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Intelligenza artificiale: da innovazione tecnologica a crescita economica inclusiva

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Workers and Generative AI: Evidence from Italy

Massimo Anelli *
Italo Colantone *
Aina Gallego **
Piero Stanig *

Abstract

Generative artificial intelligence (GenAI) is rapidly reshaping labour markets, yet we still know little about how directly exposed workers perceive it and which public policies they favour in response. We present descriptive evidence from a new survey of 711 Italian workers in 98 occupations directly exposed to GenAI. Awareness and use are high, especially among younger workers, with slight differences by education and income.

Perceptions are mixed: workers are optimistic about job autonomy, task enjoyment, and occupational pride, but more cautious about pay, career prospects, and above all job stability. Support for public intervention is broad, spanning

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both traditional redistribution and new AI-specific instruments: union codetermination in the firm, regulation, and taxation of automation. More pessimistic workers favour public intervention, while optimists oppose it, with the sharpest divergence over AI-specific policies.

Sintesi - Lavoratori e intelligenza artificiale generativa: evidenze dall'Italia

L'intelligenza artificiale generativa sta rapidamente trasformando i mercati del lavoro, ma sappiamo ancora poco su come i lavoratori direttamente esposti la percepiscano e quali politiche pubbliche preferiscano. Presentiamo evidenza descrittiva da un nuovo sondaggio su 711 lavoratori italiani in 98 occupazioni esposte all'IA generativa. La consapevolezza e l'uso sono elevati, soprattutto tra i più giovani, con leggere differenze per istruzione e reddito. Le percezioni sono variegate: i lavoratori sono ottimisti su autonomia, gratificazione nei compiti e orgoglio professionale, ma più cauti su salario, carriera e, soprattutto, stabilità di impiego. Il sostegno all'intervento pubblico è ampio e comprende sia la redistribuzione tradizionale sia nuovi strumenti specifici per l'IA: cogestione sindacale dell'impresa, regolamentazione e tassazione dell'automazione. I lavoratori più pessimisti sono a favore dell'intervento pubblico, gli ottimisti si oppongono, con divergenza più forte sulle politiche specifiche per l'IA.

JEL Classification: O33; J24; D72; H23; J58.

Parole chiave: *Intelligenza artificiale generativa; Mercati del lavoro; Preferenze per Politiche Pubbliche; Automazione; Italia.*

Keywords: Generative AI; Labour markets; Policy preferences; Automation; Italy.

1. Introduction

Generative artificial intelligence (GenAI) is rapidly reshaping labour markets across the globe. Large language models (LLMs) such as ChatGPT have reached—and in some domains surpassed—human-level performance in a wide range of cognitive tasks,[1] and their deployment in production, creativity, and decision-making processes is accelerating (Bick, Blandin and Deming, 2024). This is a pervasive transformation that stands to affect workers along multiple dimensions: job opportunities, salaries, autonomy, workplace organisation, and the very content of professional tasks. Current estimates suggest that between half and two-thirds of existing occupations are meaningfully exposed to GenAI (Eloundou, Manning, Mishkin and Rock, 2024; Zarifhonarvar, 2024), although exposure need not entail displacement. Like any technology, GenAI can substitute workers in some tasks while complementing them in others, and may create entirely new activities and economic value (Acemoglu and Restrepo, 2019). Early empirical evidence confirms that GenAI adoption can lead to both occupational contraction and expansion, with impacts distributed unequally across different groups of workers.[2] While the eventual effects on employment and wages remain uncertain, they are likely to be profound and highly heterogeneous.

Like earlier dimensions of structural change—from trade liberalisation to the robotisation of manufacturing—the diffusion of GenAI is bound to pro-

1 See, among others, McDuff, Schaekermann, Tu, Palepu, Wang, Garrison, Singhal, Sharma, Azizi, Kulkarni et al. (2025), Boiko, MacKnight, Kline and Gomes (2023), Tu, Schaekermann, Palepu, Saab, Freyberg, Tanno, Wang, Li, Amin, Cheng et al. (2025), and Tessler, Bakker, Jarrett, Sheahan, Chadwick, Koster, Evans, Campbell-Gillingham, Collins, Parkes et al. (2024).

2 See Aghion, Bunel, Jaravel, Mikaelsen, Roulet and Søgaard (2025), Teutloff, Einsiedler, Kässi, Braesemann, Mishkin and del Rio-Chanona (2025), and Hampole, Papanikolaou, Schmidt and Seegmiller (2025) on heterogeneous employment effects, and Brynjolfsson, Chandar and Chen (2025) and Lichtinger and Hosseini Maasoum (2025) on distributional consequences across worker groups.

duce distributional consequences, generating winners and losers with divergent interests and preferences (Colantone and Stanig, 2018; Milner, 2021; Anelli, Colantone and Stanig, 2021). An extensive body of research has documented how past waves of technological change have shaped workers' policy attitudes and political behaviour. In particular, exposure to industrial robots has been linked to support for radical-right and populist parties (Anelli et al., 2021; Kurer, 2020; Gallego and Kurer, 2022; Milner, 2021), rising demand for economic nationalist policies such as trade protection and immigration restrictions (Colantone and Stanig, 2018; Wu, 2022, 2023), and shifting welfare state preferences (Rehm, 2009; Cusack, Iversen and Rehm, 2006; Busemeyer, Gandenberger, Knotz and Tober, 2023). How workers react in terms of policy and political preferences matters enormously, because it conditions the scope and direction of policy intervention. The governance of the AI transition—through regulation, taxation, retraining policies, and the design of new social protections—will depend on citizens' demand for such measures.[3]

Much of the existing evidence on the political economy of structural changes concerns industrial automation and international trade, shocks that primarily affected routine workers in manufacturing. GenAI presents a qualitatively different challenge. It targets cognitive, white-collar occupations whose incumbents tend to be highly educated, relatively well-paid, and younger than the broader workforce. This profile diverges markedly from the "losers" of earlier transitions. Whether the political patterns documented for robotisation and globalisation carry over to this new setting is an open question. An emerging literature has begun to address it. Haslberger, Gingrich and Bhatia (2025) show experimentally that hands-on exposure to GenAI

3 On the broader relationship between technological change, institutions, and democratic governance, see Boix (2019), Acemoglu (2025), and Iversen and Soskice (2019).

in work tasks can activate support for social policy in the United Kingdom. Magistro, Borwein, Alvarez, Bonikowski and Loewen (2025) uncover common micro-foundations between attitudes toward AI and globalisation. Green, Grant, Evans and Inglese (2025) link AI job exposure to expectations about "winners" and "losers" and political preferences. Busemeyer, Stutzmann and Tober (2025) examine how digitalisation reshapes welfare state attitudes across European countries. More broadly, a growing number of surveys document the range of public attitudes toward AI and its governance (e.g., Zhang, 2024; Weisstanner and van Kersbergen, 2025; Haslberger and Bajka, 2025; Koenig, 2025; Baccini, Ciobanu and Pelc, 2025). This body of work, however, remains predominantly focused on Anglo-Saxon or pan-European settings, and typically relies on general-population samples rather than on workers in occupations that are directly affected by GenAI.

In this paper, we contribute to this literature by exploiting individual-level survey data on 711 workers resident in Italy who are employed across 98 occupations classified as directly exposed to GenAI.[4] We provide detailed descriptive evidence on several dimensions that are central to the political economy of this technological shift. Specifically, we begin by documenting patterns on: (1) workers' awareness of GenAI; (2) the frequency at which they use it; (3) their perceived impact of GenAI on different aspects of their job, including salary, security, and autonomy; (4) their overall assessment of GenAI as an opportunity or a threat for their occupational prospects. We then document workers' preferences regarding a broad set of public policies, encompassing traditional taxation and redistribution items as well as newer instruments directly linked to GenAI, such as workers' codetermination in

4 This sample is the control group that we use for Italy in the survey experiment presented in Anelli, Colantone, Gallego and Stanig (2026), where we also focus on Germany and the United States.

technology adoption choices, GenAI regulation, automation-related taxation and employment protection. Next, we investigate the relationship between subjective perceptions of GenAI's labour-market effects and the demand for different types of policy intervention. Finally, we discuss the implications of our findings for the design of policy responses to GenAI. In this respect, Italy represents a particularly informative setting: its labour market is characterised by comparatively rigid employment protection, a significant public sector, strong traditions of collective bargaining, and a political landscape in which populist forces are present both on the left and on the right of the political spectrum. These institutional features likely influence how workers experience technological change and form preferences over policy responses in ways that potentially differ from the Anglo-Saxon and Northern European contexts studied elsewhere.

We document four main sets of findings. First, awareness of GenAI is high and the use of LLMs is widespread among workers in exposed occupations: more than four out of five respondents are familiar with the technology, and around two thirds have used LLMs at least occasionally. Second, perceptions of GenAI's occupational consequences are nuanced. Workers are relatively optimistic about the effects on job autonomy, enjoyment, and occupational pride, yet considerably more cautious when it comes to salary and career prospects, and especially job security. Third, support for policy intervention is broad-based. Respondents express strong backing for both traditional redistributive measures and newer instruments linked to AI-driven structural change. Fourth, differences in perceptions concerning GenAI's occupational impact are reflected in differences in policy preferences: workers who are more pessimistic about GenAI are more in favour of government intervention through redistribution and regulation, while more optimistic workers

tilt in the opposite direction. The association between subjective perceptions and policy preferences is strongest for AI-specific policy instruments, while traditional redistribution items show weaker differentiation. These patterns suggest that GenAI may be opening a new dimension of policy demand that extends beyond established welfare state debates. This is bound to have significant implications for the governance of the AI transition.

Taken together, the patterns we document are consistent with a view in which workers' demand for policy intervention reflects not only the pace of technology adoption but also their assessments of how the transition is being managed, e.g., whether the costs of adjustment are cushioned, whether protection extends to AI-specific risks, and whether workers are given a voice in how new technologies are deployed at the workplace.

The remainder of the paper is organised as follows. Section 2 describes the procedure for selecting occupations that are directly exposed to GenAI. Section 3 presents the main characteristics of the survey sample. Section 4 documents GenAI awareness and prior use. Section 5 examines workers' perceptions of GenAI's labour-market impacts. Section 6 studies policy preferences. Section 7 links GenAI's impact perceptions to policy preferences. Section 8 concludes.

2. Selection of GenAI-exposed occupations

The sample includes workers employed across 98 6-digit SOC occupations that we have identified as "directly exposed" to GenAI in our own earlier work (Anelli et al., 2026). In order to select these occupations, the

following multi-stage strategy is implemented. In the first stage, we scrape occupation-level scores of AI exposure from three leading studies: Felten, Raj and Seamans (2021), Tolan, Pesole, Martínez-Plumed, Fernández-Macías, Hernández-Orallo and Gómez (2021), and Webb (2019).[5] Scores provided by Felten et al. (2021) and Webb (2019) are available at the 6-digit level of disaggregation, whereas those by Tolan et al. (2021) are only available at the higher-order 3-digit level. For consistency, we aggregate the 6-digit scores in Felten et al. (2021) and Webb (2019) at the 3-digit level using US employment weights from the Bureau of Labor Statistics (BLS). These weights are based on May 2022 estimates for the total number of employees within each 6-digit occupation in the US. As a result, we obtain three "automatability" scores for each 3-digit SOC occupation. We then run a cluster analysis across occupations on each of the three scores, separately, to assign occupations to two groups: *exposed* or *not exposed* to AI. Thus, we obtain three distinct binary classifications of SOC-3 occupations. We select all the 3-digit occupations classified as exposed to AI according to at least two out of three classifications. This step results in the selection of 39 3-digit SOC occupations (out of a total of 94 at this level of aggregation). They are reported in Appendix Table A1.

In the second stage, we focus on all the 369 6-digit SOC categories within the selected 39 3-digit occupations. Among them, we identify as directly exposed to GenAI those where *the most frequent core task* is automatable through ChatGPT. The most frequent core task for each occupation is identified from the O*NET database. In fact, the latter provides a comprehensive list of performed tasks for each occupation, complemented with data on how

5 These indices are obtained through different, yet complementary, approaches. More specifically, the scores developed by Felten et al. (2021) and Tolan et al. (2021) are based on progress in AI capabilities that are relevant to well-determined abilities and professions. Conversely, the Webb (2019) measures are based on the development of patents that are relevant for given occupation-linked tasks. We have obtained data for the three scores from the replication package of Tolan et al. (2021), available at https://repositori.upf.edu/handle/10230/55770.

frequently each given task is performed by workers employed in a given occupation.[6] To evaluate the automatability of each of the 369 occupation-specific tasks, we interrogate the OpenAI API (model gpt-4 at temperature 0). The assessment is based on the taxonomy and exposure rubric in Eloundou et al. (2024). Specifically, a task can be classified by ChatGPT in the following ways: non exposed to LLMs (coded E0); directly exposed to LLMs (coded E1); exposed by LLM-powered applications (coded E2); and exposed though image capabilities (coded E3).

Our prompt text reads:

> Please rely on the following rubric to classify different combinations of occupations and job tasks. It is crucial that you do not simply match keywords between the task descriptions and the rubric. Instead, please apply a thorough analysis, considering the overall context, required skills, and complexity of the tasks. Ensure to utilize your general knowledge about work tasks and automation possibilities in various industries. I provide the rubric below, and after that I will give you the list of occupations and tasks to be classified. Please provide the output [with] [without] explanation in the following csv format separated by semi-colons: classification; task ID; [explanation].

We then pass the classification grid developed by Eloundou et al. (2024)

6 Task frequency is computed based on survey data among workers within each occupation. In almost all cases, there is one central task that is strictly more frequent than the others. Only in a handful of cases there are two core tasks that are equally frequent. In such situations, we focus on the most important one based on the O*-NET importance scores. Furthermore, most 6-digit SOC occupations correspond to a single '6-digit SOC.00' code in O*NET. In cases where multiple correspondences exist (including '.00'), we prioritize the '.00' code, ignoring others like '.01', '.02', etc. If there is no '.00' code, but only codes like '.01', etc., we select the most frequent core task among these O*NET codes. For occupations where the last digit before the decimal in the code changes (referred to as the 'prefix'), such as 13-1020 evolving into 13-1021.00, 13-1022.00, 13-1023.00, we follow the same approach as above but consider all codes with the new prefix.

and ask ChatGPT to label each occupation-specific task 5 times. We select only those occupations where the answer is unanimously "directly exposed to LLMs" (coded E1). This leaves us with a total of 176 6-digit SOC occupations classified as directly exposed to GenAI. We finally select 98 out of these 176 to ensure representativeness in the Italian panel supplied by the third-party survey company (YouGov). The list of all 6-digit SOC occupations included in the sample is provided in Appendix Section A.4.

We select into the sample only respondents who are currently employed in one of the 98 selected occupations. Respondents report their current occupation at the very beginning of the survey through an interactive interface. The reference 6-digit SOC occupation titles are in English. The translation into Italian is done through the official cross-walk from O*NET to ISCO codes made available by the EU Commission.[7] There are some cases in which the same SOC title corresponds to multiple ISCO codes, with their corresponding official Italian denominations. In such cases, all the corresponding ISCO codes are included in the sample. The full list of included ISCO codes, with their Italian denominations, is reported in Appendix Section A.5.

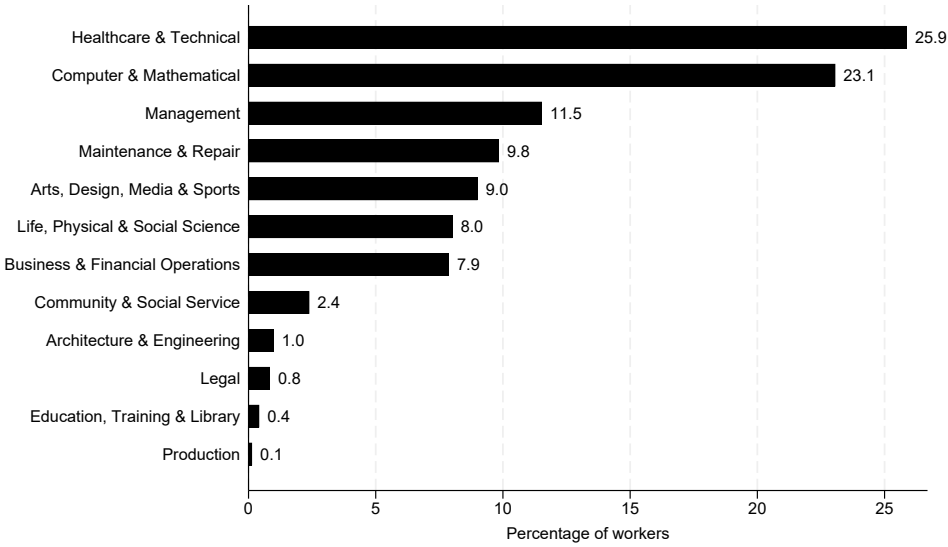
3. Sample summary statistics

Our sample of GenAI-exposed workers is composed of 711 respondents. These were interviewed by the survey company YouGov between January and February of 2025. Figure 1 shows the breakdown of sample workers by 2-digit SOC occupational categories. The most represented occupations are

7 It can be found at this link: https://esco.ec.europa.eu/en/use-esco/other-crosswalks.

in healthcare and technical (25.9%), computer and mathematical (23.1%), and management-related (11.5%) jobs.

