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OBJECTIVE VS. SUBJECTIVE MEASURES OF OCCUPATIONAL AI EXPOSURE: A COMPARATIVE ANALYTICAL APPROACH

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Abstract: *Perception of artificial intelligence (AI) represents an important indicator of how societies interpret and adapt to rapid technological change. While AI increasingly reshapes occupational structures, the divergence between objective measures of exposure and subjective perceptions remains insufficiently understood. Objective exposure can be estimated using occupational task profiles and quantitative indices, whereas subjective perception reflects deeper social, cultural and psychological mechanisms that influence how individuals internalize technological transformations. This study examines how young people evaluate AI exposure in relation to the occupations they aspire to, contrasting their assessments with established quantitative exposure indicators. Using survey data collected from 135 respondents aged 15–25, we compare perceived exposure with model-generated values to identify systematic gaps in understanding. Our results show that the quantitative model produces relatively consistent exposure levels across occupations, with most jobs falling within a moderate to high exposure range and displaying limited variation. By contrast, subjective perceptions are considerably more heterogeneous. Respondents generally assign lower exposure scores than the model predicts, indicating a tendency to underestimate the extent to which AI may affect future job content. Although the median perception score (6) is close to the model's value, the mean is significantly lower (5.5 < 6.86), reflecting a distribution skewed toward lower perceived exposure. Gendered patterns also emerge: women report a higher median perception score, potentially reflecting greater concern regarding AI-driven disruption, while men express more optimistic assessments. These findings suggest that perceived vulnerability to AI is shaped not only by occupational characteristics but also by broader cultural and social factors. Overall, the study highlights a persistent misalignment between quantitative exposure indicators and human perception, raising important implications for career guidance, skills policy and public understanding of technological change.*

Keywords: artificial-intelligence; perception; labour-market; employment; exposure.

JEL Classification: J24; O33; J21

1. Introduction

Artificial Intelligence (AI) is increasingly described as an emerging general-purpose technology with the potential to reshape labor-market dynamics. This prospect has intensified scholarly and public debates around the extent to which different occupations are exposed to AI-driven change. Foundational approaches such as Routine-Biased

Technological Change (Autor *et al.*, 2003) and Skill-Biased Technological Change (Acemoglu and Autor, 2011) established the analytical basis for assessing task-level vulnerability to automation. Building on these frameworks, a wide range of exposure indicators has been developed, including the Mean Automation Score (Gmyrek *et al.*, 2023), AI Occupational Exposure, AI Industry Exposure, the AI Geographic Exposure Indicator (Felten *et al.*, 2021), the Generative Artificial Intelligence Index (GenAI), Language Modelling–based exposure measures (Nurski and Ruer, 2024), or the GPT Exposure Rating (Eloundou *et al.*, 2023). These metrics link AI capabilities to occupational skill requirements and help map potential labor-market impacts, although no widely accepted standard has yet emerged. They also do not predict future developments and remain agnostic regarding whether AI acts as a substitute for, or a complement to, human work. Empirical patterns nevertheless show employment increases in occupations labelled as highly exposed to AI (Guarascio *et al.*, 2025). Beyond such objective assessments, a growing research strand highlights the social dimension of technological transitions, focusing on how individuals perceive AI exposure both within their occupations and across the broader labor market (Voigt, 2025). (Liu, 2021) distinguishes several interpretive lenses: a cultural perspective that examines the social, political and symbolic implications of AI in the digital transformation; a scientific perspective centered on AI as a research domain; and a technical perspective that views AI as a meta-technology reshaping production systems and occupational configurations. Understanding these perceptions is crucial for designing and adapting implementation strategies and for promoting acceptance of technological change. Studies examining perceptions in local contexts also reveal how regional economic structures and urban labor markets mediate such views. This paper brings together objective AI-exposure measures with survey evidence on individuals perceived exposure to AI.

