recent advances in generative AI, significantly amplifies these vulnerabilities. Advances in large language models are particularly well suited to automate routine cognitive tasks related to information processing, written communication and coordination, i.e. a set of tasks that is precisely at the heart of administrative and clerical occupations (Eloundou et al. 2023). This marks a clear departure from the experience of many blue-collar workers, whose core tasks remain less directly affected by current generations of AI (Felten et al. 2021). Together, these trends place white-collar administrative occupations at the center of a "double exposure", combining the pressures of traditional routine-task automation with the emerging exposure to generative AI.

Despite the scale of this transformation, we still know relatively little about how clerical and administrative white-collar workers interpret and respond to these overlapping technological pressures. Existing research on automation has tended to focus on the decline and political reactions of routine-intensive manufacturing workers. We argue that white-collar automation generates a distinctive political response. Unlike workers in routine-intensive manufacturing, whose political reactions are often rooted in fears of displacement and unemployment, white-collar workers tend to experience technological change as a continuous restructuring of everyday work. Rather than facing abrupt job destruction, clerical and administrative workers must navigate ongoing uncertainty about evolving skill requirements, shifting task profiles and their ability to keep pace with accelerating technological demands (MacDonald and Weisbach 2004; Deming and Noray 2020). The rapid diffusion of AI may further undermine expectations about the future returns to existing skills and career investments, even among workers who remain confident about their immediate employment prospects (Inglese 2026).

The central concern for such workers is thus not the threat of direct, technology-induced displacement but the challenge of continuously adapting to changing skill and task requirements while remaining in employment. In this context, the perceived pace of workplace change becomes a key source of anxiety and signals increasingly uncertain occupational prospects. Such increasing uncertainty likely places the challenge of *adaptation* to new technologies at the core of their concerns, rather than the risk of outright displacement.

Under such conditions, the political challenge is less about protecting workers from immediate labor-market shocks and more about enabling them to adjust to ongoing change. As perceptions of vulnerability shift from the threat of displacement to anxieties about skill obsolescence and falling behind, policy demands are likely to shift accordingly. Rather than prioritizing compensation for job losses, at-risk individuals need to gain time for adaptation in order to keep up with rapidly changing requirements. White-collar workers may thus place greater emphasis on steering the pace of technological change and securing the support needed to adapt through retraining and upskilling. This adaptation-oriented outlook sets white-collar responses apart from the political patterns associated with blue-collar automation and highlights the need to rethink the politics of technological disruption in the age of AI.

Research Design

Case

We test our hypotheses in Switzerland, a country where vocational education serves as the primary entry point into skilled white-collar employment. Unlike many other countries, vocational pathways are not a residual option but the dominant route into skilled employment. Around two thirds of Swiss adolescents enter an apprenticeship after compulsory schooling, while roughly one fifth attend academically oriented high schools that lead directly to university education (edk.ch 2023). As a result, vocational credentials in Switzerland often serve as gateways to stable and well-regarded careers rather than as signals of low educational attainment.

Within this system, the *Kaufmännische Lehre* – commonly referred to as the "KV" – is the single largest and most prominent apprenticeship program (gfs.bern 2025). It prepares apprentices for a wide range of white-collar occupations in offices and administration, including accounting, bookkeeping, customer service, communication and general business processes across 21 different industries. Apprentices combine firm-based training with part-time vocational schooling and typically complete their training within three to four years. According to the Federal Statistical Office, approximately 12,000 individuals obtain a vocational qualification through the KV each year, making it the most common entry pathway into white-collar work in Switzerland. Upon successful completion of the four-year training program, apprentices receive a federal vocational certificate.

The KV has traditionally enjoyed an excellent reputation and has long been regarded a "second royal road" alongside high school academic education (Aschwanden 2021). At the same time, the occupational tasks associated with KV training, particularly clerical, administrative and routine cognitive work, have been at the center of debates about digitalization and automation. Early research on computerization identified office and clerical occupations as highly susceptible to automation (Frey and Osborne 2013, 2017) and public discourse in Switzerland has increasingly framed the KV as a sector under pressure from technological change.[3] These concerns have intensified with the rapid diffusion of generative AI and large language models, which are particularly well suited to automating clerical and accounting-related tasks such as payroll, bookkeeping and administrative processing (Klaeui and Siegenthaler 2025). Their potential implications for white-collar employment have become the subject of intense public and media debate.[4]

At the same time, these developments have also reinforced the perceived need to equip office apprentices with the skills required to adapt to technological change. Reflecting this shift, the professional organization *kfmv* commissioned scientific evaluations and implemented a curriculum reform in summer 2023 at preparing apprentices for a workplace increasingly shaped by digitalization and AI.[5] The KV therefore provides an ideal setting to study how workers respond politically to technological change that is experienced not primarily as an immediate threat of displacement, but as a challenge of continuous adaptation.

Data Collection

To examine how rapid digitalization and the diffusion of AI technologies shape workers' perceptions and political preferences, we conducted an original panel survey among white-collar workers in the commercial sector. Our focus is on young adults who transition from vocational education into the labor market. This phase is particularly informative because it constitutes a key moment of expectation formation and revision: during training, apprentices develop beliefs

[3] https://www.20min.ch/story/digitalisierung-bedroht-100-000-kv-jobs-324742381757
[4] https://www.watson.ch/schweiz/wirtschaft/208274957-jeder-5-will-eine-kv-lehre-machen-doch-ki-bedroht-die-buero-jobs
[5] https://www.kfmv.ch/ueber-uns/engagement/reform-kv-lehre/erneuerungen

about their future careers, earnings prospects and job stability, which are then confronted with actual labor market experiences upon entry.

Labor market entry is a critical juncture in this regard. Once individuals leave training and begin searching for (or starting) their first jobs, they are forced to update their priors based on concrete workplace conditions and perceived demand for their skills. In occupations characterized by a high share of routine and administrative tasks, technological change may be especially salient at this stage. A large body of economic research shows that adverse labor market entry conditions can have persistent long-term effects on earnings trajectories, mobility and a range of broader socio-economic outcomes (Wachter 2020). Understanding how individuals interpret and politicize technological change at this early career stage is therefore of particular relevance.

Our target population is the full cohort of apprentices in the German-speaking Swiss commercial sector (KV) who completed their vocational training in summer 2022. In collaboration with the professional organization kfmv, we fielded a three-wave panel survey that closely tracks this cohort before and after labor market entry (see Figure 2).