Figure 1 **Distribution of sample workers across SOC-2 occupational categories**



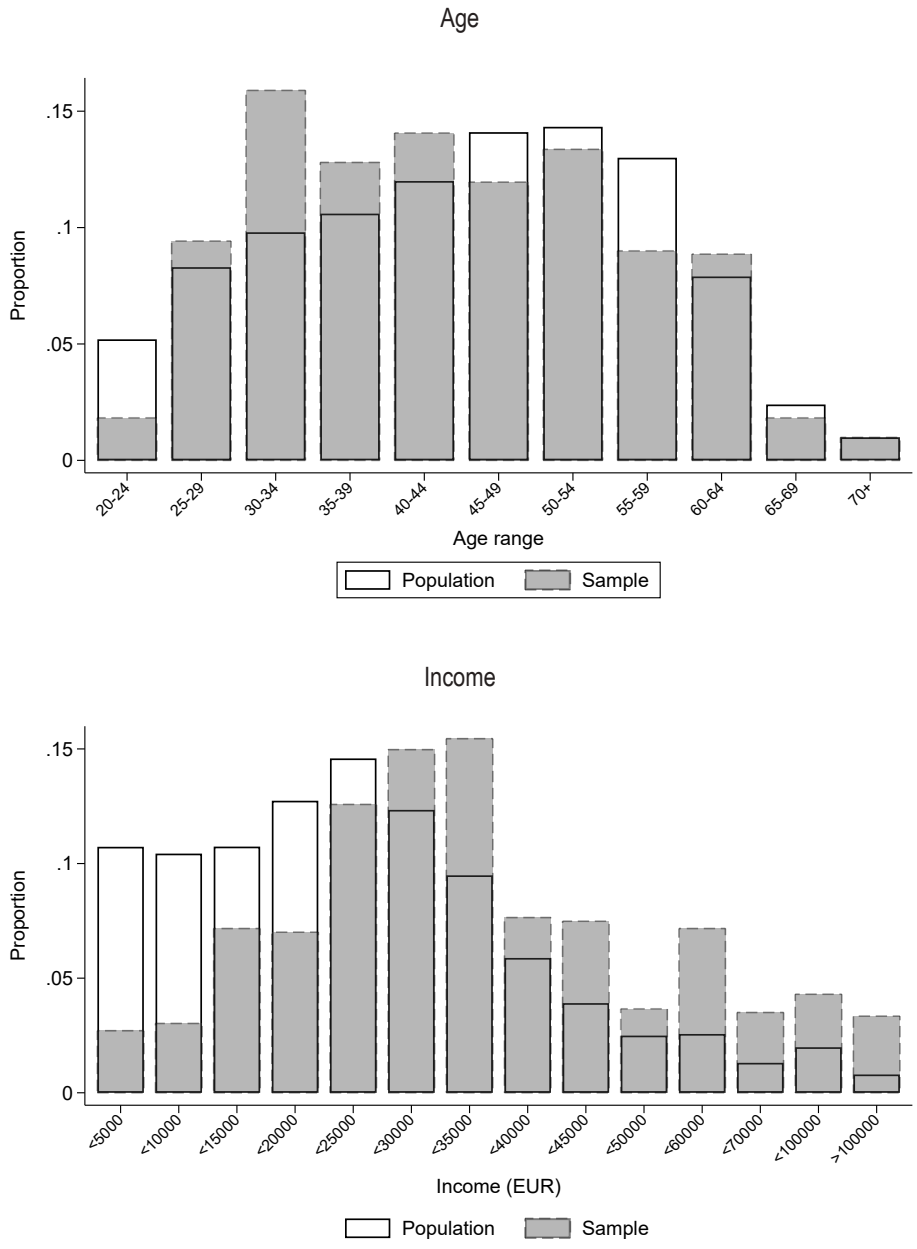
The 98 high-LLM-exposure occupations in our sample are concentrated in high-skill, cognitively intensive jobs, especially managerial, professional, and technical occupations. A back-of-the-envelope calculation places the occupations in our sample at approximately 10–20% of total Italian employment, with a central estimate of 15%.[8] This corresponds to roughly 3.5 million

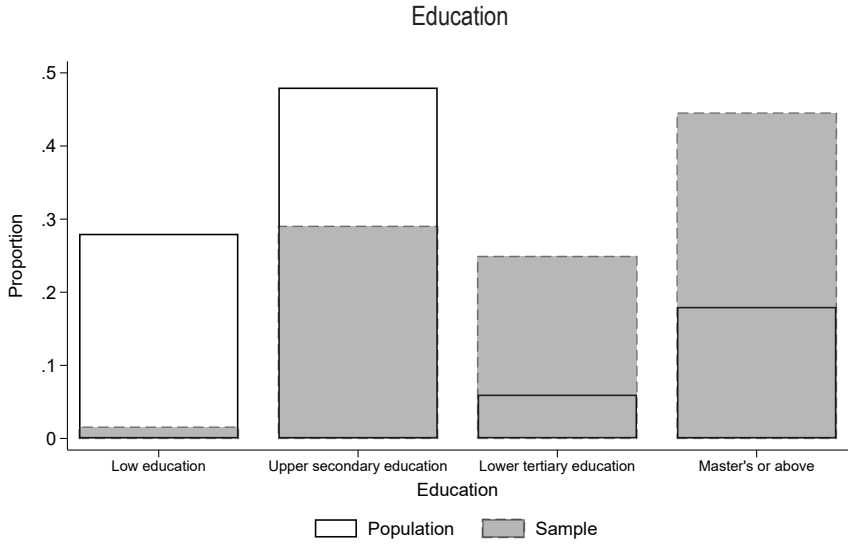
8 The lower bound (10%) maps our occupations to CP2021 five-digit units and apportions major-group employment uniformly across all units; the upper bound (20%) attributes the full employment of each matched four-digit ISCO-08 unit group (Istat, 2024, 2021; Eurostat, 2026). Italian public labour-force statistics do not release occupational employment below the one-digit major-group level, so exact headcounts for narrowly defined occupations are unavailable with public data and the uniform apportionment is the best feasible approach. As external validation, we match the same 98 occupations to the U.S. Bureau of Labor Statistics Occupational Employment and Wage Statistics (BLS OEWS, May 2022 national estimates), which reports employment at the six-digit SOC level: the 98 occupations account for approximately 22.7 million out of 147.9 million employed workers, or 15.4% of U.S. employment—consistent with the Italian 15% central estimate.

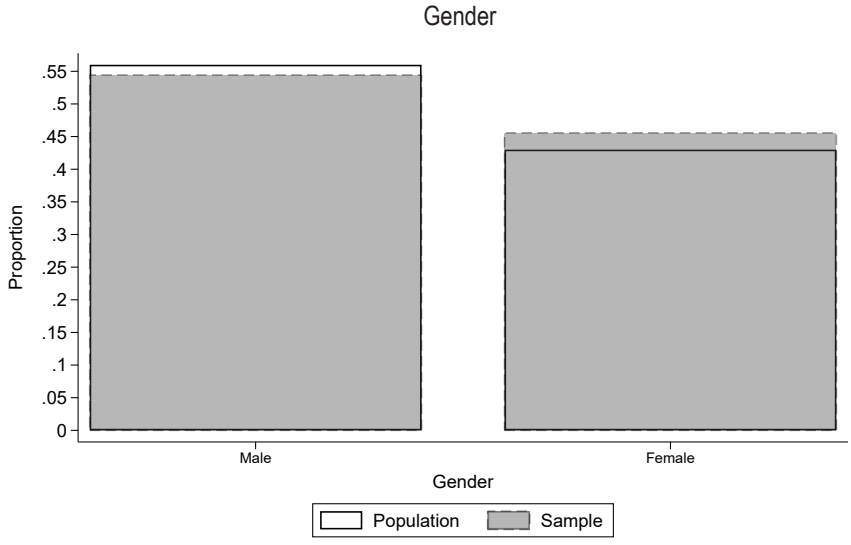
workers, or about one in seven employed persons in Italy. Hence, the sample captures a sizeable segment of the workforce, located in the occupational strata most directly affected by the technology.

In Figure 2, we compare the baseline demographic characteristics of sample workers against the overall Italian population. Specifically, the four panels present differences in the distributions by age, gender, educational attainment, and income between the sample and the overall population. On average, our sample is composed of relatively younger, more educated, and higher-income individuals. By contrast, no sizeable differences emerge regarding the breakdown by gender. More specifically, in terms of age differences, individuals aged 25 to 44 years old tend to be over-represented in our sample, whereas the population includes slightly more people aged less than 25 and over 45 years old. Moreover, the income distribution at the sample level is significantly shifted towards the right, with greater shares of workers earning above 25,000 EUR per year compared to the general population. Finally, our sample includes notably more people with at least "lower tertiary" education.

Figure 2 **Sample versus population comparisons**



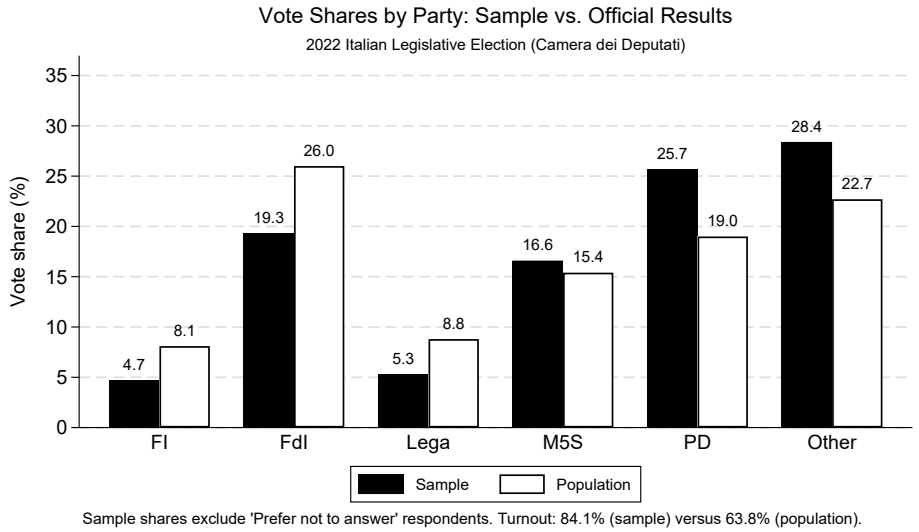




In line with their higher education, higher income, and concentration in managerial, professional, and technical occupations, respondents in our sample belong to social groups that are comparatively more politically engaged

(Istat, 2025): this pattern is reflected in our data, as can be seen in figure 3. 84.1% among our sample respondents report voting in the 2022 general election, compared with an official national turnout of 63.8% (Ministero dell'Interno – DATI, 2022). Their partisan profile also differs from the national one: among respondents who report a vote choice, support for the centre-right parties that won the 2022 election is lower than in the official results, while support for the Democratic Party and other centre-left, green, liberal, and smaller lists is higher. Still, the overall pattern indicates that GenAI-exposed workers form a sizeable and politically active constituency, leaning relatively less toward the governing centre-right than the electorate as a whole.

Figure 3 **Vote shares by party. Sample versus population comparisons**



Note: Figures refer to the 2022 Italian legislative election (Camera dei Deputati). *Sample* bars represent self-reported survey responses; *Population* bars report the official results, with vote shares sourced from Ministero dell'Interno – DATI (2022). The category "Other" includes +Europa, Alleanza Verdi e Sinistra, Azione – Italia Viva – Calenda, Italexit per l'Italia, Unione Popolare, and "Other party or candidate". Sample shares are calculated for respondents who expressed a choice (i.e., excluding the "Prefer not to answer" category).

4. GenAI awareness and prior LLM use

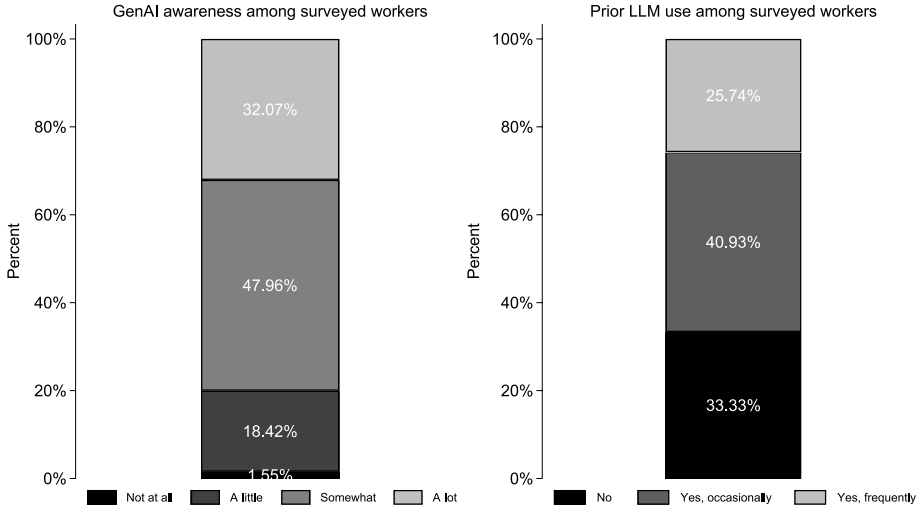
In this section, we provide evidence on workers' awareness of GenAI, and on the frequency at which they have used LLMs for work or other activities prior to the survey.[9]

The left panel of Figure 4 shows that the Italian workers in our sample display high levels of familiarity with GenAI. More than four out of five respondents report having heard at least *somewhat* about GenAI (47.96% "Somewhat" and 32.07%"A lot"), whereas only 1.55% of the sample declares no prior awareness at all. Prior LLM use is also common. As reported in the right panel, around two in three workers have used LLMs at least occasionally, and one in four reports frequent use. These figures are consistent with—though somewhat higher than—the patterns documented by the 2024 Eurobarometer survey for the Italian population as a whole (European Commission, 2024). This is expected given that our sample is restricted to workers in occupations directly exposed to GenAI, and our survey is fielded later on, at the beginning of 2025.

9 The survey questions that capture these items are: "Prior to taking this survey, how much had you heard or read about generative AI (such as ChatGPT)?" The available answers are: "Not at all" (1), "A little" (2), "Somewhat" (3), and "A lot" (4). "Have you used large language models like ChatGPT or Gemini for your work or other activities?" The available answers are: "No" (1), "Yes, occasionally" (2), and "Yes, frequently" (3).

Figure 4 Distribution of GenAI awareness and prior LLM use among sample workers. The left stacked bar chart reports respondents' self-assessed awareness of generative AI, ranging from "Not at all" and "A little" to "Somewhat" and "A lot." The right stacked bar chart shows the shares of respondents who have never used large language models (LLMs), used them occasionally, or used them frequently.

Figure 4 **GenAI awareness and prior use of LLMs**



We investigate heterogeneity in GenAI awareness and prior use along four dimensions: gender, age, educational attainment, and annual gross income. The detailed breakdowns are reported in Appendix Figures A1 and A2, while here we highlight the main patterns.

The sharpest divide is generational. Workers below the sample median age of 43 are substantially more aware and more frequent users of LLMs than their older counterparts. Among younger workers, 40.60% report having heard or read "a lot" about GenAI compared to 24.47% among older workers (Appendix Figure A1, Panel B). Younger workers are also more than twice as

likely to report frequent LLM use (36.12% vs. 16.49%), while being far less likely to have never used LLMs at all (24.78% vs. 40.96%; Appendix Figure A2, Panel B). This age gradient in GenAI adoption is notable because it suggests that the workers who are most actively engaging with the technology are also those with the longest remaining career horizons—a combination that may amplify both the perceived stakes of technological change and the demand for institutional responses to it.

Gender differences are present but more moderate. Male workers report somewhat higher awareness — 36.69% have heard "a lot" about GenAI, compared to 26.54% of women — and the share reporting only"a little" awareness is nearly double among women (24.69% vs. 13.18%; Appendix Figure A1, Panel A). The gender gap in frequent LLM use runs in the same direction, with 28.94% of men versus 21.91% of women reporting frequent use (Appendix Figure A2, Panel A).

By contrast, differences by education and income are comparatively small. The gap in high awareness between college-educated and non-college-educated respondents is roughly six percentage points, while frequent LLM use differs by less than two points (Appendix Figure A1, Panels C–D, and Appendix Figure A2, Panels C–D). The pattern across income groups is similarly muted: awareness and use do not differ substantially between above- and below-median earners. The limited role of socioeconomic status in structuring GenAI familiarity is worth noting: within occupations directly exposed to the technology, it is age—not education or income—that most clearly separates early adopters from the rest.

5. GenAI impact perceptions

We now turn to the central descriptive question of this paper: how do workers in GenAI-exposed occupations perceive the likely consequences of this technology for their occupational prospects? We examine seven perception items at two levels of detail. The first set of items asks respondents to evaluate the expected effects of GenAI on five *specific dimensions* of their job: salary and career opportunities; job security; autonomy; enjoyment of daily tasks; and occupational pride.[10] The second set of items elicits a *broader, more general assessment* of GenAI, asking respondents their opinion as to: whether this technology will make workers like themselves more productive vs. redundant; and whether they regard it overall as an opportunity or a threat.[11] Response options range from "A large threat" (1) to "A large opportunity" (5). All items are coded on a [-2,2] scale where higher values correspond to more pessimistic views. We first report baseline distributions showing the share of workers selecting each response level. For the heterogeneity analysis that follows, we linearly rescale items to [0,1] using $x^{01} = (x + 2)/4$, so that 0 represents the most optimistic response, 1 the most pessimistic, and 0.5 the neutral midpoint.

10 The survey item reads: "Do you think that generative AI (such as ChatGPT) will have mostly positive or negative effects on the following aspects of your work?" For each of the five dimensions, the response options are: Mostly positive (1), Somewhat positive (2), Neither positive nor negative (3), Somewhat negative (4), Mostly negative (5).

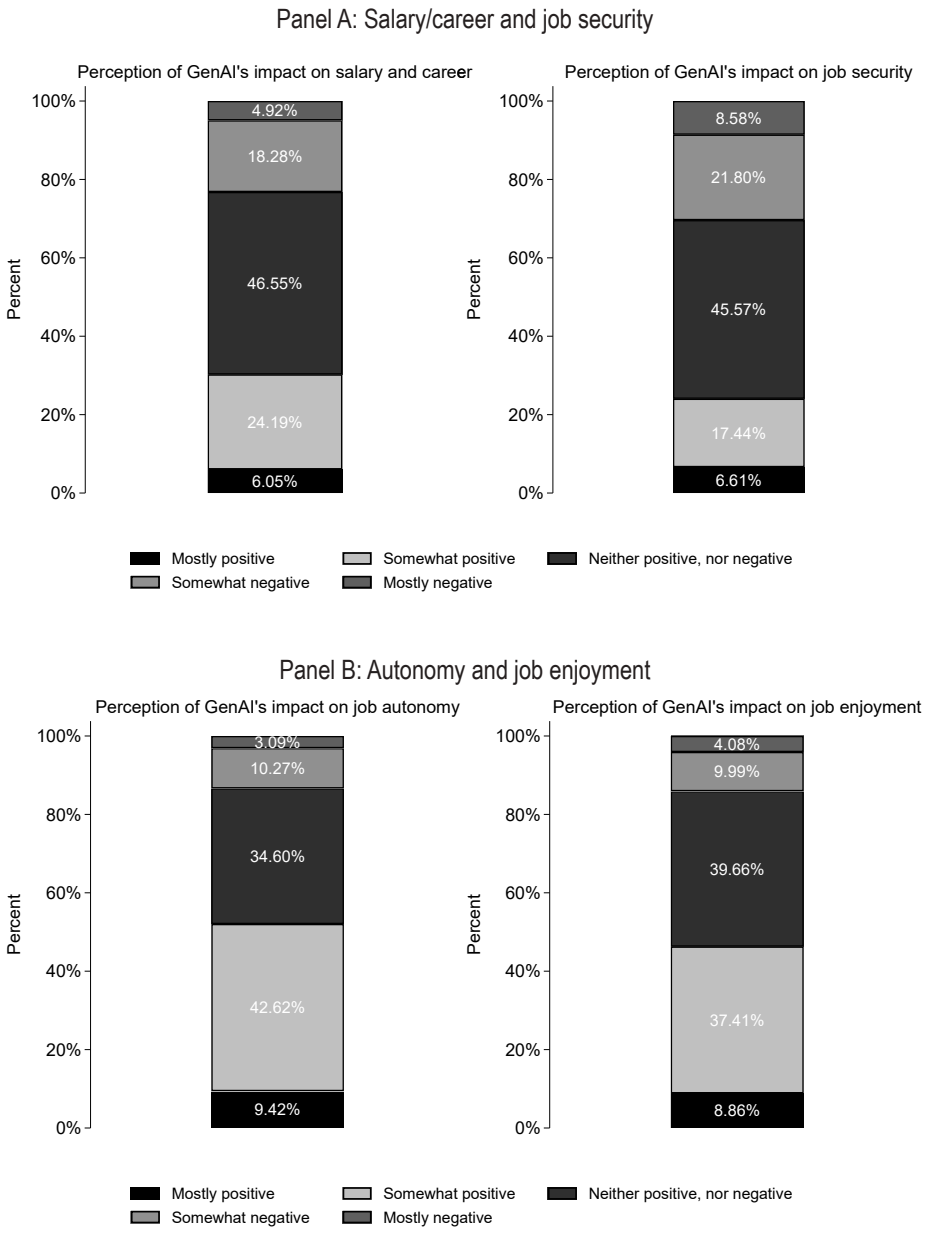
11 The redundancy item asks which statement best reflects the respondent's views: "GenAI will mostly make workers like me redundant" (1); "GenAI will have no impact on workers like me" (2); "GenAI will make workers like me more productive and better paid" (3). The threat item asks: "Do you perceive generative AI (such as ChatGPT) as more of a threat or an opportunity for workers like yourself?"

