

Less Afraid, Still Wary: Europeans' Fear of AI-Driven Job Loss Before and After Generative AI

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Abstract

Generative artificial intelligence (AI) has entered everyday work, but whether it has made people more afraid of losing their jobs is unclear. This study examines whether perceived job threat from AI changed after generative AI arrived, how digital skills and employer practices relate to that threat, and how threat and perceived benefits relate to acceptance of AI at work and to support for workplace rules. Drawing on appraisal theory, technology threat avoidance theory and the technology acceptance model, it tests six hypotheses with Eurobarometer surveys of 27 European Union countries from 2017 and 2024, using ordinal confirmatory factor analysis, invariance tests, multi-group structural equation modelling, fixed-effects regression and an artificial neural network. Perceived job threat declined in almost every country and social group, and falling unemployment explains little of the decline. Digital skills were associated with lower threat in 2017 but, with evaluations of digital technology held constant, with higher threat in 2024. Employer transparency about AI use was associated with lower threat, and employer training with greater acceptance. Acceptance rested far more on perceived benefits than on threat, and threatened employees supported workplace rules more strongly. Explaining AI use and showing its benefits may reduce fear and build acceptance.

1. Introduction

Until late 2022, most workers read about artificial intelligence (AI) rather than used it. The release of ChatGPT changed that within months, as software began drafting letters, writing code and summarising reports, tasks at the core of much white-collar work. Estimates of exposure followed quickly. About four in five US workers hold jobs in which at least a tenth of tasks could be affected by large language models (Eloundou et al. 2024), and the International Monetary Fund put the share of exposed employment at about 40% worldwide and 60% in advanced economies (Cazzaniga et al. 2024). Generative AI also reached creative and professional work that earlier automation had largely spared, prompting calls from the European labour movement for binding rules and worker consultation (Ponce Del Castillo 2024). The International Labour Organization, however, expected augmentation rather than replacement for most jobs (Gmyrek et al. 2023).

What workers believe about these changes matters in its own right. Perceived threat from smart technology is linked to weaker commitment, higher turnover intention and job insecurity (Brougham and Haar 2018; Lingmont and Alexiou 2020). Workers who expect automation to reach their jobs are more willing to retrain (Innocenti and Golin 2022), people who see AI as a danger to jobs are less willing to accept it (Vu and Lim 2022), worry about machines taking jobs is lower among people with more education and steadier finances (Muraleetharan et al. 2026), and people can fear an AI technology yet still intend to use it when they expect benefits (Cugurullo and Acheampong 2024). Public fear also feeds demand for regulation, which in Europe has already produced the AI Act (European Parliament and Council 2024a) and rules on algorithmic management in platform work (European Parliament and Council 2024b). Whether fear has grown, and what reduces it, therefore matters to employers and policymakers alike.

Three gaps motivate this study. First, it is not known whether generative AI deepened fear. Between 2012 and 2017, European attitudes to robots became more negative (Gnambs and Appel 2019), but recent surveys from the United States (Hartley et al. 2026) and Great Britain (Grant et al. 2026) begin after generative AI arrived and cannot show change. No study has compared representative samples of the European Union (EU) from before and after generative AI using identical questions and a formal test of measurement equivalence, without which an apparent change may simply reflect a shift in how respondents read the questions. Second, studies of the 2024 Eurobarometer have examined attitudes, skills and acceptance (Bharti et al. 2026; Khan et al. 2026; Piotrowski and Revtiuk 2026; Roszkowska and Wachowicz 2026), but none treats perceived job threat as the central outcome or compares it with earlier data. Third, the combined structural equation modelling (SEM) and artificial neural network (ANN) design common in technology-adoption research has mostly been applied to small convenience samples (Guo and Erdenebold 2025; Suhail et al. 2024).

The study therefore addresses three research questions (RQs):

RQ1. Did perceived job threat from AI change between 2017 and 2024, and how much of any change reflects changing national labour markets?

RQ2. How are digital skills and employer transparency related to perceived job threat, and has the link between skills and threat changed since 2017?

RQ3. How are employer training, perceived benefits and perceived job threat related to acceptance of AI at work, and how is threat related to support for workplace rules?

The study makes three contributions. It compares job-threat perceptions in representative EU samples before and after generative AI, using measures shown to be equivalent across years, and separates the change from labour-market trends. It shows that two employer practices, transparency and training, are related to different outcomes: transparency to less fear and training to greater acceptance. It also applies the SEM–ANN design to large representative samples. Section 2 develops the framework and six hypotheses, Section 3 describes the data and methods, Section 4 reports the results, Section 5 discusses them and Section 6 concludes.

2. Theoretical Background and Hypotheses

2.1. Theoretical Framework

The framework combines three theories. Appraisal theory holds that people first judge whether an event threatens something they value (primary appraisal) and then whether they can cope with it (secondary appraisal) (Lazarus and Folkman 1984). Technology threat avoidance theory (TTAT) applies this logic to information technology: users perceive a threat when a technology seems harmful and likely to affect them, and then judge whether they can avoid or cope with it (Liang and Xue 2009). Perceived job threat from AI is a primary appraisal of this kind, while digital skills act as a coping resource. The technology

acceptance model (TAM) adds that people accept a technology when they find it useful (Davis 1989; Venkatesh et al. 2003). Acceptance of AI can also be studied at several levels, from the individual user to society as a whole (Koenig 2025); the model here links the personal level (threat and the view of AI at work) to the societal level (support for rules). Because a person can believe at the same time that AI helps workers and that it destroys jobs, benefit and threat are treated as separate appraisals that jointly shape responses to AI.

Research on job insecurity adds a further distinction. Insecurity has a cognitive side, the judged likelihood of loss, and an affective side, the worry that accompanies it (Shoss 2017). The threat examined here is cognitive and sociotropic, a judgement about “people’s jobs” rather than one’s own. People often expect AI to affect others more than themselves (Barrera-Jimenez et al. 2025), an echo of the classic finding of unrealistic optimism (Weinstein 1980), and national context shapes this general threat (Shoss and Ciarlante 2022). In the resulting framework, skills and employer practices shape two appraisals of AI, threat and benefit, which in turn shape acceptance of AI at work and support for rules.

