Interdisciplinary Description of Complex Systems 24(1), 1-15, 2026

ATTITUDES, RISKS AND REGULATION: THE SOCIAL FOUNDATIONS OF AI ADOPTION IN CROATIA

Petra Palić*, Tomislav Belić and Roko Mišetić

Catholic University of Croatia
Zagreb, Croatia

DOI: 10.7906/indecs.24.1.1
Regular article

Received: 16 December 2025.
Accepted: 6 February 2026.

ABSTRACT

This study investigates how attitudes toward artificial intelligence (AI), levels of technological competence and patterns of trust shape AI adoption, perceived labour-market risks and support for regulatory measures among working-age adults in Croatia. The analysis draws on data from a nationally representative CAWI survey conducted within the project Artificial Intelligence and Social Change. A subsample of respondents aged 18-64 (N = 418) was used for this study. The questionnaire included measures of AI usage, perceptions of labour-market uncertainty, technological and scientific trust, AI self-efficacy and attitudes toward regulation. Composite scales were constructed using reliability analysis and principal component analysis. AI adoption was modelled with binary logistic regression. Results show that younger age, stronger trust in AI and higher AI self-efficacy significantly increase the likelihood of regular AI use. Labour-market risk perceptions were examined using a general linear model, revealing that pro-technology attitudes (reverse-coded transhumanism) and higher trust in science are associated with greater perceived job insecurity related to AI, while demographic variables exert minimal influence. Support for AI regulation was analysed using logistic regression with a binary outcome capturing consistent pro-regulatory preferences. AI optimism, perceived labour-market risks and perceived technological risks all significantly increase support for regulatory measures, whereas demographic factors play only a marginal role. Overall, the findings indicate that AI adoption, labour-market concerns and demand for regulation are driven primarily by attitudinal and perceptual mechanisms rather than socio-demographic characteristics. The study highlights the coexistence of AI optimism and regulatory caution, pointing to a societal demand for governance frameworks that balance technological innovation with social safeguards.

KEY WORDS

AI adoption, labour-market risks, regulation

CLASSIFICATION

JEL: J24, J49, O33

*Corresponding author, η: petra.palic@unicath.hr; -;
Catholic University of Croatia, Ilica 244, HR – 10 000 Zagreb, Croatia

INTRODUCTION

The rapid advancement of artificial intelligence (AI) and its pervasive integration across various economic sectors represent one of the defining features of contemporary technological and societal transformations. These developments directly influence labour market structures, redefine the nature of work tasks, and generate new demands for skills and competencies essential for thriving in digitalised environments. In the context of the European Union, including Croatia, AI's proliferation raises critical questions about employment security, workplace conditions, and the evolving skill profiles required for professional success. While global studies highlight mixed perceptions of AI's labour impacts, ranging from optimistic views of productivity gains to concerns over job displacement and inequality, there is a paucity of research focused on transitional economies like Croatia. In these economies, digital adoption lags behind more advanced EU members, potentially exacerbating socio-economic divides rooted in post-socialist legacies and uneven infrastructural development.

The primary objective of this study is to analyse how citizens of the Republic of Croatia perceive and interpret the impact of AI technologies on the world of work. This analysis places specific emphasis on job security, changes in working conditions, and the transformation of competency profiles needed for successful professional integration in a digitalised labour environment. Secondary objectives include examining societal patterns of AI usage and adoption, assessing perceptions of AI's effects on daily work experiences, employment stability, and long-term career sustainability. The study also evaluates support for AI regulation to balance innovation with worker protections. By employing a mixed-methods approach, including descriptive analyses, generalised linear models (GLM), and logistic regression on a weighted sample of approximately $N = 418$ respondents aged 18 to 64, this research aims to provide empirical insights into these dynamics. It draws on a nationally representative CAWI survey conducted as part of the Artificial Intelligence and Social Change project.

This study contributes to the existing literature in several ways. First, it offers a context-specific examination of AI perceptions in Croatia, filling a gap in research on Eastern European countries where AI adoption is influenced by unique socio-economic factors, such as post-socialist labour market legacies, EU integration pressures, and regional disparities in technological access. Second, by integrating theories of technology acceptance, for example Davis's Technology Acceptance Model, economic automation models, for example Acemoglu's task-based framework, and risk perception frameworks, for example Slovic's psychometric paradigm, it provides a multidisciplinary lens on AI's labour impacts. This lens highlights the role of trust, self-efficacy, and generational divides in shaping attitudes. Third, the findings inform policy recommendations for responsible AI governance, emphasising the need for targeted education, upskilling initiatives, and regulatory frameworks, such as those aligned with the EU AI Act, to mitigate risks while harnessing opportunities for inclusive growth. Empirically, the analysis reveals polarised AI usage patterns, low levels of personal job fears juxtaposed with broad market uncertainty, and strong regulatory support. These elements contribute to broader debates on 'responsible optimism' in AI-driven transitions and underscore the societal demand for governance that prioritises ethical safeguards alongside innovation.

