
ENTHUSIAST, OPTIMIST OR SKEPTIC? MAPPING AI READINESS PROFILES FOR WORKFORCE UPSKILLING

Oana-Roxana RADU

Ovidius University of Constanța, Romania

Narcis Paris BACAIȚAN

Ovidius University of Constanța, Romania

Kamer-Ainur AIVAZ

Ovidius University of Constanța, Romania

Abstract:

Are you an Enthusiast, an Optimist, or a Skeptic regarding AI adoption? The question is not merely rhetorical: as artificial intelligence reshapes labor markets at an accelerating pace, workers' orientations toward AI-driven change vary substantially across attitudinal, institutional, and individual dimensions, and these differences have direct consequences for who seeks upskilling, who benefits from it, and who is left behind. This study develops a three-profile AI readiness framework and investigates which factors predict the intention to pursue AI tools training. Drawing on original survey data collected from 357 respondents in the South-East Development Region of Romania, it has been applied K-Means cluster analysis to identify three distinct workforce profiles: Optimists, characterized by positive AI attitudes and strong organizational preparedness; Skeptics, combining negative attitudes with near-absent institutional support; and Enthusiasts, whose high AI impact perception coexists with only moderate organizational readiness. Chi-square analyses reveal that AI literacy is the only competency priority that differs significantly across profiles, following an inverted gradient, the workers most exposed to displacement risk are least likely to prioritize it, a pattern we term the AI readiness inversion. Binary logistic regression further shows that training intention is predicted by personal preparedness and positive AI attitudes, but not by organizational readiness. These findings challenge the dominant policy assumption that institutional investment in digitalization automatically generates upskilling demand and point instead to attitudinal barriers as the primary constraint on training uptake. The three-profile framework offers a practical tool for designing differentiated upskilling interventions calibrated to the heterogeneous readiness configurations found within any given workforce or region.

Key words: *AI readiness; workforce profiles; upskilling demand; cluster analysis; peripheral labour markets; future of work; digital transformation*

1. Introduction

The relationship between artificial intelligence and the future of work has become one of the most contested terrains in contemporary social science. Early quantitative projections suggesting that nearly half of all occupations in advanced economies faced a high probability of automation (Frey and Osborne, 2017) prompted widespread debate about displacement, deskilling, reskilling, and the restructuring of labour markets. Subsequent scholarship has complicated this picture considerably, arguing that technology does not operate as an autonomous force but is instead shaped by organisational choices, power relations, regulatory frameworks, platforms, and the social contexts within which it is deployed (Wajcman, 2017; Vallas and Schor, 2020). The effects of AI on employment are, in this sense, neither predetermined nor uniform, they are mediated by institutional capacities, sectoral dynamics, and, more important, by the perceptions and competencies of workers themselves.

What has received less attention in this literature is the gap between anticipation and readiness, between the widespread recognition that AI will transform work and the uneven capacity of individuals, organisations, and labour markets to absorb that transformation. At the global level, this gap is already evident. According to data compiled by the World Economic Forum; Qualtrics, 87 percent of European employers expect artificial intelligence and related information processing technologies to drive significant business transformation between 2025 and 2030 (World Economic Forum, 2025). Yet the same evidence base reveals that the lack of skilled professionals remains the most frequently cited barrier to AI adoption, reported by half of all businesses surveyed worldwide (World Economic Forum, 2025). The dominant institutional response, reskilling and upskilling existing workers, is itself unevenly distributed: 77 percent of organisations globally report prioritising workforce training for AI integration, but the demand for and access to such training varies substantially across firm size, sector, and geography (World Economic Forum, 2025). The scale of this challenge is sharpened by projections on the shifting division of labour: while human workers currently account for 47 percent of total work tasks, with technology handling 22 percent, employers worldwide anticipate a near-convergence by 2030, when the human, combined, and technology shares are each expected to stabilise at approximately one third of all tasks (Statista, 2025). This structural compression of the human work share over a five-year horizon lends particular urgency to questions about who is prepared for the transition, and on what terms.

This article argues that understanding the gap between AI anticipation and AI readiness requires moving beyond aggregate statistics to examine how workers themselves perceive, position, and prepare for AI-driven change. Attitudinal heterogeneity within labour markets is not a residual category to be corrected by better communication or more training provision; it is a social phenomenon with structural determinants that policy and scholarship alike must account for. Positive attitudes toward AI do not automatically translate into institutional preparedness, and conversely, low individual enthusiasm does not preclude awareness of AI's transformative potential. These internal tensions, which we term the *AI readiness paradox*, have direct consequences for who seeks upskilling, who benefits from it, and who is left behind.

The empirical case for this argument is developed through an analysis of the South-East region of Romania, a labour market that sits at the intersection of several vulnerabilities relevant to the European AI transition. Romania records the lowest relative AI hiring rate among all countries in a recent cross-national comparison (9.96 year-over-year ratio), placing it systematically at the periphery of the emerging AI labour market (Statista, 2025). The South-East region of Romania, designated a less developed region under EU cohesion policy, combines below-average basic digital skills, a high share of employment in sectors with significant automation exposure, and limited access to advanced digital training. It therefore constitutes a critical case for examining how AI readiness is structured at the sub-national level in a peripheral European economy, a context that is substantially underrepresented in the existing empirical literature, which remains concentrated in high-income, technologically advanced labour markets.

The study draws on original survey data collected between November and December 2025 as part of the Future of Work Compass project, coordinated by CITYINNOHUB (European Digital Innovation Hub, South-East Romania), with a sample of 357 employees across the region. Using K-Means cluster analysis, we identify three distinct AI readiness profiles in the workforce, Skeptics, Optimists, and Enthusiasts, and examine how these profiles differ in their skill priorities, training preferences, and visions of regional work futures. We further use binary logistic regression to identify the individual- and organisational-level predictors of intention to pursue AI tools training, testing whether institutional readiness or individual perception constitutes the more powerful driver of upskilling demand.

Three research questions guide the analysis. First, what distinct attitudinal and readiness profiles characterise the workforce of the South-East Romanian labour market in relation to AI-driven change? Second, how do these profiles differ in their prioritisation of future-relevant competencies and their preferences for specific forms of training? Third, which individual and organisational factors predict the intention to engage in AI tools training, and what does this imply for how upskilling demand is generated in peripheral labour markets?

The remainder of the article is structured as follows. The next section develops the theoretical framework, engaging with debates in the sociology of work, critical technology studies, and research on skill formation and digital inequalities. Section three describes the study design and analytic strategy. Sections four and five present and discuss the empirical findings. The article concludes by identifying implications for training policy design and for the broader question of who bears the costs of AI-driven labour market restructuring.

