Conditional Acceptance of Artificial Intelligence in Human Resource Management: An Exploratory Survey of Young Romanian Respondents

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Abstract

This study examines how young, digitally engaged respondents in Romania perceive the use of artificial intelligence (AI) in human resource management (HRM). Data were collected in March 2025 through an online questionnaire from a convenience sample of 60 respondents, 70% aged 18–25. Respondents reported high familiarity with AI and valued it mainly for administrative automation, but trust in the fairness of AI-assisted decisions was moderate and most rejected the idea that AI could fully replace HR specialists. Only 5% would be fully comfortable being recruited or evaluated by AI, whereas 48.3% would accept it with human validation. Support for human oversight and strict regulation was very high. Familiarity was positively associated with trust ($\rho = 0.403$, $p = 0.001$); associations with perceived replaceability did not survive correction for multiple testing. Acceptance appears conditional on governance.

Keywords: *artificial intelligence; human resource management; technology acceptance; algorithmic governance; Romania.*

JEL classification: M12, M15, O33

DOI: 10.24818/RMCI.2026.4.741

1. Introduction

Artificial intelligence (AI) is increasingly used in human resource management (HRM), from candidate screening and chatbot-based onboarding to performance analytics and workforce planning (Tambe, Cappelli & Yakubovich, 2019; Deepa et al., 2024). Organisations expect lower administrative workload, more consistent processes and more evidence-based decisions (Marler & Boudreau, 2017; Davenport, 2018).

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Human resource (HR) decisions, however, directly affect people's access to employment, careers and well-being. Algorithms trained on historical organisational data may reproduce existing inequalities while appearing objective (Köchling & Wehner, 2020), and opaque systems can weaken employees' sense of fairness and control (Lee, 2018). For this reason, the European Union's Artificial Intelligence Act (AI Act) classifies AI systems used for recruitment, promotion, task allocation and performance evaluation as high-risk and requires effective human oversight (European Parliament and Council, 2024). Whether AI is accepted in HRM therefore depends not only on technical performance but also on trust and on the governance arrangements surrounding its use.

Most evidence on these questions comes from Western Europe, North America and Asia. Less is known about young people in Central and Eastern Europe, who are highly exposed to digital technologies and are about to enter labour markets in which AI-supported HR practices are spreading. This study addresses that gap with an exploratory survey of young Romanian respondents. It asks two research questions: (RQ1) How do young Romanian respondents perceive the benefits, risks and governance of AI in HRM? (RQ2) How are familiarity with AI and trust in AI-assisted HR decisions associated with the belief that AI can fully replace HR specialists, and how is this belief associated with demand for governance?

The paper is structured as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the method, Section 4 reports the results and Section 5 discusses them in relation to previous studies. Section 6 concludes and outlines limitations and directions for future research.

2. Literature review and hypotheses

2.1. Applications and risks of AI in HRM

Early work framed AI mainly as a tool for efficiency and process automation (Davenport, 2018). Recruitment is the most studied application: machine learning and natural language processing are used to screen and rank applicants, with gains in speed and consistency (Smith et al., 2025; Deepa et al., 2024). AI is also used in onboarding, HR analytics and administrative services such as payroll and employee chatbots (Marler & Boudreau, 2017; Sharma, Bhattacharya & Bhattacharya, 2025). At the same time, the literature documents algorithmic bias and discrimination in recruitment and HR development (Köchling & Wehner, 2020), algorithmic opacity and organisational resistance (Yadav, 2025), and data protection obligations under the General Data Protection Regulation (GDPR) (European Parliament and Council, 2016). Badea et al. (2024) place these issues within a broader debate on decent work and sustainable development.