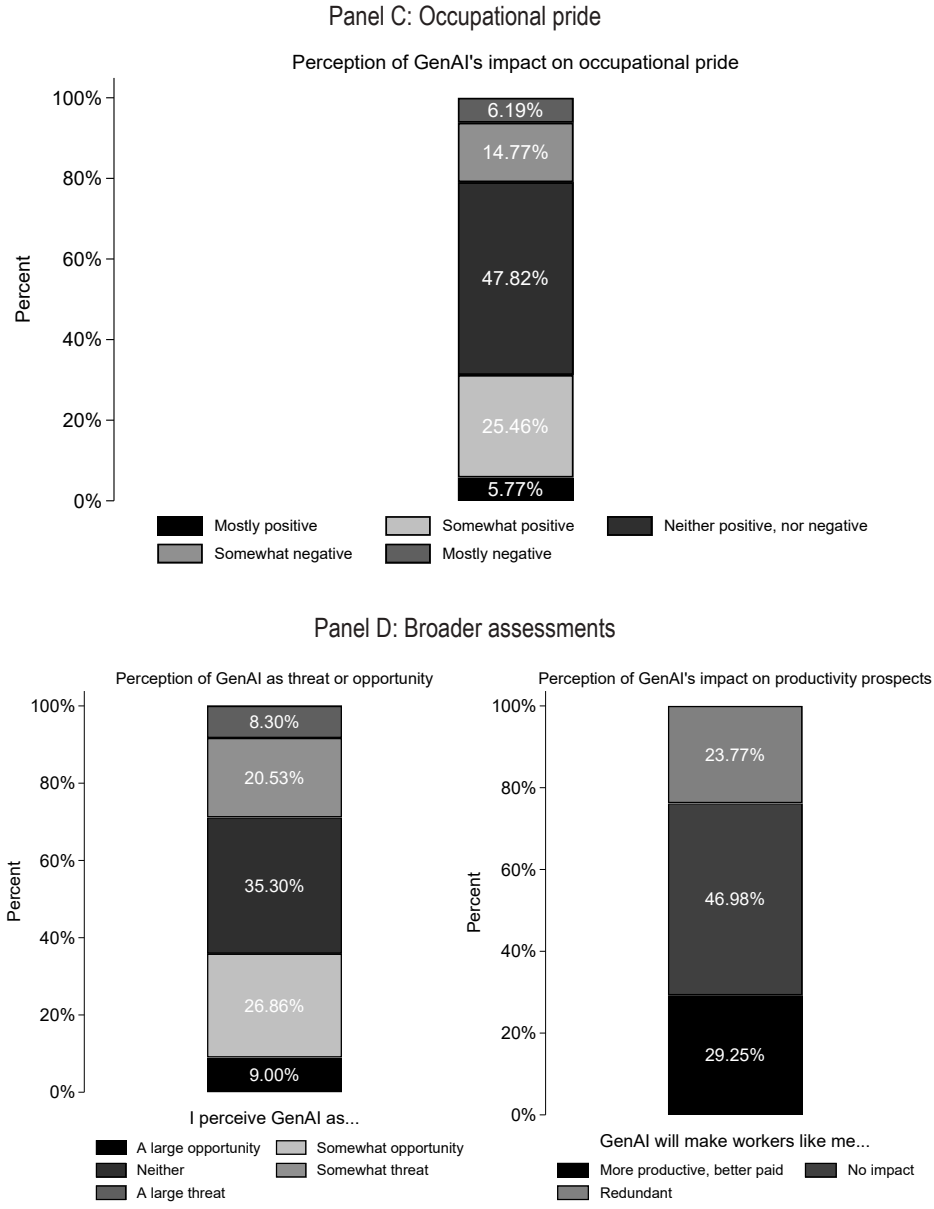
Specific dimensions of work.

A central finding is that workers distinguish sharply between the effects of GenAI on different specific aspects of their jobs. As shown in Panels A-B of Figure 5, when considering views on salary and career prospects or job security, the modal response is neutral: 46.55% and 45.57% of respondents answer "neither positive, nor negative'', respectively, and the balance between positive and negative assessments is relatively even. By contrast, when it comes to job autonomy and enjoyment of daily tasks, a majority views GenAI favourably: 52.04% regard its effects on autonomy as somewhat or mostly positive (42.62% "somewhat positive" and 9.42% "mostly positive"), and 46.27% say the same for enjoyment (37.41% and 8.86%). A similar pattern holds for occupational pride, in Panel C: positive perceptions outweigh negative ones (around 30% vs. nearly 20%), with almost half of the workers (47.82%) being neutral.

In sum, workers in GenAI-exposed occupations appear confident that the technology may improve working conditions—i.e., how they perform their tasks, how much autonomy they exercise, and how much satisfaction they derive from it—but they are considerably more cautious about whether this technological shift will translate into better material outcomes in terms of salary, career progression, and above all job security. This asymmetry is important for understanding the policy preferences documented in later sections: it suggests that the demand for protective intervention may be driven less by a fear of degraded working conditions than by uncertainty about the distributional consequences of GenAI in terms of contractual conditions and employment stability.

Figure 5 **Perceived GenAI impacts**





Notes. Panel A shows perceived impacts on salary and career opportunities (left) and job security (right). Panel B shows perceived impacts on autonomy (left) and enjoyment of daily tasks (right). Panel C reports perceived impact on occupational pride. Panel D presents broader assessments on: the opportunity-threat dimension (left) and productivity-redundancy dimension (right).

Broader, more general assessments.

In Panel D of Figure 5 we examine how workers evaluate GenAI in more general terms, i.e., as an opportunity or threat for workers like themselves, and in terms of productivity versus redundancy. The threat-opportunity assessment shows a divided distribution: 35.86% of respondents regard GenAI as "a large opportunity" or "somewhat of an opportunity", while 28.83% perceive it as "a large threat" or "somewhat of a threat", with the remainder taking a neutral position. The productivity-redundancy item paints a similar picture: 29.25% of respondents expect GenAI to make workers like themselves more productive and better paid, whereas 23.77% anticipate redundancy. These broader assessments confirm that workers in exposed occupations hold genuinely mixed views: GenAI is not perceived as unambiguously beneficial, nor as uniformly threatening.

Heterogeneity in perceptions.

Is there noticeable heterogeneity in GenAI impact perceptions across different demographic groups? We address this question in Figures 6 and 7, for the five specific work dimensions and the broader assessments, respectively. The heterogeneity analysis is based on conditional means on the [0,1] rescaled survey items by gender, age, education, and income.

Overall, perceptions concerning the five specific dimensions of work are pretty uniform across demographic groups, with some nuances. Age differences are essentially absent: all five specific dimensions are virtually identical for workers above and below the median age of 43, with job security attracting the greatest pessimism (mean around 0.52) and autonomy the greatest optimism (mean around 0.39) in both groups (Figure 6, Panel B). Similarly, perception gaps on the specific work dimensions between college-educated

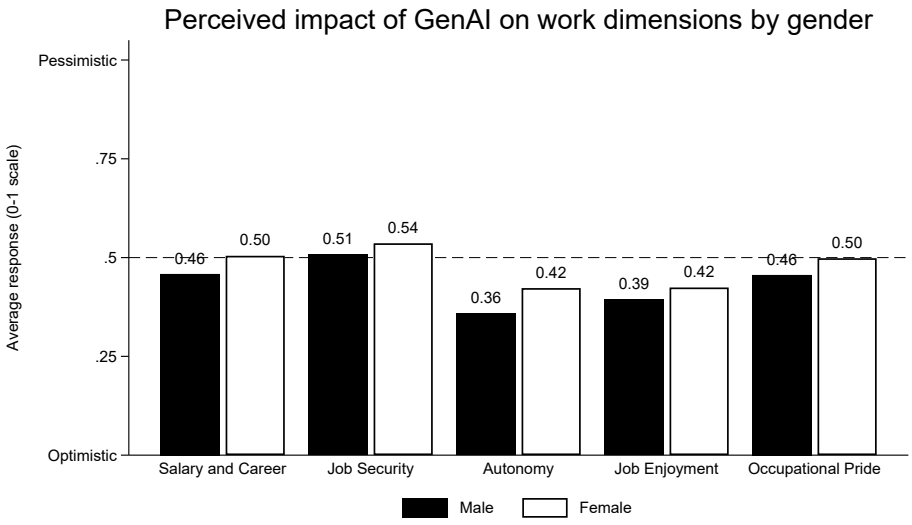
and non-college-educated workers are negligible; if anything, college-educated respondents appear slightly more pessimistic across the board (Figure 6, Panel C). Income differences are likewise minimal, with both above- and below-median income groups expressing their highest concern over job security and their greatest optimism over autonomy (Figure 6, Panel D).

Some more heterogeneity emerges when considering gender. Female respondents are more pessimistic than male respondents on all five specific work dimensions, with the largest gap observed for perceived impacts on autonomy. Job security is the dimension where gender differences are smallest, and where concern is highest for both groups (Figure 6, Panel A). Interestingly, however, this gender gap narrows substantially—and even reverses direction—when respondents assess GenAI in broader terms. In fact, as shown in Panel A of Figure 7, men appear slightly more pessimistic when evaluating GenAI as an opportunity or threat for workers like themselves, and when assessing the technology in terms of productivity versus redundancy.

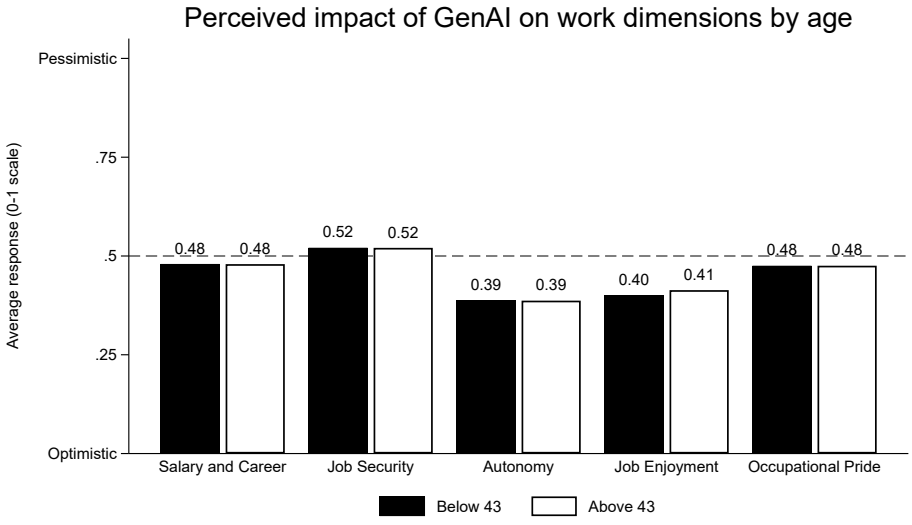
Broader assessments of GenAI reveal clearer socioeconomic gradients than the items on specific dimensions of work. Relatively older workers tend to be more pessimistic than younger ones on both broader perception items (Figure 7, Panel B). Similarly, respondents without college education are notably more pessimistic than more educated workers (Figure 7, Panel C). The same is true for below-median income workers compared to above-median workers (Figure 7, Panel D). This pattern—limited heterogeneity in how workers assess GenAI's effects on specific aspects of their daily work, but sharper divides in how they evaluate its broader consequences for their occupational prospects—are consistent with the idea that concerns about GenAI are less about the technology's immediate impact on task performance and more about its implications for job security and material well-being.

Figure 6 **Perceived impact of GenAI on work dimensions by demographic group**

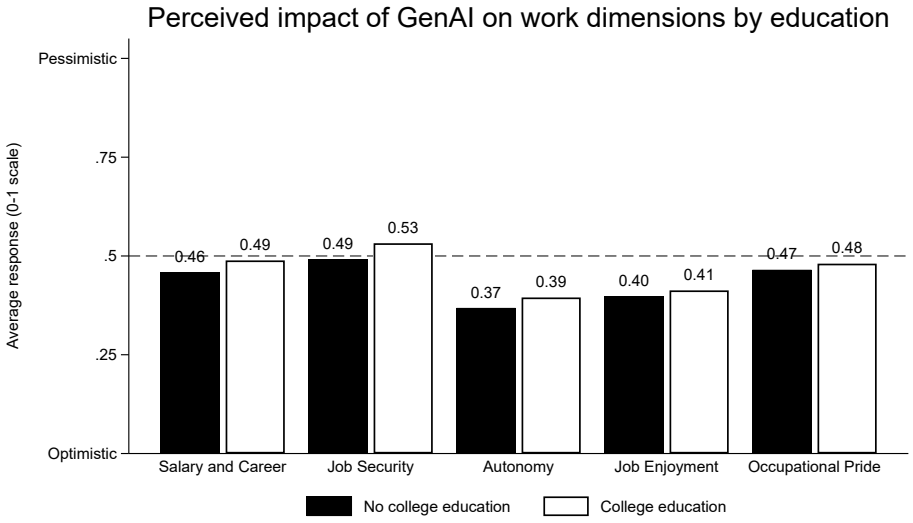
Panel A: By gender



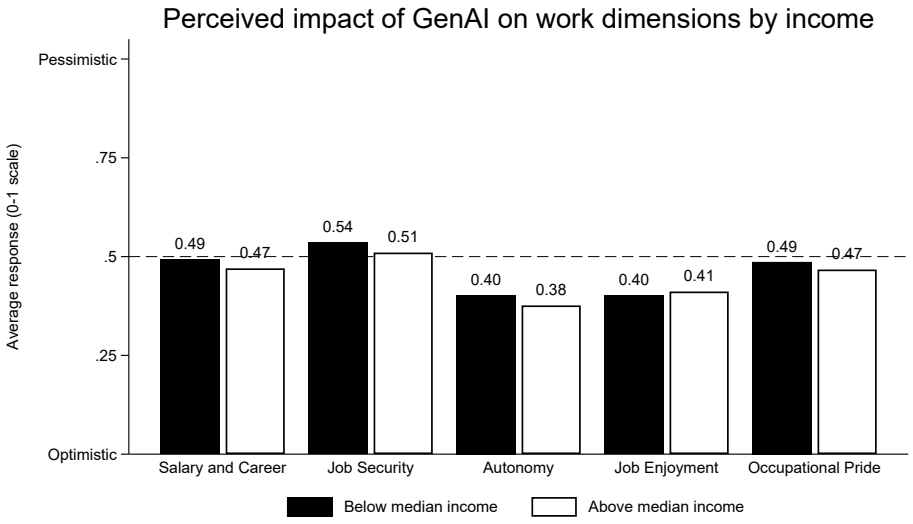
Panel B: By age



Panel C: By education



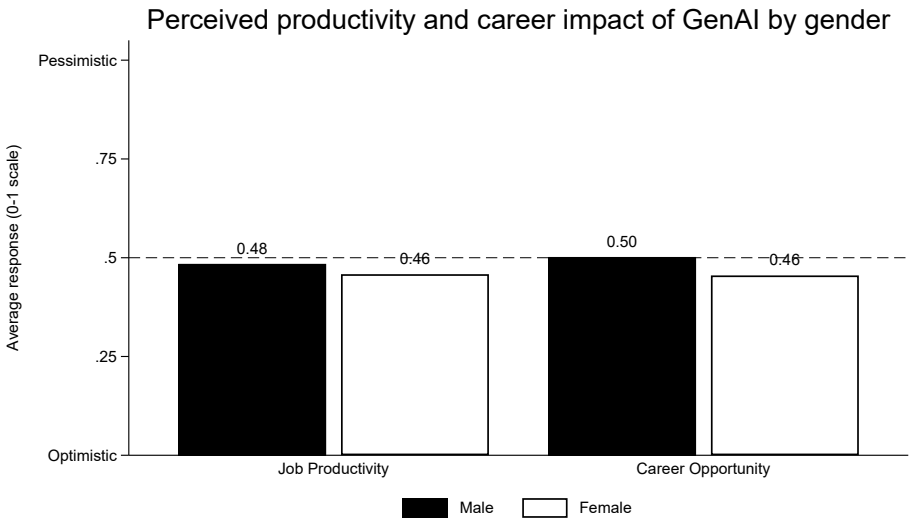
Panel D: By income



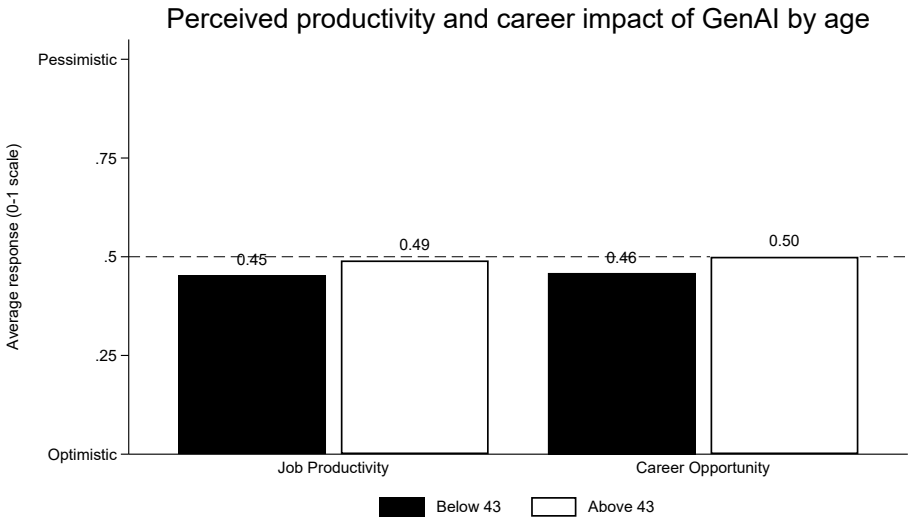
Notes. Bars report mean responses on a 0–1 scale for five specific dimensions of work: salary and career, job security, autonomy, enjoyment, and occupational pride. Higher values indicate more pessimistic assessments.