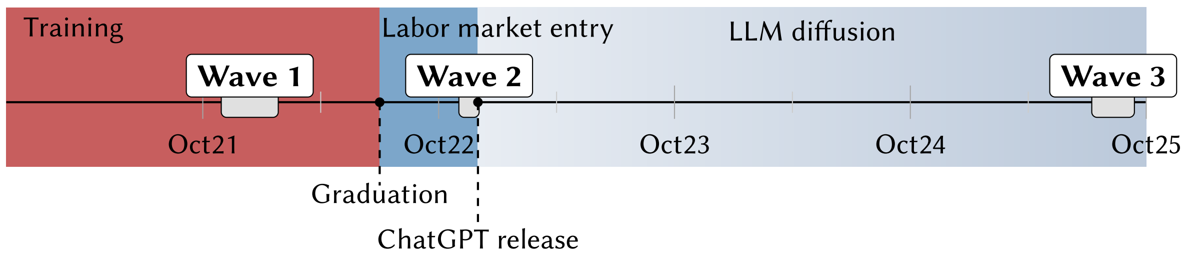


Figure 2: Timeline Survey Design

The first wave was conducted in November 2021, during the final year of vocational training and before graduation. This initial survey was distributed through vocational schools, which are the only institutions holding comprehensive contact information for apprentices during training. This procedure ensured full coverage while preserving respondent anonymity. We received responses from a total of N=2'273 apprentices. After graduation, vocational schools are no longer involved and subsequent waves hence relied on direct re-contact of respondents who had participated in earlier waves and consented to follow-up surveys. Individual-level panel linkage is therefore possible for respondents who voluntarily provided contact information. The second wave was fielded in October to November 2022, shortly after labor market entry and, by coincidence, completed just before the public release of ChatGPT on November 30, 2022 (N=2'002). The third wave was conducted in summer 2025, after the widespread diffusion of large language models and AI-based tools in office and administrative work. We approached all respondents who had participated in either of the previous waves and consented to be contacted again. The relatively long interval between Waves 2 and 3, combined with partly outdated email contact information, resulted in a considerably reduced sample size of N=548. We assessed potential differences in the panel structure but find no evidence of concerning selective attrition (see Figure A.1).

The specific timing of our data collection yields a particularly informative panel structure. The first wave captures baseline perceptions prior to labor market entry, the second wave captures early post-entry experiences immediately before the sudden public breakthrough of generative AI and the third wave captures attitudes and preferences after the widespread adoption of LLMs and the experience of exposure to AI-driven workplace change. Together, these waves allow us to study within-individual changes in perceptions of technology, automation risk and support for steering, investment and compensation policies throughout a period of unusually rapid technological transformation among a particularly exposed group of labor market entrants.

Operationalization

We measure policy preferences using three survey items corresponding to the three types of policy responses introduced above. These items cover compensation, investment and steering policies. Together, investment and steering represent adaptation oriented policy responses, whereas compensation captures ex post financial protection against labor market risks. All items were measured on identical five-point Likert scales ranging from strong disagreement to strong agreement (see Table 1). This common scaling facilitates direct comparison across policy domains and over time.

Figure 3 shows the baseline distribution of support for the three policy dimensions. Support for investment policies is highest overall, with responses strongly concentrated at the upper end of the scale. Compensation policies also receive broad support, though their distributions are more dispersed and centered closer to the scale midpoint. Support for steering policies, operationalized

Table 1: Operationalization of Policy Preferences

Policy dimension	Wording: The government should...	Scale
Compensation	...provide a financial safety net for unemployed people.	1–5
Investment	...support people in their education and in finding a job.	1–5
Steering	...slow down the pace of digitalization.	1–5

here as slowing down the pace of digitalization, is markedly lower: roughly half of the sample expresses disagreement, about a third is undecided and around 13% support such regulatory intervention. While steering policies are the least popular policy response, support for slowing down the pace of digitalization appears higher than in earlier studies. For example, Gallego et al. (2022) report that less than 5% of respondents in a 2018 sample of the Spanish workforce supported slowing down technological change.

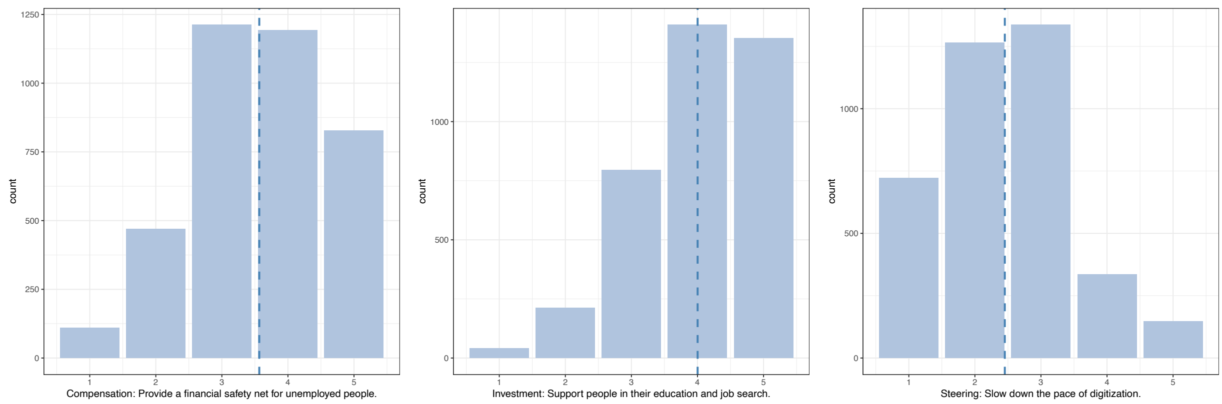


Figure 3: Distribution of Policy Support (Pooled Across Waves)

We measure individual exposure to digitalization using four survey items capturing complementary dimensions of technological change at work (see Table 2). These include perceived task automatability, subjective assessments of digitalization-related risks to one's own career, general evaluations of digitalization as a risk rather than an opportunity and perceived labor market difficulty for individuals with a commercial vocational degree. To capture overall exposure to digitalization, we construct a composite subjective *exposure index* based on four survey measures. The opportunity–risk item is recoded such that higher values consistently indicate greater perceived risk. All components are rescaled to a common 0–1 range within survey waves and combined using an unweighted average. The index is calculated using all available components for each respondent, i.e. observations with no valid component measures are coded as missing. Higher values of the index indicate greater perceived exposure to digitalization.

Table 2: Operationalization of Exposure to Digitalization

Variable	Survey item wording	Scale
Difficulty finding a job	How difficult do you think it is today to find a job with a commercial vocational degree?	1–4
Perceived threat	How strongly do you feel that digitalization threatens your own professional future?	0–10
Digitalization as risk	Do you see digitalization in the clerical sector more as an opportunity or as a risk?	1–4
Task automatability	What share of daily tasks in clerical occupations could theoretically be automated?	0–100
Exposure index	Unweighted average of the four within-wave standardized exposure measures	0–1

Empirical Approach

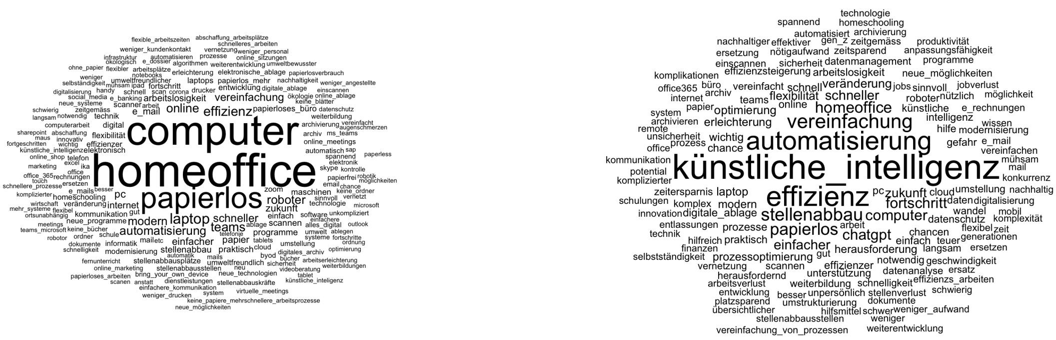
We exploit the three-wave panel structure of the data to analyze how perceptions of digitalization and related policy preferences evolve over time. First, we document descriptive changes in how respondents perceive digitalization at the workplace across survey waves, with particular attention to shifts between wave 2 and wave 3, corresponding to the period before and after the widespread diffusion of large language models. This descriptive analysis establishes that perceptions of digitalization change meaningfully over the course of the fieldwork period.