LITERATURE REVIEW

The rapid advancement of AI has spurred extensive research on its implications for labour markets, societal attitudes, and regulatory needs. Economic analyses, such as [1] and [2], underscore AI's dual role in enhancing productivity while potentially displacing routine jobs, leading to skill-biased technological change and increased inequality. These studies reveal that AI's labour-market effects are heterogeneous, with higher exposure in sectors reliant on automation, as evidenced by empirical data from online vacancies and occupational restructuring [3, 4]. Recent evidence from the United States indicates that AI adoption impacts specific tasks rather than entire occupations, with employment in high-exposure roles declining, though offset by firm-level productivity gains and overall employment growth [5]. Similarly, AI is augmenting tasks in software development and writing, affecting higher-wage workers and potentially leading to wage erosion through surveillance, while automation risks remain low at 1-2% of the workforce over the next two decades. In parallel, sociological perspectives emphasise perceptual factors, [6] demonstrate that public trust in AI varies globally, influenced by cultural contexts and media portrayals, while [7] highlight biases in AI-mediated hiring that exacerbate social inequalities. A critical aspect of AI adoption involves technological competencies, particularly self-efficacy, which refers to individuals' confidence in their ability to use AI tools effectively. Research grounded in the Technology Acceptance Model (TAM) shows that self-efficacy significantly influences AI adoption intentions and behaviours. For instance, [8] found that AI self-efficacy positively affects generative AI usage, with users' perceived competence enhancing their willingness to integrate these tools into work processes. In educational contexts, which often mirror labour-market skill demands, a weak but significant positive correlation exists between AI tool use and academic self-efficacy, suggesting that familiarity with AI can bolster confidence in handling complex tasks [9]. However, low self-efficacy can indirectly lead to AI dependency through increased academic stress and heightened performance expectations, potentially reducing creativity and critical thinking [10]. These findings align with broader literature indicating that digital competencies, including multimodal literacy and self-efficacy, are key predictors of AI tool adoption in higher education and professional settings, where perceived ease of use mediates acceptance. Trust emerges as a pivotal construct in AI adoption literature, intersecting with competencies to shape perceptions of risk and opportunity. Drawing from Merton's sociology [11] of science and conceptualisation of scientific trust, studies show that epistemic confidence in technology fosters acceptance but can also heighten awareness of risks [12]. For instance, [4] argue that AI's virtual agglomeration effects amplify employment impacts, particularly in knowledge-based economies, where competencies in AI literacy are essential for adaptation. In the European context, AI adoption is influenced by infrastructural and cultural factors, with 13,5% of EU companies using AI in 2024, rising to higher rates among large enterprises (41%), though disparities persist across regions and firm sizes [13]. Recent analyses based on large-scale professional networking data suggest that generative AI has the potential to augment or disrupt approximately 61% of jobs across the European Union, with disproportionate effects on women and younger workers, particularly in sectors such as technology and financial services. These findings highlight the growing importance of upskilling in AI literacy and soft skills. Broader Eastern European trends suggest slower AI diffusion due to post-socialist legacies and uneven digital access, with limited empirical work in Croatia highlighting a gap in understanding attitudinal drivers. Regulatory discussions, informed by [14], advocate for worker protections against algorithmic management, aligning with OECD and ILO frameworks that stress inclusive governance to prevent labour-market polarisation. Overall, the literature indicates that while AI offers macroeconomic benefits, its social adoption hinges on addressing perceptual uncertainties, enhancing digital competencies, and implementing targeted policies to build self-efficacy and mitigate risks.

METHODOLOGY

SAMPLE

The analysis presented in this paper is based on data collected within the broader national project *Artificial Intelligence and Social Change*. Details concerning the data collection procedure, the CAWI technique, the representativeness of the initial sample, and compliance with international research standards are provided in the introductory article of this thematic issue. In this study, we focus specifically on the implications of AI for labour markets. To ensure that the analyses reflect the population that participates – or is expected to participate – in the labour market, we restricted the original representative sample of 500 respondents to individuals aged 18 to 64. This filtering criterion is consistent with definitions of the working-age population (15 to 64) used by the OECD and the ILO, resulting in an analytical sample of 418 respondents. This subsample is appropriate for examining attitudes and perceptions related to artificial intelligence in the active labour force.

INSTRUMENT AND MEASURES

The questionnaire used in the study included a series of items designed to measure different aspects of citizens' attitudes toward artificial intelligence, its perceived effects on the labour market, and their views on the appropriate level of institutional regulation. Most items were measured using five-point Likert scales, where higher scores indicate a higher intensity of the measured construct (1 – strongly disagree, ..., 5 – strongly agree). A smaller number of items employed alternative response formats.

The selection of items included in the analyses was guided by recent literature on artificial intelligence and labour markets, perceptions of technological risks, trust, and inequality, as well as recent empirical studies on AI adoption and perception conducted in the Croatian and Central European context [15-17]. This body of research informed the inclusion of attitudinal and self-efficacy-based measures capturing trust in AI and perceived competence, alongside socio-demographic predictors. This includes empirical work on occupational exposure to AI [2], labour-market restructuring and employment effects [1, 4], algorithmic management and worker protection [14], inequalities and biases in AI-mediated hiring [7], as well as global, consultancy-led research on public perceptions of and trust in AI, based on large-scale international surveys. A complete list of all questionnaire items used in the present study is provided in Appendix, organised by thematic domain and measurement scale.

OPERATIONALISATION OF VARIABLES AND COMPOSITE SCALES

The analysis included three categories of variables: individual sociodemographic variables (gender, age, region), dichotomous variables created for the purposes of the regression models, and composite scales. Composite scales were constructed to reduce item-specific measurement error and increase the reliability of the underlying constructs. They were calculated as mean scores of their respective items, and internal consistency was assessed using Cronbach's α. Negatively worded items were reverse-coded to ensure that higher values consistently represented higher levels of the intended construct (e.g., greater perceived risk, benefit, or support). All composite variables were standardised (Z-scores) to allow comparability across regression models. Operational definitions of all variables are provided below.