2.2. Familiarity, trust and the delegation of HR decisions to AI

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains acceptance mainly through performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). A meta-analysis of digital HRM confirms the relevance of UTAUT but also shows that AI-based HR systems raise additional concerns about surveillance, opacity and accountability (Theres & Strohmeier, 2024). Prior exposure tends to make the capabilities of a technology more visible and to lower uncertainty about its use. In a large United States survey, people who had heard more about AI use in workplaces were more open to AI reviewing job applications (Rainie et al., 2023), and in several judgement tasks lay people preferred algorithmic to human advice (Logg, Minson & Moore, 2019, Croitoru, G., et al., 2026). Familiarity may therefore increase the belief that AI can take over HR tasks entirely.

H1: Familiarity with AI is positively associated with the belief that AI can fully replace HR specialists.

Research on trust in automation shows that trust guides how much people rely on automated systems and how much authority they delegate to them (Lee & See, 2004). Reviews of human trust in AI confirm that perceived reliability and fairness are central to this process (Glikson & Woolley, 2020). In HR settings, however, people often judge algorithmic decisions on tasks that require human skills as less fair and less trustworthy than equivalent human decisions (Lee, 2018), and highly automated job interviews are evaluated less favourably than interviews conducted by people (Langer, König & Papathanasiou, 2019). These reservations imply that trust is the critical condition for delegating HR decisions to AI: respondents who do trust AI to make accurate and fair HR decisions should be more willing to see it replace human specialists.

H2: Trust in the ability of AI to make fair and accurate HR decisions is positively associated with the belief that AI can fully replace HR specialists.

2.3. Human oversight and governance

Because full automation of HR decisions remains contested, recent work favours hybrid configurations in which humans retain final authority. Bar-Gil, Ron & Czerniak (2024) argue that ethical principles such as transparency, fairness and accountability must be embedded throughout the life cycle of people analytics projects. People who have seen algorithms err tend to avoid them and prefer human judgement, a pattern known as algorithm aversion (Dietvorst, Simmons & Massey, 2015, Antohi, V. M., et al., 2022). Human oversight is now also a legal requirement for high-risk AI systems in the European Union (European Parliament and Council, 2024). Across eight European countries, including Romania, citizens identify legal and ethical rules as key conditions for trusting AI (Scantamburlo et al., 2025, Murariu, S., et al., 2025). If governance is a safeguard against the

limits of automation, respondents who believe that AI can fully replace HR specialists should see less need for it.

H3: The belief that AI can fully replace HR specialists is negatively associated with demand for governance (human oversight, regulation and disclosure of decision logic).

3. Methodology

The study uses an exploratory, cross-sectional survey design. Data were collected between 26 and 30 March 2025 through an online questionnaire (Google Forms) distributed through academic networks, professional contacts and social media. Convenience sampling produced 60 complete responses from Romania. The sample is young (70% aged 18–25) and predominantly low-income (41.7% earned less than 2,000 RON net per month), which suggests that many respondents were students or early-career individuals; occupational status was not measured (Table 1).

Table 1. Socio-demographic profile of the sample (n = 60)

Characteristic	Category	n	%
Gender	Female	31	51.7
	Male	29	48.3
Age	18–25 years	42	70.0
	26–30 years	6	10.0
	31–35 years	6	10.0
	36–40 years	5	8.3
	Over 40 years	1	1.7
Monthly net income	Below 2,000 RON	25	41.7
	2,000–3,000 RON	8	13.3
	3,000–4,000 RON	11	18.3
	4,000–5,000 RON	8	13.3
	Over 5,000 RON	8	13.3

Source: Developed by the authors based on the research results.

Participation was voluntary and anonymous. Respondents gave informed consent before completing the questionnaire, and no personally identifiable data were collected, in line with the GDPR (European Parliament and Council, 2016). Data collection took place before the obligations of the AI Act for high-risk systems became applicable.

The questionnaire was developed by the authors for this study, drawing on the constructs of technology acceptance (Venkatesh et al., 2003) and trust in automation (Lee & See, 2004). It contained ten substantive questions and three socio-demographic questions. Table 2 reports the wording of each item and the construct it measures. Likert items used a 1–7 scale and were recoded to a

symmetric −3 to +3 scale (score − 4), with 0 as the neutral midpoint, so that positive values indicate agreement and negative values disagreement. To describe mean scores, we used our own convention: values from −0.99 to +0.99 are interpreted as moderate, from 1.00 to 1.99 as high and from 2.00 upwards as very high (symmetrically for negative values).