Second, we examine over-time developments in policy preferences using within-individual comparisons. Focusing on pre–post changes within the same respondents, we assess how support for different policy responses evolves as individuals enter the labor market and as digitalization becomes more salient. These analyses rely on individual fixed-effects models, which isolate within-person changes over time and net out all time-invariant individual characteristics. Note that the combination of a highly homogeneous sample in terms of training, occupation and age, together with substantial within-individual variation over time, provides considerably stronger empirical leverage than broad cross-sectional analyses, which primarily capture occupational differences in exposure and policy preferences.

Third, we assess the extent to which the observed over-time changes in policy preferences can be accounted for by a risk–insurance logic. Building on models of political preference formation under economic risk, we examine how perceived exposure to digitalization relates to policy preferences. We analyze this relationship both in between-individual regressions with controls for key sociodemographic and workplace characteristics and in within-individual fixed-effects models. The latter provide a conservative test by linking within-person increases in perceived exposure to corresponding shifts in policy preferences. Together, these analyses allow us to evaluate the explanatory power of a risk–insurance mechanism for the over-time changes documented above.

Perceptions of Digitalization and AI at the Workplace

Figure 4 illustrates how respondents' associations with digitalization in clerical occupations evolve between 2021 and 2025, based on an open-ended question asking for the first three words that come to mind. The word clouds are constructed from cleaned and harmonized text responses, aggregating terms by survey wave after standardizing references to artificial intelligence and removing stopwords. Appendix Table A.2 reports the twenty most frequent terms in each year along with English translations.



(a) 2021

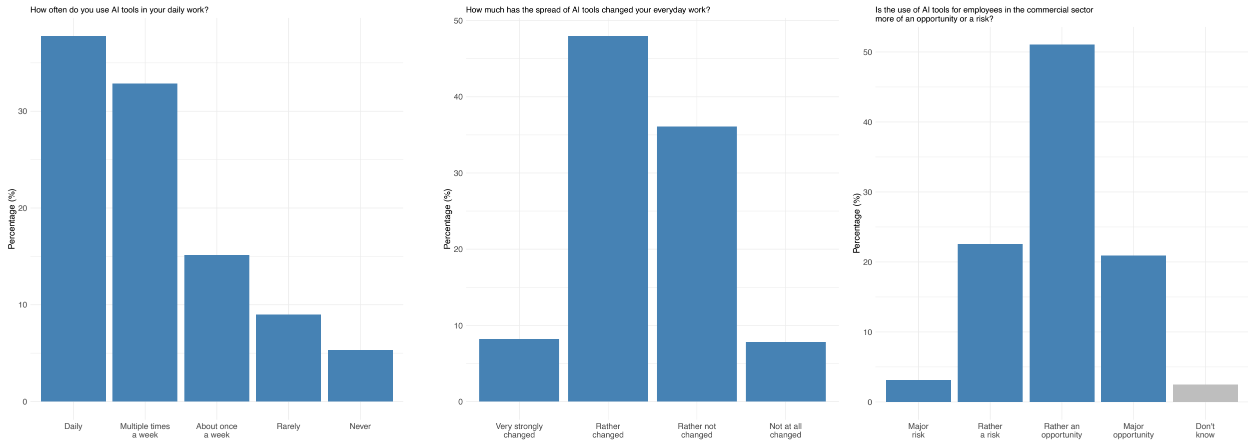
(b) 2025

Figure 4: How Respondents Reason about Digitalization at the Workplace

The comparison reveals a clear and striking shift in how digitalization is understood. In 2021, responses are dominated by generic and largely descriptive terms such as *home office, computer, paperless* and *laptop*, reflecting established digital work practices rather than transformative change. References to automation are present but relatively peripheral. By contrast, responses in 2025 are markedly more specific and centered on artificial intelligence and automation. Artificial intelligence ("*künstliche intelligenz*") becomes the single most frequent term, followed by concepts such as efficiency, automation and simplification ("*vereinfachung*"), with explicit references to ChatGPT emerging among the most common associations. At the same time, terms related to job loss, such as job cuts ("*stellenabbau*"), become more salient, though they remain embedded in a broader narrative emphasizing productivity gains and process optimization rather than imminent displacement. Overall, the shift from generic digitalization to AI-driven automation narratives suggests a substantial updating of how digitalization at work is perceived during the observation period.

The qualitative shift toward AI-centered and automation-related associations is mirrored in respondents' reported work practices and perceptions in 2025. Figure 5 provides an overview of AI use and perceived impacts at a point when large language models had become widely available. The results suggest that AI tools have become an integral part of everyday work for many young professionals in the commercial sector: a clear majority of respondents use AI at least multiple times per week, with a substantial share reporting daily use. Correspondingly, most respondents report that the spread of AI has meaningfully changed their daily work. At the same time, these changes are not predominantly perceived as threatening. When asked whether the use of AI tools in the commercial sector represents more of an opportunity or a risk, respondents lean toward opportunity-based assessments, while only a small minority view AI primarily as a risk. Taken together, this snapshot points to a strong perception of ongoing and deep AI-driven transformation in everyday work, which is not primarily experienced as a threat but comes with a growing pressure to adapt within existing jobs.

Figure 6 underscores that respondents are not naive about the implications of AI-driven change. When asked to estimate the share of daily tasks in clerical occupations that could theoretically be automated, respondents report substantial automation potential. The distribution in 2025, after the widespread diffusion of LLMs, shifts clearly to the right relative to 2021 (mean: 57% vs.



(a) Frequency of Use

(b) Degree of Change

(c) Risk Perception

Figure 5: How AI Affects Respondents' Daily Work

48%).[6] These estimates are remarkably aligned with a measure by Arntz et al. (2016), which suggests that 57% of activities in the commercial sector are potentially substitutable by technology. The shift over time indicates a growing awareness of the expanding scope of tasks that could be taken over by machines. Together with the evidence on AI use and perceived change, these patterns reinforce the interpretation that digitalization is experienced as an ongoing and potentially challenging process of adaptation but not so much as an immediate threat of technology-induced displacement.