Figure 7 **Broader GenAI assessments by demographic group**

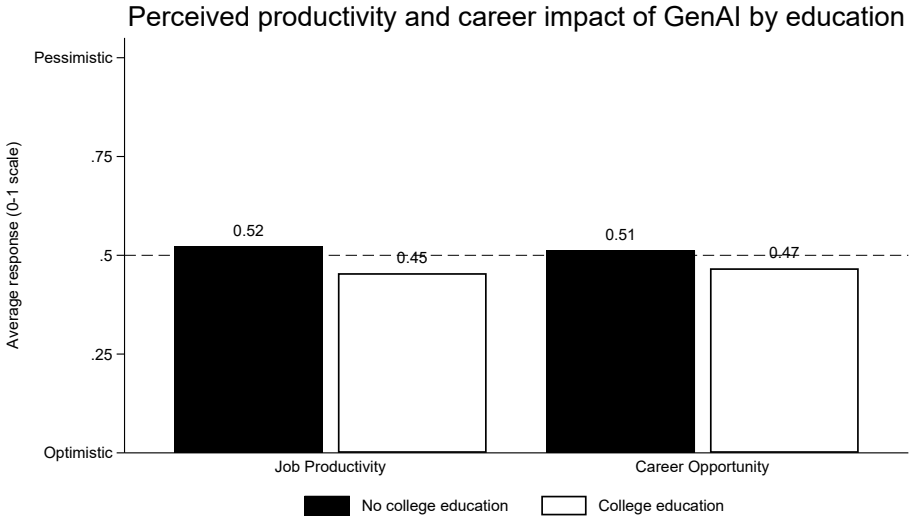
Panel A: By gender



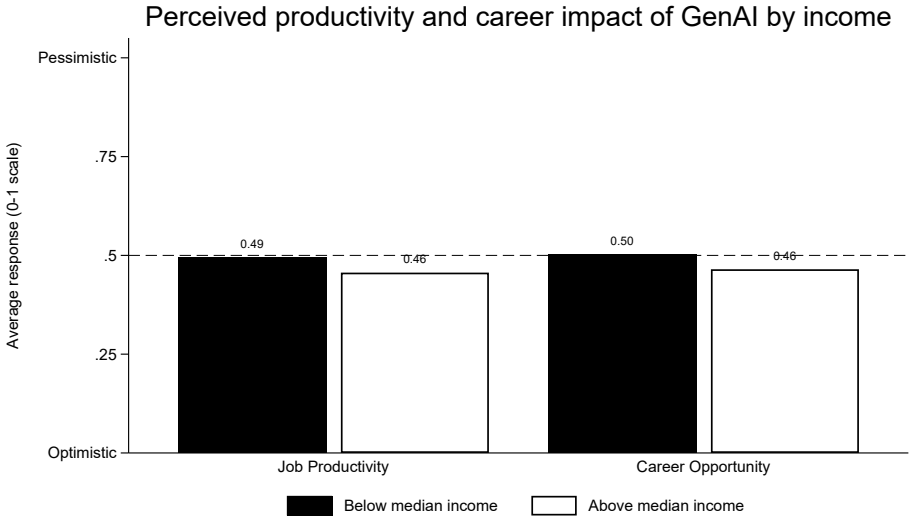
Panel B: By age



Panel C: By education



Panel D: By income



Notes. Bars report mean responses on a 0–1 scale for broader assessment items. Higher values indicate more pessimistic assessments.

Additional heterogeneity analysis by NUTS-1 macro region of residence, and by party voted in the last election, is reported in Appendix Section A.2. Concerning geographical differences, workers in the North East and the North West tend to display somewhat more pessimistic views on specific work dimensions, especially salary and career prospects and job security. Conversely, workers in the Centre and in the South are relatively more pessimistic when it comes to broader assessments of GenAI's impact. As for political differences, radical left voters (AVS and Unione Popolare) tend to be the most pessimistic about the new technology, while center-liberal voters (Azione and +Europa) are among the most optimistic. Differences among voters of the main parties are relatively muted. The full set of breakdowns is reported in Appendix Figures A3–A8.

6. Policy preferences

In this section, we document workers' preferences across three families of policy areas. The first encompasses traditional taxation and redistribution items, as well as active labour market policies. The second covers new policy instruments that have gained prominence in the public debate specifically in the context of AI-driven structural change, such as taxation of automation and regulation of AI. The third covers two broader ideological orientations that have been connected to structural economic changes in earlier work: economic nationalism and left-wing authoritarianism.

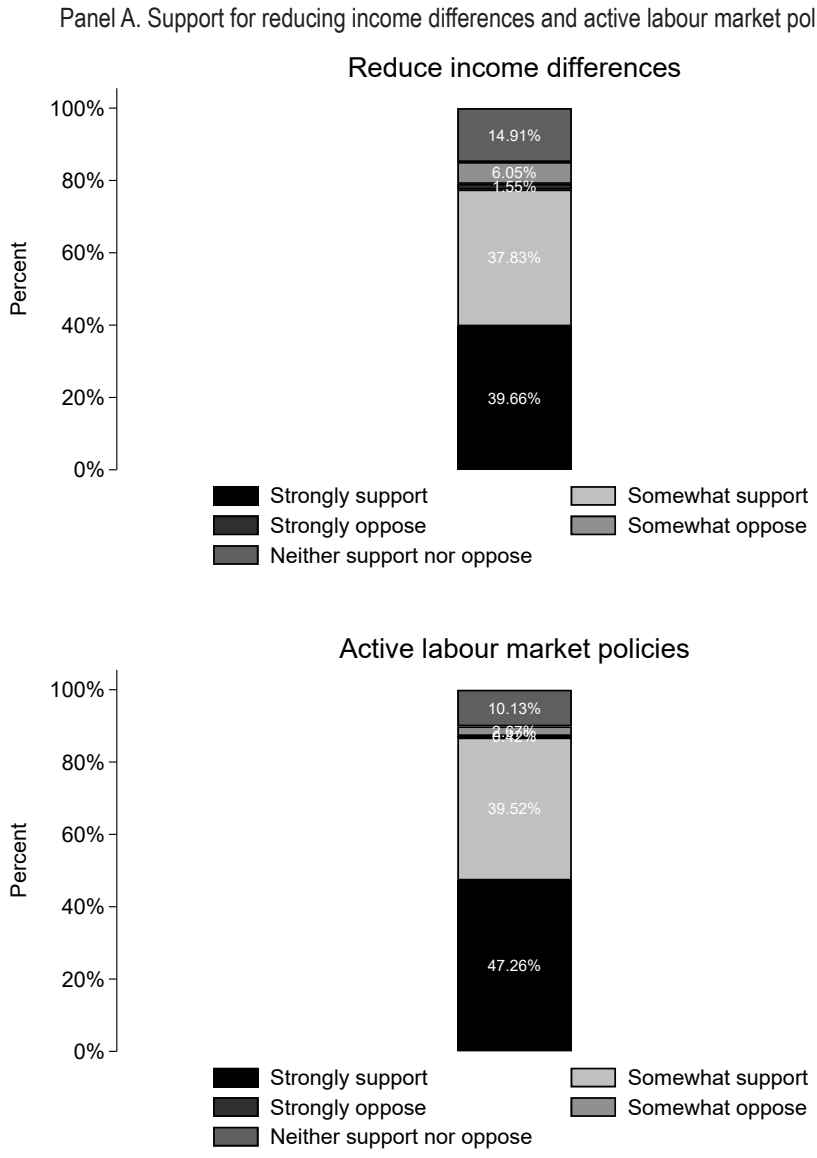
Traditional policies.

We examine six items: (1) general support for taxation and redistribution aimed at reducing income differences; (2) support for active labour-market policies; (3) support for unemployment benefits; (4) support for early retirement policies; (5) support for the introduction of a minimum wage in Italy; and (6) support for a tax on the "super-rich". All items are coded so that higher values correspond to stronger support for the policy. The first five items are measured on five-point Likert scales ranging from *Strongly oppose* to *Strongly support*. The super-rich item is measured on an original 0–10 scale, which we discretise into five levels: [0;2], [2;4], [4;6], [6;8], [8;10].[12]

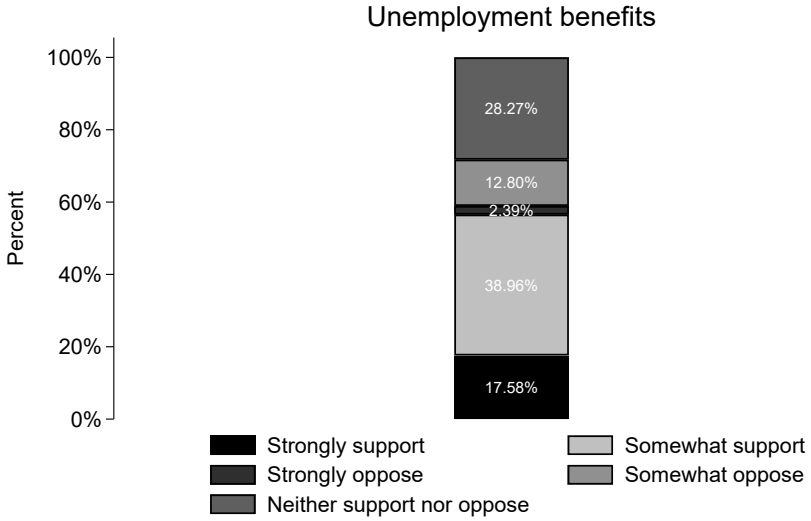
Results are reported in Figure 8. The overarching finding is that support for redistribution is broad-based among Italian workers in GenAI-exposed occupations. Active labour-market policies command near-unanimous backing (roughly 87% somewhat or strongly support, with the largest share of "strongly support" at 47%), followed by support for the minimum wage (80%), reducing income differences (77%), taxation of the super-rich (76%), early retirement (75%), and unemployment benefits (56%, with a notably larger neutral share of 28%).

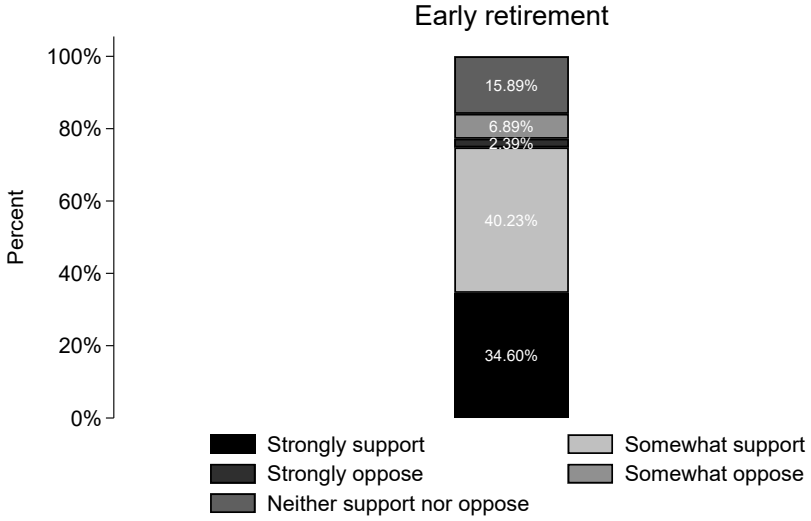
12 The redistribution item asks whether respondents agree that "it is the government's responsibility to reduce income differences between the rich and poor by raising taxes on higher earners and providing income assistance to people with lower incomes". The three labour-market policy items ask whether respondents support the government: (i) offering high-quality, free training programs for unemployed workers to learn new jobs; (ii) spending more money on unemployment benefits for those who lose their jobs; and (iii) introducing legislation to make it easier for workers to retire earlier. The minimum wage item asks about support for "introducing a minimum wage of 9 Euros an hour". The super-rich tax item asks about support for "a special yearly tax of [2% / 10%] on people with more than [10 million / 1 billion EUR in wealth]"; it randomizes the level of taxation (2% vs. 10%), the wealth threshold for identifying the super-rich (10 million vs. 1 billion EUR), and also the level at which the tax would be implemented (national vs. international). We pool answers across all versions of this question.

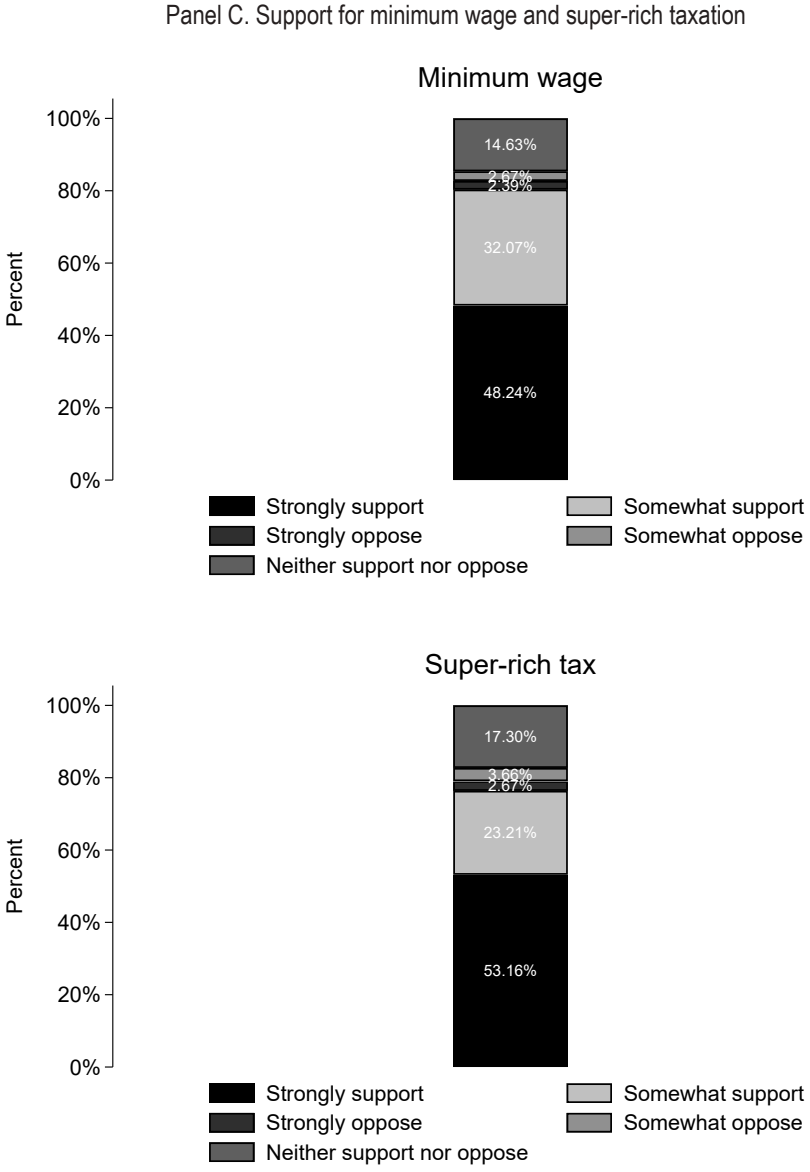
Figure 8 **Distribution of support for traditional policies**



Panel B. Support for unemployment benefits and early retirement







Notes. Panel A shows support for reducing income differences (left) and active labour market policies (right). Panel B shows support for unemployment benefits (left) and early retirement (right). Panel C shows support for introducing a minimum wage of 9 EUR/hour (left) and a special yearly tax on the super-rich (right).

New policy instruments.

We examine the following five items: (1) support for raising taxes on companies that adopt robots and algorithms to replace human workers; (2) support for a policy bundle that connects an automation tax to specific redistribution measures such as retraining displaced workers; (3) support for government regulation of GenAI; (4) support for legislation granting workers a codetermination role in company decisions concerning the introduction of new technologies; and (5) support for employment protection for workers who become redundant due to structural changes. All items are coded so that higher values correspond to stronger support for the policy. Items 1, 3, and 4 are measured on five-point Likert scales. Items 2 and 5 are measured on an original 0–10 scale, which we discretise into five levels: [0;2], [2;4], [4;6], [6;8], [8;10].[13]

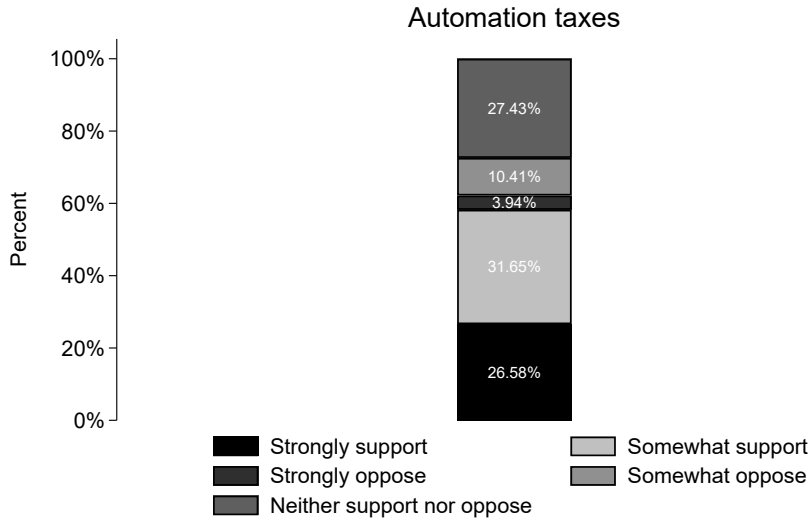
Results are reported in Figure 9. Support for these new policy instruments is also generally positive, though somewhat more nuanced than for traditional policies. Codetermination commands the broadest support: 68.36% of respondents somewhat or strongly agree (48.95% and 19.41%, respectively). Automation taxes attract a combined support share of 58.23% (31.65%

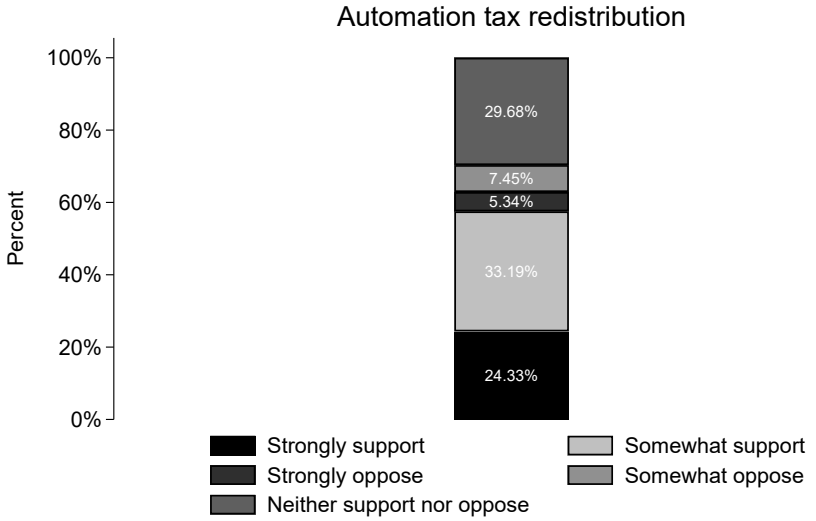
13 The first item asks "Do you support or oppose increasing taxes for companies that adopt robots and algorithms to replace human workers?". The second item bundles taxation with redistribution measures; specifically it randomizes three forms of taxation (five years of payroll taxes paid upfront for each employee eliminated through automation; portion of company stocks placed into a public trust as companies automate jobs; tax on the work performed by a robot), and three forms of spending (to create new jobs for displaced workers; to support and retrain displaced workers; to pay a universal dividend to every citizen); we pool answers across all versions of this question. The third item asks"Some people believe that governments should strictly regulate GenAI (such as ChatGPT). Others oppose such regulations. On a scale from 1 (not intervene) to 5 (regulate most strictly), what should governments do?". The fourth item asks"Do you agree or disagree with this statement: we need legislation that grants representatives of workers the right to participate in companies' decisions concerning the introduction of new technologies". The fifth item asks "There are differing views on whether governments should intervene when companies decide to lay off workers [to substitute them with robots / to substitute them with artificial intelligence / to offshore the jobs abroad]. Where would you place yourself on a scale from 0 (business should have freedom on lay-off decisions) to 10 (governments should find ways to prohibit such lay-offs); where the causes of lay-offs are randomized, and we pool answers across different versions of the question.

somewhat and 26.58% strongly support). On GenAI regulation, 53.17% of respondents fall on the more interventionist side of the scale (34.6% favour relatively strict regulation and 18.57% the strictest option), while only 10.69% of respondents prefer minimal or no intervention (3.8% and 6.89%, respectively). A substantial moderate bloc of 36.15% selects the middle category of regulating lightly, indicating that many workers favour some regulatory oversight without draconian control.