AI adoption was measured using item q1 ('How often do you use different AI tools?') on a four-point frequency scale. This is in line with prior Croatian research on generative AI use, which treats behavioural intention as the key indicator of adoption [15]. For hypothesis testing (**H_1**), a binary variable REG_USER was created: respondents selecting the highest category ('often', value 4) were coded as regular users (1), and all others as non-regular users (0). Perceived labour-market risks (PLMR), formulated as **H_2**, were operationalised using Principal Component Analysis (PCA), which identified a single underlying component capturing expectations regarding job security, occupational sustainability, and the balance between emerging and disappearing jobs. PCA was appropriate given that the items represent related but conceptually distinct domains of labour-market transformation. This operationalisation follows literature highlighting the role of automation and AI in reshaping labour demand, job displacement, and skill adaptation [1, 3, 4], as well as research on algorithmic management and perceived structural insecurity [14]. It also aligns with recent Croatian research documenting public concern regarding the broader societal implications of AI [17]. The resulting component score was used as a continuous indicator of perceived labour-market risk. All items are listed in the Appendix.

Support for AI regulation (**H3**) was initially measured with three items capturing concern about AI misuse, preferences for public-sector governance and support for stricter regulation to protect workers' rights (Q14, Q15, Q22). Because these items span conceptually distinct dimensions, the resulting composite showed low internal consistency ($\alpha = 0{,}57$) and was not used as a scale in the analyses. For hypothesis testing, we therefore constructed a binary outcome variable (SUPPORT_REG). Respondents who expressed strong agreement on both key items – concern about AI misuse (Q14) and support for stricter regulation to protect workers' rights (Q22) − were coded as 1 = high and consistent support for regulation (Q14 + Q22 $\geq$ 8), while all others were coded as 0. This operationalisation identifies respondents with consistent pro-regulatory attitudes rather than isolated single-item agreement.

Trust in AI (TRUST) was measured using three items assessing perceived usefulness of AI tools, their integration into everyday life, and expectations regarding their future necessity. The scale showed high internal consistency ($\alpha = 0{,}84$) and is conceptually aligned with existing international surveys of AI acceptance. AI self-efficacy (SELFEFF) was measured with three items capturing respondents' perceived understanding of AI tools, knowledge about their use, and confidence in using them effectively. The inclusion of self-efficacy as a predictor is supported by prior research demonstrating its central role in explaining generative AI adoption [15]. The scale demonstrated satisfactory reliability ($\alpha = 0{,}72$). Trust in science (SCITRUST) was measured through five items assessing whether AI tools are perceived to enhance objectivity, quality, accessibility, and ethical standards in scientific work. The scale showed high internal consistency ($\alpha = 0{,}89$). Technological risk perception (TECH_RISK) was derived from five items originally measuring openness toward transhumanist scenarios (TRANSHUM). Items were reverse-coded so that higher values represent greater discomfort, caution, or scepticism toward radical technological change. The scale demonstrated excellent internal consistency ($\alpha = 0{,}92$). Labour-market optimism (OPTIMISM) regarding AI was measured with a single item (Q20R) assessing expectations that AI will create more jobs than it eliminates. A planned composite including items Q7 and Q9 was discarded because it overlapped conceptually with the TRUST scale, which would have undermined discriminant validity.

STATISTICAL ANALYSIS

The statistical analysis was conducted in several stages. First, descriptive statistics were computed for all individual items and composite scales to examine distributions, central tendencies, and variability. Because the original dataset was weighted by key demographic characteristics, all analyses were performed on weighted data to preserve sample representativeness.

The first and third hypotheses – focused on predictors of AI tool use (**H1**) and predictors of support for AI regulation (**H3**) – were tested using binary logistic regression. This method was selected because both dependent variables were dichotomous, making logistic regression an appropriate framework for modelling the probability of belonging to a target category (regular users; supporters of regulation). Logistic models allow estimation of the effects of psychological, perceptual and sociodemographic predictors on outcome probabilities, consistent with methodological recommendations for analysing binary dependent variables in the social sciences [18]. The second hypothesis, aimed at identifying predictors of perceived labour-market risks, was examined using a GLM, as the outcome variable was continuous. Preliminary diagnostic checks confirmed that the assumptions for linear regression were met, allowing interpretation of the relative contributions of psychological, perceptual and sociodemographic predictors to the intensity of perceived labour-market risks. This modelling approach is consistent with recommended applications of the GLM framework in social-science research [19].

All models included control variables commonly identified as relevant in research on digital behaviour and technological adaptation – namely age, gender and region. Before interpreting results, we examined key assumptions of logistic and linear modelling, including multicollinearity (VIF), model fit for logistic regression (Hosmer-Lemeshow test), classification performance (AUC) and pseudo-R^2 indices. For the linear model, additional diagnostics assessed the normality and homoscedasticity of residuals in line with standard guidelines for regression analysis in the social sciences [19]. All statistical analyses were conducted using IBM SPSS Statistics 21.