2. Literature review

The relationship between technological progress and work has historically followed a cyclical pattern, both in terms of expectations and public sentiment. In his influential essay *The Distribution of Work and Income*, Leontief (1982) speculated that continued technological development might eventually reduce the need for human labor as dramatically as industrialization once displaced horses. His concern centered on the possibility of deep structural underemployment brought about by automation. Langlois (2003) later expanded this line of thinking by examining the long-run co-evolution of humans and machines, emphasizing that the distribution of tasks between them is repeatedly renegotiated as new technologies emerge. A major conceptual shift in studying how technology affects labor came with the task-based framework introduced by Autor, Levy, and Murnane (Autor *et al.*, 2003). Their model differentiated tasks into routine and non-routine, as well as cognitive and manual, and proposed that machines tend to replace routine work while enhancing non-routine cognitive activities. This insight became the cornerstone of the Routine-Biased Technological Change (RBTC) hypothesis, which views production as a set of tasks that can be assigned either to labor or capital. This framework helped establish the narrative of technology as an external shock to which workers must continually adapt, while questions of human agency and social interpretation received comparatively little attention. Acemoglu and Autor (2011) reframed the discussion through the Skill-Biased Technological Change (SBTC) perspective, arguing that advanced technologies raise the demand for skilled labor while diminishing opportunities for workers engaged in routine or lower-skill activities. DeCanio (2016) introduced the elasticity of substitution between labor and capital into production models, making it possible to quantify the complementarity–substitution dynamic. The emergence of extensive occupational datasets such as O*NET then enabled researchers to operationalize these theoretical categories by mapping task content across occupations. Frey and Osborne (2017) intensified public debate by estimating that nearly half of U.S. jobs faced a high probability of computerization. Their results prompted critiques such as that of Arntz et al. (2017), who argued that occupation-level estimates overstate risk by ignoring task variation within occupations. The development of machine-learning tools led to more refined approaches. Brynjolfsson et al. (Brynjolfsson *et al.*, 2018) introduced the Suitability for Machine Learning (SML) index to capture which tasks are more exposed to AI systems. The rapid diffusion of Large Language Models (LLMs) and generative AI further reshaped both measurement practices and theoretical debates. Eloundou et al. (2023) showed that most U.S. occupations include at least some tasks that could be potentially affected by LLMs. Other scholars, including Fernández-Macías and Bisello (2022) and Gmyrek et al. (2023), advanced composite task-level indicators, that contributed to a growing methodological convergence on how exposure is measured. While none of these indicators has become a universally accepted benchmark, together they provide increasingly comparable ways to examine how is perceived technological vulnerability. Empirical evidence, however, challenges the assumption that high exposure necessarily leads to employment decline. Guarascio and Reljić (2025) suggest a gap between perceived threat and actual labor-market outcomes. This divergence between measurable exposure and subjective interpretation has emerged as a central issue in contemporary research. At a broader economic scale, Brynjolfsson and Unger (2023) contrast pessimistic and optimistic scenarios with respect to productivity gains, inequality, and industrial concentration linked to AI adoption. Understanding how individuals perceive AI exposure today requires integrating the task-based analytical tradition with insights from socio-cognitive research on technological anxiety, trust, and adaptation. An increasing number of studies focus explicitly on perceptions, how AI is anticipated, interpreted, and evaluated, rather than estimating exposure solely through task taxonomies. Large-scale surveys illustrate these dynamics: in the United States, PEW Research Center (2025) reports that more workers feel worried (52%) than optimistic (36%) about AI's future role at work, with younger and more educated groups expressing relatively more confidence. Similarly, the European Commission's Special Eurobarometer finds strong overall support for AI use, yet accompanied by persistent concerns that AI may eliminate more jobs than it creates ('Special Eurobarometer SP554 : Artificial Intelligence and the future of work', 2025).