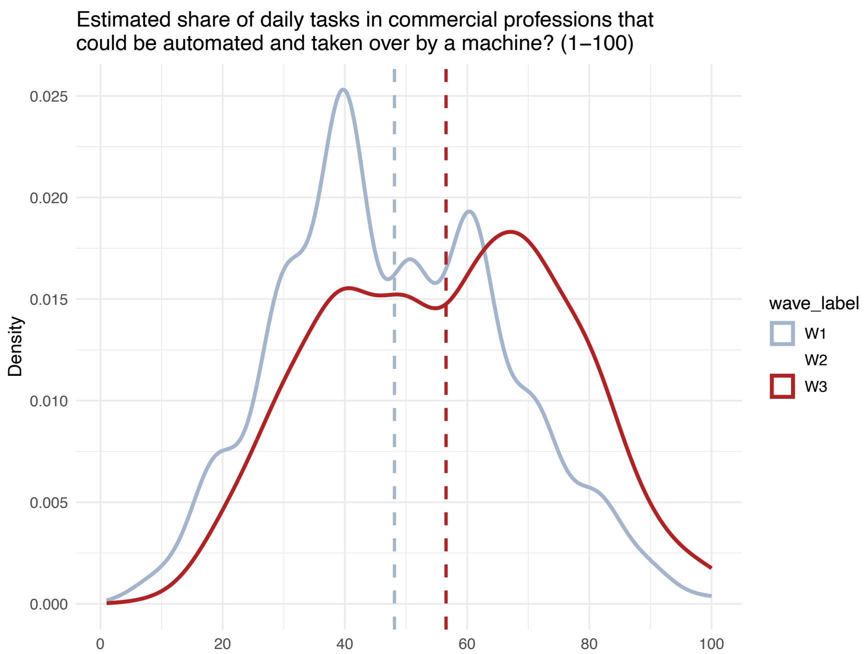


Figure 6: Estimated share of automatable tasks

[6]The question was not asked in the 2022 wave of the panel.

Digitalization and Political Preferences

Over-Time Development of Political Preferences

In this section, we turn to the political implications of changing interpretations of digitalization at the workplace. Figure 7 documents pronounced over-time changes in policy preferences using only within-individual variation. Relative to wave 2, respondents in wave 3 exhibit a clear shift in their policy preferences. Notably, this shift contrasts with developments between wave 1 and wave 2. As respondents transition from the final phase of vocational training into labor market entry, support for the different policy instruments remains remarkably stable. The marked changes between wave 2 and wave 3 therefore do not reflect a gradual life-cycle or labor market entry effect, but marks a distinct break in the trajectory of policy preferences. The results thus point to a substantial reorientation of political attitudes over a short period, coinciding with a phase of rapidly accelerating technological change.

Most importantly, this reorientation is centered on adaptation rather than compensation. Support increases substantially for investment policies that help workers adapt through education and training and for steering policies that slow the pace of digitalization to provide more time for adjustment. In contrast, support for ex post compensation policies remains essentially unchanged. The observed shift in policy demand therefore reflects a greater emphasis on facilitating adaptation to technological change rather than compensating workers after displacement.

Of course, we have to be cautious in interpreting these over time changes solely as political responses to the diffusion of LLMs since many other potential explanatory factors evolve over time. That said, several features of our study design and the observed pattern of results mitigate common concerns. First, the sample is highly homogeneous in terms of age, educational trajectory and occupational environment, which reduces the likelihood that compositional change or divergent life-course trajectories drive the results. Second, the non-monotonic pattern across the three waves is difficult to reconcile with gradual attitudinal change or labor market entry alone and instead points to a discrete contextual shift affecting respondents simultaneously. Third, the observed changes are selective. Rather than a general increase in support for government inter-

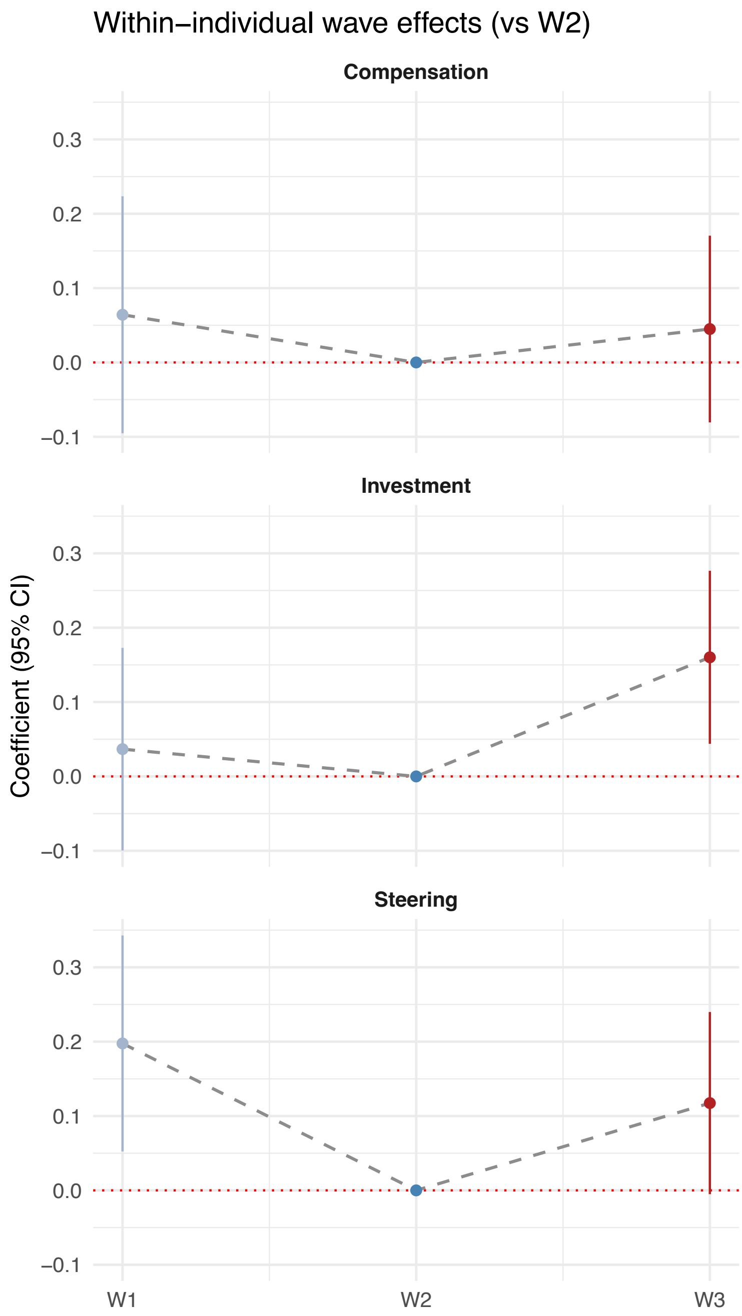
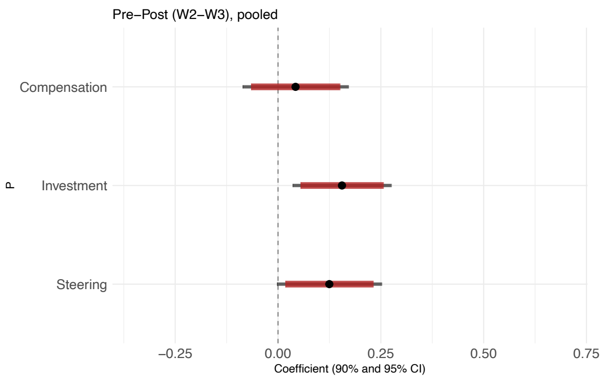
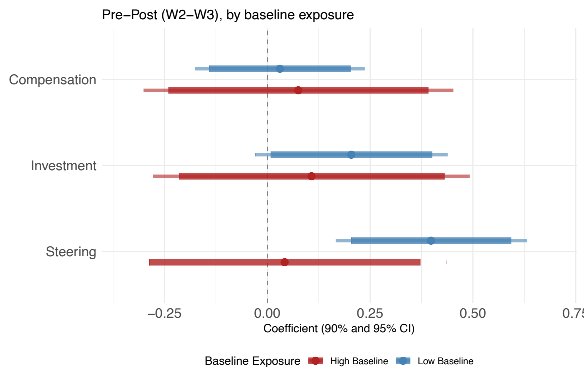