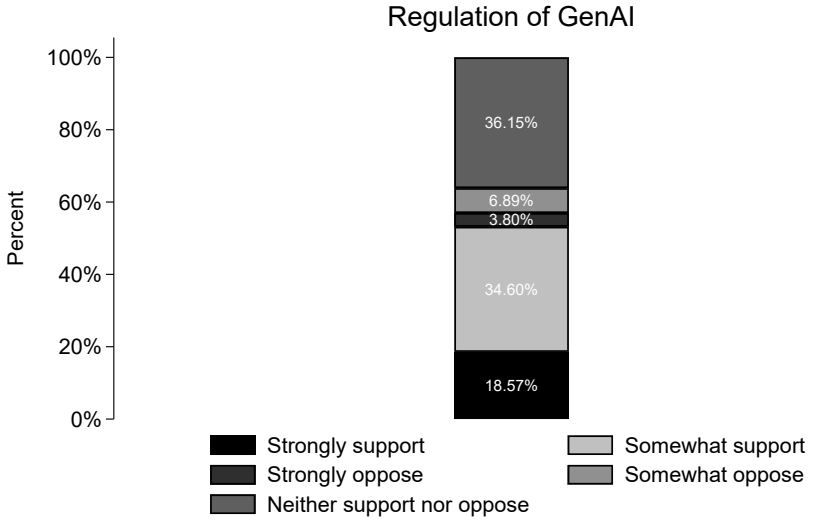
Figure 9 **Distribution of support for new policies**

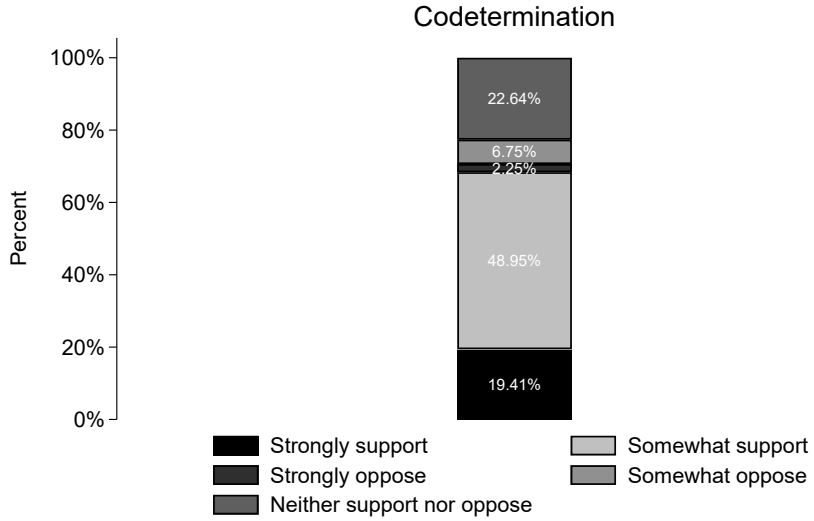
Panel A. Support for robot taxes and automation tax-redistribution scheme



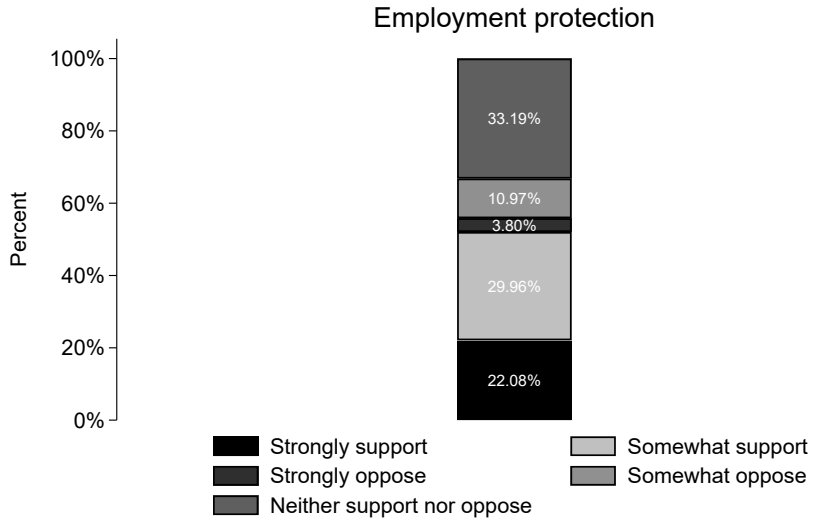


Panel B. Support for government regulation of GenAI and codetermination





Panel C. Support for employment protection



Notes. Panel A shows support for increasing taxes on companies that adopt robots and algorithms to replace human workers (left) and automation-tax-financed redistribution (right). Panel B shows support for GenAI regulation (left) and legislation granting worker representatives the right to participate in companies' decisions on new technology (right). Panel C shows support for employment protection under structural changes.

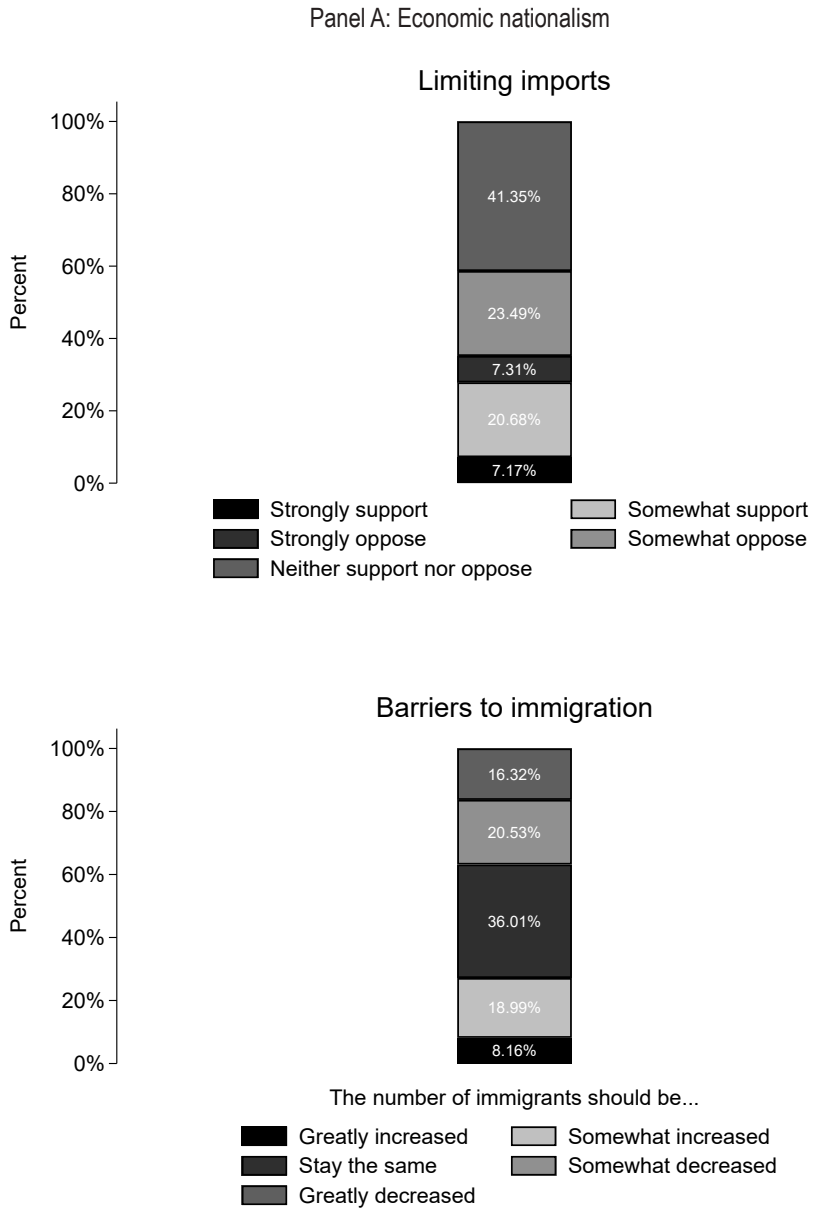
The remaining two items—automation-tax-financed redistribution and employment protection—both attract majority support, although backing is somewhat firmer for the former. Specifically, automation-tax-financed redistribution receives a total support share of 57.52% (33.19% somewhat and 24.33% strongly), with 12.79% opposed and 29.68% neutral. Employment protection is supported by 52.04% (29.96% somewhat and 22.08% strongly), with 14.77% opposed and a comparatively larger neutral share of 33.19%. Taken together, these results indicate that respondents are broadly receptive to compensatory policies addressing technological change, with somewhat firmer backing for redistribution financed through automation taxes than for direct employment protection.

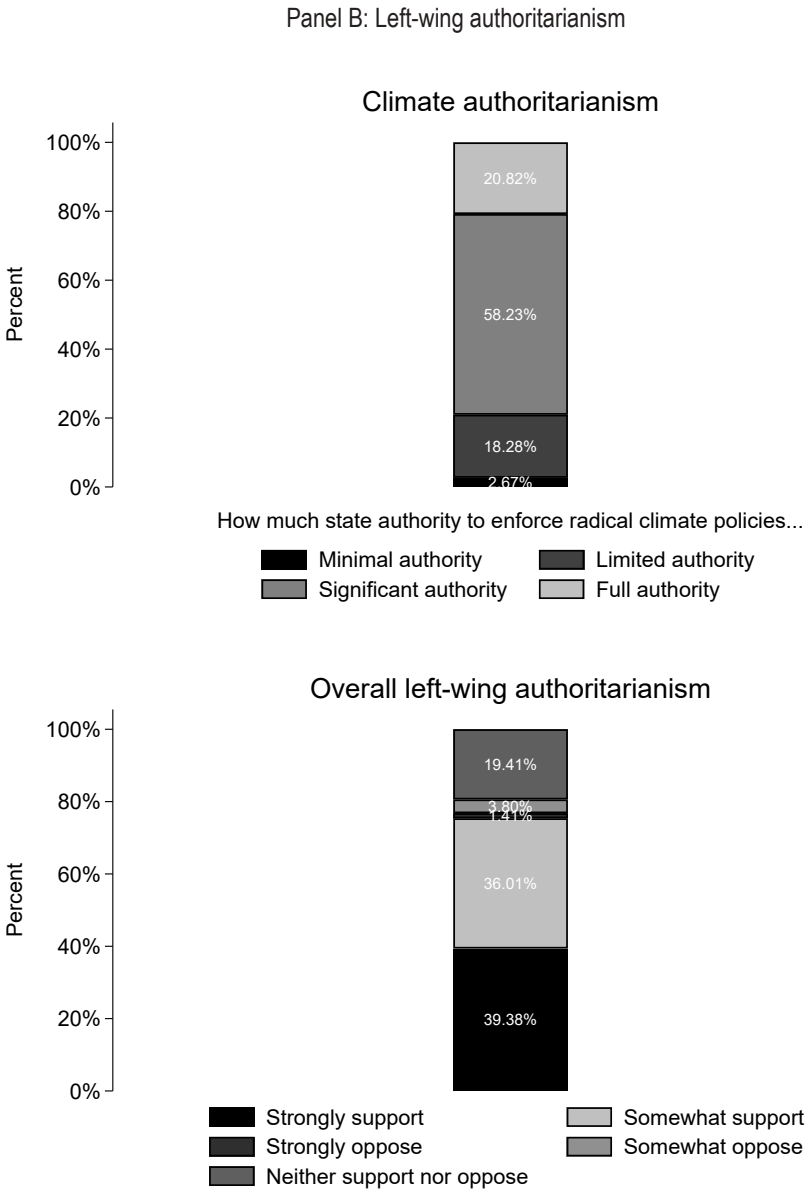
Economic nationalism and left-wing authoritarianism.

We examine two items characterizing economic nationalist ideological orientations: (1) support for trade restrictions; and (2) support for restrictions to immigration. Answer to both items are on 5-point Likert scales, with higher values denoting more protectionist and anti-immigration stances.[14] Results are reported in Panel A of Figure 10. Preferences on import restrictions are fairly balanced: 41.35% of respondents take a neutral position, while 27.85% favour new limits (20.68% somewhat and 7.17% strongly) and 30.8% oppose them (23.49% somewhat and 7.31% strongly). Immigration attitudes are broadly centred but tilted toward restriction: 36.01% prefer the status quo, 36.85% favour decreasing immigration (20.53% somewhat and 16.32% greatly), and 27.15% favour increasing it (18.99% somewhat and 8.16% greatly).

14 The first item asks "Some people have suggested placing new limits on imports in order to protect Italy's jobs. Others say that such limits would raise consumer prices and hurt Italy's exports. Do you support or oppose placing new limits on imports?". The second item asks "Do you think the number of immigrants permitted to come to Italy to live should be increased, left the same as it is now, or decreased?"

Figure 10 **Distribution of ideological orientations**





Notes. Panel A shows support for placing new limits on imports (left) and preferences regarding the number of immigrants permitted to come to Italy (right). Panel B shows support for government authority to enforce strict environmental regulations (left) and the overall left-wing authoritarianism index (right).

Next, we consider two items capturing left-wing authoritarianism. The first item is an index of climate authoritarianism, eliciting respondents' preferences as to whether the government should enforce strict environmental regulations, even if it means overriding individual freedoms and business interests. The second item is a broader index of left-wing authoritarianism, combining (through a simple average) the climate item with two additional items on: (i) support for laws that allow surveilling, restricting, or banning political parties that put forward anti-democratic ideologies; and (ii) support for laws that require schools to teach children about Italy's history with racism, sexism and homophobia. The climate authoritarianism item is answered on a 4-point Likert scale, while the other two items are on a 5-point scale. Higher scores denote more authoritarian stances.[15]

Results are reported in Panel B of Figure 10. Support for strong state authority on climate policy is widespread: nearly four respondents out of five fall on the more interventionist side (58.23% "significant authority" and 20.82% "full authority'), with only 2.67% favouring minimal authority. The left-wing authoritarianism index is similarly concentrated at the upper end: three respondents out of four (75.39%) fall in the "supportive" categories (36.01% somewhat and 39.38% strongly), with very little mass in the lower tail. These patterns are consistent with the profile of Gen-AI exposed workers, who tend to be relatively younger, more educated, and higher-income compared to the general population, as documented in Section 3.

15 The climate authoritarianism item asks "How much authority should the government have to enforce strict environmental regulations, even if it means overriding individual freedoms and business interests?", with answers ranging from minimal to full authority. The item on anti-democratic parties asks "Some countries have laws that allow surveilling, restricting, or banning political parties that put forward anti-democratic ideologies. Do you support or oppose such laws?", with answers ranging from strongly oppose to strongly support. The item on education asks "Do you support or oppose laws that require schools to teach children about our history with racism, sexism and homophobia?", with answers ranging from strongly oppose to strongly support.

7. From impact perceptions to policy preferences

The two preceding sections have documented GenAI's impact perceptions and policy preferences separately. We now ask whether the two are related. For instance, do workers who hold more pessimistic views about GenAI's occupational consequences also express stronger demand for policy intervention compared to workers who are more optimistic about it? Is there heterogeneity in this pattern between traditional policy measures and new, AI-related instruments?

To examine this, we split the sample in two groups and compare policy preferences between workers who are relatively optimistic vs. pessimistic about the impact of GenAI on their occupational prospects. The split is based on the median value of a composite score of perceived GenAI's impact. This is obtained in two steps. First, we take the average score across the five items referring to the impact of GenAI on specific dimensions of work (i.e., salary and career opportunities, job security, autonomy, enjoyment of daily tasks, and occupational pride). Second, we average the resulting score with answers to the two items capturing broader assessments of GenAI's impact (i.e., opportunity vs. threat; productivity vs. redundancy). The resulting index ranges from -2 (most optimistic) to +2 (most pessimistic), with a median value of -0.07.

The results of this descriptive analysis are reported in Figures 11 and 12. Specifically, in Figure 11 we document average answers in the two groups for each policy item. Items are divided in three sets: in Panel A we focus on traditional policy preferences; in Panel B on new policy instruments; in Panel C on economic nationalism and left-wing authoritarianism. In Figure 12, we condense the between-groups comparisons into a single coefficient plot cov-

ering all policy items. Each reported coefficient is the difference in mean support for a given policy item between pessimistic and optimistic respondents, so that positive values denote stronger support for the policy by pessimistic workers.[16]

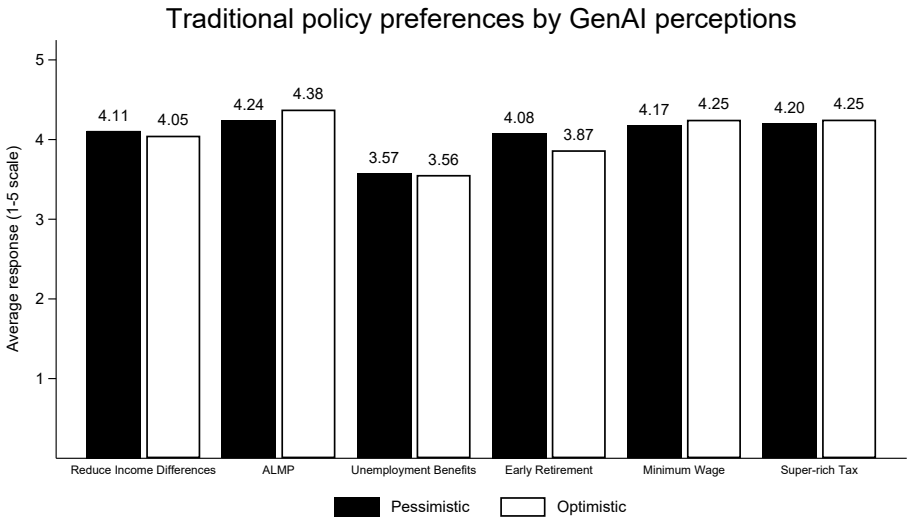
Three patterns stand out. First, gaps are generally modest for traditional policy items, confirming that support for these policies is broadly shared across perception groups. Only two differences between groups are statistically significant: (1) pessimistic workers are on average more in favour of early retirement policies, and (2) less in favour of active labour market policies compared to optimistic workers. Second, the largest gaps in preferences emerge for new policy instruments directly tied to technological change, where pessimistic workers are always significantly more in favour of policy interventions. In particular, the most pronounced differences are observed for the automation tax (≈ 0.6) and GenAI regulation (≈ 0.4). Third, ideological orientations display a mixed profile. There are no significant differences when focusing on climate authoritarianism and broader left-wing authoritarian orientations. Conversely, pessimistic respondents are somewhat more supportive of limiting imports, and significantly more supportive of restricting immigration.

Taking stock of this evidence, subjective assessments of GenAI risk appear to correlate most directly with demand for new protective and regulatory instruments, while differences in traditional policy items are mostly negligible. Pessimism about GenAI is also associated with demand for economic nationalism, especially in terms of limiting immigration, but not with left-wing authoritarian orientations.

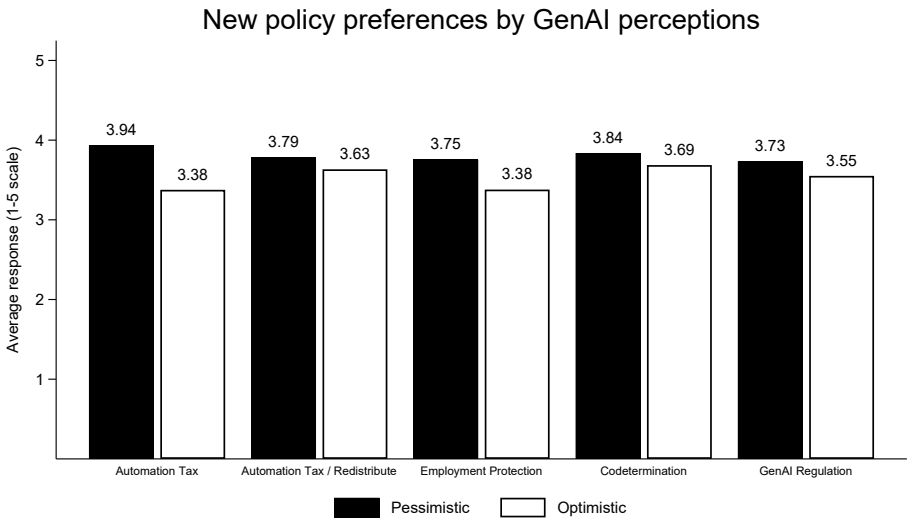
16 For this analysis, all items are standardized on a common 1–5 scale.