2. Theoretical Framework

2.1. AI and the transformation of work: beyond technological determinism

Scholarly engagement with the relationship between technology and work has long been shaped by a tension between determinist and constructivist accounts. Determinist perspectives, whether optimistic or pessimistic in their projections, treat technology as an

exogenous force that acts upon labour markets, restructuring occupational profiles and redistributing tasks between human and machine in ways often framed by technical feasibility (Frey and Osborne, 2017; Acemoglu and Restrepo, 2019). This view draws on Acemoglu and Restrepo's (2019) task-based framework, which identifies a displacement effect where automation replaces labour in specific tasks, potentially offset by a reinstatement effect through the creation of new, labour-intensive tasks. Constructivist and critical perspectives, by contrast, insist that technological change is socially produced and politically mediated, reflecting choices that are neither neutral nor inevitable (Wajcman, 2017; Pfeiffer, 2022; Vallas and Schor, 2020). Pfeiffer (2022) argues that digitalization serves primarily to accelerate the realisation of value on markets rather than to transform productive relations, such that the displacement of labour is not merely a technical byproduct but also reflects the exercise of market power, where AI facilitates competition between localities and compresses the labour share of value added (Marx, 1976, cited in Pfeiffer, 2022; Acemoglu and Restrepo, 2019).

This distinction has practical consequences for how readiness for AI-driven change is conceptualised. If technology operates deterministically, readiness is merely a matter of technical skill acquisition to win the race between education and technology (Goldin and Katz, 2008, cited in Acemoglu and Restrepo, 2019). If, however, the trajectory of AI adoption is contingent and contested, readiness is better understood as a relational and attitudinal construct, shaped by workers' sense of agency and their trust in organisational responses. Treating workers' perceptions not as measurement error but as substantively meaningful social data allows us to understand how individuals respond to technological change in an environment where productive capacity is increasingly subordinated to the imperatives of value realisation (Pfeiffer, 2022).

Moreover, different methodological approaches produce substantially different estimates regarding automation exposure, suggesting that labour market risks should not be interpreted as fixed predictions but rather as scenario-dependent assessments (Otoi et al., 2022).

2.2. AI readiness as a stratified construct

The concept of readiness for technological change has been operationalised in several ways in the literature, ranging from technical skill inventories to broader assessments of digital competence. The present study draws a conceptual distinction between three analytically separable dimensions of AI readiness, each of which maps onto a distinct layer of the employment relationship.

The first dimension is attitudinal: how workers perceive the impact of AI on their working lives, including whether they view it as a threat, an opportunity, or a neutral transformation. There is growing recognition that the effects of technological change on labour markets are neither uniform nor predetermined: automation simultaneously displaces and complements human labour, generating uneven outcomes across occupational and skill groups (Autor, 2015; Yao et al., 2026; Munteanu et al., 2020). Workers' positioning within these restructured labour markets shapes not only their material exposure to AI-driven change but also their attitudinal responses to it, a relationship that is structured by occupational

position, prior experience of organisational change, and broader dispositions toward uncertainty and risk. Recent research also suggests that AI readiness is influenced not only by cognitive evaluations but also by affective dimensions. Emotional attachment, perceived friendship, and trust toward AI systems significantly increase individuals' willingness to engage with AI and share information (Pelau et al., 2024; Ionașcu et al., 2025).

The second dimension is institutional: the extent to which organisations are equipped to support AI integration, including investment in infrastructure, change management capacity, and structured training provision. Organisational readiness for digital transformation varies substantially across firm size and sector, and there is consistent evidence that smaller firms and those operating in less digitalised environments are systematically less prepared (European Commission, 2025). In peripheral labour markets such as the South-East Romanian region, where the proportion of micro and small enterprises is high and sectoral exposure to automation is concentrated in lower-skill occupations, this institutional layer is particularly consequential (Bătrâncea et al., 2026).

The third dimension is individual: workers' own assessment of their personal preparedness for AI-driven change, encompassing both their sense of competence and their awareness of the gap between current and required capabilities. This dimension is closely related to what the DigComp 3.0 framework articulates as digital self-efficacy in relation to AI systems, encompassing the knowledge, skills and attitudes required to engage critically and confidently with AI-enabled digital environments (Cosgrove and Cachia, 2025). Personal preparedness is analytically distinct from both attitude and organisational readiness: an individual may hold a positive view of AI while recognising that their own skills require substantial development, or may feel personally prepared in a context where the organisation offers minimal support.

The interaction among these three dimensions, and the patterns of alignment and misalignment between them, constitutes the primary object of empirical inquiry in this study. As the findings will show, it is precisely where these dimensions diverge that the most theoretically interesting and policy-relevant configurations emerge.

Previous Romanian evidence indicates that perceptions of AI are characterised by a dual perspective, with respondents simultaneously recognising opportunities for productivity and innovation while expressing concerns regarding job displacement and future employability (Istudor et al., 2025). This suggests that AI readiness should be understood as a multidimensional construct rather than a simple positive–negative attitude continuum.

Also, recent evidence from South-East Romania further suggests that both students and faculty predominantly perceive AI as a tool for augmentation rather than complete human replacement, although perceptions vary depending on professional background and perceived labour market vulnerability (Aivaz et al., 2026).

2.3. Skill formation and training demand in the context of AI

The question of which competencies are prioritised in the context of AI-driven change has attracted considerable empirical attention at the macro level. Global employer surveys

indicate that analytical thinking, resilience and adaptability, and technology literacy are currently ranked among the most valued core skills for the period 2025 to 2030, while AI and big data competencies are identified by 87 percent of employers as the single most rapidly increasing skill requirement (World Economic Forum, 2025). These aggregate patterns, however, obscure significant heterogeneity in how individual workers prioritise skill development and how that prioritisation varies with attitudinal and institutional context.

Critical perspectives on skill formation emphasise that demand for training is not simply a rational response to objectively identified skill gaps. Grugulis and Stoyanova (2011) have demonstrated that skill itself is a multifaceted and contested construct whose assumed relationship to performance outcomes is empirically difficult to establish, calling into question the premise that either workers or employers can straightforwardly assess the returns to specific training investments. At the organisational level, Morandini et al. (2023) identify the cost of AI-specific training, the challenge of guiding employees through the change process, and the difficulty of ensuring fairness and inclusion as persistent structural barriers that limit the capacity of organisations to translate training intentions into actual upskilling provision. In peripheral labour markets characterised by high proportions of SMEs, limited employer investment in training, and high uncertainty about the trajectory of AI adoption, these barriers are likely to be particularly pronounced, with the result that the motivational structure of training demand may differ substantially from what aggregate surveys suggest.

Beyond digital competencies, recent studies also underline the importance of sustainability-oriented competencies within public organisations, suggesting that future workforce development requires integrated digital and green capability frameworks (Grigorescu et al., 2023).