Figure 7: Preferences over Time

vention, respondents become more supportive only of steering and investment policies, whereas support for compensation remains stable. While multiple factors may contribute to the observed shifts, we find it difficult to identify an alternative explanation that accounts equally well for both the timing and the selective structure of the over-time changes. We therefore interpret these trends as evidence that the diffusion of LLMs coincided with and plausibly contributed



(a) W2 to W3, pooled



(b) W2 to W3, by baseline exposure

Figure 8: Pre-Post Effects by Baseline Exposure

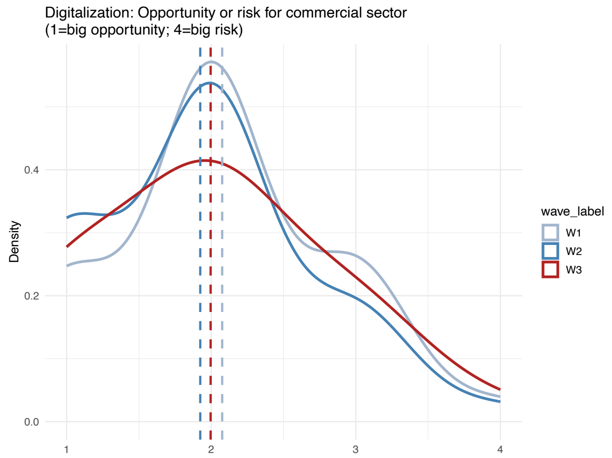
to, a marked reconfiguration of policy preferences among young white-collar workers toward adaptation rather than compensation.

To further contextualize these developments, we examine whether the increase in policy support differs by respondents' perceived exposure to digitalization, measured at baseline in wave 2 (that is, prior to the diffusion of LLMs). Figure 8 focuses on changes between wave 2 and wave 3: the left panel reproduces the average within-individual effects documented in Figure 7 above, while the right panel disaggregates these effects by baseline exposure. This comparison allows us to assess whether the post–wave 2 shift reflects differential responses across subgroups or broader updating of preferences.

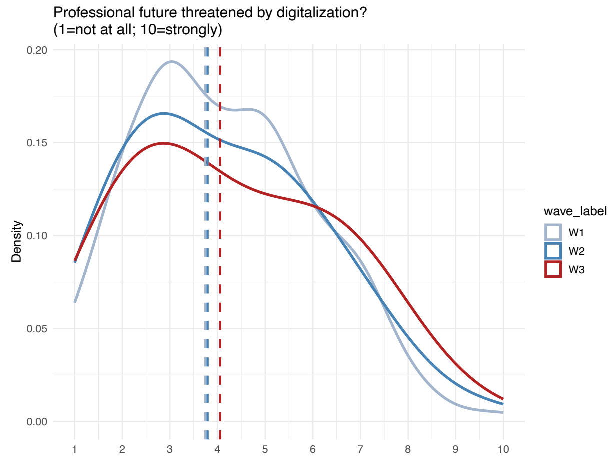
If anything, the observed increase in policy support, especially for steering policies, after the public release of ChatGPT and other LLMs is more pronounced among respondents with *lower* baseline exposure to digitalization. This pattern is consistent with a catch-up effect rather than diverging preferences: respondents who initially may have underestimated their exposure to AI-driven change appear to update most strongly once the capabilities of LLMs and generative AI become salient. As a result, this brings their policy preferences closer in line with those who already perceived higher levels of exposure in previous waves. For compensation and investment, the magnitude of the over-time increase is very similar across exposure groups, indicating that the post–wave 2 shift is broadly shared rather than driven by one of the subgroups.

Is Support for Policy Intervention Motivated by Risk-Insurance?

The over-time analyses point to a sharp and broadly shared increase in support for government intervention after wave 2. Having established that policy preferences moved in a more interventionist direction over a short period, we next turn to the question of mechanism. In particular, we examine whether these changes can be explained by a risk–insurance logic, asking whether individual-level changes in perceived exposure to digitalization translate into corresponding changes in policy demand. As a first step, Figure 9 shows simple over-time descriptives of perceived automation risk, which show a modest but systematic increase in risk perceptions over the same period.



(a) Risk or Opportunity



(b) Threat to Future

Figure 9: Risk Perceptions Over Time

We first examine the relationship between perceived exposure to digitalization and policy preferences using between-individual regression models. Figure 10 reports these associations, controlling for key sociodemographic characteristics and workplace conditions in a highly homogeneous sample drawn from a single occupational group. This design reduces confounding from between-occupation variation that likely affects many cross-sectional studies of automation and policy preferences. Across specifications, higher perceived exposure is associated with stronger support for government intervention in all three policy domains. The estimated coefficients are weakest for compensation, which reaches only marginal significance. They are more pronounced for investment, while support for steering policies exhibits the strongest and most consistent association with perceived exposure. Taken together, the between-individual results suggest that respondents who perceive themselves as more exposed to digitalization tend to express greater demand for policy intervention, consistent with a broad risk–insurance logic.