Figure 11 **Policy preferences and perceived GenAI impact**

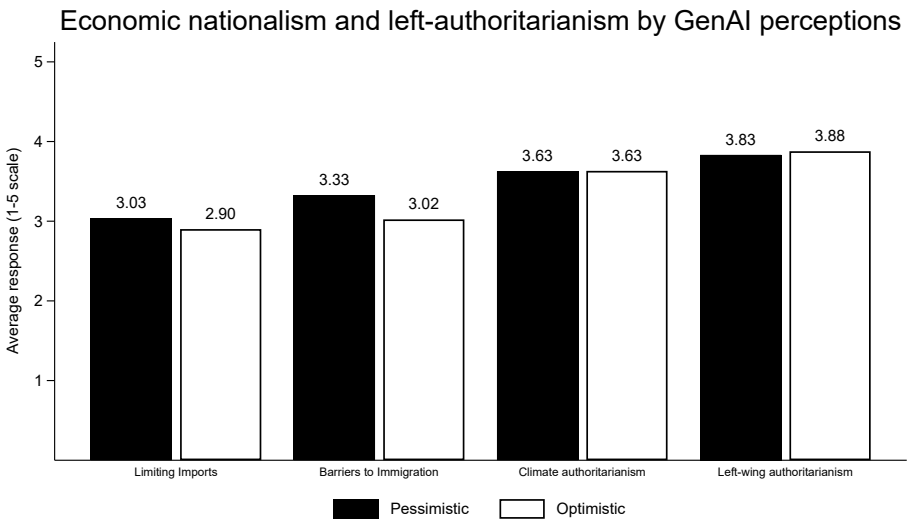
Panel A: Traditional policies



Panel B: New policy instruments

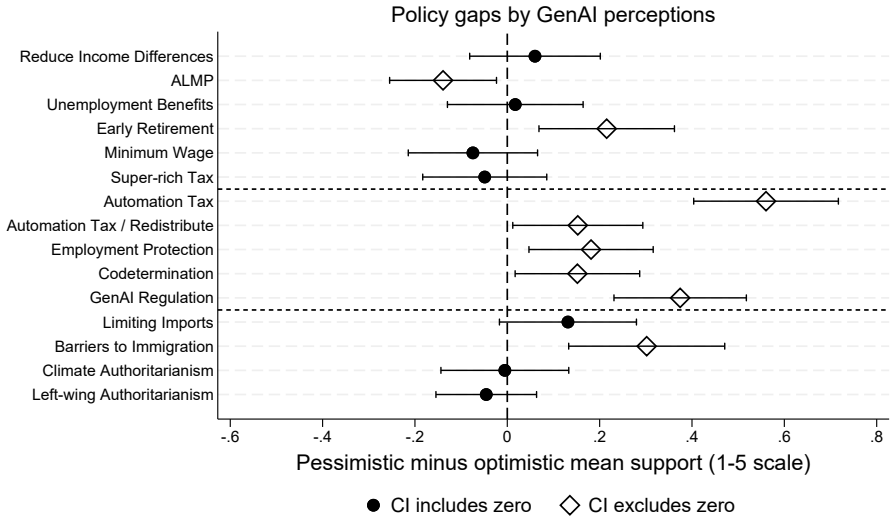


Panel C: Economic nationalism and left-wing authoritarianism



Notes. Bars report mean responses on a common 1–5 scale for respondents with relatively optimistic vs. pessimistic perceptions of GenAI's occupational impact (i.e., below vs. above median of the composite index). Higher values indicate stronger support for a given policy item. Panel A covers traditional policy items; Panel B covers new, AI-related policy instruments; Panel C covers economic nationalism and left-wing authoritarianism.

Figure 12 **Policy gaps by GenAI perceptions**



Note: Each reported coefficient is the difference in mean support for a given policy item between pessimistic and optimistic respondents, so that positive values denote stronger support for the policy by pessimistic workers. All items are standardized on a common 1–5 scale. Horizontal lines indicate 95% confidence intervals. Dashed separators distinguish policy areas.

8. Conclusion

This paper has provided descriptive evidence on how workers employed in occupations directly exposed to generative AI perceive this technology, and how their perceptions relate to policy preferences. Using original survey data on 711 workers in Italy across 98 narrowly defined occupations, we have documented several findings. First, awareness of GenAI is high and prior use of large language models is widespread, with marked heterogeneity by age: younger workers are substantially more engaged with the technology than their older counterparts, while differences by education and income are

comparatively limited. Second, workers' perceptions of GenAI's occupational consequences are nuanced rather than uniformly positive or negative. Respondents are relatively optimistic about the effects of GenAI on job autonomy, task enjoyment, and occupational pride, yet considerably more cautious about salary and career prospects and, above all, job security.

Third, support for policy intervention is broad-based. Workers in exposed occupations express strong backing for traditional redistributive measures as well as for newer instruments specifically tied to AI-driven structural change, including codetermination, GenAI regulation, automation-related taxation, and employment protection. Fourth, there is a correlation between perceptions of GenAI's occupational impact and policy preferences. Specifically, workers who are more pessimistic about this technology tend to support relatively more government interventions, especially in terms of AI-related policy tools. Finally, workers with more pessimistic views are somewhat more supportive of trade and migration restrictions, which characterize economic nationalist policy bundles. Conversely, they show no higher support for left-wing authoritarian policies.

The evidence presented in this paper offers a starting point for reflecting on the governance of the GenAI transition. The broad support for both traditional and AI-specific policy instruments indicates that workers do not view the challenge posed by GenAI as one of post-production redistribution alone: they also favour production-stage governance mechanisms—such as codetermination and regulation—that shape how the technology is introduced in the workplace. At the same time, the finding that perceived vulnerability to GenAI correlates with demand for government intervention suggests that it may be difficult to obtain broad political support for policy platforms aimed at managing this technological transition by balancing the interests of rela-

tive winners and losers. In fact, while vulnerable workers demand stronger government intervention, those who expect to benefit from the transition are more in favour of a laissez-faire approach. Such a divide in public opinion poses an important challenge for policy makers who are called to govern the GenAI transition.

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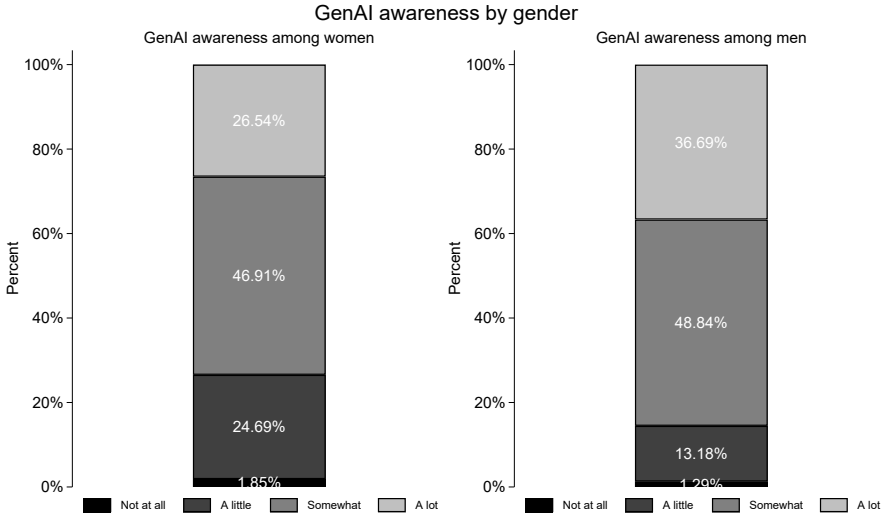
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Appendix

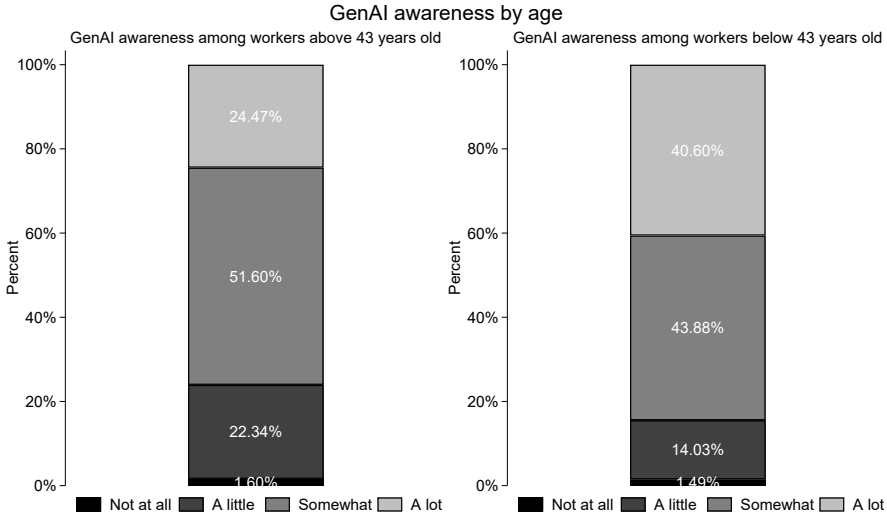
A1. Supplementary figures

Figure A1 **Distribution of GenAI awareness by demographic group**

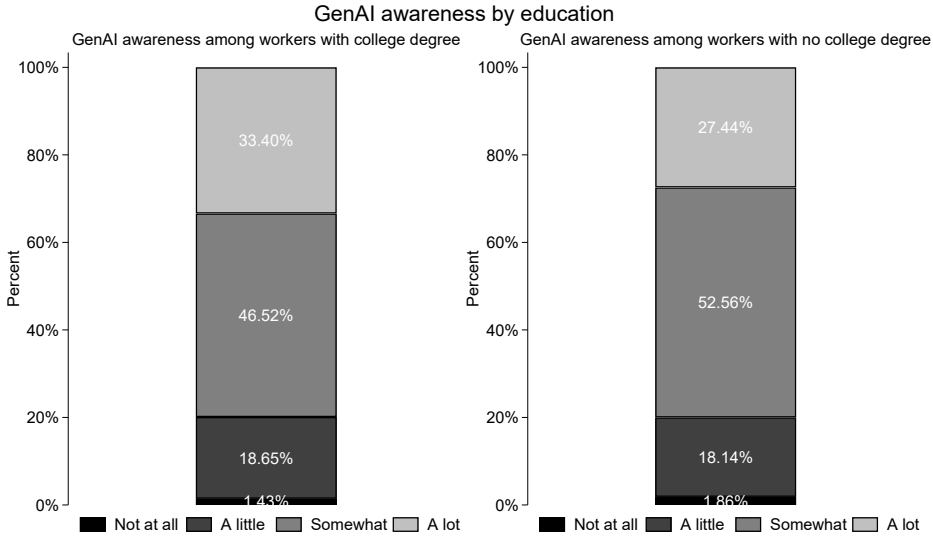
Panel A: By gender



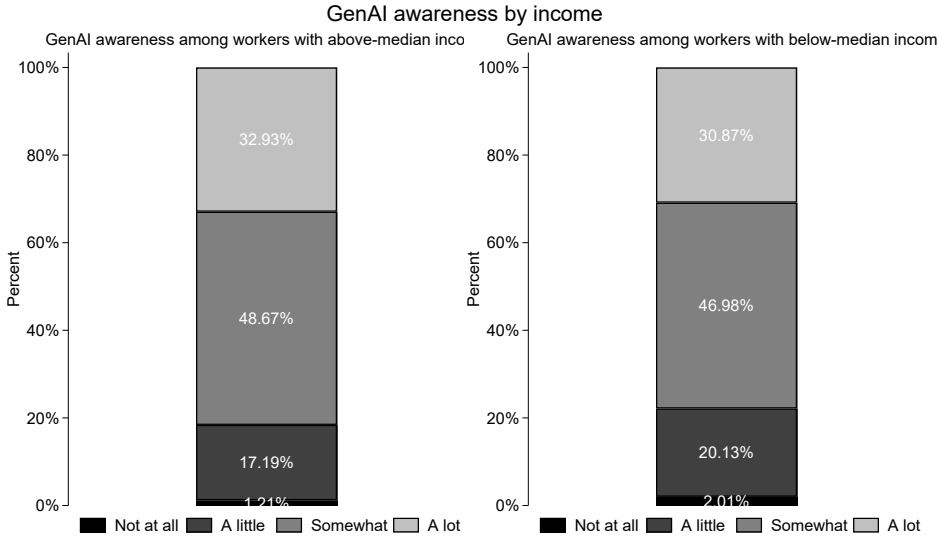
Panel B: By age



Panel C: By education

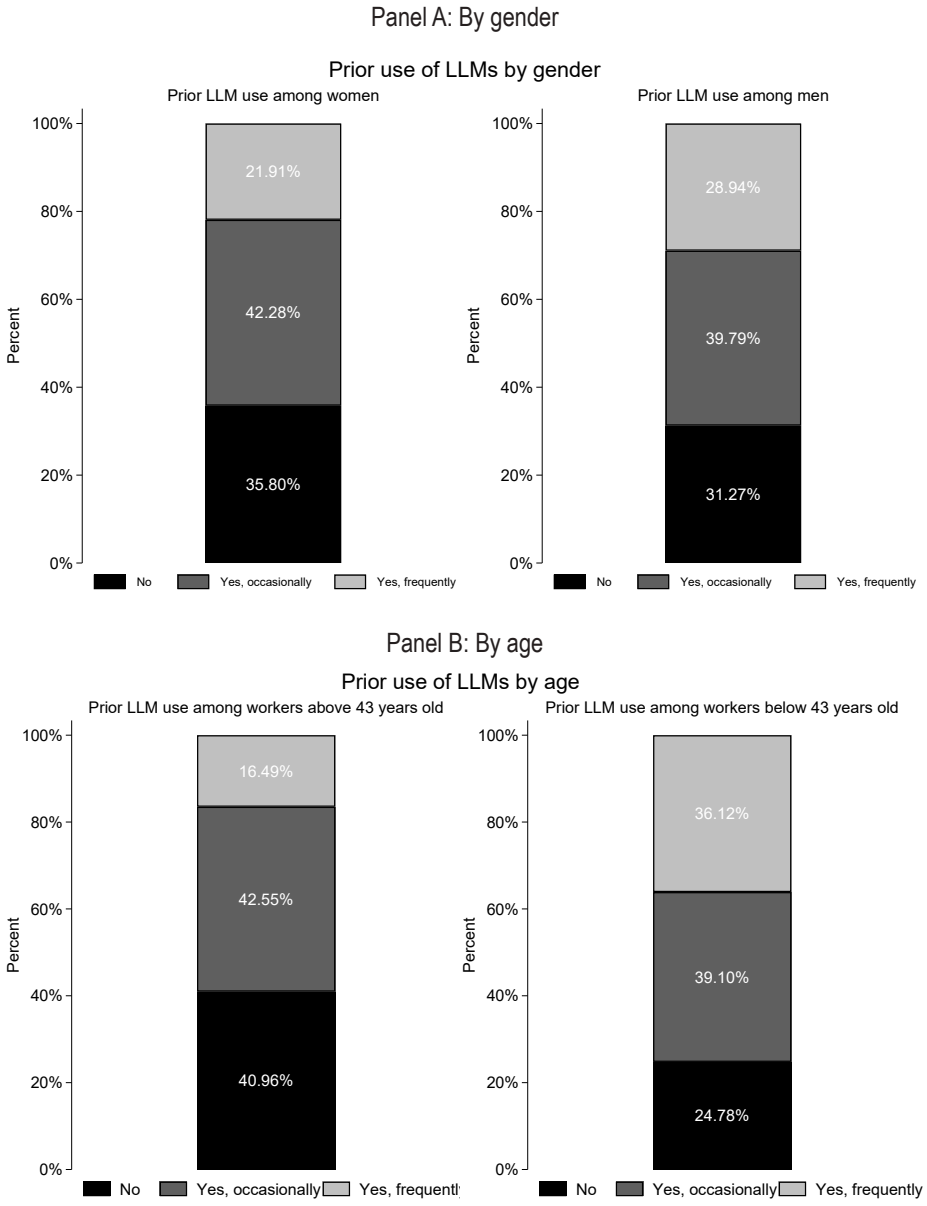


Panel D: By income

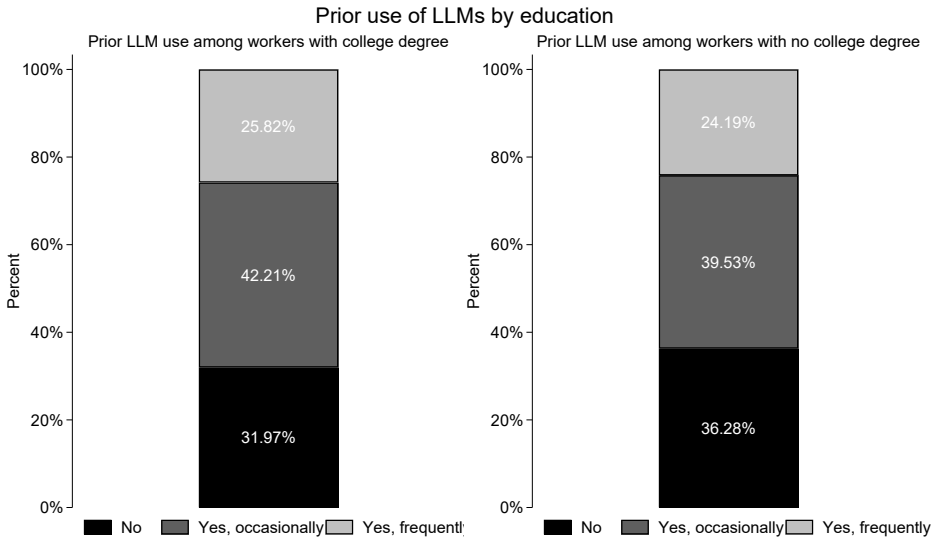


Notes. Each panel shows the distribution of self-assessed GenAI awareness ("Not at all," "A little," "Somewhat," "A lot") for the indicated demographic subgroups.

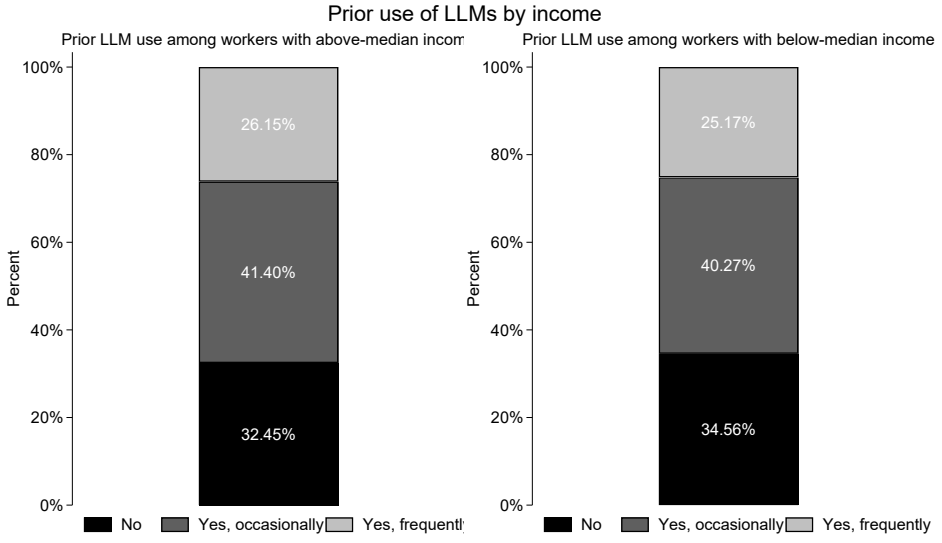
Figure A2 **Distribution of prior LLM use by demographic group**



Panel C: By education



Panel D: By income



Notes. Each panel shows the distribution of prior LLM use ("No," "Yes, occasionally," "Yes, frequently") for the indicated demographic subgroups.