2.4. Digital inequalities and the periphery

A substantial body of research has documented the uneven geographic distribution of digital transformation across European regions, with less developed regions systematically lagging in digital skill levels, enterprise digitalisation, and access to innovation ecosystems. Romania's position in this landscape is marked by a distinctive paradox: while the country leads the European Union in fixed connectivity infrastructure, with very high-capacity network coverage of 95.9 percent and the highest broadband adoption rates in the EU, it simultaneously ranks last among member states in basic digital skills, with only 27.7 percent of the population reaching the basic digital competence threshold compared to the EU average of 55.6 percent (European Commission, 2025). Enterprise-level AI adoption compounds this picture further: only 3.1 percent of Romanian firms were using AI technology in 2024, well below the EU average of 13.5 percent, with particularly pronounced gaps among SMEs (European Commission, 2025). The South-East region, designated as a less developed region under EU cohesion policy, concentrates these vulnerabilities: limited employer investment in advanced digital training, a high share of employment in sectors with significant automation exposure, and structural barriers to scaling up digital innovation at firm level. This combination, strong physical infrastructure paired with weak human capital and organisational readiness, constitutes a specific

configuration of digital inequality that the literature on peripheral regions has not yet fully theorised. The present study situates its empirical findings explicitly within this context, treating regional peripherality not as a background condition but as a constitutive feature of the readiness configurations it identifies.

3. Method and Data

3.1 Research context and data collection

This study draws on original survey data collected between 7 and 25 November 2025 as part of the *Future of Work Compass* project, coordinated by CITYINNOHUB, the European Digital Innovation Hub for the South-East Development Region of Romania. The questionnaire was administered online via Microsoft Forms and distributed through the CITYINNOHUB institutional network, encompassing SMEs, local public authorities, educational institutions, and regional development partners. The study received institutional ethical approval and all participation was voluntary and informed. A total of 357 valid responses were obtained, with no missing data on any core analytical variable. Respondents were drawn primarily from Constanța county (87.4%), were predominantly female (63.6%), skewed toward younger age groups (55.7% under 25), and included a high proportion of students and educators (75.9%), reflecting the composition of the CITYINNOHUB ecosystem.

3.2 Measures

The survey instrument comprised 17 items organised into four thematic sections: respondent profile, labour market transformations, future competencies, and work vision. From the full instrument, eight variables were selected for analysis, spanning three analytical roles: clustering inputs, validation and comparison variables, and regression outcome. These are described in Table 1.

Table 1. Survey variables: operationalisation and analytical role

Variable	Code	Q	Scale / type	Anchors / categories	Role in analysis
AI impact perception	AP	Q7	Ordinal, 1–5	1 = <i>Very negative (replaces jobs)</i> → 5 = <i>Very positive (creates opportunities)</i>	Clustering input; regression predictor
Organisational readiness for digital transformation	OR	Q8	Ordinal, 0–4	0 = <i>Not prepared at all</i> → 4 = <i>Fully prepared</i>	Clustering input; regression predictor
Personal preparedness for AI-driven	PR	Q13	Ordinal, 1–4	1 = <i>Not at all prepared</i> → 4 = <i>Fully prepared</i>	Clustering input; regression

change					predictor
Perceived role of AI agents in future work	RA	Q11	Ordinal, 1–5	1 = <i>No significant role</i> → 5 = <i>Majority replacer of human roles</i>	Cluster validation; regression predictor
Vision of work in the region by 2030	VM	Q15	Nominal, 5 categories	More digitalised; more flexible; more human-centred; more competitive; more technology-dependent	Cluster validation
Competency priorities (8 items)	Comp_Cog Comp_Adapt Comp_Digit Comp_Comuni Comp_Leader Comp_Creativ Comp_Verde Comp_Empatie	Q12	Binary, 0/1	Derived from multi-select item (max. 3 choices): analytical thinking, adaptability, AI literacy, communication, leadership, creativity, green thinking, emotional intelligence	Cluster comparison (chi-square)
Training preferences (5 items)	Form_AI Form_Dig Form_Lead Form_Verde Form_Mkt	Q14	Binary, 0/1	Derived from multi-select item (max. 3 choices): AI tools, basic digital skills, digital leadership, green competencies, digital marketing	Cluster comparison (chi-square)
AI tools training intention	Form_AI	Q14	Binary, 0/1	0 = <i>Not selected</i> ; 1 = <i>Selected</i> (subset of Form_*)	Regression outcome

Source: Items created and organized by the authors using IBM SPSS Statistics 28.

The three clustering variables, AP, OR, and PR, were selected because they operationalise the three analytically distinct dimensions of AI readiness developed in the theoretical framework: the attitudinal, the institutional, and the individual. Spearman correlation analysis confirmed that each variable contributes distinct information while sharing sufficient variance to justify joint cluster analysis (AP–OR: $r=.334$; AP–PR: $r=.333$; OR–PR: $r=.362$; all $p<.001$). RA was excluded from the clustering solution on both theoretical and empirical grounds: conceptually, it captures respondents' anticipated trajectory of AI displacement rather than their current readiness configuration; empirically, it showed no significant association with OR ($r=.062$, $p=.245$), indicating that its variance structure is not aligned with the three clustering inputs. RA was subsequently used alongside VM to validate the cluster solution externally. VM, derived from a single-choice item on respondents' vision of work in their region by 2030, provides an attitudinally

grounded criterion variable that is conceptually adjacent to but analytically independent of the clustering inputs.

The competency priority variables (*Comp_**) and training preference variables (*Form_**) were each derived from multi-select items allowing up to three choices, and dichotomised at the item level to yield binary indicators of selection for each option. These variables were used exclusively in the cluster comparison analyses reported in Section 4.4. *Form_AI*, the specific indicator of interest in AI tools training, was additionally used as the dependent variable in the binary logistic regression model, as it represents the upskilling modality most directly relevant to AI readiness in the context of this study.

3.3 Analytic strategy

Data analysis proceeded in three stages, implemented in IBM SPSS Statistics 28.

In the first stage, descriptive statistics and Spearman rank correlations were computed for all core variables to assess distributional properties and inter-variable associations, and to verify the suitability of the selected clustering inputs.

In the second stage, a K-Means cluster analysis was conducted on the three readiness variables (AP, OR, PR) to identify distinct workforce profiles. The number of clusters was set to $k=3$, determined iteratively on the basis of theoretical interpretability and solution stability, with convergence achieved at iteration 3. Cluster validity was assessed through two complementary procedures. First, one-way Kruskal-Wallis tests examined whether the resulting clusters differed significantly on the two external validation variables, perceived role of AI agents (RA) and vision of work in the region by 2030 (VM; Q15), neither of which entered the clustering solution. Significant Kruskal-Wallis results were followed by pairwise Mann-Whitney post-hoc comparisons with Bonferroni correction. Second, chi-square tests of independence examined whether clusters differed in their prioritisation of future-relevant competencies (Q12) and their preferences for specific training modalities (Q14), with effect sizes reported as Cramér's V .