2.2. Fear of Job Loss Before and After Generative AI

Theory points in opposite directions for the trend between 2017 and 2024. Earlier automation research centred on routine manual and clerical work (Acemoglu and Restrepo 2020; Frey and Osborne 2017). Generative AI changed this profile: language models perform well at writing, analysis and coding, so the most exposed jobs are now better paid and held by more educated people (Eloundou et al. 2024; Felten et al. 2021). If fear follows salience, it should have risen, extending the earlier negative drift (Gnambs and Appel 2019). Familiarity, however, tends to make attitudes more positive (Zajonc 1968), and early evidence shows productivity gains rather than mass displacement. In a large customer-support firm, agents given an AI assistant resolved about 15% more issues per hour (Brynjolfsson et al. 2025), and ChatGPT cut the time needed for professional writing tasks by about 40% while improving quality (Noy and Zhang 2023), and Australian workers who used generative AI reported more control over their work with no rise in burnout (Thorpe et al. 2026). Labour markets also tightened: EU unemployment fell from 8.3% in 2017 to 6.0% in 2024 (Eurostat 2026c), and fear of automation is higher where economic conditions are worse (Dekker et al. 2017). Because theory points both ways, RQ1 is posed as an open question rather than a hypothesis.

2.3. Digital Skills as a Coping Resource

Digital skills are the most direct coping resource. People who feel able to use new technology should expect to adapt and should therefore feel less threatened (Liang and Xue 2009). Skills predicted acceptance of AI in 2017 (Vu and Lim 2022) and more positive attitudes in 2024 (Bharti et al. 2026; Khan et al. 2026), technical digital ability has been linked to lower AI anxiety among trainee teachers (Ayduğ and Altınpulluk 2025), and less-educated people fear automation more (Włoch et al. 2025). Skilled people also judge digital technology more favourably, and such general evaluations act as a lens through which AI is interpreted. The evaluation of digital technology is therefore included in the model as a control, so that the skills–threat link is not confused with a general liking for technology.

H1. Digital skills are negatively related to perceived job threat.

2.4. Employer Practices

Employers largely determine how workers first encounter AI. Transparency should matter because it reduces uncertainty. Change that is announced but left unexplained invites rumour and worst-case thinking, whereas realistic communication during organisational change reduces uncertainty and its harmful effects (Schweiger and DeNisi 1991). Trust in AI also depends on understanding what a system does (Glikson and Woolley 2020), acceptance of AI is often conditional on transparency and human oversight (Mallouhy 2026), and among Europeans who expected AI to replace people, those whose employer was open about its AI use viewed AI less negatively (Bharti et al. 2026), although openness about AI tools does not always raise trust in them (Huynh and Aichner 2025).

H2. Employer transparency about AI use is negatively related to perceived job threat.

Training is a coping resource of a different kind. Upskilling is widely seen as the main way to keep workers useful as tasks change (Morandini et al. 2023), and training makes the practical uses of AI visible. In surveys by the Organisation for Economic Co-operation and Development (OECD), outcomes for workers were better where employers trained and consulted them (Lane et al. 2023), employer support for AI was associated with more positive attitudes through higher skills (Khan et al. 2026), and in a deliberative poll, people who learned about concrete uses of AI became more supportive of them (Arnesen et al. 2025).

H3. Employer training is positively related to a favourable view of AI at work.

2.5. Appraisals and Responses to AI

TAM and TTAT together imply that acceptance rises with perceived usefulness and falls with perceived threat (Davis 1989; Liang and Xue 2009). In a German comparison of the public and AI experts, overall judgements of AI scenarios rested mainly on expected benefits, although the public gave risks more weight than experts did (Brauner et al. 2026). The relative weight of benefit and threat matters in practice: if benefits dominate, reassurance about jobs will do less for acceptance than showing what AI offers.

H4. Perceived benefits of AI are positively related to a favourable view of AI at work.

H5. Perceived job threat is negatively related to a favourable view of AI at work.

People who feel threatened also look for protection, which at work usually takes the form of rules on privacy, monitoring and automated decisions. British panel data show that workers in occupations more exposed to AI, and those who expect AI to harm their prospects, favour government regulation of AI more strongly (Grant et al. 2026), and across ten European countries people who see more risk in AI prefer government regulation to industry self-regulation (Wilczek et al. 2025). The link matters for policy because it indicates whether demand for rules will fade if fear subsides.

H6. Perceived job threat is positively related to support for rules on AI at work.

2.6. Research Model and Gaps

Figure 1 Research model and hypotheses. Ovals are multi-item (latent) constructs and rectangles single-item measures. Solid arrows show the six hypothesised paths with their expected signs; the dashed oval and arrows show evaluation of digital technology, which is included as a control. H1 is tested in 2017, in 2024 and among employees in 2024; H2–H6 are tested among employees in 2024

Table 1
Closest prior studies and the gaps addressed.

Study	Data	Outcome	Gap addressed here
Gnambs and Appel (2019)	Eurobarometer 2012–2017	Attitudes to robots	No wave after generative AI; no workplace factors
Vu and Lim (2022); Shoss and Ciarlante (2022)	Eurobarometer 2017	Acceptance; workforce threat	Single year; no employer practices
Khan et al. (2026); Piotrowski and Revtiuk (2026); Bharti et al. (2026)	Eurobarometer 2024	Attitudes and acceptance	Threat not the outcome; single year
Grant et al. (2026); Hartley et al. (2026)	Great Britain; United States, 2024–2026	Regulation; job-loss fears	One country; no baseline before generative AI
Suhail et al. (2024); Guo and Erdenebold (2025)	Student surveys	AI adoption (SEM–ANN)	Small convenience samples; no job threat

3. Data and Methods

3.1. Research Design

The study follows a three-stage quantitative design (Fig. 2). Stage 1 prepares the two survey waves, assesses reliability and validity, and tests whether the shared constructs mean the same thing in both years. Stage 2 estimates the change in threat (RQ1) and the structural models that test H1 to H6 (RQ2 and RQ3). Stage 3 uses an ANN to check for non-linear effects and to rank predictors.

3.2. Data

The data come from Eurobarometer 87.1, fielded on 18–27 March 2017 (European Commission and European Parliament 2021), and Eurobarometer 101.4, fielded in April–May 2024 and published as Special Eurobarometer 554 (European Commission 2025; European Commission 2024). The 2024 module partly replicates the 2017 module. Both waves use multi-stage random probability samples of residents aged 15 and over, with about 1000 interviews per country (about 500 in Cyprus, Luxembourg and Malta), mostly face to face. The United Kingdom was removed from the 2017 file so that both waves

cover the same 27 member states, leaving 26,555 respondents in 2017 and 26,404 in 2024. Post-stratification weights, rescaled to a mean of one in each year, were used throughout; EU-level estimates use the EU27 population weights.

3.3. Measures

All attitude items have four-point scales and were recoded so that higher values mean more agreement, a more positive evaluation or greater importance; “don’t know” and “not applicable” answers were treated as missing (Table 2). Each multi-item construct has a two-letter code (for example, SK for digital skills), and its items are numbered (SK1–SK4). The threat items and the “AI helps people do their jobs” item are worded identically in both years. The 2024 skills question added a reference to AI, so the change in mean skills is not interpreted.