RESULTS

DESCRIPTIVE STATISTICS

Use of Artificial Intelligence (AI Adoption)

Within the working-age sample (N = 418), the frequency of AI tool use shows substantial variation, Figure 1. Almost one fifth of respondents (19,8%) do not use AI tools at all, and a further 22,1% report using them only rarely (a few times per year). Occasional use (a few times per month) is reported by 28,5%, while regular use (weekly or daily) accounts for 29,7% of participants. These patterns indicate that AI adoption among the Croatian working population spans the full spectrum of usage intensity, suggesting that AI is in a diffusion phase but not yet firmly embedded in everyday work routines.

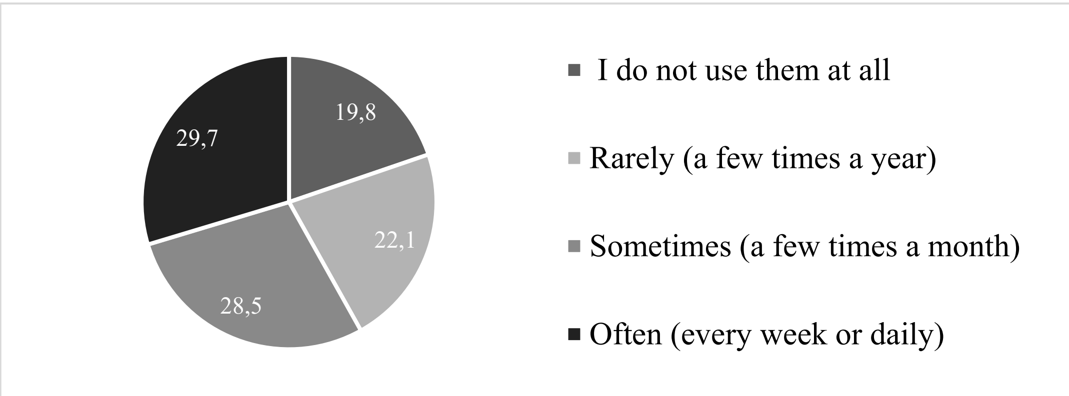

Figure 1. Frequency of AI tool use among the working-age population.

Beyond usage frequency, response distributions indicate generally positive attitudes toward the usefulness and future relevance of AI tools, Figure 2. A majority (62%) agree that AI can assist with everyday tasks, and almost half (41%) state that such tools are already part of their daily activities. Expectations of future integration are even stronger: over half (53%) believe that AI tools will become necessary in everyday life in the coming years. Self-reported familiarity with AI is more evenly distributed – around 43% feel at least somewhat familiar with how AI works, while about one quarter disagree. Taken together, these findings point to a broadly positive orientation toward AI, accompanied by substantial variation in familiarity and perceived everyday embeddedness. These descriptive patterns form the basis for analysing the predictors of actual AI adoption (**H_1**).

Labour-market risk perceptions

The distributions of items related to labour-market risks indicate that respondents hold moderately cautious but differentiated views about the impact of artificial intelligence on employment. A majority do not expect direct personal job displacement: 55% disagree with the statement that AI will replace jobs in their field and force them to change occupation, while only about one fifth (21%) agree. This pattern suggests low perceived immediate vulnerability and a sense of relative job security. Perceptions regarding the importance of acquiring AI-related skills for retaining one's job are more evenly split: roughly one third (36%) consider such skills important, another third (35%) disagree, and 29% express a neutral view. This indicates that some workers anticipate the need for technological upskilling, whereas others do not yet perceive a clear connection between AI and their own career trajectories. Furthermore, almost half of respondents (47%) do not believe that AI development will create more jobs than it will eliminate, while only 14% express optimism. Unlike the previous two items, disagreement here reflects scepticism toward the positive macro-economic effects of AI. Overall, respondents tend not to feel personally threatened by AI, yet they view the technology as a potential source of structural labour-market uncertainty, accompanied by a moderate sense of need for technological adaptation.