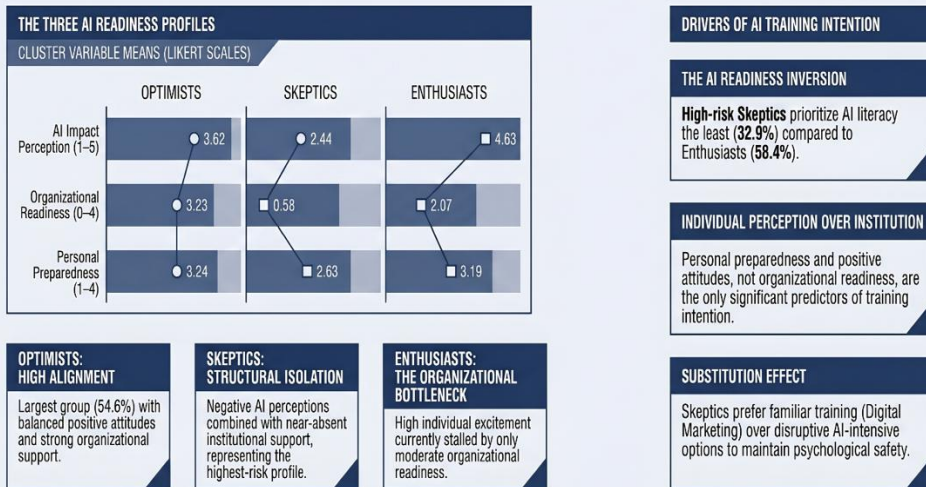
In the third stage, binary logistic regression was used to identify the individual- and organisational-level predictors of AI tools training intention (*Form_AI*). All four core variables (AP, OR, PR, RA) were entered simultaneously using the Enter method. Model fit was evaluated using the omnibus chi-square test, Nagelkerke R^2 , and the Hosmer-Lemeshow goodness-of-fit test. Odds ratios and 95% confidence intervals are reported for all predictors.

4. Results/findings

The key findings of this study are summarised in Figure 1 and developed in detail in the sections that follow.

AI READINESS PROFILES: MAPPING WORKFORCE ATTITUDES AND UPSKILLING DEMAND

CONTEXT SUMMARY: Research on 357 South-East Romanian employees identifies how attitudinal, institutional, and individual dimensions converge to create distinct **AI Readiness Profiles**, revealing a **critical Readiness Inversion** where those most at risk are least likely to prioritize AI literacy.



Source: Created by the authors using NotebookLm

4.1 Descriptive statistics

Descriptive statistics for the four core variables are presented in Table 2. The sample showed a moderately positive average perception of AI's impact on employment (AP: $M=3.63$, $SD=1.07$, $Mdn=4.00$), suggesting that respondents lean toward viewing AI as an opportunity rather than a threat, though with considerable individual variation. Organisational readiness (OR: $M=2.39$, $SD=1.27$, $Mdn=3.00$) reflects a context of partial and uneven institutional preparedness. Personal preparedness (PR: $M=3.10$, $SD=0.64$, $Mdn=3.00$) was the least dispersed variable in the set, indicating broad convergence around a position of partial individual readiness regardless of attitudinal or institutional context. The perceived role of AI agents (RA: $M=3.92$, $SD=1.22$, $Mdn=4.00$) was the highest-scoring variable, with nearly half of respondents (47.6%, $n=170$) selecting the maximum value, pointing to widespread anticipation of AI as a co-worker or displacement force in future work.

Table 2. Descriptive statistics for core variables (N=357)

Variable	M	SD	Mdn	Min	Max
AI impact perception (AP)	3.63	1.07	4.00	1	5
Organisational readiness (OR)	2.39	1.27	3.00	0	4
Personal preparedness (PR)	3.10	0.64	3.00	1	4
Perceived role of AI agents (RA)	3.92	1.22	4.00	1	5

Source: Created by the authors using IBM SPSS Statistics 28.

4.2 AI readiness profiles: K-Means cluster solution

K-Means cluster analysis with $k=3$ converged at iteration 3 and produced a solution with well-separated profiles. Table 3 presents the final cluster centers and within-cluster means for each variable.

Table 3. Final cluster centers and within-cluster descriptive statistics

	Optimists (n=195, 54.6%)	Skeptics (n=73, 20.4%)	Enthusiasts (n=89, 24.9%)
AP — AI impact perception	3.62 (SD=0.87)	2.44 (SD=0.82)	4.63 (SD=0.49)
OR — Organisational readiness	3.23 (SD=0.59)	0.58 (SD=0.80)	2.07 (SD=0.93)
PR — Personal preparedness	3.24 (SD=0.51)	2.63 (SD=0.76)	3.19 (SD=0.60)

Note. AP scale 1–5; OR scale 0–4; PR scale 1–4. Inter-cluster distances: Optimists–Skeptics = 2.963; Skeptics–Enthusiasts = 2.709; Optimists–Enthusiasts = 1.540.

Source: Created by the authors using IBM SPSS Statistics 28.

The **Optimists** (n=195, 54.6%) constitute the largest and most balanced profile. Respondents hold a moderately positive perception of AI's impact (AP=3.62), work in organisations with solid digital readiness (OR=3.23 — the highest in the solution), and report partial personal preparedness (PR=3.24). This is the only cluster in which institutional and attitudinal readiness are broadly aligned.

The **Skeptics** (n=73, 20.4%) represent the highest-risk profile. AI impact perception is predominantly negative (AP=2.44) and organisational readiness is near-absent (OR=0.58 — close to the scale minimum of 0). Notably, personal preparedness (PR=2.63), while the lowest in the solution, remains in the partial preparedness range, suggesting that even the most sceptical and institutionally unsupported respondents retain some degree of self-assessed individual readiness. The Skeptics cluster is the most structurally isolated, with the largest inter-cluster distances to both Optimists (2.963) and Enthusiasts (2.709).

The **Enthusiasts** (n=89, 24.9%) are defined by the highest AI impact perception in the solution (AP=4.63, close to the scale maximum), combined with only moderate organisational readiness (OR=2.07) and personal preparedness (PR=3.19) comparable to the Optimists. This profile reveals a structural tension: strong individual enthusiasm for AI coexists with limited institutional support, pointing to a bottleneck at the organisational level that may prevent enthusiastic workers from translating their attitudes into actual readiness.