Table 2
Constructs, items and data used.

Construct (code)	Items (abbreviated wording)	Data
Digital skills (SK)	Sufficiently skilled in digital technology: in daily life (SK1); to do your job (SK2) ^a ; for a future job (SK3) ^a ; to benefit from online learning (SK4)	2017, 2024
Evaluation of digital technology (EV)	Impact of recent digital technologies on the economy (EV1), society (EV2), your quality of life (EV3)	2017, 2024
Perceived job threat (TH)	“Due to the use of robots and AI, more jobs will disappear than new jobs will be created” (TH1); “Robots and AI steal people’s jobs” (TH2)	2017, 2024
Perceived benefits of AI (BE)	AI is good for society because it helps people do their jobs (BE1); does boring or repetitive jobs (BE2); increases work pace (BE3); supports accurate workplace decisions (BE4); should be used more widely outside work (BE5)	2024
Employer training	Employer provides the tools or training needed to work with recent digital technologies, including AI (single item)	2024, employees
Employer transparency	Employer has informed you about the use of digital technologies, including AI, to manage workplace activities (single item; any “yes” answer = 1, “no” = 0)	2024, employees
View of AI at work	How positively or negatively you perceive robots and AI in the workplace (single item)	2024
Support for workplace rules (RU)	Importance of protecting privacy (RU1), banning fully automated decisions (RU2), limiting automated monitoring (RU3), transparency in human-resource uses (RU4), involving workers (RU5)	2024
Note: ^a Asked mainly of people in work; the cross-year model uses SK1 and SK4, and the employee model uses all four.		

Controls are age, gender, education (age on leaving full-time education), difficulty paying bills, daily internet use, living in a large town and occupational status (seven groups, with office or managerial employees as the reference). Country-level unemployment, the Gini coefficient of disposable income and gross domestic product (GDP) per head in purchasing power standards come from Eurostat (Eurostat 2026a; Eurostat 2026b; Eurostat 2026c).

3.4. Analytical Procedure

Measurement. Confirmatory factor analysis (CFA) for ordinal items used the weighted least squares mean- and variance-adjusted estimator (WLSMV), which suits four-point items (Li 2016). Reliability was assessed with Cronbach's alpha (α ; the Spearman–Brown coefficient for two-item scales gives the same value to two decimals (Eisinga et al. 2013)) and composite reliability (CR), and convergent validity with the average variance extracted (AVE), both computed from standardised loadings (Fornell and Larcker 1981). Discriminant validity was checked in two ways: by the Fornell–Larcker criterion and by heterotrait–monotrait (HTMT) ratios below 0.85 (Henseler et al. 2015). Benchmarks were α and CR ≥ 0.70 , AVE ≥ 0.50 , comparative fit index (CFI) and Tucker–Lewis index (TLI) ≥ 0.95 , root mean square error of approximation (RMSEA) ≤ 0.06 and standardised root mean square residual (SRMR) ≤ 0.08 (Hu and Bentler 1999). Single-item measures were entered as observed variables.

Invariance. Configural, threshold, metric and scalar models were compared across years (Wu and Estabrook 2016), accepting each step when CFI fell by no more than 0.010 and RMSEA rose by no more than 0.015 (Chen 2007; Cheung and Rensvold 2002).

Change over time (RQ1). The latent mean difference was taken from the scalar model. The year effect was then re-estimated in a pooled SEM with controls and in a two-way fixed-effects regression of the mean threat score on year, country indicators, controls and the three country variables, with standard errors clustered by country.

Structural models (RQ2 and RQ3). Model A is a multi-group SEM by year with equal loadings and thresholds, in which skills predict evaluations and threat, and evaluations predict threat; it tests H1 in both years, and equality of the skills–threat path across years was tested with a Wald test and an adjusted chi-square difference test (Satorra 2000). Model E, for employees in 2024, tests H1 to H6. Besides the six hypothesised paths, it contains the paths needed to avoid omitted-variable bias: skills, training and transparency predict evaluations and benefits, evaluations predict benefits and threat, training predicts threat, transparency and skills predict the view of AI at work, and benefits predict support for rules; skills, training and transparency are allowed to correlate, as are the residuals of benefits and threat. These control paths are reported in Online Resource 1.

Reporting. β denotes a standardised coefficient (SEM paths and standardised regression coefficients), b an unstandardised coefficient from the fixed-effects regressions and r a correlation.

ANN. SEM captures linear relationships and does not rank predictors by their contribution to prediction; ANNs complement it on both counts. Following the two-stage design (Liébana-Cabanillas et al. 2017),

the main predictors of each SEM and key socio-demographic controls entered unweighted multilayer perceptrons with one hidden layer of six sigmoid nodes, trained with the Adam optimiser and early stopping on inputs scaled to 0–1. Ten-fold cross-validation was repeated with three seeds, and root mean squared error (RMSE) was compared between training and test folds to detect overfitting. Predictor importance was measured by permutation on the test folds (Breiman 2001; Fisher et al. 2019) and normalised so that the most important input equals 100%.

All SEMs used survey weights and pairwise handling of missing data, and were estimated in R 4.3.3 with lavaan 0.6–17 (Rosseel 2012) and semTools 0.5–6 (Jorgensen et al. 2022). Regressions and ANNs were run in Python with statsmodels and scikit-learn (Pedregosa et al. 2011).

3.5. Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author used LLMs(Claude/ChatGPT) in order to assist with drafting and language editing of the manuscript. After using this tool, the author reviewed and edited the content as needed and took full responsibility for the content of the publication.

4. Results

4.1. How Opinions Changed

Fear of AI-driven job loss was lower in 2024 than in 2017 on both threat items (Table 3). Evaluations of digital technology cooled as well, and agreement that AI helps people do their jobs fell slightly. The decline in threat was broad (Fig. 3). Agreement that AI steals jobs fell in 25 of 27 countries (in France by less than 0.1 point) and rose only in Belgium and Sweden. It also fell in every social group: by 6.2 to 9.0 points across education levels (4.8 among those still studying), 6.0 to 8.8 points across age bands, and 3.2 to 10.4 points across occupational groups. Among employees in 2024, 70.8% said their employer provided the necessary tools or training, but only 49.3% said their employer had informed them that digital technologies, including AI, are used to manage workplace activities.

Table 3
Share of EU27 respondents agreeing, 2017 and 2024 (weighted %).

Item	2017	2024	Change (points)
Robots and AI steal people's jobs	76.3	69.0	-7.4
More jobs will disappear than new jobs will be created	79.6	70.9	-8.7
AI is good for society because it helps people do their jobs	72.3	67.3	-5.0
Digital technology has a positive impact on the economy	84.5	73.7	-10.8
... on society	71.4	62.4	-8.9
... on quality of life	77.5	71.7	-5.8
Note: Changes computed from unrounded shares. "Don't know" excluded.			