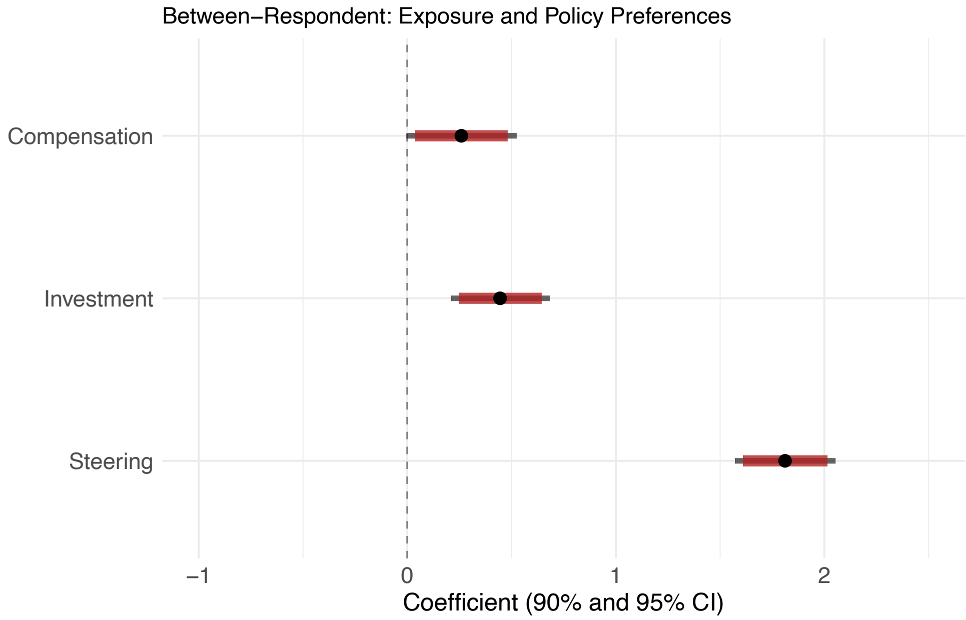


Figure 10: Exposure and Preferences: Between-Respondents

To provide a more conservative test of the risk–insurance mechanism, we next examine whether within-individual changes in perceived exposure to digitalization are associated with corresponding changes in policy preferences. Figure 11 presents estimates from individual fixed-effects models, which exploit over-time variation within respondents and net out all time-invariant individual characteristics. In contrast to the between-individual results, only support for steering policies responds systematically to within-individual exposure updating. When respondents perceive an increase in their exposure to digitalization, they become significantly more supportive of slowing the pace of digitalization. The corresponding estimate for investment, which also facilitates adapation, is positive but imprecisely estimated. In contrast, the estimates for compensation are statistically indistinguishable from zero.

These findings point to a political response that is shaped less by fears of imminent job loss than by pressures of adaptation to ongoing technological change. Such adaptation can be achieved either by gaining time to deal with change or by direct support in further training. We find strong and consistent support for the first and weaker and more imprecise support for the second policy response. In contrast, increasing exposure to AI and automation does not translate into stronger

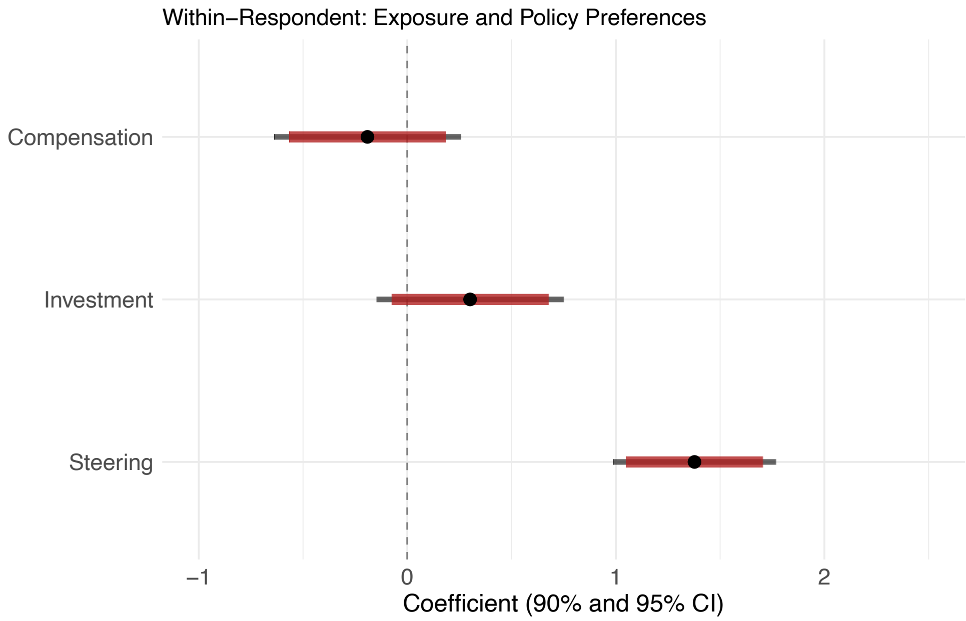


Figure 11: Exposure and Preferences: Within-Respondents

demands for compensation, the policy response typically associated with displacement risk. This pattern is consistent with an interpretation in which uncertainty arises from continuous transformation within existing jobs rather than from expectations of outright dismissal. Support for steering policies and, to a lesser extent, investment policies thus appear to reflect a broader demand for adaptation rather than compensation. Steering policies provide workers with more time to adjust to technological change, while investment policies support them in acquiring the skills needed to remain employable. In that sense, the selective link between individual exposure updating and support for steering policies complements the broader over-time shift toward adaptation and suggests that the politics of AI among white-collar workers are better understood as a politics of adaptation than of compensation.

Does Adaptation Demand Complicate Welfare Coalitions?

The empirical analysis above focuses exclusively on white-collar workers. While this provides important analytical leverage for studying within-group variation in AI exposure, it does not allow us to directly assess whether the adaptation-oriented response we document is distinctive to white-collar occupations. Our theoretical argument implies a simple observable implication:

because white-collar workers are more likely to experience technological change as continuous transformation requiring adaptation, they should place relatively greater emphasis on adaptation policies than blue-collar workers. The latter, by comparison, are more likely to frame technological change in terms of job displacement and income loss and therefore place relatively greater weight on compensation. This does not imply that the two groups fundamentally disagree about policy. Rather, both may support adaptation and compensation, but white-collar workers should prioritize adaptation more strongly relative to compensation.

To examine this implication, we draw on a comparative survey on attitudes toward technological change conducted in five European countries in early 2023 (Gallego and Kuo 2026). Restricting the sample to employed respondents, we compare clerical workers (ISCO 4), who closely resemble the occupational profile of our main sample, with blue-collar workers (ISCO 7–9). Following our theoretical framework, we distinguish between adaptation and compensation policies. The adaptation index combines support for retraining with two steering measures that seek to regulate or slow technological change, whereas the compensation index captures support for unemployment benefits and an unconditional minimal income. We then compute an adaptation–compensation gap, where positive values indicate that respondents place greater emphasis on adaptation than on compensation.[7]

Figure 12 presents the results. White-collar clerks exhibit a consistently larger adaptation–compensation gap than blue-collar workers. While both groups tend to support policies that facilitate adjustment to technological change, white-collar workers place systematically greater relative emphasis on adaptation than on ex-post income protection. The pattern is remarkably consistent across institutional contexts. Although the country-specific subgroup comparisons are estimated with limited precision owing to the relatively small occupational subsamples, the adaptation premium among white-collar workers emerges in all five countries.

These descriptive comparisons provide independent evidence consistent with our theoretical argument. The occupational difference appears to concern the relative priority attached to adapta-

[7]Because our theory is perhaps most applicable to workers who perceive technology as threatening, we additionally estimate the same comparison among respondents above the median of a technology threat index combining perceived negative workplace impacts and subjective substitution (Appendix Figure A.2).