3. Methodology

The present research aims to measure young people's perceived exposure to Artificial Intelligence (AI) in relation to the occupations they aspire to, in order to identify prevailing perception patterns — *pessimistic, realistic*, or *optimistic* — regarding AI's future impact on employment. A total of 135 respondents, aged between 15 and 25 years, participated in the survey conducted between September and October 2025. Data were collected in person during dedicated meetings and youth-oriented workshops, rather than through open online distribution. This approach ensured a more focused and contextually relevant sample, engaging participants already involved in discussions on future skills, technology, and the labour market. The questionnaire was designed and administered using the GLIDE platform and aimed to capture both subjective perceptions and objective exposure indicators. It included the following variables: *participant name* (for internal tracking only, anonymized in analysis); *gender*; e*ducational level; desired job*, selected from a predefined list of occupations, searchable through a bar interface; *job group/category* automatically assigned based on the selected occupation; *perceived exposure score*, rated by participants on a 1–10 scale, where *1* indicated no exposure and *10* indicated very high exposure and *Calculated AI Exposure*. Data analysis relied on descriptive and inferential statistics to identify general patterns and central tendencies in participants perceived exposure scores. Each desired occupation was then associated with an existing AI exposure index, allowing a comparison between participants' subjective assessments and the objective exposure levels attributed to those occupations. This comparison highlights potential perception gaps and offers insights into how young people understand the relationship between AI and the future of work. To enable robust inferential testing and ensure adequate sample size (minimum 3 observations), the detailed occupational codes were aggregated into four ISCO-08 major groups: Managers (ISCO 1), Professionals (ISCO 2), Technicians & Associate Professionals (ISCO 3) and Service, Crafts & Manual Occupations (ISCO 4-9). The test evaluates H0 : the distribution of perception scores is identical across all major occupational groups. Tests were running within each occupational major groups by gender and educational level. Results were generated only where subgroup sizes permitted the non-parametric comparison. Statistical analysis was conducted in Python using pandas, matplotlib, scipy, seaborn and statsmodels package.

4. Results and discussions

The data collected from 135 participants offers a nuanced perspective on how young people perceive the impact of artificial intelligence (AI) on their professional future.

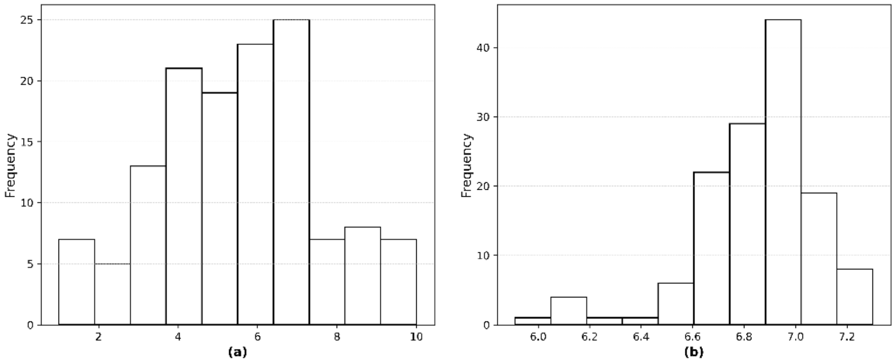

Figure 1: Distribution of AI Exposure: **(a)** perceived and **(b)** calculated
Source: Survey data processed by the authors in Python

The distribution of responses shown in Figure 1a is concentrated around values Q1=4 and Q3=7, with a min=1, max = 10, and exhibits positive skewness, meaning more respondents selected higher values. The median is 6, which is greater than the mean, confirming a right-skewed distribution. Overall, perception is moderate.
3.1.2. Aggregate level results Although the objective level of AI exposure across different professions falls within a relatively narrow range (5.9–7.3), participants' responses span the full scale from 1to 10. This wide variation highlights not only the diversity of opinions, but also the intensity of the social imagination surrounding technology. Comparing overall perceived, survey-based subjective AI exposure (Answers) with the objective, calculated AI exposure (AIE), the mean of perceived values are much lower than the calculated: 5.51 vs 6.86. Distribution for each variable are presented in Figure 2:

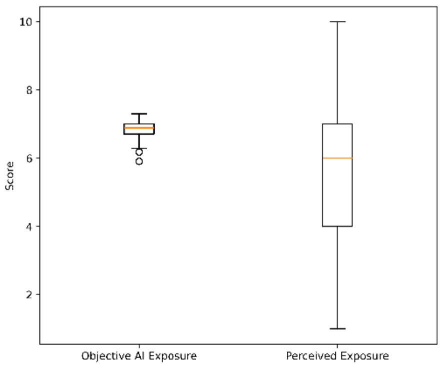

Figure 2: Distribution of perceived and calculated AI exposure
Source: Survey data processed by the authors in Python

Both mean and median values are lower in case of answers than the model predicted values. Spreads are narrow for calculated values (6.7 – 7.3) compared to much wider for answers (4 – 7). On calculated values outliers are few and close to whiskers values, while in case of perception outliers are present at the low and high end (1 and 10). The discrepancy between objective estimates and subjective perceptions suggests that AI is not interpreted solely in technical terms, but through symbolic, emotional, and cultural lenses. For some young people, AI represents a promise of progress, for others, a source of uncertainty or even threat. These perceptions reflect not only levels of information, but also how individuals project their professional identity and the values they associate with work. Occupational group analysis (see Figure 3) reveals consistent differences in perception. Participants aspiring to management roles (24%) tend to underestimate AI's impact, relying on interpersonal and decision-making skills. In contrast, those in technical fields such as IT, engineering, and the natural sciences (13,3%, where median scores exceed 7) express heightened awareness of automation risks. Professions involving manual labor, protective services, or creative roles (e.g., dancers, actors, food processing workers) report scores below 5, suggesting a lower perceived vulnerability. These patterns reflect how the nature of professional activity: algorithmic vs. human-centered, shapes expectations about AI.

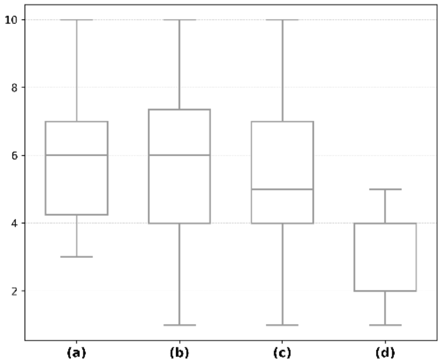

Figure 3: Distribution of perceived AI exposure across major occupational groups: (a) = Managers (ISCO 1), (b) = Professionals (ISCO 2), (c) = Services & Manual Workers (ISCO 4-9), (d) = Technicians (ISCO 3).
Source: Survey data processed by the authors in Python

Creative fields such as arts and design show marked polarization: some participants view AI as a tool for expression, while others see it as a direct rival to creativity. Meanwhile, young people envisioning careers in health (9.6%) and education (8.1%) tend to see AI as a complementary tool, indicating confidence in the human dimension of their work. From the selected 19 groups only 3 was rate higher than model's values: data clerks, drivers and ICT specialists. As you can see in Figure 3, the main pattern is a strong variation of spread between occupational groups, suggesting differences in perception consistency. The most heterogenous major group is Professionals (ISCO 2), while in technical related field (Technicians ISCO 3) exhibit the narrowest quartile band, suggesting consistent perceptions. In most of these occupations respondents underestimates exposure. Large variations can be observed within sales workers and judiciary, social and cultural professions. At gender-based level (see Figure 4), female participants reported a median score of 6.00, while male participants had a median of 5.00, both below the overall sample average (6.86).