A2. Additional heterogeneity: regions and party voted

Figure A3 **Perceived impact of GenAI on work dimensions by NUTS-1 region: North East, North West, Centre, South, and Islands.**

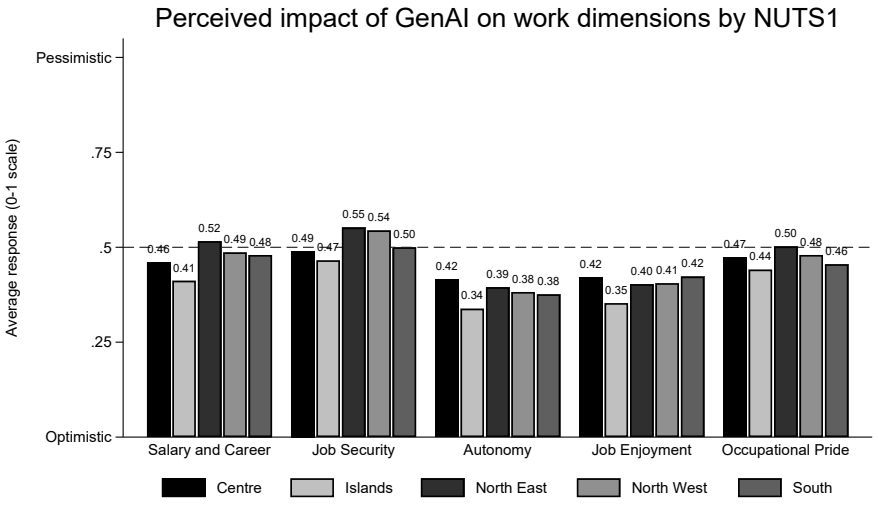


Figure A4 **Broader assessments of GenAI's impact by NUTS-1 region: North East, North West, Centre, South, and Islands.**

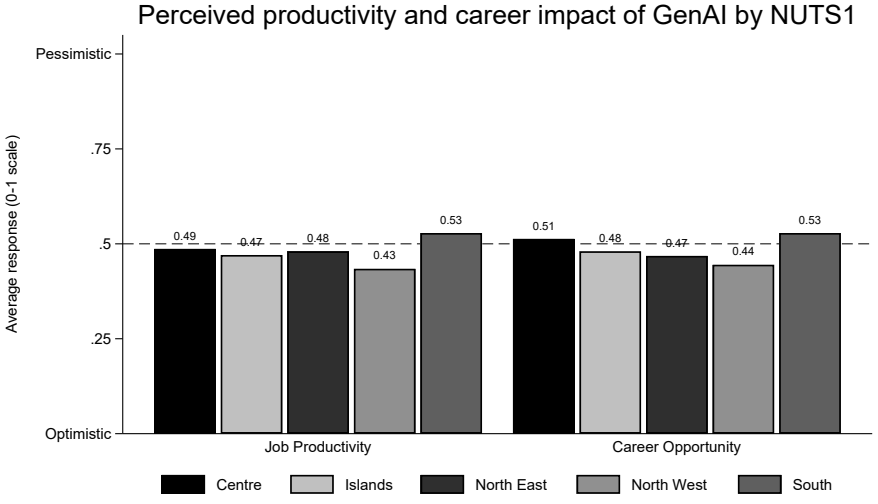


Figure A5 **Perceived impact of GenAI on work dimensions by last party voted among left-bloc voters, including +Europa, Alleanza Verdi e Sinistra (AVS), Movimento 5 Stelle (M5S), Partito Democratico (PD), and Unione Popolare.**

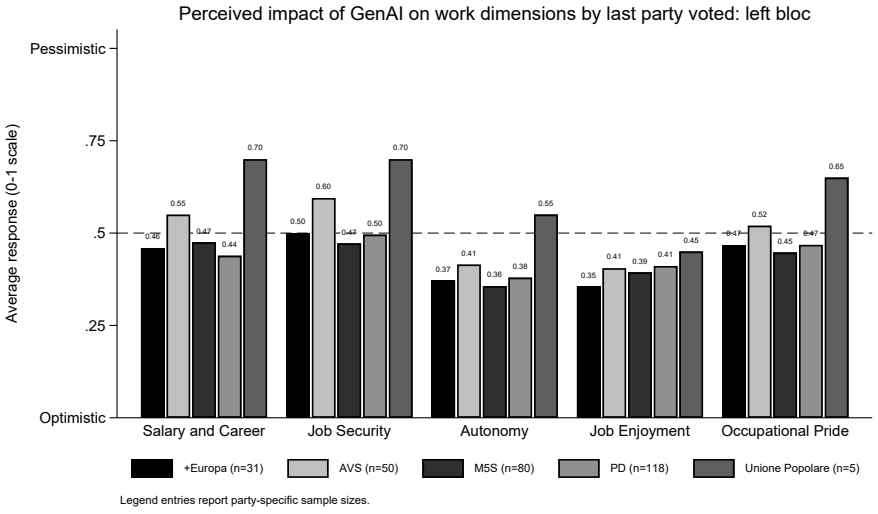


Figure A6: **Perceived impact of GenAI on work dimensions by last party voted among centre-right, right, and residual groups, including Azione, Forza Italia, Fratelli d'Italia, Lega, and respondents who selected other parties or preferred not to answer.**

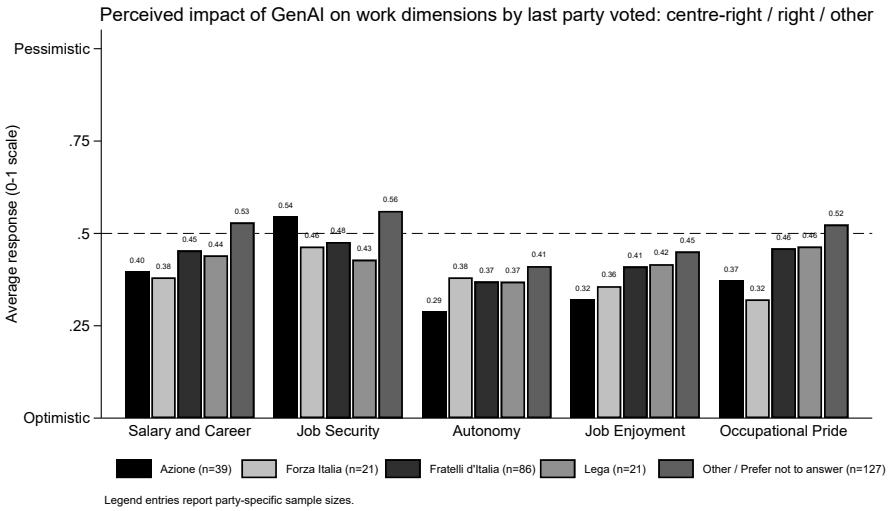


Figure A7 **Broader assessments of GenAI's impact by last party voted among left-bloc voters, including +Europa, Alleanza Verdi e Sinistra (AVS), Movimento 5 Stelle (M5S), Partito Democratico (PD), and Unione Popolare.**

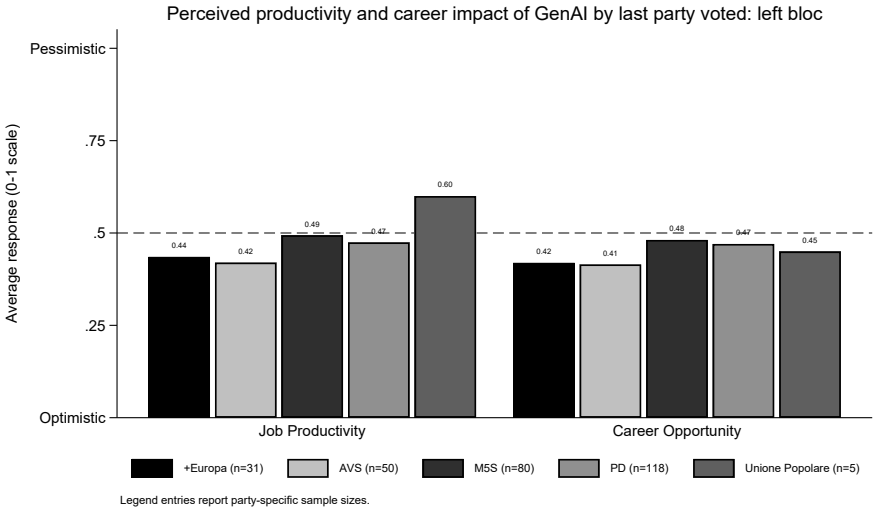
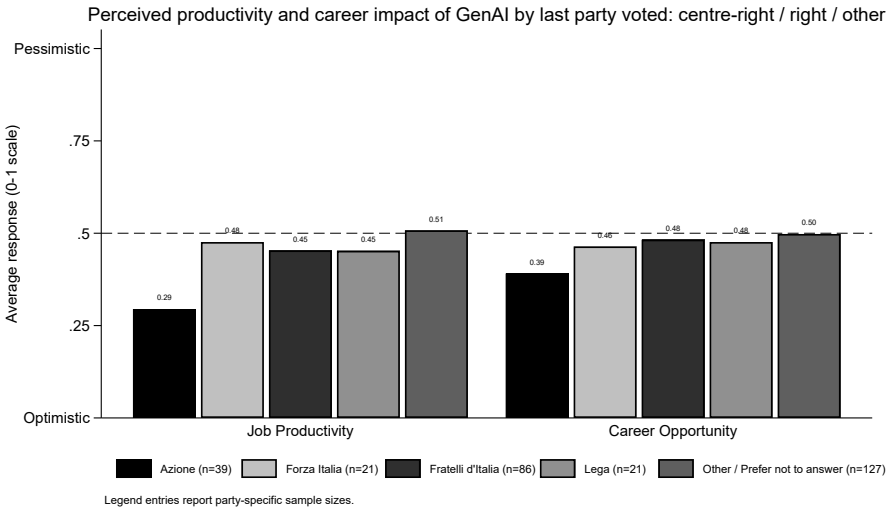


Figure A8 **Broader assessments of GenAI's impact by last party voted among centre-right, right, and residual groups, including Azione, Forza Italia, Fratelli d'Italia, Lega, and respondents who selected other parties or preferred not to answer.**



A3. List of SOC-3 occupations classified as exposed to GenAI

Table A1: **3-digit SOC occupations classified as exposed to GenAI**

11-2000	Advertising, Marketing, Promotions, Public Relations, and Sales Managers
11-3000	Operations Specialties Managers
11-9000	Other Management Occupations
13-1000	Business Operations Specialists
13-2000	Financial Specialists
15-1200	Computer Occupations
15-2000	Mathematical Science Occupations
17-1000	Architects, Surveyors, and Cartographers
17-2000	Engineers
17-3000	Drafters, Engineering Technicians, and Mapping Technicians
19-1000	Life Scientists
19-2000	Physical Scientists
19-3000	Social Scientists and Related Workers
19-4000	Life, Physical, and Social Science Technicians
19-5000	Occupational Health and Safety Specialists and Technicians
21-1000	Counselors, Social Workers, and Other Community and Social Service Specialists
21-2000	Religious Workers
23-1000	Lawyers, Judges, and Related Workers
23-2000	Legal Support Workers
25-2000	Preschool, Elementary, Middle, Secondary, and Special Education Teachers
27-1000	Art and Design Workers
27-4000	Media and Communication Equipment Workers
29-1000	Healthcare Diagnosing or Treating Practitioners
29-2000	Health Technologists and Technicians
45-1000	Supervisors of Farming, Fishing, and Forestry Workers
45-4000	Forest, Conservation, and Logging Workers
47-1000	Supervisors of Construction and Extraction Workers
47-2000	Construction Trades Workers
47-4000	Other Construction and Related Workers

47-5000	Extraction Workers
49-1000	Supervisors of Installation, Maintenance, and Repair Workers
49-2000	Electrical and Electronic Equipment Mechanics, Installers, and Repairers
49-3000	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers
51-1000	Supervisors of Production Workers
51-5100	Printing Workers
51-8000	Plant and System Operators
53-2000	Air Transportation Workers
53-4000	Rail Transportation Workers
53-5000	Water Transportation Workers

A4. List of 6-digit SOC occupations classified as directly exposed to GenAI

Occupation List - SOC

SOC Code	SOC Title
11-3021	Computer and Information Systems Managers
11-3061	Purchasing Managers
11-9199	Managers, All Other
13-1031	Claims Adjusters, Examiners, and Investigators
13-1041	Compliance Officers
13-1071	Human Resources Specialists
13-1081	Logisticians
13-1111	Management Analysts
13-1121	Meeting, Convention, and Event Planners
13-1131	Fundraisers
13-1141	Compensation, Benefits, and Job Analysis Specialists
13-1161	Market Research Analysts and Marketing Specialists
13-1199	Business Operations Specialists, All Other
13-2011	Accountants and Auditors
13-2020	Property Appraisers and Assessors

SOC Code	SOC Title
13-2031	Budget Analysts
13-2041	Credit Analysts
13-2052	Personal Financial Advisors
13-2053	Insurance Underwriters
13-2072	Loan Officers
13-2082	Tax Preparers
13-2099	Financial Specialists, All Other
15-1211	Computer Systems Analysts
15-1212	Information Security Analysts
15-1221	Computer and Information Research Scientists
15-1231	Computer Network Support Specialists
15-1232	Computer User Support Specialists
15-1241	Computer Network Architects
15-1242	Database Administrators
15-1243	Database Architects
15-1244	Network and Computer Systems Administrators
15-1251	Computer Programmers
15-1253	Software Quality Assurance Analysts and Testers
15-1254	Web Developers
15-1255	Web and Digital Interface Designers
15-1299	Computer Occupations, All Other
15-2011	Actuaries
15-2031	Operations Research Analysts
15-2051	Data Scientists
17-2081	Environmental Engineers
17-3022	Civil Engineering Technologists and Technicians
17-3027	Mechanical Engineering Technologists and Technicians
17-3029	Engineering Technologists and Technicians, Except Drafters, All Other
19-1029	Biological Scientists, All Other
19-2031	Chemists
19-2041	Environmental Scientists and Specialists, Including Health

SOC Code	SOC Title
19-2042	Geoscientists, Except Hydrologists and Geographers
19-3022	Survey Researchers
19-3033	Clinical and Counseling Psychologists
19-3034	School Psychologists
19-4021	Biological Technicians
19-4061	Social Science Research Assistants
19-5011	Occupational Health and Safety Specialists
19-5012	Occupational Health and Safety Technicians
21-1012	Educational, Guidance, and Career Counselors and Advisors
21-1013	Marriage and Family Therapists
21-1015	Rehabilitation Counselors
21-1018	Substance Abuse, Behavioral Disorder, and Mental Health Counselors
21-1021	Child, Family, and School Social Workers
21-1022	Healthcare Social Workers
21-1023	Mental Health and Substance Abuse Social Workers
21-1091	Health Education Specialists
21-1092	Probation Officers and Correctional Treatment Specialists
21-1093	Social and Human Service Assistants
21-1094	Community Health Workers
23-1012	Judicial Law Clerks
23-2011	Paralegals and Legal Assistants
23-2093	Title Examiners, Abstractors, and Searchers
25-2059	Special Education Teachers, All Other
27-1011	Art Directors
27-1014	Special Effects Artists and Animators
27-1022	Fashion Designers
27-1024	Graphic Designers
27-1025	Interior Designers
27-1026	Merchandise Displayers and Window Trimmers
27-4011	Audio and Video Technicians
29-1031	Dietitians and Nutritionists

SOC Code	SOC Title
29-1051	Pharmacists
29-1071	Physician Assistants
29-1122	Occupational Therapists
29-1123	Physical Therapists
29-1126	Respiratory Therapists
29-1127	Speech-Language Pathologists
29-1141	Registered Nurses
29-1171	Nurse Practitioners
29-1229	Physicians, All Other
29-2052	Pharmacy Technicians
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers
49-2011	Computer, Automated Teller, and Office Machine Repairers
49-2021	Radio, Cellular, and Tower Equipment Installers and Repairers
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment
49-3011	Aircraft Mechanics and Service Technicians
49-3023	Automotive Service Technicians and Mechanics
51-8012	Power Distributors and Dispatchers
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers
53-2011	Airline Pilots, Copilots, and Flight Engineers
53-2012	Commercial Pilots
53-5011	Sailors and Marine Oilers

A5. List of corresponding ISCO codes, in Italian

SOC Code	ISCO Code	ISCO Title
11-3021	2529.8	Responsabile della Sicurezza TIC
11-3021	3513.1	Responsabile della Comunicazione di Dati Aeronautici
11-3061	1324.8.2	Responsabile degli Acquisti
11-9199	1112.2	Console
11-9199	1112.3.1	Ambasciatore/Ambasciatrice
11-9199	1120.1	Direttore di Strutture Zoologiche e Faunistiche/Direttrice di Strutture Zoologiche e Faunistiche
11-9199	1213.1	Responsabile di Conformity e Sicurezza Informatica nel Gioco Online
11-9199	1219.1.2	Responsabile della Sicurezza
11-9199	1219.4	Responsabile di Reparto
11-9199	1219.5.3	Responsabile di Centrale Elettrica
11-9199	1223.1	Responsabile di Prodotto
11-9199	1223.2.1.1	Responsabile dello Sviluppo di Abbigliamento
11-9199	1223.2.1.3	Responsabile dello Sviluppo di Giochi
11-9199	1321.2.1.2	Responsabile della Produzione di Abbigliamento
11-9199	1321.2.1.3	Responsabile della Produzione Alimentare
11-9199	1322.1	Responsabile di Miniera
11-9199	1322.1.1	Responsabile della Produzione Mineraria
11-9199	1322.2	Responsabile di Cava
11-9199	1324.7	Responsabile di Stazione Ferroviaria
11-9199	1324.8.1	Responsabile della Pianificazione della Produzione
11-9199	1330.8	Responsabile dei Rapporti con i Fornitori di Infrastrutture TIC
11-9199	1343.1	Responsabile di Casa di Riposo
11-9199	2431.15	Responsabile Beni e Servizi
11-9199	2434.2	Responsabile dello Sviluppo Commerciale delle TIC
11-9199	2519.2	Responsabile del Controllo TIC
11-9199	2619.1	Responsabile dei Contratti
11-9199	2619.12	Responsabile delle Questioni Regolamentari