4.3 Cluster validation

External validity of the three-cluster solution was assessed using Kruskal-Wallis tests on two variables not included in the clustering procedure: perceived role of AI agents in future work (RA) and vision of work in the region by 2030 (VM).

The perceived role of AI agents (RA) did not differ significantly across clusters ($H=4.90$, $df=2$, $p=.086$). Mean ranks were 159.08 for Skeptics, 180.24 for Optimists, and 192.61 for

Enthusiasts. This null result carries substantive weight: even respondents with predominantly negative AI attitudes and near-absent organisational readiness anticipate a significant transformative role for AI in the workplace. Awareness of AI's impact is thus uniform across readiness profiles, what differentiates the clusters is not recognition of AI's significance but orientation toward it.

Vision of work in the region by 2030 (VM) differed significantly across clusters ($H=12.04$, $df=2$, $p=.002$), with mean ranks following a clear gradient: Skeptics=144.42, Optimists=184.89, Enthusiasts=194.46. Pairwise Mann-Whitney post-hoc comparisons, evaluated against a Bonferroni-adjusted threshold of $\alpha=.017$, confirmed that Skeptics differed significantly from both Optimists ($U=5508.5$, $Z=-2.989$, $p=.003$) and Enthusiasts ($U=2333.5$, $Z=-3.226$, $p=.001$), while Optimists and Enthusiasts did not differ from each other ($U=8216.5$, $Z=-0.765$, $p=.444$). This pattern indicates a binary rather than gradient structure in regional work visions: the substantive divide separates those with negative AI attitudes from those with positive attitudes, regardless of whether the latter are institutionally supported.

Taken together, the validation results confirm that the cluster solution captures meaningful and externally coherent differences in how respondents perceive AI and envision the future of work, while also demonstrating that awareness of AI's transformative potential cuts across all three profiles.

4.4 Competency priorities and training preferences by cluster

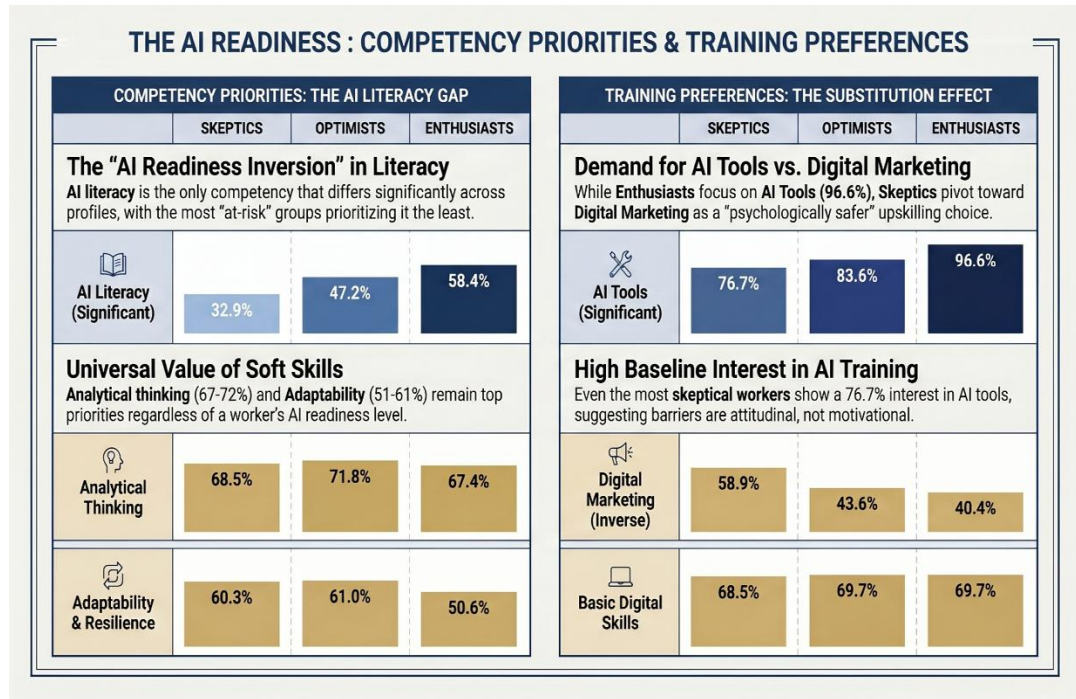
Chi-square analyses examined associations between cluster membership and each of eight competency priorities and five training modalities. Results are summarised in Table 4 and illustrated in Figure 2.

Table 4. Competency priorities and training preferences by AI readiness profile

Item	Skeptics	Optimists	Enthusiasts	$\chi^2(2)$	p	V
Competency priorities						
Analytical thinking	68.5%	71.8%	67.4%	0.66	.718	.043
Adaptability & resilience	60.3%	61.0%	50.6%	2.90	.234	.090
AI literacy	32.9%	47.2%	58.4%	10.51	.005	.172
Communication & collaboration	46.6%	31.8%	38.2%	5.18	.075	.120
Leadership & social influence	20.5%	20.0%	22.5%	0.23	.892	.025
Creativity & innovation	45.2%	38.5%	30.3%	3.85	.146	.104
Green thinking	8.2%	8.2%	16.9%	5.38	.068	.123
Emotional intelligence	17.8%	21.5%	15.7%	1.46	.482	.064
Training preferences						
AI tools in current practice	76.7%	83.6%	96.6%	13.96	<.001	.198
Basic & intermediate digital skills	68.5%	69.7%	69.7%	0.04	.980	.011
Digital leadership & change management	63.0%	74.4%	70.8%	3.34	.188	.097
Green & sustainability competencies	30.1%	27.2%	20.2%	2.33	.312	.081
Digital marketing & branding	58.9%	43.6%	40.4%	6.45	.040	.134

Source: Created by the authors using IBM SPSS Statistics 28.

Figure 2. Competency priorities and training preferences by AI readiness profile: the AI readiness inversion and the substitution effect.



Source: Created by the authors using NotebookLm

Among the eight competency items, only AI literacy differed significantly across clusters ($\chi^2=10.51$, $df=2$, $p=.005$, $V=.172$), with a monotonically increasing gradient from Skeptics (32.9%) to Optimists (47.2%) to Enthusiasts (58.4%). The cluster with the greatest exposure to displacement risk is thus also the least likely to prioritise AI literacy, a finding the study terms the *AI readiness paradox*. The remaining seven competencies did not differ significantly (all $p \geq .068$), confirming that analytical thinking, adaptability, communication, leadership, creativity, green thinking, and emotional intelligence are perceived as universally relevant across all profiles.