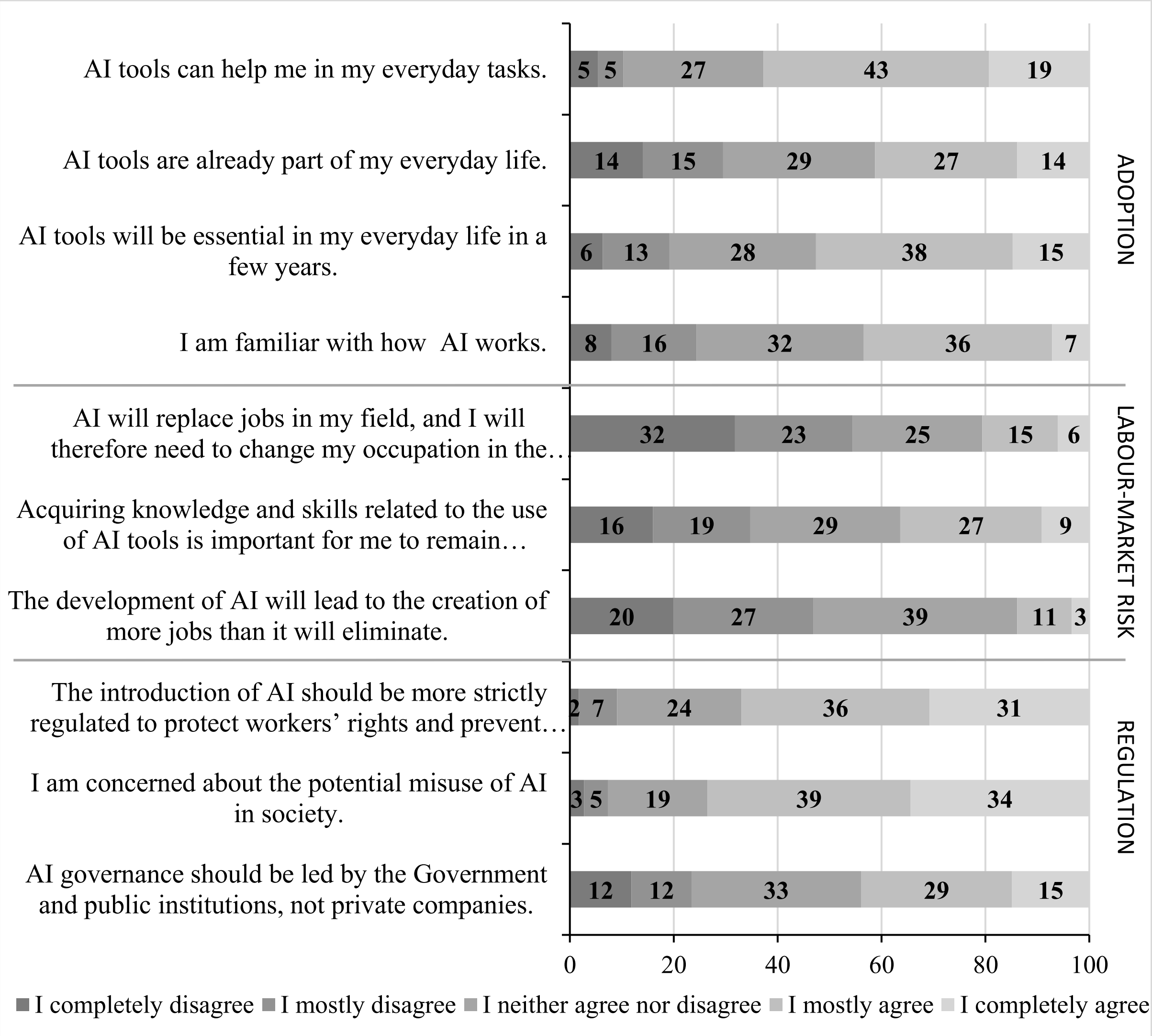

Figure 2. Distributions of responses to AI-related items: adoption, labour-market risks, and regulation.

Attitudes toward AI regulation

Respondents' attitudes toward the regulatory aspects of artificial intelligence reveal high levels of concern and broad support for stronger oversight. The strongest agreement appears for the statement that AI development and deployment should be more strictly regulated to protect workers' rights: 67% of respondents agree, while only 9% disagree. This indicates a strong societal consensus on the need for preventive institutional action in light of potential inequalities and risks. Similarly, a large majority (73%) report concern about the potential misuse of AI in society, suggesting that perceptions of ethical and safety risks are widespread. Views on who should have primary responsibility for governing AI systems are more differentiated. Although 44% agree that AI governance should be led by public institutions rather than private companies, nearly one quarter (24%) disagree, and about one third (33%) remain neutral. This suggests that while general support for regulation is clear, preferences regarding the appropriate governance structure are less consolidated. Overall, respondents view AI as a technology that requires robust institutional oversight, expressing high concern over potential negative consequences but only moderate consensus about which actors should serve as the primary regulators.

Descriptive statistics of composite scales

A summary of descriptive statistics for the composite scales is presented in Table 1. Levels of trust in artificial intelligence (TRUST) are moderate (M = 3,40, SD = 0,98), indicating that respondents generally perceive AI tools as useful and relevant, though not fully integrated into everyday activities. Similarly, trust in science in the context of AI use (SCITRUST) shows moderate values (M = 3,36, SD = 0,82). AI self-efficacy (SELFEFF) also lies at a mid-range level (M = 3,13, SD = 0,87), consistent with the distribution of individual items and reflecting heterogeneous levels of technological confidence among workers. Perceived technological risk (TECH_RISK) is notably high (M = 4,07, SD = 1,00), whereas transhumanism as a positive orientation toward radical technological enhancement shows the lowest mean levels (TRANSHUM; M = 1,93, SD = 1,00). Labour-market optimism (OPTIMISM) shows moderate but somewhat polarized expectations (M = 3,50, SD = 1,03), indicating that respondents are divided regarding whether AI will create more jobs than it eliminates. The standardised labour-market risk component (PLMR_PCA), derived through principal component analysis, spans a wide range (Min = –1,98; Max = 2,81), confirming substantial individual differences in how respondents assess the impact of artificial intelligence on job stability and labour-market dynamics. These descriptive patterns provide the quantitative foundation for the regression analyses presented in the following sections.

Table 1. Descriptive statistics for composite scales and key variables.