4.2. Reliability, Validity and Measurement Invariance

The measurement models fitted well: in 2017, CFI = 0.998, TLI = 0.997, RMSEA = 0.023 and SRMR = 0.018; in 2024, CFI = 0.994, TLI = 0.989, RMSEA = 0.040 and SRMR = 0.025; and for employees, CFI = 0.968, TLI = 0.962, RMSEA = 0.040 and SRMR = 0.050. Table 4 and Fig. 4 report reliability and validity. All loadings exceeded 0.60, and α (0.76–0.89) and CR (0.82–0.93) exceeded 0.70 for every construct. AVE exceeded 0.50 for all constructs except perceived benefits (0.48), whose convergent validity is therefore borderline. HTMT ratios were all below 0.85 (maximum 0.70). The Fornell–Larcker criterion was met for every pair except benefits and evaluations of digital technology, where the square root of AVE (0.69) was slightly below their correlation ($r = 0.72$). A model merging the two into a single factor fitted significantly worse than the model keeping them separate (scaled $\Delta\chi^2 = 525.2$, $df = 4$, $p < 0.001$; $\Delta CFI = -0.014$), and the 95% confidence interval of their correlation (0.69 to 0.74) was well below one, so the two were kept as distinct constructs (Online Resource 1, Tables S1 and S2).

Table 4
Reliability and validity of the multi-item constructs.

Model	Construct	Items	Loadings	α	CR	AVE	$\sqrt{AVE}$	Max r	Max HTMT
2017	Digital skills	2	0.91–0.95	0.89	0.93	0.86	0.93	0.44	0.43
	Evaluation	3	0.77–0.91	0.84	0.88	0.71	0.84	0.44	0.43
	Job threat	2	0.77–0.93	0.77	0.84	0.73	0.86	0.20	0.21
2024	Digital skills	2	0.89–0.93	0.85	0.90	0.82	0.91	0.62	0.58
	Evaluation	3	0.81–0.86	0.82	0.87	0.69	0.83	0.62	0.58
	Job threat	2	0.72–0.97	0.77	0.85	0.74	0.86	0.18	0.17
Employees 2024	Digital skills	4	0.85–0.89	0.89	0.93	0.77	0.88	0.58	0.54
	Evaluation	3	0.78–0.84	0.80	0.86	0.67	0.82	0.72	0.70
	Perceived benefits	5	0.62–0.82	0.78	0.82	0.48	0.69	0.72	0.70
	Job threat	2	0.83 (equal)	0.76	0.82	0.69	0.83	0.17	0.14
	Support for rules	5	0.71–0.84	0.85	0.90	0.63	0.80	0.43	0.38
Note: α = Cronbach's alpha (weighted). CR and AVE computed from standardised loadings. Max r = largest absolute latent correlation with another construct; discriminant validity under the Fornell–Larcker criterion requires $\sqrt{AVE} > \text{Max } r $. Employee threat loadings were constrained to be equal. Full matrices are given in Online Resource 1, Table S1.									

The three shared constructs were measured equivalently in both years (Table 5). The largest change in fit, at the scalar step, was $\Delta CFI = -0.003$ and $\Delta RMSEA = +0.007$, well within the cut-offs, so latent means can be compared.

Table 5
Measurement invariance across 2017 and 2024.

Model	χ^2 (scaled)	df	CFI	RMSEA	Δ CFI	Δ RMSEA
Configural	615.0	22	0.997	0.032	–	–
Equal thresholds	673.8	29	0.996	0.029	0.000	–0.003
Equal loadings (metric)	659.2	33	0.996	0.027	0.000	–0.002
Equal intercepts (scalar)	1173.3	37	0.993	0.034	–0.003	+ 0.007
Note: Scaled χ^2 values from WLSMV are not directly comparable across steps; decisions rest on Δ CFI and Δ RMSEA.						

4.3. Change in Threat and the Role of Labour Markets (RQ1)

In the scalar model, latent threat in 2024 was 0.28 standard deviations (SD) lower than in 2017 (95% confidence interval (CI) –0.31 to –0.24). Evaluations of digital technology fell by a similar amount (0.29 SD). In the pooled SEM, where the year coefficient is expressed in standard deviations of latent threat, the year difference was $\beta = -0.28$ on its own, fell only slightly with individual controls ($\beta = -0.24$) and returned to $\beta = -0.28$ when skills and evaluations were added (Online Resource 1, Table S3). Adding national unemployment, inequality and income without country fixed effects made the year difference non-significant, but that model mainly compares high- and low-unemployment countries; the fixed-effects estimates, which compare each country with itself, address change more directly. Within countries, threat fell by $b = -0.18$ on the 1–4 scale, and by $b = -0.14$ after controls and the three country variables ($p < 0.001$). Each percentage point of unemployment was associated with slightly more threat ($b = 0.010$, $p = 0.09$). Given the 2.3-point fall in EU unemployment, this estimate accounts for about one-eighth of the decline, although its confidence interval spans none to a little over a quarter. Inequality and income showed no detectable association. Perceived job threat therefore declined, the decline is unlikely to be a measurement artefact, and labour markets appear to explain only a small part of it.

4.4. Skills and Threat in Both Years (H1)

Model A fitted well (CFI = 0.990, TLI = 0.984, RMSEA = 0.023, SRMR = 0.014). Skills were associated with more positive evaluations in both years, and evaluations with lower threat, an association that more than doubled by 2024 (Table 6). The direct path from skills to threat, however, reversed. Holding evaluations and controls constant, more skilled respondents felt less threatened in 2017 ($\beta = -0.09$, $p < 0.001$) but slightly more threatened in 2024 ($\beta = 0.06$, $p = 0.008$). H1 is therefore supported for 2017 but not for 2024, and the difference between the two years was significant (Wald $\chi^2 = 21.2$, $df = 1$, $p < 0.001$). The controls show who fears AI most. In both years threat was higher among women ($\beta = 0.05$ in both years), among people with less education and among those who struggled to pay their bills; in 2024 the unemployed stood out ($\beta = 0.09$ relative to office employees). Model A explained 9% of the variance in threat in 2017 and 7% in 2024.

Table 6
Model A: structural paths by year (standardised coefficients, β).

Path	2017	2024	Wald χ^2 (1 df)
Skills → evaluation	$\beta = 0.511$ ***	$\beta = 0.630$ ***	89.9 ***
Skills → threat (H1)	$\beta = -0.089$ ***	$\beta = 0.055$ **	21.2 ***
Evaluation → threat	$\beta = -0.074$ ***	$\beta = -0.161$ ***	14.2 ***
Note: *** $p < 0.001$; ** $p < 0.01$. Controls included (Online Resource 1, Table S4). Adjusted χ^2 difference tests gave the same conclusions.			