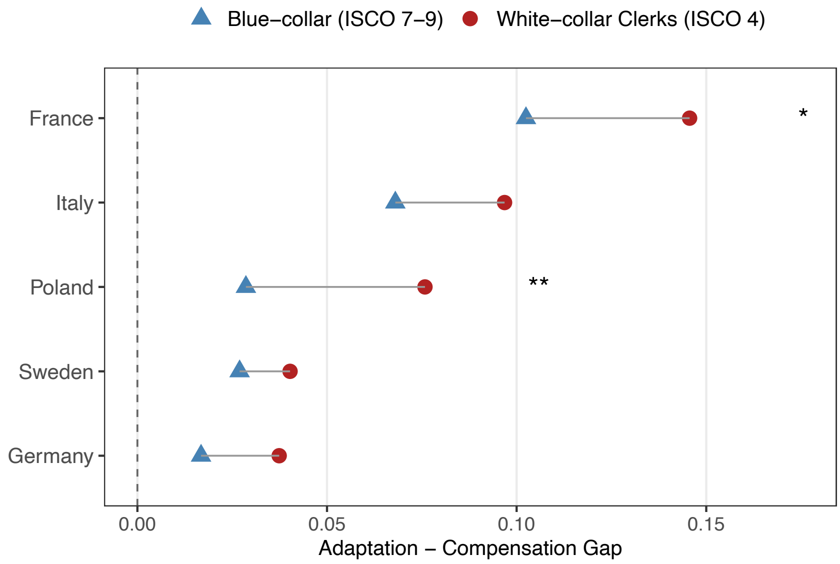


Figure 12: Relative Priority for Adaptation over Compensation by Occupational Class. Data from Gallego and Kuo (2026). Dots show country-level means for white-collar clerks (ISCO 4, red circles) and blue-collar workers (ISCO 7–9, blue triangles). Significance stars indicate within-country differences based on two-sample t-tests (* $p<0.10$, ** $p<0.05$, *** $p<0.01$).

tion rather than a fundamental disagreement over its desirability. Across all five countries, the adaptation–compensation gap is positive for both occupational groups, indicating that blue-collar workers also prioritize adaptation over compensation, albeit less strongly than white-collar workers. This pattern closely mirrors the adaptation-oriented response observed in our panel study and suggests that the distinctive policy profile of white-collar workers is one of degree rather than kind.

This finding also points to an important implication for the politics of AI. Rather than dividing workers into opposing camps, AI-driven technological change may broaden the coalition supporting adaptation-oriented policies. The distinctive contribution of white-collar workers therefore lies not in advocating a fundamentally different policy agenda, but in increasing the political salience of adaptation-oriented responses to technological change. As AI reaches occupations that have historically been relatively insulated from automation, white-collar workers may become an important source of political demand for investment and steering policies. The comparison further suggests that this shift could prove politically feasible, as blue-collar workers also favor adaptation over compensation in absolute terms, even if they attach relatively greater weight to compensation.

Conclusion

This paper provides systematic evidence on how white-collar workers respond politically to AI-driven automation. We focus on labor market entrants in highly exposed office occupations, a group that recent research characterizes as "canaries in the coal mine" because they are among the first to directly experience the consequences of technological innovation (Brynjolfsson et al. 2025). Drawing on a unique three-wave panel that tracks this cohort before and after the widespread diffusion of large language models, we document a political response that differs markedly from patterns observed in research on blue-collar automation. White-collar workers do not primarily experience AI as an imminent threat of job loss but as a source of ongoing uncertainty about the pace of technological change and their ability to keep up with evolving skill requirements. This uncertainty generates demand for policies that enable adaptation to continuous transformation. Rather than demanding greater compensation, exposed white-collar workers primarily support adaptation policies, combining steering policies that shape the pace of technological change with investment policies that facilitate continuous education and skill development.

Such an adaptation-oriented logic complements the compensation-focused preferences documented in earlier studies of blue-collar automation, where perceived risk of displacement has been shown to create demand for passive or compensatory social policy. Our suggestive comparative evidence suggests that blue-collar respondents, too, are in favor of adaptation, even if less strongly than their white-collar counterparts. Rather than reflecting a fundamental divide, the occupational gap we document appears to be one of degree rather than kind. As AI reaches occupations historically insulated from automation, the resulting political demand may broaden rather than fragment: adaptation-oriented policies, such as steering and investment measures, could offer a shared agenda capable of unifying support for government action, rather than dividing it along conventional occupational lines. This suggests that adaptation-oriented politics may come to define the policy space of the emerging AI era.

The generalizability of our findings warrants careful consideration given our specific research design. Our sample is drawn from Switzerland's dual vocational training system, where commercial apprenticeships constitute a well-regarded pathway into skilled white-collar employment. Graduates of this program have strong foundations for continuous skill development and a pronounced awareness of the importance of ongoing learning. The Swiss labor market context more generally – characterized by low unemployment and a strong demand for knowledge-intensive labor – is likely to reduce the perceived risk of prolonged joblessness and dampen demand for state intervention across the board.[8] These scope conditions may therefore primarily compress the overall level of policy demand rather than shape its specific structure. Where labor market insecurity is higher and demand for government intervention is stronger, occupational differences in the structure of policy preferences may express themselves more clearly. This could suggest that our main findings, if anything, represent a lower bound on how distinctive white-collar policy demands are across a broader range of institutional contexts.

Our findings have important implications for policy and politics. The adaptation-oriented response we document reflects a broader shift in the politics of automation. Exposure is no longer isolated in manufacturing but affects office workers and high-skilled professionals, which may explain why debates about the governance and regulation of AI seem far more salient compared to previous technological transitions. For policymakers and scholars alike, our findings suggest that the debate should extend beyond the traditional contrast between compensation and investment to include steering policies that shape the direction and pace of technological change. More broadly, they point to the importance of adaptation as a policy strategy that combines investment in workers' skills with steering the speed of technological transformation. As the group of exposed workers grows, adaptation-oriented policies, particularly steering policies, may prove more electorally attractive than generic pledges to support education or transfers. Whether this potential translates into political mobilization remains an open question, but the preferences we document suggest fertile ground for political competition over how technological change should be governed and managed.

[8] While our sample consists of young labor market entrants, we find comparable risk perceptions in a parallel survey of workers aged 45 and above, suggesting that age alone does not account for the adaptation logic we observe.

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Data Availability Statement

The data underlying this article will be made available in the Harvard Dataverse upon publication.