Variable	*N*	Min.	Max.	Mean	Std. Deviation
Age (years)	418	18,00	64,00	43,82	13,66
Trust in AI (TRUST)	418	1,00	5,00	3,40	0,98
Trust in Science (SCITRUST)	418	1,00	5,00	3,36	0,82
Transhumanism orientation (TRANSHUM)	418	1,00	5,00	1,93	1,00
Perceived technological risk (TECH_RISK)	418	1,00	5,00	4,07	1,00
AI self-efficacy (SELFEFF)	418	1.00	5.00	3.13	0.87
AI labour-market optimism (OPTIMISM)	418	1,00	5,00	3,50	1,03
Perceived labour-market risks (PLMR_PCA)	418	–1,98	2,81	0,00	1,00
Valid *N* (listwise)	418				

PREDICTORS OF AI ADOPTION

To examine which factors predict regular use of artificial intelligence tools, a binary logistic regression was employed with a dichotomous criterion (1 – regular users, 0 – all others). The model demonstrated strong statistical adequacy, as indicated by a significant omnibus test ($\chi^2(9) = 225,48$, $p < 0,001$) and a high Nagelkerke R^2 (0,59), suggesting that the included predictors explain a substantial share of the variance in AI adoption. Model fit was satisfactory (Hosmer-Lemeshow $p < 0,665$), and overall classification accuracy reached 83,4 %, correctly identifying 90,4 % of non-regular users and 66,7 % of regular users.

Several predictors emerged as statistically significant, Table 2. Trust in AI (TRUST) is the strongest positive predictor (B = 2,044, $p < 0,001$; OR = 7,72), indicating that respondents who perceive AI tools as useful and integrated into daily life have almost eight times higher odds of being regular users. AI self-efficacy (SELFEFF) also significantly increases the likelihood of regular use (B = 0,862, $p < 0,001$; OR = 2,37), highlighting the central role of perceived competence in the adoption process. Age is a significant negative predictor (B = –0,442, $p < 0,008$; OR = 0,64). Expressed in years, this implies that every five-year increase in age reduces the odds of regular AI use by approximately 15%, reflecting a generational gradient in adoption. Gender is not a significant predictor (B = 0,306, $p < 0,361$; OR = 1,36). Regional differences are largely nonsignificant compared with the reference category (City of Zagreb), with one exception: respondents from Dalmatia show significantly higher odds of regular AI use (B = 1,443, $p < 0,008$; OR = 4,23), suggesting a notably higher concentration of intensive users in that region.

Overall, the results indicate that psychological and cognitive factors – primarily trust in AI and perceived self-efficacy – are the key drivers of regular AI use, while sociodemographic characteristics exert weaker and more limited effects. Age remains the only consistent demographic predictor. These findings align with expectations that AI adoption is shaped principally by individuals' orientations toward technology and their subjective assessment of digital competence.

Table 2. Predictors of AI adoption (Logistic Regression). Outcome variable: regular (1 – regular user, 0 – all others). All continuous predictors are z-standardised. Odds ratios (OR) greater than 1 indicate increased likelihood of supporting regulation.

Parameter	B	S.E.	Wald	Sig.	OR	95% CI	
						Lower	Upper
Female (ref = male)	0,306	0,335	0,833	0,361	1,358	0,704	2,619
Age	–0,442	0,166	7,077	0,008	0,643	0,464	0,890
Trust in AI	2,044	0,258	62,698	0,000	7,719	4,654	12,800
AI self-efficacy	0,862	0,214	16,246	0,000	2,367	1,557	3,599
Region: Zagreb (ref)			17,930	0,003			
Northern Croatia	0,683	0,433	2,484	0,115	1,979	0,847	4,624
Slavonia	–0,624	0,543	1,319	0,251	0,536	0,185	1,553
Lika, Kordun, Banovina	–0,266	0,500	0,284	0,594	0,766	0,287	2,042
Istria, Kvarner, Gorski kotar	–0,840	0,866	0,941	0,332	0,432	0,079	2,358
Dalmatia	1,443	0,547	6,953	0,008	4,234	1,448	12,375
Constant	–2,176	0,419	26,990	0,000	0,113		

DETERMINANTS OF LABOUR-MARKET RISK PERCEPTIONS

To test the second hypothesis, a GLM was estimated with perceived labour-market risk (PLMR_PCA) as the dependent variable and age, gender, trust in science and technological orientations (transhumanism scale) as predictors. Levene's test supported the assumption of homoscedasticity ($F(1,422) = 2,41$, $p = 0,121$). The model was statistically significant and explained approximately 20% of the variance in perceived labour-market risk ($R^2 = 0{,}216$; adj. $R^2 = 0{,}208$), indicating a moderate level of explanatory power.

Two predictors were statistically significant, Table 3. Stronger transhumanist orientations – reflecting openness toward advanced technological augmentation – were associated with higher perceived labour-market insecurity (B = 0,313, $p < 0{,}001$, partial $\eta^2 = 0{,}098$). Higher trust in science also increased perceived risks (B = 0,252, $p < 0{,}001$, partial $\eta^2 = 0{,}068$). This pattern may reflect that individuals with greater confidence in scientific processes are also more aware of the disruptive potential of AI for employment and occupational structures. Demographic predictors played a limited role. Age was marginally significant (B = –0,078, $p = 0{,}086$), with younger adults reporting slightly higher concern, while gender did not contribute meaningfully to the model ($p < 0{,}649$). Including regional dummies did not improve model fit in any meaningful way. Furthermore, the pattern and strength of key predictors (trust in science and transhumanist orientation) remained unchanged. For parsimony and interpretative clarity, we therefore report the model without regional controls.

Overall, the findings indicate that perceived labour-market risk is shaped primarily by technological belief systems and broader epistemic trust, rather than by socio-demographic characteristics. Regional differences were significant at the block level ($p < 0{,}008$), with region Dalmatia showing systematically lower levels of perceived labour-market risk compared with the reference category (City of Zagreb). This suggests potential spatial variation in how AI-related labour-market vulnerabilities are interpreted across the country.