4.5. Employees in 2024 (H1–H6)

The employee structural model, Model E, fitted acceptably (CFI = 0.961, TLI = 0.948, just below the 0.95 benchmark, RMSEA = 0.034, SRMR = 0.041) and explained 18% of the variance in threat, 60% in benefits, 63% in the view of AI at work and 33% in support for rules (Table 7; Fig. 5). Five of the six hypotheses were supported.

Table 7
Model E: hypothesised paths for employees, 2024 (standardised coefficients, β).

No.	Path	β	95% CI	p	Result
H1	Digital skills → job threat	$\beta = 0.371$	0.310, 0.433	< 0.001	Not supported (positive)
H2	Employer transparency → job threat	$\beta = -0.205$	-0.254, -0.156	< 0.001	Supported
H3	Employer training → view of AI at work	$\beta = 0.128$	0.091, 0.165	< 0.001	Supported
H4	Perceived benefits → view of AI at work	$\beta = 0.636$	0.594, 0.678	< 0.001	Supported
H5	Job threat → view of AI at work	$\beta = -0.220$	-0.252, -0.189	< 0.001	Supported
H6	Job threat → support for rules	$\beta = 0.332$	0.295, 0.369	< 0.001	Supported
Note: Controls: age, gender, education, bill difficulties, daily internet use, large town and manual or service job. Control paths are in Online Resource 1, Table S4.					

Among employees, the positive skills–threat path (H1) needs careful reading. Skills and threat were almost uncorrelated on their own (latent $r = -0.04$). Skilled employees evaluated digital technology more favourably ($\beta = 0.53$), and favourable evaluations went with lower threat ($\beta = -0.28$); once evaluations and education were held constant, the remaining association between skills and threat was positive. This pattern indicates a suppression effect (MacKinnon et al. 2000). Weighted regressions on averaged item scores gave a positive coefficient in all three specifications tested ($\beta = 0.03$ to 0.10 ; significant once

education is controlled; Online Resource 1, Table S5), so the direction does not depend on the latent specification.

The two employer practices were related to different outcomes. Employees whose employer had informed them about AI use reported less threat (H2, $\beta = -0.21$), but transparency was not directly related to their view of AI at work ($\beta = 0.03$, $p = 0.11$). Training, by contrast, was not related to threat ($\beta = 0.02$, $p = 0.36$) but was associated with a more favourable view of AI at work (H3, $\beta = 0.13$).

The view of AI at work depended far more on perceived benefits (H4, $\beta = 0.64$) than on threat (H5, $\beta = -0.22$), and the two beliefs were nearly unrelated (latent $r = -0.07$). Threat was associated with stronger support for rules (H6, $\beta = 0.33$), and benefit beliefs with even stronger support ($\beta = 0.41$).

4.6. ANN Results

The networks did not overfit: training and test errors were almost identical (Online Resource 1, Table S6). The view of AI at work was predicted well (test $R^2 = 0.45$), with perceived benefits by far the most important input and threat second (Fig. 6). Threat was hard to predict (test $R^2 = 0.05$ among employees and 0.08 in the pooled data), and the non-linear model did no better than the SEM. Among employees, transparency was the most important input for threat and training the least important, as in the SEM. In the pooled data, the survey year ranked third, after evaluations and education.

4.7. Summary of Hypothesis Tests

Table 8 summarises the hypothesis tests.

Table 8
Summary of hypothesis tests.

Hypothesis	Evidence	Result
H1: Digital skills → job threat (-)	2017: $\beta = -0.089$; 2024: $\beta = 0.055$; employees 2024: $\beta = 0.371$	Supported in 2017 only
H2: Employer transparency → job threat (-)	$\beta = -0.205$	Supported
H3: Employer training → view of AI at work (+)	$\beta = 0.128$	Supported
H4: Perceived benefits → view of AI at work (+)	$\beta = 0.636$	Supported
H5: Job threat → view of AI at work (-)	$\beta = -0.220$	Supported
H6: Job threat → support for rules (+)	$\beta = 0.332$	Supported

5. Discussion

5.1. Fear Declined Between 2017 and 2024 (RQ1)

Europeans became less inclined to believe that AI destroys jobs between 2017 and 2024, a period that included the arrival of generative AI. The decline passed a strict test of measurement equivalence, appeared in almost every country and group, and owed little to better labour markets. It reverses the earlier drift towards more negative attitudes (Gnambs and Appel 2019).

Three explanations fit the evidence, and the data cannot fully separate them. Familiarity tends to soften attitudes (Zajonc 1968). Experience so far has looked more like help than replacement, with productivity gains in field studies (Brynjolfsson et al. 2025; Noy and Zhang 2023) and no significant rise in layoffs in exposed US occupations (Hartley et al. 2026). Concern may also be moving from losing jobs towards how AI is used on workers: in 2024, between 77% and 86% of respondents rated each proposed workplace rule as important, although rules were not asked about in 2017. Fear also fell less among the highly educated (6.5 points) than among the least educated (9.0 points), which partly fits the argument that generative AI reaches more educated workers. Two waves cannot show that generative AI caused the change, as the pandemic and remote work also intervened, and the threat items followed questions about robots in daily life in 2017 but about the workplace in 2024. Identical wording and the invariance results make a pure measurement artefact unlikely, but order effects cannot be excluded.

5.2. Skills, Transparency and Threat (RQ2)

In 2017, skilled people felt less threatened, as appraisal theory predicts. By 2024, with evaluations held constant, skilled respondents felt somewhat more threatened, and among employees the positive association was clearer. Skills were still linked to lower threat through more positive evaluations of digital technology, whose association with threat more than doubled by 2024, but the direct coping role of skills had disappeared. This fits the new pattern of exposure, in which generative AI reaches the cognitive tasks of skilled workers (Eloundou et al. 2024; Felten et al. 2021; Ponce Del Castillo 2024), and one interpretation is that knowing more about technology sharpens awareness of what it can replace. An alternative explanation is measurement: the 2024 skills question added a reference to AI, so it may partly capture people who use AI, and use itself is associated with more fear (Hartley et al. 2026). Invariance tests reduce but do not remove this concern. Either way, the contrast with earlier work, which linked skills to greater acceptance of AI (Vu and Lim 2022), suggests that the role of skills depends on what the technology can do at the time. Because the positive association appears through suppression, this interpretation needs testing with direct measures of personal exposure.