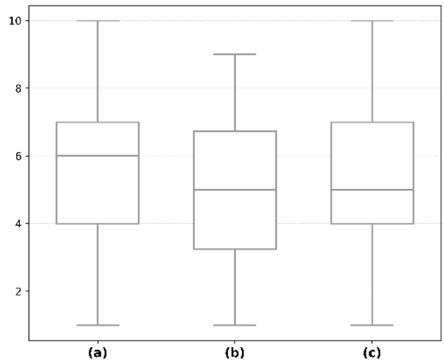

Figure 4: Distribution of perceived AI exposure by genre **(a)** Female, **(b)** Male, **(c)** Anonymous
Source: Survey data processed by the authors in Python

Woman's' interquartile range are narrower than male respondent's', suggesting a more homogenous view. Male respondents have a lower median and upper quartile, suggesting a more confident or optimistic perception, while women's narrower spread suggest a more homogenous views. These differences may be linked to distinct vocational orientations, varying levels of technological familiarity, and cultural or educational influences. Across these segments, three distinct patterns of technological perception emerge: realist, a balanced view, closely aligned with objective estimates; pessimist, an overestimation of risks, common in technical and creative domains; optimist: an underestimation of AI's disruptive potential, typical of professions centered on human interaction. The Spearman correlation analysis reveals a weak positive correlation. The result is statistically significant (ρ = 0.241, p = 0.0048) indicating that perceptions are partial aligned with objective exposure scores. The magnitude of the coefficient suggests that subjective assessments only partially reflect the corresponding objective measurements. These findings imply that individuals possess some intuitive understanding of occupational vulnerability to AI. Regression model has a value of $R^2 = 0.075$, which indicate that the model explains 7.5% of the variance. Values presented in Table 1. Show that the key predictor (objective AI Exposure) has a positive and statistically significant relation with perceived exposure (β = 2.205, p = 0.008). In contrast, variables genres and educational level do not significantly predict perceived exposure, with coefficients close to zero, suggesting that perceived AI Exposure is not shaped strongly by these control variables.

Table 1. Results of linear regression analysis for predictors of AI Exposure perceptions

	Coefficient	**Std_Error**	**t_Statistic**	**p_Value**
Intercept	-9,216	5,570	-1,655	0,100
C(Gen)[T.F]	0,062	0,479	0,130	0,897
C(Gen)[T.M]	-0,694	0,512	-1,356	0,177
C(Educational_Level)[T.University]	-0,438	0,392	-1,117	0,266
Q('AI Exposure')	2,205	0,811	2,718	0,008

Source: Survey data processed by the authors in Python

Overall, the model indicates that objective exposure is the only variable that significantly explains perceived AI exposure, although the predicting power of the model remains modest. Residual diagnostics presented in Figure 5 indicate that model assumptions are acceptable, with residuals normally distributed and show no strong heteroscedasticity pattern.

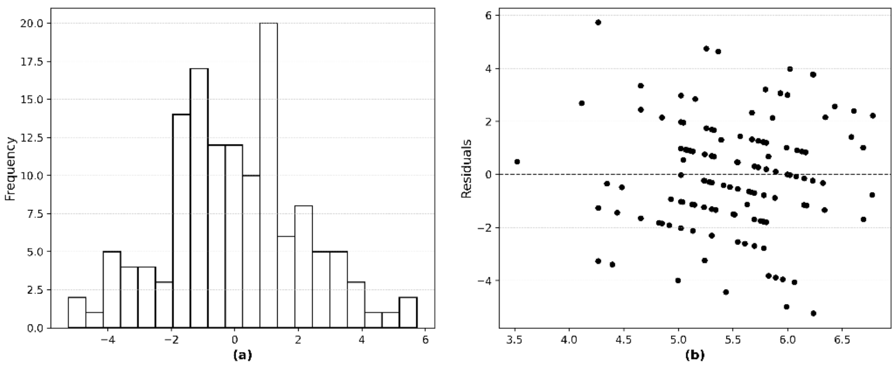

Figure 5. Residual diagnostic: residuals histogram **(a)** and fitted vs residuals **(b)**
Source: Survey data processed by the authors in Python

We first examined whether perceived AI Exposure differ across the four major ISCO-08 groups. Overall, the Kruskal-Wallis test showed a statistically significant difference in perceived AI Exposure between the four major occupational groups (H = 10, p = 0.013). This supports the assumption that students differentiate occupational risks depending of the nature of the job. Kruskal-Wallis tests were performed separately to assess whether perceived exposure differed by gender and by educational level. Results are presented in Tabel 2.