Table 2. Questionnaire items and operationalisation of constructs

Construct	Item (English translation)	Format
Familiarity	Q1. How familiar are you with the use of artificial intelligence?	Likert 1–7
Perceived benefit	Q2. To what extent can AI in HR processes improve the employee experience?	Likert 1–7
Trust	Q3. How much do you trust that AI can make correct and fair decisions in recruitment and performance management?	Likert 1–7
Main advantage	Q4. What is the main advantage of using AI in HR processes?	Single choice (4)
Perceived risks	Q5. What are the risks of using AI in recruitment?	Multiple choice (4)
Personal acceptance	Q6. Would you be comfortable being recruited or evaluated by an AI-based system?	Single choice (4)
Perceived replaceability	Q7. To what extent can AI fully replace HR specialists?	Likert 1–7
Preferred application	Q8. Which AI application in HR seems most useful to you?	Single choice (4)
Trust determinant	Q9. Which factor would most influence your trust in AI used in HR?	Single choice (4)
Governance demand ($\alpha = 0.803$)	Q10.1. AI should be used only under constant human supervision of decision-making. Q10.2. AI use in HR should be regulated by strict rules. Q10.3. Companies using AI in HR should be required to report publicly how algorithmic decisions are made.	Likert 1–7; index = mean of 3 items

Note: Response options for Q4–Q6, Q8 and Q9 are listed in Table 4. Questions Q11–Q13 (age, gender, income) are summarised in Table 1.
Source: Developed by the authors based on the research results.

Except for governance demand, each construct is measured by a single item; Cronbach's alpha is therefore reported only for the three governance items ($\alpha = 0.803$). Because the items are ordinal and the sample is small, associations were tested with Spearman's rank correlation (two-tailed). For each coefficient we report the t approximation given in Equation (1), with $n - 2$ degrees of freedom:

$$t = \rho\sqrt{[(n - 2)/(1 - \rho^2)]} \quad (1)$$

We also report a 95% confidence interval (CI) based on Fisher's z transformation with the standard error proposed by Bonett & Wright (2000). Since four correlations were tested, we also apply a Bonferroni-adjusted threshold of $\alpha = 0.0125$. The hypotheses were specified after data collection, when the item labels were checked against the questionnaire wording; all tests are therefore exploratory and identify associations that warrant confirmatory research, not causal effects. With $n = 60$, the power to detect a population correlation of 0.20 is about 33% (65% for 0.30), so non-significant results cannot be read as evidence of no association.

4. Results

4.1. Perceptions of AI in HRM

Respondents reported high familiarity with AI (M = 1.92) and agreed that AI can improve the employee experience (M = 1.37; 76.7% agreement). Trust that AI can make correct and fair decisions in recruitment and performance management was moderate (M = 0.03), with respondents almost evenly split between agreement (36.7%) and disagreement (38.3%). Most respondents rejected the idea that AI can fully replace HR specialists (M = −0.85; 60.0% disagreement). Support for governance was very high: 85.0% agreed that AI should be used only under constant human supervision and 86.7% that its use should be strictly regulated (Table 3).

Table 3. Likert items – descriptive statistics (scale −3 to +3, n = 60)

Item	M	SD	% agree (+1 to +3)	Interpretation
Q1. Familiarity with AI	1.92	1.20	85.0	High
Q2. AI can improve employee experience	1.37	1.56	76.7	High
Q3. Trust in fair and correct AI decisions	0.03	1.51	36.7	Moderate
Q7. AI can fully replace HR specialists	−0.85	1.61	20.0	Moderate
Q10.1. Constant human supervision	2.10	1.47	85.0	Very high
Q10.2. Strict regulation	2.17	1.43	86.7	Very high
Q10.3. Public disclosure of decision logic	1.75	1.76	78.3	High
Governance demand index (Q10)	2.01	1.32	–	Very high

Source: Developed by the authors based on the research results.