SOC Code	ISCO Code	ISCO Title
11-9199	3119.13	Coordinatore della Conformità di Gasdotti e Oleodotti/Coordinatrice della Conformità di Gasdotti e Oleodotti
11-9199	3339.5	Agente Letterario/Agente Letteraria
11-9199	5221.1	Commerciante al Dettaglio
13-1031	3315.5	Liquidatore Danni/Liquidatrice Danni
13-1041	1212.2.1	Diversity Manager
13-1041	2619.2	Medico Legale
13-1041	3112.1.2	Ispettore di Edifici/Ispettrice di Edifici
13-1041	3257.1	Ispettore Sanitario Ambientale/Ispettrice Sanitaria Ambientale
13-1041	3331.2.1	Specialista Import-Export
13-1041	3354.2	Funzionario Incaricato del Rilascio di Licenze/Funzionaria Incaricata del Rilascio di Licenze
13-1071	2423.3	Responsabile delle Risorse Umane
13-1081	2149.2.6	Ingegnere Logistico
13-1081	2421.5	Analista della Logistica
13-1111	2413.2	Analista Middle Office
13-1121	3332.2	Programmatore e Gestore di Eventi/Programmatrice e Gestore di Eventi
13-1131	2432.3	Responsabile Raccolta Fondi
13-1131	3343.1.3	Assistente alla Raccolta Fondi
13-1141	2423.5	Analista del Lavoro
13-1161	1213.2.3	Responsabile delle Politiche per il Turismo
13-1161	2431.10	Consulente di Marketing
13-1161	2431.11	Analista di Ricerche di Mercato
13-1161	2431.14	Esperto in Pricing/Esperta in Pricing
13-1161	2513.2	Esperto di Ottimizzazione per i Motori di Ricerca/Esperta di Ottimizzazione per i Motori di Ricerca
13-1161	4227.1	Intervistatore per Ricerche di Mercato/Intervistatrice per Ricerche di Mercato
13-1199	2133.6	Coordinatore di Programmi Ambientali/Coordinatrice di Programmi Ambientali
13-1199	2431.10.2	Responsabile del Commercio Online

SOC Code	ISCO Code	ISCO Title
13-1199	2519.4	Disaster Recovery Analyst TIC
13-1199	3435.11	Location Manager
13-1199	5414.1.8	Consulente di Sicurezza
13-2011	2411.1	Esperto Contabile/Esperta Contabile
13-2020	3315.6	Stimatore/Stimatrice
13-2020	3315.7	Perito Immobiliare/Perita Immobiliare
13-2031	2411.1.4	Analista di Bilancio
13-2041	3312.2.1	Analista Creditizio/Analista Creditizia
13-2052	2412.4	Pianificatore Finanziario
13-2053	3321.3	Assicuratore/Assicuratrice
13-2072	3312.5	Consulente Prestiti
13-2082	2411.1.12	Fiscalista
13-2099	2411.1.9	Analista Frodi Finanziarie
13-2099	2412.1	Valutatore di Imprese
13-2099	2412.11	Investitore di Rischio
15-1211	2511.13	Analista di Sistemi TIC
15-1211	2512.2	Analista Software
15-1212	2529.7	Tecnico della Sicurezza Informatica
15-1221	2511.1	Specialista Informatico/Specialista Informatica
15-1231	2522.1.1	Amministratore di Rete Informatica/Amministratrice di Rete Informatica
15-1232	3512.1	Operatore del Servizio Assistenza TIC/Operatrice del Servizio Assistenza TIC
15-1241	2153.1	Ingegnere delle Telecomunicazioni
15-1241	2523.1	Pianificatore delle Risorse TIC/Pianificatrice delle Risorse TIC
15-1241	2523.2	Architetto di Rete Informatica
15-1241	2523.3	Ingegnere di Rete Informatica
15-1242	2521.1	Amministratore del Database/Amministratrice del Database
15-1243	2521.2	Progettista di Database
15-1243	2521.4	Esperto di Integrazione dei Database/Esperta di Integrazione dei Database
15-1243	2521.5	Progettista di Data Warehouse

SOC Code	ISCO Code	ISCO Title
15-1244	2522.1	Amministratore di Sistemi TIC/Amministratrice di Sistemi TIC
15-1251	2512.4	Sviluppatore di Software/Sviluppatrice di Software
15-1253	2519.7	Collaudatore di Software/Collaudatrice di Software
15-1254	2513.5	Sviluppatore Web/Sviluppatrice Web
15-1255	2166.6	Progettista di Giochi Digitali
15-1255	2513.3	Progettista di Interfacce Utente
15-1299	1330.7	Project Manager TIC
15-1299	1349.11	Responsabile della Gestione Documentale
15-1299	2165.3	Specialista in Sistemi Informativi Geografici
15-1299	2511.14	Architetto di Sistemi TIC
15-1299	2511.14.1	Architetto di Blockchain
15-1299	2512.4.1	Sviluppatore di Blockchain/Sviluppatrice di Blockchain
15-1299	2529.2	Esperto di Informatica Forense/Esperta di Informatica Forense
15-1299	2529.3	Ingegnere della Sicurezza dei Sistemi Integrati
15-1299	2529.4	Hacker Etico/Hacker Etica
15-1299	3514.1	Webmaster
15-2011	2120.1	Consulente Attuariale
15-2031	2421.3	Responsabile Business Intelligence
15-2051	1342.1	Responsabile di Informatica Medica
15-2051	2421.1	Analista di Business
15-2051	2511.4	Data Scientist
15-2051	3252.2	Responsabile del Servizio Cartelle Cliniche
17-2081	2143.1	Ingegnere Ambientale
17-3022	3112.1	Tecnico dell'Ingegneria Civile
17-3027	3115.1	Tecnico Meccanico
17-3027	3115.1.4	Tecnico di Ingegneria Automobilistica
17-3029	2141.2	Esperto di Tecnologie per il Confezionamento di Cibi e Bevande/Esperta di Tecnologie per il Confezionamento di Cibi e Bevande
17-3029	3115.1.18	Tecnico Ferroviario
17-3029	3115.1.7	Tecnico di Ingegneria Navale

SOC Code	ISCO Code	ISCO Title
17-3029	3116.1.3	Tecnico Addetto alla Campionatura Colori
17-3029	3119.12	Tecnico Specializzato in Fotonica
17-3029	3119.4	Tecnico di Messa in Servizio
17-3029	3119.6	Tecnico dello Sviluppo di Calzature
17-3029	3119.7	Tecnico di Produzione di Calzature
17-3029	3132.5	Tecnico Addetto a Impianti di Trattamento delle Acque Reflue
17-3029	7543.5	Specialista in Prove Non Distruttive
19-1029	2131.3	Bioinformatico/Bioinformatica
19-1029	2131.4	Biologo/Biologa
19-1029	2131.4.8	Genetista
19-2031	2113.1	Chimico
19-2041	1349.13	Responsabile della Protezione Ambientale
19-2041	2133.5	Ecologo/Ecologa
19-2041	2133.7	Specialista in Scienze dell'Ambiente
19-2041	2143.2	Esperto Ambientale/Esperta Ambientale
19-2041	2422.12	Funzionario Addetto alle Politiche Pubbliche/Funzionaria Addetta alle Politiche Pubbliche
19-2041	2422.12.5	Funzionario Addetto alle Politiche Ambientali/Funzionaria Addetta alle Politiche Ambientali
19-2042	2114.1	Geologo/Geologa
19-3022	2120.2	Demografo/Demografa
19-3022	2632.6.1	Ricercatore di Sociologia/Ricercatrice di Sociologia
19-3022	3341.6	Responsabile di Indagine Statistica e Rilevazione Dati
19-3022	4227.2	Rilevatore di Censimento/Rilevatrice di Censimento
19-3033	2634.2	Psicologo/Psicologa
19-3034	2634.2.2	Psicologo Scolastico/Psicologa Scolastica
19-4021	3141.2.3	Tecnico Biologo
19-4061	2310.1.41	Ricercatore Universitario/Ricercatrice Universitaria
19-5011	3257.5	Ispettore in Materia di Salute e Sicurezza sul Lavoro/Ispettrice in Materia di Salute e Sicurezza sul Lavoro
19-5012	2263.3	Responsabile del Servizio di Prevenzione e Protezione

SOC Code	ISCO Code	ISCO Title
19-5012	3112.2	Ispettore di Cantiere/Ispettrice di Cantiere
19-5012	3117.4	Ispettore per la Sicurezza nelle Miniere/Ispettrice per la Sicurezza nelle Miniere
19-5012	3257.6	Ispettore in Materia di Salute e Sicurezza nei Trasporti/Ispettrice in Materia di Salute e Sicurezza nei Trasporti
21-1012	2359.1	Tutor Universitario/Tutor Universitaria
21-1012	2359.2	Coordinatore dei Servizi di Supporto allo Studio Universitario/Coordinatrice dei Servizi di Supporto allo Studio Universitario
21-1012	2359.8	Consulente Scolastico/Consulente Scolastica
21-1012	2423.1	Consulente per l'Orientamento Professionale
21-1012	3312.7	Coordinatore dei Prestiti Universitari/Coordinatrice dei Prestiti Universitari
21-1013	2635.1.4	Terapista di Coppia
21-1015	2635.3.22	Tecnico del Reinserimento e dell'Integrazione Sociale
21-1018	2635.1.2	Consulente della Tossicodipendenza e dell'Alcolismo
21-1018	2635.3.17	Assistente Sociale nell'Ambito della Salute Mentale
21-1021	2635.3.10	Assistente Sociale Scolastico/Assistente Sociale Scolastica
21-1021	2635.3.2	Assistente Sociale per l'Infanzia
21-1021	3412.4.3	Assistente Sociale per Minori
21-1021	3412.4.5	Assistente Sociale Familiare
21-1021	3412.4.6	Assistente Sociale Specializzato in Affidamento Familiare/Assistente Sociale Specializzata in Affidamento Familiare
21-1022	2635.3.14	Assistente Sociale per Anziani
21-1022	2635.3.16	Assistente Sociale Medico-Ospedaliero/Assistente Sociale Medico-Ospedaliera
21-1022	2635.3.20	Assistente Sociale in Cure Palliative
21-1023	2635.1	Consulente Sociale
21-1023	2635.1.5	Consulente per la Violenza di Genere
21-1023	2635.3.19	Assistente Sociale Militare
21-1023	2635.3.24	Assistente Sociale per le Dipendenze
21-1023	3412.4.8	Assistente Sociale Psichiatrico/Assistente Sociale Psichiatrica

SOC Code	ISCO Code	ISCO Title
21-1091	2422.12.12	Funzionario Addetto alle Politiche Sanitarie/Funzionaria Addetta alle Politiche Sanitarie
21-1091	2422.6	Consulente Sanitario/Consulente Sanitaria
21-1091	5142.12	Consulente Dimagrimento
21-1092	2635.3.21	Addetto alla Sorveglianza di Persone in Libertà Vigilata/Addetta alla Sorveglianza di Persone in Libertà Vigilata
21-1093	3412.5	Ausiliario Socio-Assistenziale/Ausiliaria Socio-Assistenziale
21-1094	3253.1	Operatore Sanitario di Comunità/Operatrice Sanitaria di Comunità
23-1012	3411.5	Assistente Giudiziario/Assistente Giudiziaria
23-2011	3411.7	Consulente Giuridico/Consulente Giuridica
23-2093	3334.2.1	Responsabile di Transazioni Immobiliari
25-2059	3422.4	Istruttore Sportivo/Istruttrice Sportiva
27-1011	2654.1	Direttore Artistico/Direttrice Artistica
27-1014	2166.1	Esperto in Modellazione 3D/Esperta in Modellazione 3D
27-1014	2166.13	Artista di Effetti Speciali
27-1014	2166.2	Layout Artist, Animazione
27-1014	2166.3	Animatore Digitale/Animatrice Digitale
27-1014	2166.3.1	Animatore 3D/Animatrice 3D
27-1014	2651.10	Artista Storyboard
27-1014	2651.11	Artista Video
27-1022	2163.1.3	Stilista di Moda
27-1024	2166.9	Designer Grafico/Designer Grafica
27-1025	3432.1	Architetto di Interni/Architetta di Interni
27-1026	3432.6	Stilista della Presentazione
27-4011	3435.3	Tecnico Audio
27-4011	3521.1	Tecnico Audiovisivo
27-4011	3521.1.1	Microfonista
27-4011	3521.1.10	Tecnico del Suono
27-4011	3521.1.11	Tecnico Video
27-4011	3521.1.3	Tecnico di Attrezzature a Noleggio per Spettacoli
27-4011	3521.1.6	Tecnico di Registrazione in Studio

SOC Code	ISCO Code	ISCO Title
27-4011	7312.2	Tecnico degli Strumenti
29-1031	2265	Dietologi e Nutrizionisti
29-1051	2262	Farmacisti
29-1071	3256.1	Assistente Medico-Sanitario/Assistente Medico-Sanitaria
29-1071	3259.1	Tecnico Anestesista
29-1122	2269.4	Terapista Occupazionale
29-1122	2269.5	Assistente del Terapista Occupazionale
29-1122	2359.5	Esperto di Tecnologie Assistive/Esperta di Tecnologie Assistive
29-1123	2264.2	Fisioterapista
29-1126	3211.1	Perfusionista
29-1126	3259.7	Tecnico di Funzionalità Respiratoria
29-1127	2266.2	Logopedista
29-1141	2221.1	Infermiere di Pratica Avanzata/Infermiera di Pratica Avanzata
29-1141	2221.2	Infermiere Generalista/Infermiera Generalista
29-1141	2221.3	Infermiere Specialista/Infermiera Specialista
29-1141	2222.1	Ostetrico/Ostetrica
29-1171	2221	Specialisti in Scienze Sanitarie Infermieristiche
29-1229	2131.6	Immunologo/Immunologa
29-1229	2211.1	Medico Generico
29-1229	2212.1	Medico Specialista
29-2052	3213.2	Tecnico Farmaceutico
49-1011	1439.4	Responsabile di Officina di Autoriparazione
49-1011	3115.1.6	Supervisore della Manutenzione Industriale
49-1011	3122.4.14	Supervisore nel Settore della Meccanica di Precisione
49-1011	3123.1.26	Supervisore Conservazione delle Risorse Idriche
49-1011	7231.9	Responsabile Manutenzione Veicoli
49-2011	7422.2	Tecnico Riparatore di Hardware
49-2021	3522.1	Tecnico dell'Ingegneria delle Telecomunicazioni
49-2021	7422.1	Responsabile della Manutenzione dell'Infrastruttura di Comunicazione
49-2021	7422.3.1	Riparatore di Telefonia Cellulare/Riparatrice di Telefonia Cellulare

SOC Code	ISCO Code	ISCO Title
49-2021	7422.4	Radiotecnico
49-2021	7422.6	Addetto alla Manutenzione delle Apparecchiature di Telecomunicazione/Addetta alla Manutenzione delle Apparecchiature di Telecomunicazione
49-2094	7421.3	Tecnico Riparatore di Elettronica di Consumo
49-3011	7232.5	Tecnico di Manutenzione Aeromobili
49-3023	7231.10	Meccanico Autoriparatore/Meccanica Autoriparatrice
51-8012	3131.3.1	Tecnico Addetto alla Distribuzione di Energia Elettrica
51-8012	3131.3.2	Operatore di Sistemi di Trasmissione di Energia Elettrica/Operatrice di Sistemi di Trasmissione di Energia Elettrica
51-8093	3134.3	Operatore di Sala di Controllo di Raffineria di Petrolio/Operatrice di Sala di Controllo di Raffineria di Petrolio
51-8093	3134.4	Operatore di Sistemi di Pompaggio del Petrolio/Operatrice di Sistemi di Pompaggio del Petrolio
51-8093	8131.8	Addetto a Servizi d'Ispezione per il Trasporto del Petrolio/Addetta a Servizi d'Ispezione per il Trasporto del Petrolio
53-2011	3153.2	Pilota di Aeromobili
53-2012	3153.2.2	Pilota Commerciale
53-5011	8350.1	Nostromo
53-5011	8350.2	Marinaio Addetto al Servizio di Coperta
53-5011	8350.3	Addetto ai Macchinari per la Navigazione Interna/Addetta ai Macchinari per la Navigazione Interna
53-5011	8350.5	Marittimo
53-5011	8350.6	Mozzo
53-5011	8350.7	Marinaio

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ECONOMIA ITALIANA 2026/2

Intelligenza artificiale: da innovazione tecnologica a crescita economica inclusiva

Il volume, editor **Alessandra Bonfiglioli** (Università di Bergamo), **Gino Gancia** (Università di Milano Bicocca) e **Paola Profeta** (Università Bocconi), offre un'attualissima analisi degli effetti dell'Intelligenza Artificiale sul sistema economico.

Una nuova *general purpose technology* suscita previsioni estreme: un'accelerazione senza precedenti della crescita per alcuni, la sostituzione del lavoro umano per altri. Se l'IA sta già cambiando organizzazioni e compiti cognitivi, resta da capire, osservano gli editor, "*attraverso quali meccanismi questi cambiamenti possano tradursi in trasformazioni dell'intero sistema economico e sociale*".

Il filo conduttore dei cinque saggi è una domanda: **quali condizioni consentono all'IA di trasformarsi da innovazione tecnologica in crescita economica inclusiva?** Tre le questioni in gioco: gli effetti dell'IA sulla produttività, la redistribuzione di opportunità e rischi tra lavoratori, famiglie e imprese, il ruolo delle politiche pubbliche.

Flavio Calvino e Antonio Ughi leggono la diffusione dell'IA come un processo sistemico, i cui benefici dipendono da un ecosistema favorevole all'innovazione. **Sergio Galletta** ricostruisce le prime evidenze empiriche sull'IA generativa: la questione non è più il potenziale trasformativo dell'IA, ma le condizioni per una diffusione efficace e socialmente desiderabile. L'indagine di **Massimo Anelli, Italo Colantone, Aina Gallego e Piero Stanig** sui lavoratori italiani più esposti all'IA generativa rileva insieme ottimismo, cautela e una crescente domanda di politiche pubbliche. **Emilio Colombo e Francesco Trentini** propongono la famiglia, anziché il singolo lavoratore, come unità di analisi degli effetti distributivi: un meccanismo di assicurazione informale. Infine **Mauro Caselli, Enrico Cristofoletti e Andrea Fracasso** mostrano che le imprese italiane che adottano l'IA investono di più anche in benessere organizzativo, salute e sicurezza dei lavoratori.

Ne emerge un'immagine dell'IA diversa da quella del dibattito pubblico: "*non una tecnologia che produce automaticamente vincitori e vinti*", ma un insieme di innovazioni il cui impatto dipende dall'interazione tra progresso tecnico, organizzazione economica e istituzioni. Di qui le tre indicazioni di policy degli editor: **investimenti complementari, gestione della transizione occupazionale, governance dell'innovazione**. Come nelle rivoluzioni tecnologiche del passato, tutto dipenderà dalla capacità di imprese, lavoratori e istituzioni di riorganizzarsi.

Completano il numero l'*intervento* di **Carmine Di Noia**, con un'ampia ricerca (450 partecipanti, Authority incluse) sull'uso dell'IA nella finanza italiana, e la *rubrica* di **Massimiliano Parco** su sicurezza energetica, materie prime e nuove dipendenze.

ECONOMIA ITALIANA nasce nel 1979 per approfondire e allargare il dibattito sui nodi strutturali e i problemi dell'economia italiana, anche al fine di elaborare adeguate proposte strategiche e di *policy*. L'Editrice Minerva Bancaria è impegnata a portare avanti questa sfida e a fare di Economia Italiana il più vivace e aperto strumento di dialogo e riflessione tra accademici, *policy makers* ed esponenti di rilievo dei diversi settori produttivi del Paese.

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