A. Appendix

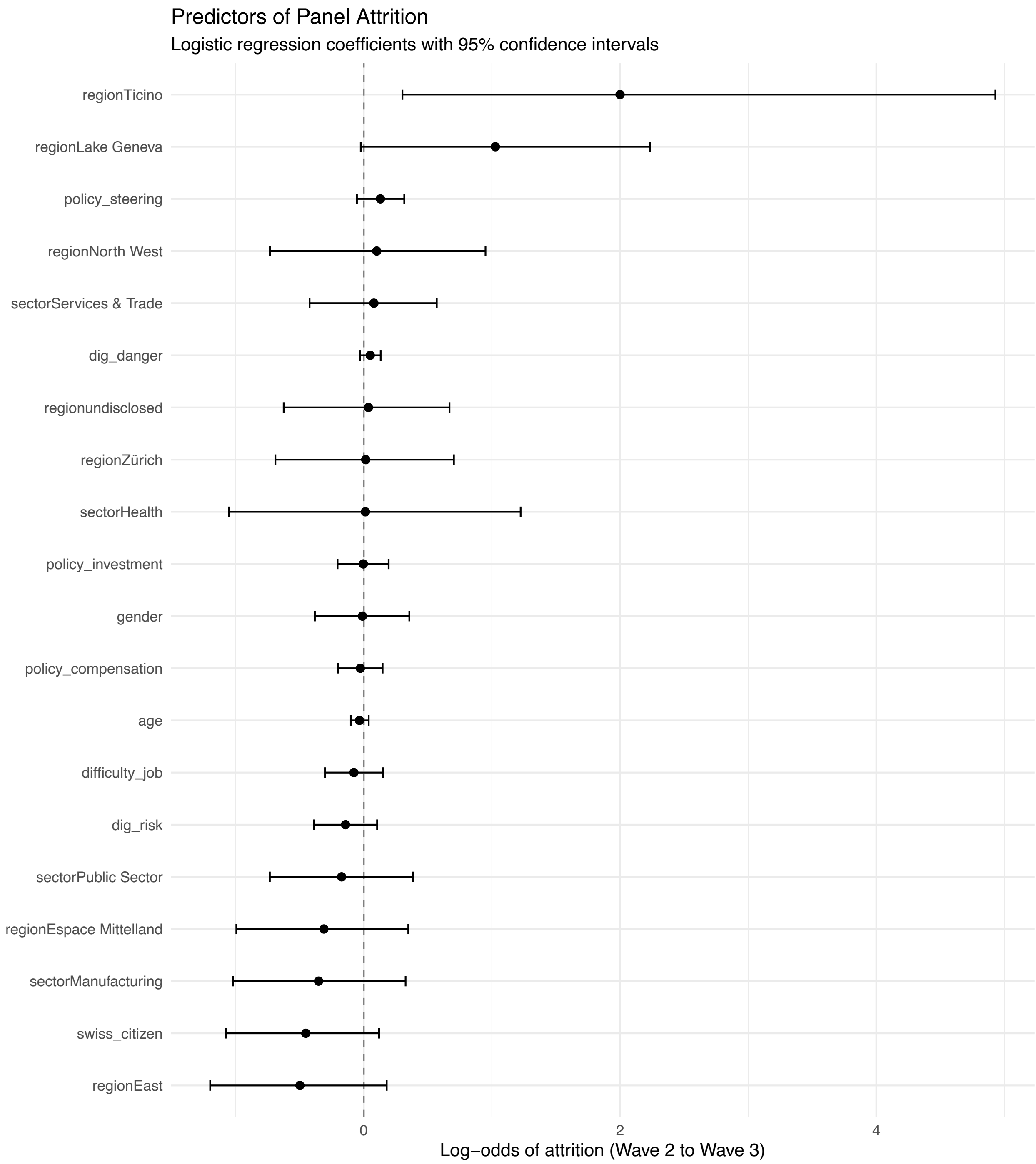

Figure A.1: Evaluation of selective attrition

Table A.1: Correlation Matrix of Exposure Measures

	Difficulty	Threat	Risk	Automat	Index
Difficulty finding a job	1.00	0.15	0.09	-0.01	0.63
Perceived threat from digitalization	0.15	1.00	0.30	0.28	0.69
Digitalization as risk (recoded)	0.09	0.30	1.00	0.15	0.69
Task automatability	-0.01	0.28	0.15	1.00	0.53
Exposure index	0.63	0.69	0.69	0.53	1.00

Table A.2: Top 20 Terms Associated with Digitalization in 2021 and 2025

	2021			2025		
	Term	**EN**	**Count**	**Term**	**EN**	**Count**
1	homeoffice	*home office*	176	künstliche_intelligenz	*artificial intelligence*	113
2	computer	*computer*	155	effizienz	*efficiency*	84
3	papierlos	*paperless*	106	automatisierung	*automation*	75
4	laptop	*laptop*	39	vereinfachung	*simplification*	48
5	effizienz	*efficiency*	33	stellenabbau	*job cuts*	39
6	teams	*Teams (software)*	31	papierlos	*paperless*	34
7	online	*online*	29	homeoffice	*home office*	29
8	automatisierung	*automation*	28	chatgpt	*ChatGPT*	25
9	roboter	*robots*	28	computer	*computer*	25
10	modern	*modern*	26	fortschritt	*progress*	25
11	schneller	*faster*	24	einfacher	*easier*	20
12	vereinfachung	*simplification*	23	schneller	*faster*	19
13	pc	*PC*	21	zukunft	*future*	16
14	einfacher	*easier*	19	veränderung	*change*	14
15	zukunft	*future*	18	flexibilität	*flexibility*	12
16	papier	*paper*	17	optimierung	*optimization*	12
17	arbeitslosigkeit	*unemployment*	16	erleichterung	*relief*	11
18	e_mail	*email*	16	laptop	*laptop*	11
19	internet	*internet*	16	modern	*modern*	10
20	stellenabbau	*job cuts*	14	prozessoptimierung	*process optimization*	10
	Total		2692	**Total**		1553

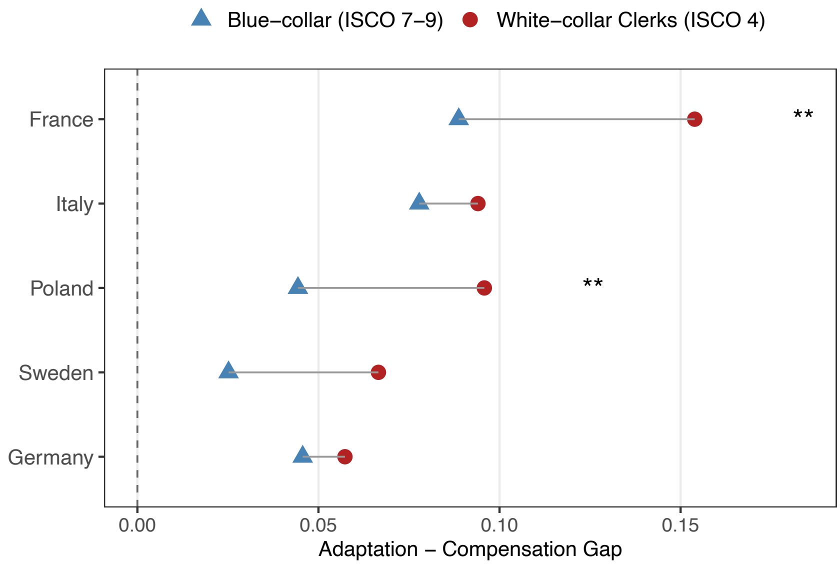

Figure A.2: Relative Priority for Adaptation over Compensation by Occupational Class for respondents who feel exposed to technological change. Exposure is defined as being above the median of a technology threat index combining perceived negative workplace impacts and subjective substitution. Data from Gallego and Kuo (2026). Dots show country-level means for exposed white-collar clerks (ISCO 4, red circles) and exposed blue-collar workers (ISCO 7–9, blue triangles). Significance stars indicate within-country differences based on two-sample t-tests (* $p<0.10$, ** $p<0.05$, *** $p<0.01$).