Among training preferences, two significant associations emerged. AI tools training showed the strongest association with cluster membership ($\chi^2=13.96$, $df=2$, $p<.001$, $V=.198$), increasing monotonically from Skeptics (76.7%) to Optimists (83.6%) to Enthusiasts (96.6%). Even among Skeptics a clear majority expressed interest, suggesting that the barrier to upskilling is attitudinal and institutional rather than motivational. Digital marketing training showed an inverse pattern ($\chi^2=6.45$, $df=2$, $p=.040$, $V=.134$): Skeptics preferred it most (58.9%), compared to Optimists (43.6%) and Enthusiasts (40.4%), consistent with a substitution effect in which a more familiar, less AI-intensive training option is preferred by the most sceptical cluster.

4.5 Predictors of AI tools training intention

Binary logistic regression examined the predictors of intention to pursue AI tools training (Form_AI). The overall model was statistically significant ($\chi^2(4)=24.29$, $p<.001$) and accounted for 11.7% of variance in training intention (Nagelkerke $R^2=.117$). Model calibration was excellent, with a non-significant Hosmer-Lemeshow test ($\chi^2(8)=3.30$, $p=.914$). Results are presented in Table 5.

Table 5. Binary logistic regression predicting AI tools training intention

Predictor	B	SE	Wald	P	OR	95% CI
AI impact perception (AP)	0.433	0.159	7.41	.006	1.54	[1.13, 2.11]
Organisational readiness (OR)	-0.140	0.139	1.02	.313	0.87	[0.66, 1.14]
Personal preparedness (PR)	0.682	0.263	6.75	.009	1.98	[1.18, 3.31]
Perceived role of AI agents (RA)	0.170	0.121	1.98	.159	1.19	[0.94, 1.50]
Constant	-2.057	0.822	6.26	.012	—	—

Source: Created by the authors using IBM SPSS Statistics 28.

Two predictors reached statistical significance. Personal preparedness (PR) was the strongest predictor ($B=0.682$, $p=.009$): each one-unit increase on the four-point scale nearly doubled the odds of intending to pursue AI tools training ($OR=1.98$, 95% CI [1.18, 3.31]). AI impact perception (AP) was also a significant positive predictor ($B=0.433$, $p=.006$), with each unit increase multiplying the odds by 1.54 (95% CI [1.13, 2.11]). Organisational readiness (OR : $p=.313$) and perceived role of AI agents (RA : $p=.159$) were not significant after controlling for the other variables.

These findings indicate that AI training demand is driven primarily by individual-level factors, personal preparedness and positive attitudes toward AI, rather than by institutional context. The non-significance of organisational readiness suggests that being embedded in a digitally prepared organisation does not independently increase the likelihood of seeking AI training once individual perceptions are accounted for.

5. Discussions

5.1 Three profiles and the structure of attitudinal heterogeneity

The three AI readiness profiles identified in this study confirm that workers' orientations toward AI-driven change are not randomly distributed but structured along meaningful and theoretically coherent lines. The Optimists, Skeptics, and Enthusiasts differ most sharply on the institutional dimension: organisational readiness ranges from near-absence among Skeptics ($OR=0.58$) to solid preparedness among Optimists ($OR=3.23$), making it the primary axis of differentiation in the cluster solution. This finding is consistent with the broader evidence on firm-level AI adoption in peripheral European economies, where smaller organisations and those operating in less digitalised environments are systematically less equipped to support technological transitions (European Commission, 2025).

More surprising is what does not differentiate the clusters: personal preparedness (PR) converges narrowly across all three profiles, with means ranging from 2.63 to 3.24 on a four-point scale. Workers locate themselves in a broadly similar position of partial individual readiness regardless of whether they view AI positively or negatively, and regardless of the institutional context in which they work. This suggests that self-assessed preparedness functions less as a reflection of actual capability and more as a relatively stable attitudinal baseline, one that training policy frameworks need to probe more carefully rather than take at face value.

Perhaps most consequential is the Enthusiasts profile, which combines the highest AI impact perception in the solution (AP=4.63) with only moderate organisational readiness (OR=2.07). Strong individual enthusiasm for AI coexists here with limited institutional support, producing a configuration in which workers are attitudinally ahead of their organisations. In peripheral labour markets, where organisational capacity to invest in digital transformation is structurally constrained, this decoupling may be a widespread and underdiagnosed condition, one that aggregate policy frameworks, calibrated to national or sectoral averages, are poorly equipped to address.

5.2 The AI readiness inversion

The most theoretically provocative finding of this study concerns the relationship between risk exposure and skill prioritisation. Among the eight competency items examined, AI literacy is the only one that differs significantly across clusters, and it does so in a direction that runs counter to what a rational upskilling logic would predict. Skeptics, who combine negative AI attitudes with near-absent organisational readiness and thus face the greatest structural exposure to displacement, are the least likely to prioritise AI literacy (32.9%), compared to Optimists (47.2%) and Enthusiasts (58.4%). We term this the *AI readiness inversion*: the workers most in need of AI-related competencies are least inclined to identify them as a priority.

This pattern is not easily explained by a lack of awareness. The validation analysis in Section 4.3 established that all three clusters anticipate a significant transformative role for AI in the workplace. Skeptics do not dismiss AI's impact, they are simply more negatively oriented toward it. The inversion therefore operates at the level of motivation rather than information: negative attitudes toward AI appear to suppress the prioritisation of AI-specific competencies even when workers recognise that such competencies will be consequential. This is consistent with Pfeiffer's (2022) argument that workers' responses to technological change are shaped not only by rational calculation but by their broader positioning within production relations, a positioning that includes their sense of whether upskilling is a realistic or worthwhile investment given the institutional context they inhabit.

The training preference data reinforces this interpretation through a complementary mechanism. Skeptics show the highest preference for digital marketing training (58.9%), substantially above Optimists (43.6%) and Enthusiasts (40.4%). This inverse pattern suggests a substitution effect: when AI-specific upskilling feels misaligned with one's attitudes or organisational environment, a more familiar and less disruptive training option becomes relatively more attractive. Digital marketing occupies a middle ground, it is

digitally adjacent without being AI-intensive, and may therefore function as a psychologically safer upskilling choice for workers who are resistant to or excluded from the AI transition. Taken together, these findings suggest that the gap between who needs AI training and who seeks it is not merely a communication or access problem amenable to standard outreach interventions. It reflects a deeper attitudinal structure that shapes demand before supply even enters the equation.

5.3 Individual over institutional: the drivers of upskilling demand

The regression analysis adds a further layer of complexity to the picture by identifying which factors independently predict the intention to pursue AI tools training. Two variables reached significance: personal preparedness (PR, OR=1.98) and AI impact perception (AP, OR=1.54). Organisational readiness (OR) and perceived role of AI agents (RA) did not. This pattern has a clear interpretive logic: the decision to seek AI training is driven primarily by how workers feel about AI and how prepared they consider themselves to be — not by whether the organisation they work in is digitally equipped to support that transition.