Table 3. GLM results for perceived labour-market risks associated with AI. Dependent Variable: PLMR_PCA (standardized). Partial η^2 is interpreted according to Cohen's guidelines (0,01 = small effect; 0,06 = medium effect; 0,14 = large effect). All continuous predictors are z-standardised.

Parameter	**B**	**Std. Error**	***t***	**Sig.**	**95% CI**		**Partial Eta Squared**
					Lower	**Upper**	
Intercept	0,010	0,061	0,162	0,871	–0,109	0,129	0,000
Female (ref = male)	–0,041	0,090	–0,455	0,649	–0,219	0,136	0,000
Age	–0,078	0,045	–1,722	0,086	–0,166	0,011	0,007
Trust in science	0,252	0,046	5,533	0,000	0,162	0,341	0,068
Transhumanism	0,313	0,046	6,765	0,000	0,222	0,404	0,098

PREDICTORS OF SUPPORT FOR AI REGULATION

Support for AI regulation was examined using binary logistic regression, with the dependent variable defined by the most stable metric criterion: respondents who expressed strong concern about potential AI misuse (Q14) and strong support for stricter regulation to protect workers' rights (Q22), such that Q14 + Q22 $\geq$ 8, were coded as 1, while all others were coded as 0. This specification showed superior model calibration (Hosmer-Lemeshow $\chi^2(8) = 12142$, $p = 0{,}134$) while retaining the same predictor structure as alternative, less restrictive definitions. Correlation matrices confirmed the absence of multicollinearity (all correlations < 0,45). The model was statistically significant (Omnibus $\chi^2(6) = 49{,}33$, $p = 0{,}001$) explaining approximately 15% of the variance (Cox-Snell $R^2 = 0{,}112$; Nagelkerke $R^2 = 0{,}151$). Classification accuracy was 67,4%, representing a meaningful improvement over the baseline model, and the model showed acceptable discrimination (AUC = 0,70).

AI optimism emerged as the strongest predictor (OR ≈ 2,0, $p = 0{,}001$): each one-SD increase in optimism doubled the odds of supporting regulation. Perceived labour-market risks also substantially increased support (OR ≈ 1,7, $p = 0{,}001$). as did perceived technological risks (OR

≈ 1,4. p = 0,01). Age showed a positive and significant effect (OR ≈ 1,3-1,4). indicating that older adults express stronger demands for regulatory oversight. Trust in science was also a positive predictor, suggesting that individuals with greater confidence in scientific institutions are more inclined to favour regulatory safeguards. Gender was not significant.

Overall. findings indicate a pattern of ‘responsible optimism’: individuals who perceive both the opportunities and risks of AI tend to support regulatory frameworks that ensure transparency, accountability and worker protection.

Table 4. Predictors of Support for Stronger AI Regulation (Logistic Regression). Outcome variable = SUPPORT_REG (1 = strong support for AI regulation. 0 = otherwise). All continuous predictors are z-standardised. Odds ratios (OR) greater than 1 indicate increased likelihood of supporting regulation.

Parameter	B	S.E.	Wald	Sig.	OR	95% CI	
						Lower	Upper
Female (ref = male)	–0,313	0,226	1,925	0,165	0,731	0,470	1,138
Age	0,382	0,112	11,694	0,001	1,466	1,177	1,825
AI Optimism	0,653	0,142	21,057	0,000	1,922	1,454	2,541
Labour-Market Risk Perception	0,487	0,136	12,857	0,000	1,628	1,247	2,125
Trust in Science	0,262	0,126	4,354	0,037	1,300	1,016	1,664
Technological Risk Perception	0,331	0,121	7,515	0,006	1,392	1,099	1,763
Constant	0,707	0,153	21,414	0,000	2,028		

CONCLUSION

The core empirical contribution of this study lies in its rigorous differentiation between the attitudinal and perceptual drivers of AI adoption, labour-market concerns, and regulatory demand, demonstrating their decisive superiority over mere socio-demographic characteristics in the Croatian context. The analysis moves beyond descriptive observations to establish robust predictive models, highlighting specific psychological and cognitive variables crucial for navigating the AI transition. The findings from the binary logistic regression on AI adoption are particularly salient for innovation policy. The odds ratio (OR) of 7,72 for Trust in AI and 2,37 for AI Self-Efficacy, far exceeding the marginal effects of age or region, underscore a critical insight: AI diffusion is primarily a function of perceived utility and competence, rather than simply access or exposure. This challenges simplistic ‘digital divide’ narratives rooted solely in age or infrastructure. From an economic perspective, this suggests that the optimal policy lever for accelerating beneficial AI adoption is not general technology subsidies, but rather targeted interventions focused on cognitive skill enhancement (AI literacy, self-efficacy training) and trust-building measures (transparency, accountability frameworks) that reduce the perceived psychological cost of adoption. The GLM results for PLMR introduce a significant nuance. The positive correlation between pro-technology attitudes (reverse-coded transhumanism) and higher PLMR reveals an ‘informed structural anxiety’. Those who are generally optimistic and knowledgeable about technological progress are precisely the individuals who acknowledge the systemic risks of job displacement and task redefinition, often drawing on a more informed assessment of models like the task-based framework of [1]. The fact that demographic variables exerted minimal influence on risk perception (low explanatory power in the GLM) confirms that the fear is structural and economy-wide, not merely a reflection of individual job insecurity linked to age or gender. This is a macro-economic warning signal: the labour market is perceived as fundamentally unstable due to technological forces.