Transparency was among the strongest correlates of lower threat in the SEM and the most important input for threat in the ANN, yet it was not directly related to how positively employees viewed AI at work; it was associated with less fear, not with more enthusiasm. This is consistent with research on uncertainty during organisational change (Schweiger and DeNisi 1991), on transparency and replacement concerns (Bharti et al. 2026) and on conditional acceptance of AI (Mallouhy 2026). The gap between practices is notable: seven in ten employees reported training, but only about half had been informed about AI use, which makes transparency the more neglected of the two.

5.3. Training, Benefits, Threat and the Demand for Rules (RQ3)

Acceptance of AI at work rested mainly on what employees thought AI offered. Benefit and threat beliefs were nearly independent, so many employees saw AI as useful and as dangerous at the same time, which supports treating usefulness and threat as separate appraisals (Davis 1989; Liang and Xue 2009) and echoes evidence that people may fear an AI technology yet still adopt it when they expect benefits (Cugurullo and Acheampong 2024). Training was the employer practice linked to acceptance, in line with OECD evidence (Lane et al. 2023) and the skills route reported by Khan et al. (2026), but it was not linked to lower threat, which mirrors the finding that retraining did not buffer insecurity related to smart technology (Lingmont and Alexiou 2020). Support for rules was not confined to the fearful; employees who valued AI also supported rules, which fits British evidence that optimism does not reduce support for regulation (Grant et al. 2026). The weak prediction of threat, by both the SEM and the ANN, suggests that fear of AI-driven job loss behaves more like a shared social belief than a personal calculation (Barrera-Jimenez et al. 2025; Shoss and Ciarlante 2022).

5.4. Theoretical Implications

The findings extend appraisal theory and TTAT in three ways. First, the coping role of skills depends on time and context: it weakened between 2017 and 2024, a period in which AI moved into cognitive work, so models estimated on data from before 2022 should not be assumed to hold today. Second, threat and benefit are separate appraisals with partly separate antecedents, and integrated acceptance models should include both. Third, employer practices are not a single form of “organisational support”. Transparency may work through reduced uncertainty and training through visible benefits, so the two should be modelled separately.

5.5. Practical and Policy Implications

Employers should tell workers how AI is used in hiring, scheduling, monitoring and assessment. Being informed was among the strongest correlates of lower fear, yet only about half of employees had been informed. Transparency should be combined with training: training did not reduce fear, but it was the clearest employer-side route to acceptance. Communication about AI is likely to work better when it shows concrete benefits than when it only offers reassurance about jobs. Managers should also recognise that skilled professionals are not immune to AI anxiety, so upskilling programmes may need to address job security as well as competence.

For policy, demand for workplace AI rules is broad and is unlikely to fade as fear declines, because it comes from people who welcome AI as well as from those who fear it. Protections of the kind found in the AI Act and the platform work directive, covering privacy, monitoring and human review, are therefore unlikely to run against public opinion, and may help to sustain acceptance. If fear of job loss behaves more like a shared belief than a personal calculation, public information that tracks the actual labour-market effects of AI may matter as much as individual retraining programmes.

5.6. Limitations and Future Research

Several limitations apply. Two cross-sections show that fear fell but not why, and cannot separate generative AI from other changes; panel data or further waves could trace causes. Within each year the paths are associations, and attitudes may shape what employees report about their employers; field experiments on employer communication would give stronger evidence. The survey was not designed for this model: threat has two items, training and transparency one each, and perceived benefits only narrowly missed the AVE benchmark, so purpose-built scales would allow finer distinctions, for example between general and personal threat (Schepman and Rodway 2020). The skills item gained a reference to AI and the questionnaire context changed between waves, which may affect the comparison of the skills–threat path, and all constructs come from the same interview, which leaves some risk of common method variance (Podsakoff et al. 2003). The suppression effect for skills should be confirmed by linking responses to occupation-level exposure scores. Some 2024 interviews in five countries were conducted by live video. Finally, the country-level tests rest on 27 countries observed twice, and the findings cover the EU only; attitudes may differ where social protection is weaker, including in emerging economies.

6. Conclusions

Fear of losing jobs to machines did not deepen across Europe after generative AI arrived. Between 2017 and 2024, perceived job threat fell in almost every country and social group, and lower unemployment appears to explain only a small part of that fall. The role of skills changed as well: skilled people felt less threatened in 2017, but by 2024, once their views of digital technology were taken into account, they reported somewhat more threat, perhaps because they see more clearly what AI can do. At work, fear and acceptance responded to different things. Transparency was associated with less fear, training and perceived benefits with greater acceptance, and benefits counted for far more than fear. People who feared AI supported rules, and so did many who welcomed it.

Declarations

Competing interests.

The author has no relevant financial or non-financial interests to disclose.

Ethics approval.

This study is a secondary analysis of anonymised survey data that are publicly available from the GESIS Data Archive. No new data were collected, and ethics approval was not required.

Consent to participate.

Not applicable. Respondents gave their consent to the original survey organisers when the Eurobarometer interviews were conducted.

Consent for publication.

Not applicable.

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Author Contribution

A.V.: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review and editing. R.K.G.: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review and editing. Both authors read and approved the final manuscript.

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Data Availability

The data analysed in this study are publicly available. The Eurobarometer 87.1 (2017) and Eurobarometer 101.4 (2024) survey data can be obtained free of charge from the GESIS Data Archive after registration (study ZA6861, <https://doi.org/10.4232/1.13738>; study ZA8844, <https://doi.org/10.4232/1.14471>). The country-level indicators are available from Eurostat (unemployment, une_rt_a; Gini coefficient, ilc_di12; GDP per capita in PPS, tec00114). The analysis code is available from the corresponding author on request.

Code availability.

The analysis code is available from the author on request.