This finding has significant implications for how upskilling demand is theorised in peripheral labour markets. The dominant policy assumption, embedded in EU cohesion frameworks and national digitalisation strategies alike, is that improving organisational digital readiness will generate upward pressure on training demand, that institutional investment creates the conditions for individual upskilling. The regression results complicate this assumption. In the South-East Romanian context, at least, organisational readiness does not independently predict training intention once individual perceptions are controlled for. Workers in digitally unprepared organisations are not systematically less likely to seek AI training than their counterparts in more prepared environments, provided their attitudes and self-assessed preparedness are comparable.

This does not mean that organisational context is irrelevant, the cluster analysis clearly shows that it is the primary axis of differentiation between readiness profiles. Rather, it suggests that organisational readiness and training demand operate through different causal pathways. Institutional preparedness shapes the broader readiness configuration of a workforce, including the attitudinal climate in which workers develop their orientations toward AI. But at the point of individual training decisions, it is perception and attitude that carry the explanatory weight. For training providers and policymakers operating in peripheral regions, this distinction matters: interventions targeted exclusively at organisational infrastructure may not translate into increased training uptake unless they are accompanied by strategies that address workers' attitudinal orientations directly.

5.4 Peripheral labour markets and the limits of aggregate policy frameworks

The findings of this study acquire additional significance when read against the structural context of the South-East Development Region. Romania occupies a paradoxical position in the European digital landscape: it leads the EU in fixed connectivity infrastructure while ranking last in basic digital skills, with only 27.7% of the population

reaching the basic digital competence threshold compared to an EU average of 55.6% (European Commission, 2025). Enterprise-level AI adoption compounds this picture, only 3.1% of Romanian firms were using AI technology in 2024, well below the EU average of 13.5% (European Commission, 2025). The South-East region concentrates these vulnerabilities further, combining limited employer investment in advanced digital training, a high share of employment in sectors with significant automation exposure, and structural barriers to scaling digital innovation at firm level.

Against this backdrop, the readiness configurations identified in this study are not merely attitudinal phenomena, they are, at least in part, the product of structural conditions that workers inhabit rather than choose. The near-absence of organisational readiness among Skeptics ($OR=0.58$) is unlikely to reflect individual organisational failure alone; it is more plausibly a signature of the broader institutional environment of a less developed region, in which the proportion of micro and small enterprises is high, investment in digital transformation is constrained, and the spillover effects of innovation ecosystems are limited. Similarly, the Enthusiasts' structural tension, high attitudinal positivity paired with only moderate institutional support, may reflect a workforce that has been exposed to the global discourse on AI through education and media, but whose organisational environment has not kept pace.

These configurations point to a fundamental limitation of aggregate policy frameworks calibrated to national or EU-wide averages. When Romania's AI adoption rate is reported as 3.1%, or when the South-East region is classified as a less developed region under cohesion policy, these aggregate designations obscure the internal heterogeneity that this study surfaces. Within a single peripheral region, over half the workforce holds broadly positive orientations toward AI and works in organisations with solid digital readiness, while one in five workers combines negative attitudes with near-absent institutional support. Treating this region as a uniform policy target, for instance, by deploying standard AI literacy programmes or generic digitalisation incentives, risks misallocating resources and failing to reach the workers most exposed to displacement risk.

What peripheral labour markets require, this study suggests, is a differentiated policy architecture that maps readiness profiles at the sub-regional level and designs interventions accordingly. For Skeptics, the priority is attitudinal re-engagement before skill delivery, addressing the motivational barriers that suppress AI literacy prioritisation before investing in training supply. For Enthusiasts, the binding constraint is organisational rather than individual, and policy levers should focus on supporting SMEs to build the institutional capacity that would allow enthusiastic workers to translate their attitudes into productive AI engagement. For Optimists, the challenge is consolidation: sustaining the alignment between attitudinal, institutional, and individual readiness as AI adoption accelerates and the demands on all three dimensions intensify.

5.5 Limitations

Several limitations of this study should be acknowledged. First, the sample was recruited through the CITYINNOHUB institutional network, which introduces a self-selection bias: respondents are likely more engaged with digital transformation issues than

the broader regional workforce, and the high proportion of students and educators (75.9%) means that the findings are not straightforwardly generalisable to the employed population of the South-East region as a whole. The profiles identified here should be interpreted as characterising the CITYINNOHUB ecosystem constituency rather than the regional labour market in its entirety.

Second, all variables are based on self-report, which introduces the possibility of social desirability bias and limits the extent to which self-assessed preparedness can be equated with actual competence. As noted in Section 5.1, the narrow convergence of PR across clusters may partly reflect this measurement limitation rather than genuine attitudinal similarity.

Third, the cross-sectional design of the study precludes causal inference. The regression model identifies associations between individual perceptions and training intention, but cannot establish whether positive attitudes toward AI generate upskilling demand, whether prior upskilling experience generates positive attitudes, or whether both are driven by a third variable such as educational attainment or occupational position.

Fourth, the geographic concentration of the sample in Constanța county (87.4%) limits the extent to which findings can be taken as representative of the South-East region as a whole, which encompasses five additional counties with potentially different economic profiles and workforce compositions.

Finally, the K-Means algorithm assumes spherical clusters of approximately equal variance and is sensitive to the initial placement of centroids. While the three-cluster solution demonstrated good theoretical interpretability and external validity, alternative clustering approaches, such as hierarchical clustering or latent profile analysis, may yield different or more nuanced solutions and should be explored in future work.

6. Conclusions

This study set out to examine how workers in a peripheral European labour market perceive, position, and prepare for AI-driven change, and to identify the attitudinal and institutional factors that structure their upskilling demand. Using K-Means cluster analysis on original survey data collected in the South-East Development Region of Romania, we identified three distinct AI readiness profiles, Optimists, Skeptics, and Enthusiasts, and showed that these profiles differ meaningfully in their competency priorities, training preferences, and visions of regional work futures. Binary logistic regression further established that training intention is driven primarily by individual-level factors, personal preparedness and positive AI attitudes, rather than by organisational readiness.

Three findings stand out as theoretically and practically consequential. First, organisational readiness is the primary axis of differentiation between readiness profiles, confirming that the institutional layer of the employment relationship is the binding constraint on AI readiness in peripheral labour markets, more so than individual attitudes or self-assessed competence. Second, the AI readiness inversion, the finding that Skeptics, who face the greatest structural exposure to displacement, are least likely to prioritise AI literacy, demonstrates that the gap between who needs AI upskilling and who seeks it is attitudinally structured, and cannot be closed by training supply interventions

alone. Third, the decoupling of organisational readiness from individual training intention suggests that institutional and motivational barriers operate through different causal pathways, and must be addressed by correspondingly differentiated policy instruments.