The most compelling policy implication emerges from the analysis of support for AI regulation. The simultaneous, significant influence of AI Optimism, Perceived Technological Risk, and Labour-Market Risk on pro-regulatory preferences (SUPPORT_REG) solidifies the concept of Responsible Optimism. The public demands a social contract for AI. They are not Luddites; they seek to harvest the productivity gains promised by AI (optimism) but only under the assurance that institutional guardrails are in place to mitigate potential societal (technological risk) and individual economic harm (labour-market risk). This strong preference for institutional oversight where 67% agree on stricter regulation for worker protection provides an empirical mandate for aligning national policy with proactive governance models, such as those established by the EU AI Act.

In conclusion, this study demonstrates that the Croatian public views the AI transition through a highly perceptual lens, making attitudes and trust the central focus for both descriptive analysis and prescriptive policy. The findings advocate for a dual policy strategy: first, invest in human capital through focused AI self-efficacy training to unlock the adoption potential; and second, urgently establish a robust, transparent, and protective regulatory regime to assuage the 'informed structural anxiety' and fulfil the strong public demand for responsible innovation. The coexistence of high optimism and profound regulatory caution is the defining feature of this transitional economy's relationship with artificial intelligence.

APPENDIX A: QUESTIONNAIRE AND MEASUREMENT INSTRUMENTS

SOCIODEMOGRAPHIC VARIABLES

Age
Open-ended: 'How old are you?'

Gender
1 = Male
2 = Female

Region of Residence
1 = Zagreb
2 = Northern Croatia
3 = Slavonia
4 = Lika. Kordun and Banija
5 = Istria. Croatian Littoral and Gorski Kotar
6 = Dalmatia

AI ADOPTION (H_1)

Variable: REG_USER
Binary variable derived from Q1:
1 = regular user ('often – every week or daily').
0 = all others.

Q1. How often do you use different AI tools?
a) I do not use them at all
b) Rarely (a few times a year)
c) Sometimes (a few times a month)
d) Often (every week or daily)
e) I'm not sure

PERCEIVED EVERYDAY USEFULNESS OF AI TOOLS

Variable: TRUST (α = 0,84)
Measures perceived usefulness and integration of AI tools into everyday life.
Q7. AI tools can help me in my everyday tasks.
Q8. AI tools are already part of my everyday life.
Q9. AI tools will be essential in my everyday life in a few years.

AI Self-Efficacy

Variable: AI_EFFICACY (α = 0,72)
Q10. I am familiar with how AI works.
Q17. I believe I have sufficient knowledge about AI tools such as ChatGPT.
Q18R. Without assistance, it would be difficult for me to master the use of AI tools. *(reverse-scored)*

SUPPORT FOR AI REGULATION (H_3)

Variable: SUPPORT_REG
Binary variable derived from Q14, Q22:
1 = high and consistent support for regulation – assigned when the sum of Q14 + Q22 ≥ 8 (i.e. both items rated 4 or 5 on the Likert scale)
0 = all other respondents
Q14. I am concerned about the potential misuse of artificial intelligence (AI) in society
~~**Q15.** AI governance should be led by the Government of Croatia. together with international bodies. scientific institutions and the public. rather than by private companies.~~
Q22. The introduction of artificial intelligence should be more strictly regulated to protect workers' rights and prevent further increases in labour-market inequalities.
Note: The original *REG_POLICY* composite (Q14, Q15, Q22) was not used due to low internal reliability (α = 0.57). The binary SUPPORT_REG variable was selected because it demonstrated the best model calibration in the logistic regression used to test H3.

AI OPTIMISM

Variable: OPTIMISMAI
Operated as a single-item measure (Q20R) in the final specification.
Q20R. I believe that AI will create more jobs than it will eliminate. *(reverse-scored when used as optimism)*

LABOUR-MARKET RISK PERCEPTION (H_2)

Variable: PLMR_PCA
Composite extracted via PCA from three items, Q20R is reverse-scored.
Q20R. I believe that AI will create more jobs than it will eliminate. *(reverse-scored)*
Q21. I am afraid that I could lose my job because of the development of AI.
Q23. To keep my job, I will need to acquire knowledge and skills related to AI tools.

TRUST IN THE SCIENTIFIC USE OF AI TOOLS

Variable: SCITRUST (α = 0,89)
Q24. I think that using AI tools helps scientists be more objective in their work.
Q25. I think that using AI tools helps scientists achieve higher-quality results.
Q26. AI tools help scientists make more cautious, evidence-based conclusions.
Q27. AI tools help scientists access other researchers' studies more easily.
Q28. Scientists use AI tools ethically in their work.

TRANSHUMANISM ACCEPTANCE AND TECHNOLOGICAL RISK

Variable: TRANSHUM (α = 0,92)
Willingness to integrate technology into the human body.
Q29. I am willing to augment my body with technology that allows control of devices through thought.
Q30. ... with technology that improves health-related bodily functions.
Q31. ... with technology enabling contactless everyday actions (e.g. payments, access).
Q32. ... with technology that could give me above-average physical abilities.
Q33. I would consider cryonic preservation (freezing my body) in the hope that future technology could revive it.

Variable: TECH_RISK (reverse-scored version of TRANSHUM)
Captures discomfort, caution, and perceived ethical/technological risks.
(*Higher scores ↔ higher perceived technological risk.*)

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