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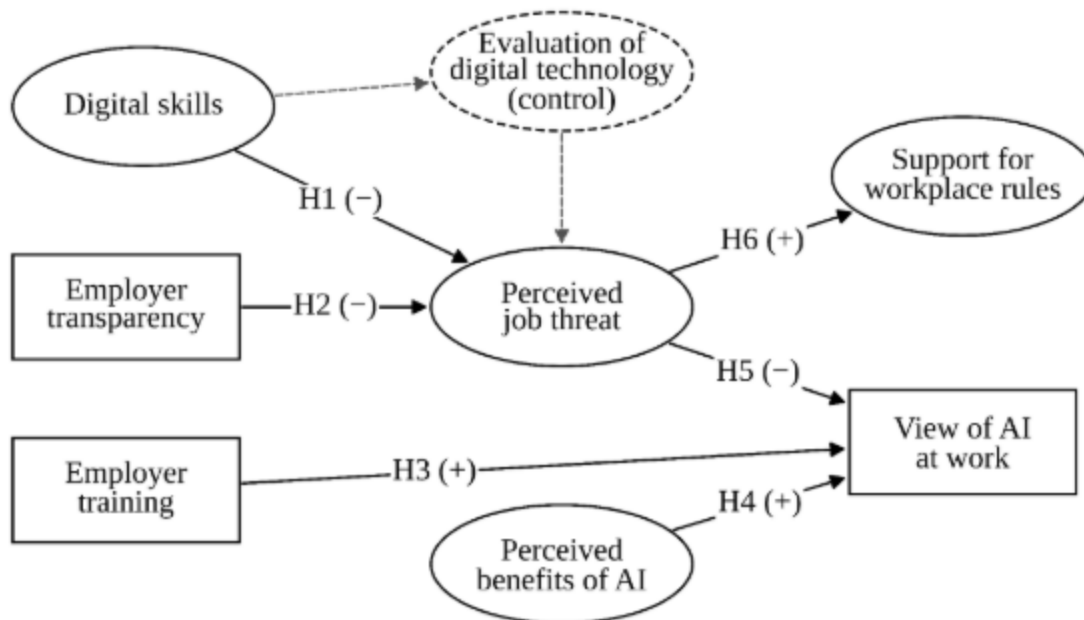
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Figures



Solid arrows: hypotheses (expected sign). Dashed: control path.

Figure 1

Research model and hypotheses. Ovals are multi-item (latent) constructs and rectangles single-item measures. Solid arrows show the six hypothesised paths with their expected signs; the dashed oval and arrows show evaluation of digital technology, which is included as a control. H1 is tested in 2017, in 2024 and among employees in 2024; H2–H6 are tested among employees in 2024