The categorical items point in the same direction (Table 4). Efficiency was by far the most frequently cited advantage (55.0%), and administrative automation was seen as the most useful application (48.3%), whereas candidate screening was chosen by only 13.3%. Selection errors (73.3%) and the absence of a human

component in decision-making (71.7%) were the most frequently cited risks. When asked whether they would be comfortable being recruited or evaluated by AI, only 5.0% answered without reservation; 48.3% would accept it with human validation, 28.3% were undecided and 18.3% preferred an exclusively human process. Human validation of decisions was also the factor most likely to increase trust (45.0%).

Table 4. Categorical items – frequencies (n = 60)

Item and response option	n	%
Q4. Main advantage (single choice)		
Efficiency and reduced process time	33	55.0
Objectivity and elimination of prejudice	14	23.3
Cost reduction	9	15.0
Personalised employee experience	4	6.7
Q5. Risks in recruitment (multiple choice)		
Errors in candidate selection	44	73.3
Lack of a human component in decision-making	43	71.7
Discrimination or algorithmic bias	29	48.3
Lack of transparency of selection algorithms	22	36.7
Q6. Comfortable being recruited or evaluated by AI (single choice)		
Yes, completely comfortable	3	5.0
Yes, but I would also want human validation	29	48.3
Not sure, it depends on how the technology is used	17	28.3
No, I prefer an exclusively human process	11	18.3
Q8. Most useful application (single choice)		
Automation of administrative tasks	29	48.3
Chatbots for employee support and onboarding	12	20.0
Performance analysis and development recommendations	11	18.3
Candidate screening in recruitment	8	13.3
Q9. Factor that would most increase trust (single choice)		
Validation of decisions by human specialists	27	45.0
Explainability and transparency of decisions	16	26.7
Protection of personal data	10	16.7
Reputation and reliability of the system	7	11.7

Note: Q5 allowed multiple answers, so its percentages sum to more than 100% (138 selections from 60 respondents).
Source: Developed by the authors based on the research results.

4.2. Hypothesis tests

Table 5 reports the Spearman correlations. Familiarity was positively associated with the belief that AI can fully replace HR specialists ($\rho = 0.257$, $p = 0.047$), which supports H1 at the 0.05 level; however, the confidence interval reaches zero and the result does not survive the Bonferroni correction. Trust in fair

and correct AI decisions was also positively associated with perceived replaceability ($\rho = 0.271$, $p = 0.036$), supporting H2 at the 0.05 level but not after correction. The association between perceived replaceability and governance demand was negative, as expected, but not significant ($\rho = -0.195$, $p = 0.135$); H3 is therefore not supported.

Table 5. Spearman correlations and hypothesis tests (n = 60)

Relationship	ρ	95% CI	t	p	Result
H1: Familiarity (Q1) – Perceived replaceability (Q7)	0.257	[−0.00; 0.48]	2.028	0.047	Supported at α = 0.05; not after Bonferroni
H2: Trust (Q3) – Perceived replaceability (Q7)	0.271	[0.01; 0.49]	2.142	0.036	Supported at α = 0.05; not after Bonferroni
H3: Perceived replaceability (Q7) – Governance demand (Q10)	−0.195	[−0.43; 0.06]	−1.514	0.135	Not supported
Exploratory: Familiarity (Q1) – Trust (Q3)	0.403	[0.16; 0.60]	3.357	0.001	Significant, also after Bonferroni

Note: Two-tailed tests. Bonferroni-adjusted threshold $\alpha = 0.05/4 = 0.0125$. 95% CI based on Fisher's z with the Bonett & Wright (2000) standard error.
Source: Developed by the authors based on the research results.

The strongest association was found in the exploratory analysis: respondents who reported higher familiarity with AI also expressed more trust in the ability of AI to make fair and correct HR decisions ($\rho = 0.403$, $p = 0.001$, 95% CI [0.16; 0.60]).