Table 2: Results of Kruskal-Wallis tests

ISCO Supergroup	**KW Statistic (Gender)**	**p-value (Gender)**	**KW Statistic (Education)**	**p-value (Education)**
Managers (ISCO 1)	1,309	0,520	0,847	0,357
Professionals (ISCO 2)	2,033	0,362	0,172	0,678

ISCO Supergroup	KW Statistic (Gender)	p-value (Gender)	KW Statistic (Education)	p-value (Education)
Services & Manual (ISCO 4–9)	0,128	0,720	4,160	0,041
Technicians (ISCO 3)	0,034	0,853	2,274	0,132

Source: Survey data processed by the authors in Python

Across major groups, no statistically significant gender-based differences were observed. Male and female respondents perceived similar AI Exposure within the same occupational group. For educational level, only the Professionals group had sufficient cases to perform test and the results were also non-significant differences ($p > 0.24$). Overall, these findings indicate that perceptions remain relatively homogenous within each category, regardless of gender or educational background. These orientations should not be reduced to mere estimation errors; rather, they represent expressions of professional identity and cognitive strategies for managing uncertainty. Emotions such as curiosity, fear, and hope play a key role in shaping these perceptions. Overall, the findings reveal a generalized ambivalence in how young people relate to AI: curiosity mixed with caution, information tempered by vulnerability. This ambivalence underscores the need for critical digital literacy and educational spaces that encourage reflection on one’s personal relationship with technology. Rather than categorizing perceptions as “right” or “wrong,” it is more productive to interpret them as indicators of how the emerging generation internalizes the transformations of the labor market. These insights invite deeper reflection on how young people’s perceptions may influence educational choices, career orientation, and strategies for adapting to an increasingly AI-driven economy.

5. Conclusions

In this study, we aimed to identify how young people perceive the exposure of their desired future occupations to Artificial Intelligence (AI) and to explore whether these perceptions reflect predominantly pessimistic, realistic, or optimistic expectations about the future of work. Overall, we can conclude that there is a divergence between quantitative model and human perception. As possible interpretation hypothesis we mention the invulnerability bias (Barrera-Jimenez et al., 2025), when respondents underestimating AI exposure in their desired jobs and believe that AI will affect others’ jobs more than their own jobs, correlated with limited understanding of how AI automates specific task. Another cause could be the optimism bias, when individuals minimize automation risk to preserve career confidence. We should also consider, as a possible interpretation, the generalization of the model, specifically, how it applies its calculations of AI Exposure across different occupations based on the composition of tasks within each occupation. This study demonstrates that young people's perceptions of artificial intelligence (AI) extend beyond technical assessments and reflect a complex understanding shaped by symbolic, emotional, and identity-related factors. AI is perceived as a transformative force with the potential to redefine both the structure and meaning of work, and this perception varies significantly depending on occupational field, gender, and professional aspirations. These differentiated perceptions (ranging from cautious realism to optimistic underestimation) highlight the role of professional identity in shaping attitudes toward technological change. They influence not only career choices but also how young people prepare for integration into a digitalized economy. The findings underscore the importance of developing differentiated educational policies that account for the diversity of perceptions and the specific needs of each demographic segment. Digital competence and critical thinking about AI should be embedded across the curriculum, not only in STEM disciplines, but also in the humanities, social sciences, and creative fields. This approach can help ensure equitable and flexible preparation for a labor market in continuous transformation. From an economic perspective, young people's perceptions of AI may shape labor supply dynamics, levels of professional adaptability, and the degree of openness to technological innovation. In this sense, AI is not merely a technological challenge, but also a marker of society's capacity to manage change. Understanding these perceptions is essential for designing sustainable strategies for integrating AI into the economy, with a focus on inclusion, resilience, and innovation.

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