Together, these findings make a case for moving beyond aggregate readiness frameworks toward sub-regional, profile-sensitive approaches to AI workforce policy. The heterogeneity surfaced within a single peripheral region, where over half the workforce holds broadly positive orientations toward AI while one in five combines negative attitudes with near-absent institutional support, illustrates the cost of treating geographically or administratively defined labour markets as uniform policy targets. Effective intervention requires first mapping the attitudinal and institutional landscape at a granular level, and then designing differentiated responses: attitudinal re-engagement strategies for Skeptics, organisational capacity-building for Enthusiasts, and consolidation support for Optimists.

More broadly, this study contributes to the emerging literature on AI readiness as a stratified, multi-dimensional construct whose components do not necessarily co-vary. Positive attitudes do not guarantee institutional preparedness; institutional preparedness does not automatically generate upskilling demand; and self-assessed individual readiness may remain stable across widely divergent attitudinal and organisational contexts. Understanding these decouplings, and the structural conditions that produce them, is, we argue, a prerequisite for designing AI workforce transitions that are both effective and equitable, particularly in the peripheral regions that the existing empirical literature has largely left unexamined.

7. References:

- Acemoglu, D. and Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2), 3-30. <https://doi.org/10.1257/jep.33.2.3>
- Aivaz, K.-A.; Teodorescu, D.; Radu, O.R.(2026) Replacement vs. Augmentation: An Analysis of Romanian Students and Faculty Views of the Impact of AI on the Labor Market. *Systems* 2026, 14, 323. <https://doi.org/10.3390/systems14030323>
- Autor, D.H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3), 3-30. <https://doi.org/10.1257/jep.29.3.3>
- Batrancea, L. M., Akgüller, Ö., Balci, M. A., Nichita, A., & Rus, M. I. (2026). Decoding digital market power: a network-based framework for consumer behaviour and strategic advantage. *Journal of Marketing Analytics*, 1-27. <https://doi.org/10.1057/s41270-026-00472-4>
- Batrancea, L. M., Nichita, A., Ikeda, W. E., Forte, D., Tulai, H., & Rus, M. I. (2026). Do spin-offs signal an effective restructuring strategy to shareholders? A global study on the short-and long-term performance of parent companies. *Borsa Istanbul Review*. <https://doi.org/10.1016/j.bir.2026.100836>
- Cosgrove, J. and Cachia, R. (2025). *DigComp 3.0: European Digital Competence Framework, fifth edition*. Luxembourg: Publications Office of the European Union. <https://doi.org/10.2760/0001149>
- European Commission (2025). *Digital Decade 2025 Country Reports: Romania*. Commission Staff Working Document SWD(2025) 294 final, Part 23/27. Brussels: European Commission.

- Frey, C.B. and Osborne, M.A. (2017). The Future of Employment: How Susceptible Are Jobs to Computerisation? *Technological Forecasting and Social Change*, 114, 254-280. <https://doi.org/10.1016/j.techfore.2016.08.019>
- Grigorescu, A., Munteanu, I., Dumitrica, C.-D., & Lincaru, C. (2023). Development of a Green Competency Matrix Based on Civil Servants' Perception of Sustainable Development Expertise. *Sustainability*, 15(18), 13913. <https://doi.org/10.3390/su151813913>
- Grugulis, I. and Stoyanova, D. (2011). Skill and Performance. *British Journal of Industrial Relations*, 49(3), 515-536. <https://doi.org/10.1111/j.1467-8543.2010.00779.x>
- Ionașcu, A. E., Bocanet, V. I., Asaloș, N., Lazăr, C. M., Spătariu, E. C., Barbu, C. A., & Nancu, D. (2025). Shifting Perceptions and Behaviors: The Impact of Digitalization on Banking Services. *Journal of Theoretical and Applied Electronic Commerce Research*, 20(4), 295. <https://doi.org/10.3390/jtaer20040295>
- Istudor, N., Dinu, V., Șerban-Oprescu, G. L., Badea, L., Iacob, S. E., & Hrebenciuc, A. (2025). Exploring business students' perceptions of artificial intelligence's impact on the labor market: a pilot study. *Journal of Business Economics and Management*, 26(3), 744-762. <https://doi.org/10.3846/jbem.2025.24349>
- Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D. and Pietrantoni, L. (2023). The Impact of Artificial Intelligence on Workers' Skills: Upskilling and Reskilling in Organisations. *Informing Science: The International Journal of an Emerging Transdiscipline*, 26, 39-68. <https://doi.org/10.28945/5078>
- Munteanu, I., Grigorescu, A., Condrea, E., & Pelinescu, E. (2020). Convergent Insights for Sustainable Development and Ethical Cohesion: An Empirical Study on Corporate Governance in Romanian Public Entities. *Sustainability*, 12(7), 2990. <https://doi.org/10.3390/su12072990>
- Otoiu, A., Titan, E., Paraschiv, D. M., Dinu, V., & Manea, D. I. (2022). Analysing labour-based estimates of automation and their implications. A comparative approach from an economic competitiveness perspective. *Journal of Competitiveness*, 14(3), 133. <https://doi.org/10.7441/joc.2022.03.08>
- Pelau, C., Dabija, D.-C., & Stanescu, M. (2024). Can I trust my AI friend? The role of emotions, feelings of friendship and trust for consumers' information-sharing behavior toward AI. *Oeconomia Copernicana*, 15(2), 407-433. <https://doi.org/10.24136/oc.2916>
- Pfeiffer, S. (2022). *Digital Capitalism and Distributive Forces*. Bielefeld: transcript Verlag. <https://doi.org/10.1515/9783839458938>
- Statista (2025). *Artificial Intelligence (AI) Job Market*. Hamburg: Statista. [Compiled from: World Economic Forum/Qualtrics Future of Jobs Survey 2024; McKinsey and Company/Stanford University AI Index 2025; LinkedIn/Lightcast 2024]
- Vallas, S. and Schor, J.B. (2020). What Do Platforms Do? Understanding the Gig Economy. *Annual Review of Sociology*, 46, 273-294. <https://doi.org/10.1146/annurev-soc-121919-054857>
- Wajcman, J. (2017). Automation: Is It Really Different This Time? *British Journal of Sociology*, 68(1), 119-127. <https://doi.org/10.1111/1468-4446.12239>
- World Economic Forum (2025). *The Future of Jobs Report 2025*. Geneva: World Economic Forum. https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf
- Yao, Q., Jahanshahi, H., Batrancea, L. M., Alotaibi, N. D., & Rus, M.-I. (2022). Fixed-Time Output-Constrained Synchronization of Unknown Chaotic Financial Systems Using Neural Learning. *Mathematics*, 10(19), 3682. <https://doi.org/10.3390/math10193682>