5. Discussion

The first finding is that acceptance of AI in HRM is conditional. Respondents valued AI for administrative tasks but were cautious about its role in evaluative decisions: only one in twenty would be fully comfortable being recruited or evaluated by AI, and most rejected the idea that AI could replace HR specialists. This mirrors international evidence: in the United States, 71% of adults opposed AI making final hiring decisions (Rainie et al., 2023); potential applicants prefer human to AI evaluation of interviews (Mirowska & Mesnet, 2022); and highly automated interviews are evaluated less favourably than human-led ones (Langer, König & Papathanasiou, 2019, Bugheanu, A. M., et al., 2026). Young Romanian respondents thus appear to share the reservations documented in other countries, rather than being uncritical adopters because of their digital exposure.

Second, familiarity was associated with more trust and, more weakly, with a stronger belief that AI can replace HR specialists. This is consistent with

evidence that people who have heard more about AI use in workplaces are more open to its use in hiring (Rainie et al., 2023) and with algorithm appreciation in judgement tasks (Logg, Minson & Moore, 2019). It also fits the finding from Poland that general trust in technology is the strongest predictor of employees' trust in AI (Łapińska et al., 2021): familiarity may partly reflect a broader positive orientation towards technology. Algorithm aversion appears mainly after people see algorithms make mistakes (Dietvorst, Simmons & Massey, 2015, Cristache, N., et al., 2025), an experience that few respondents in this young sample are likely to have had in an HR context. Because all measures are self-reported single items collected at the same time, common-method variance may inflate these associations, and their direction cannot be established.

Third, demand for human oversight and regulation was very high and was not significantly related to the belief that AI can replace HR specialists. Even respondents who were more optimistic about AI did not reject governance. This pattern is consistent with the view that oversight functions as a shared norm rather than as a reaction of the most sceptical respondents, and it matches the European finding that legal and ethical rules are seen as preconditions for trust in AI (Scantamburlo et al., 2025). It also matches the approach of the AI Act, which requires human oversight for AI systems used in recruitment and employee evaluation (European Parliament and Council, 2024). Respondents' preference for human validation and explainability as trust factors supports the recommendations of Bar-Gil, Ron & Czerniak (2024) for embedding transparency and accountability in HR analytics projects.

From a theoretical perspective, the results suggest that models of AI acceptance in HRM should include trust and governance-related constructs alongside performance expectancy, as argued by Theres & Strohmeier (2024) and Glikson & Woolley (2020). From a managerial perspective, and within the limits of an exploratory study, the findings suggest that organisations introducing AI in HR may gain acceptance more easily if they start with administrative applications, keep humans responsible for evaluative decisions, and explain how algorithmic recommendations are produced.

6. Conclusions

This study explored how young, digitally engaged respondents in Romania perceive AI in HRM. Respondents were familiar with AI and saw its value mainly in administrative automation, but their trust in AI-assisted HR decisions was moderate, few would accept being evaluated by AI without human validation, and most rejected the idea that AI can replace HR specialists. Support for human supervision, regulation and transparency was high (means between 1.75 and 2.17 on a −3 to +3 scale) and was not significantly associated with the perceived replaceability of HR specialists. Familiarity was positively associated with trust, whereas the associations proposed in H1 and H2 were weak and did not survive correction for multiple testing.

The study has several limitations. The sample is small (n = 60), non-probabilistic and concentrated among young, low-income respondents, and occupational status was not measured, so the findings cannot be generalised to the Romanian workforce. Most constructs were measured with single items, the hypotheses were specified after data collection, and the statistical power to detect weak associations was limited. The governance items also showed a ceiling effect (57–63% of respondents chose the highest scale point), which restricts variance and makes associations with governance demand (H3) harder to detect. Without an older comparison group, the study cannot show whether the observed patterns are specific to younger cohorts, and without data from other countries it cannot test cross-national differences. Future research should use validated multi-item scales, larger stratified samples, comparisons across generations and countries, and longitudinal designs.

Data availability: The anonymised dataset and the calculation files are available from the corresponding author upon reasonable request.

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