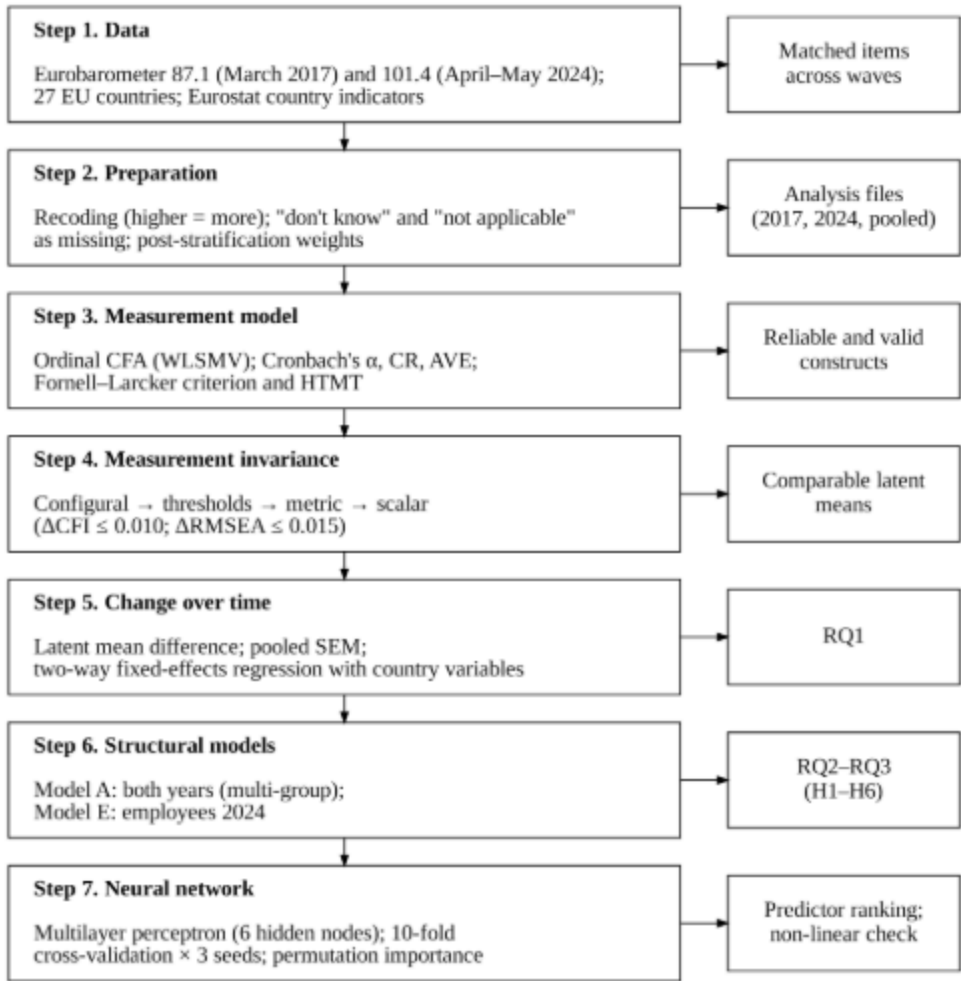


Figure 2

Research design and analytical steps

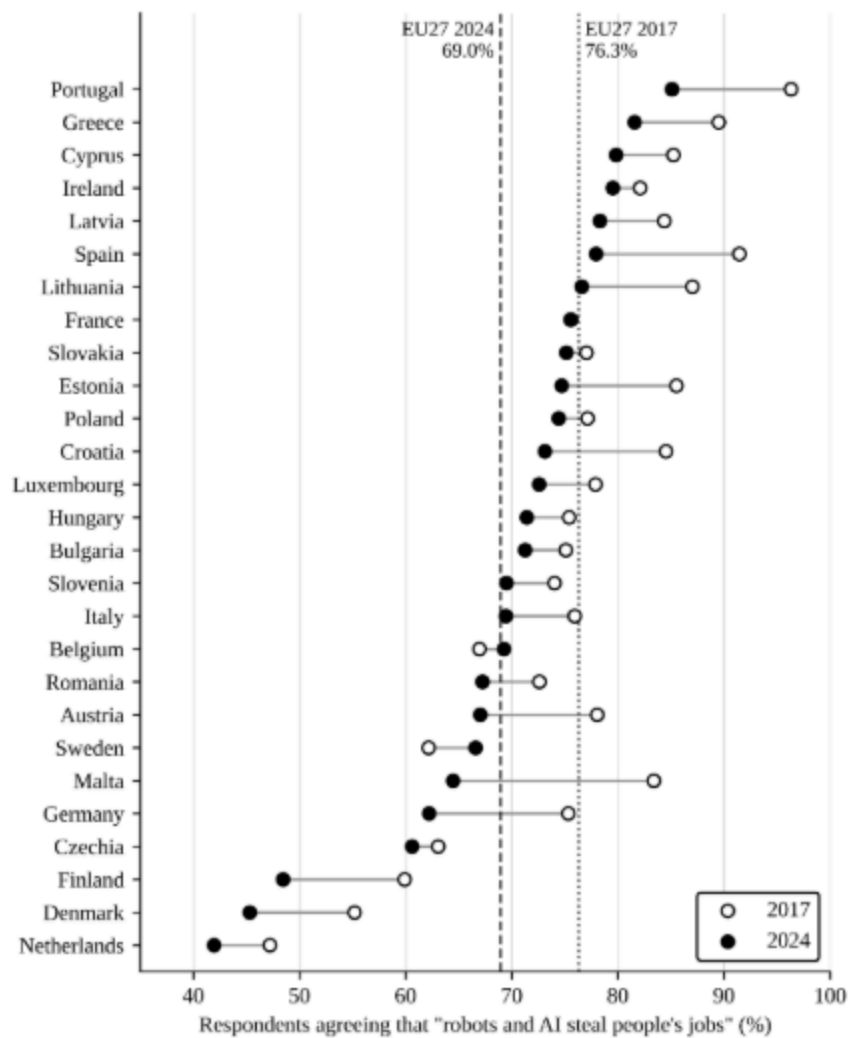


Figure 3

Share agreeing that "robots and AI steal people's jobs" by country, 2017 and 2024. Open circles 2017, filled circles 2024; national weights. Vertical lines show the EU27 averages (EU27 weights)

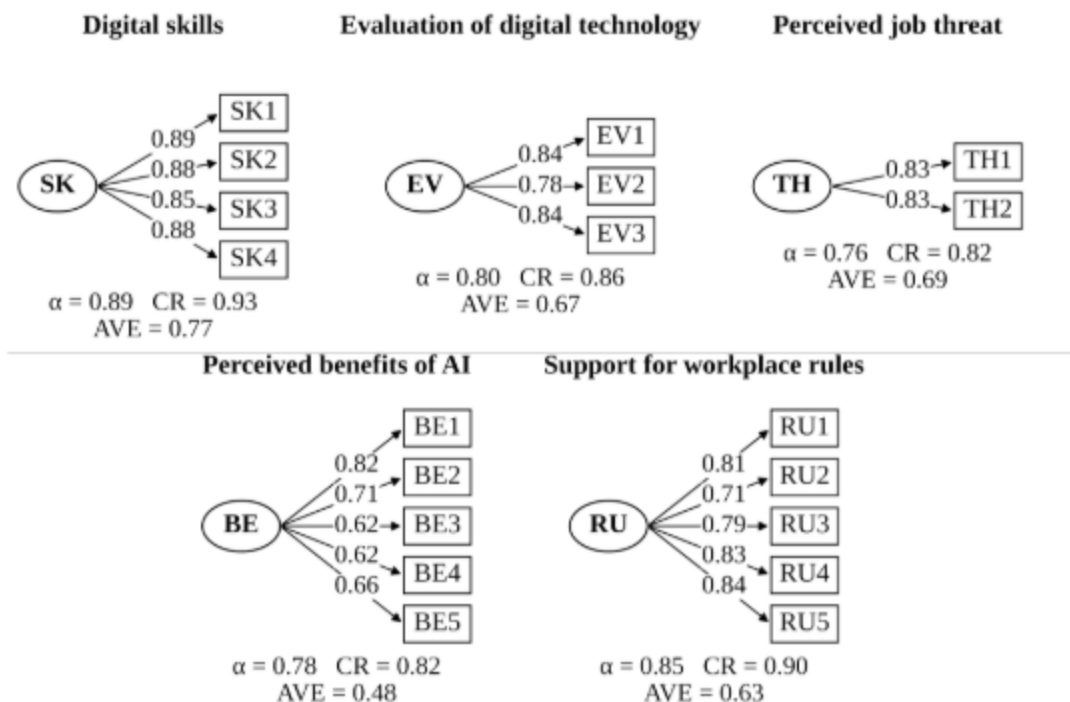
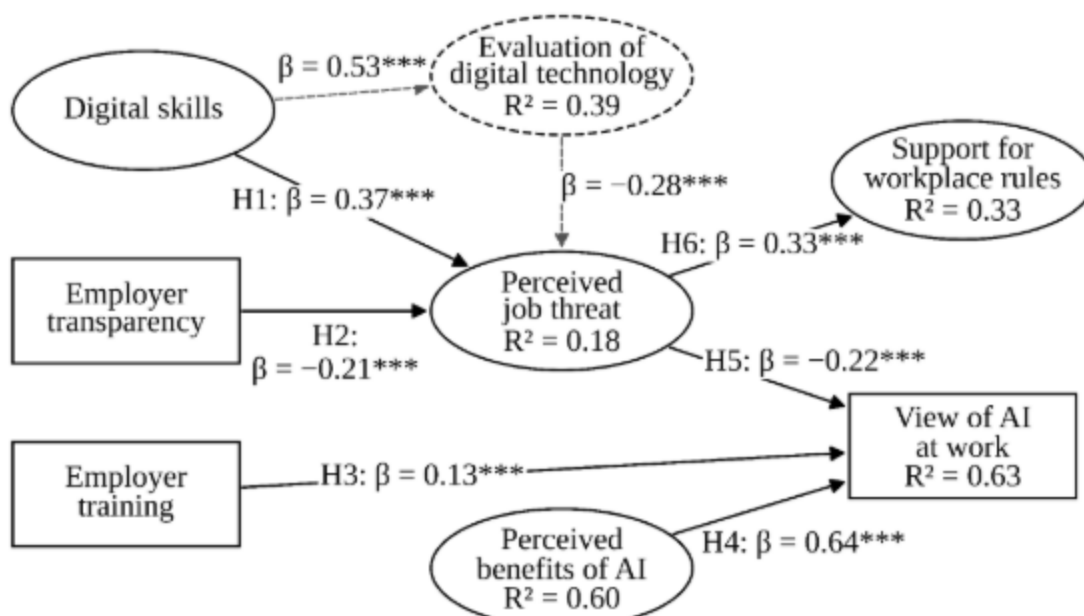


Figure 4

Measurement model for employees, 2024. Ovals are the constructs: SK = digital skills; EV = evaluation of digital technology; TH = perceived job threat; BE = perceived benefits of AI; RU = support for workplace rules. Rectangles are the survey items (wording in Table 2). Numbers on the arrows are standardised loadings; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted



Solid arrows: hypothesised paths. Dashed: control paths. *** $p < 0.001$.

Figure 5

Structural model for employees, 2024 (Model E). Values are standardised path coefficients (β); *** $p < 0.001$. Solid arrows are the hypothesised paths and dashed arrows two control paths through evaluation of digital technology. Other control paths and socio-demographic controls are not drawn (Online Resource 1, Table S4)

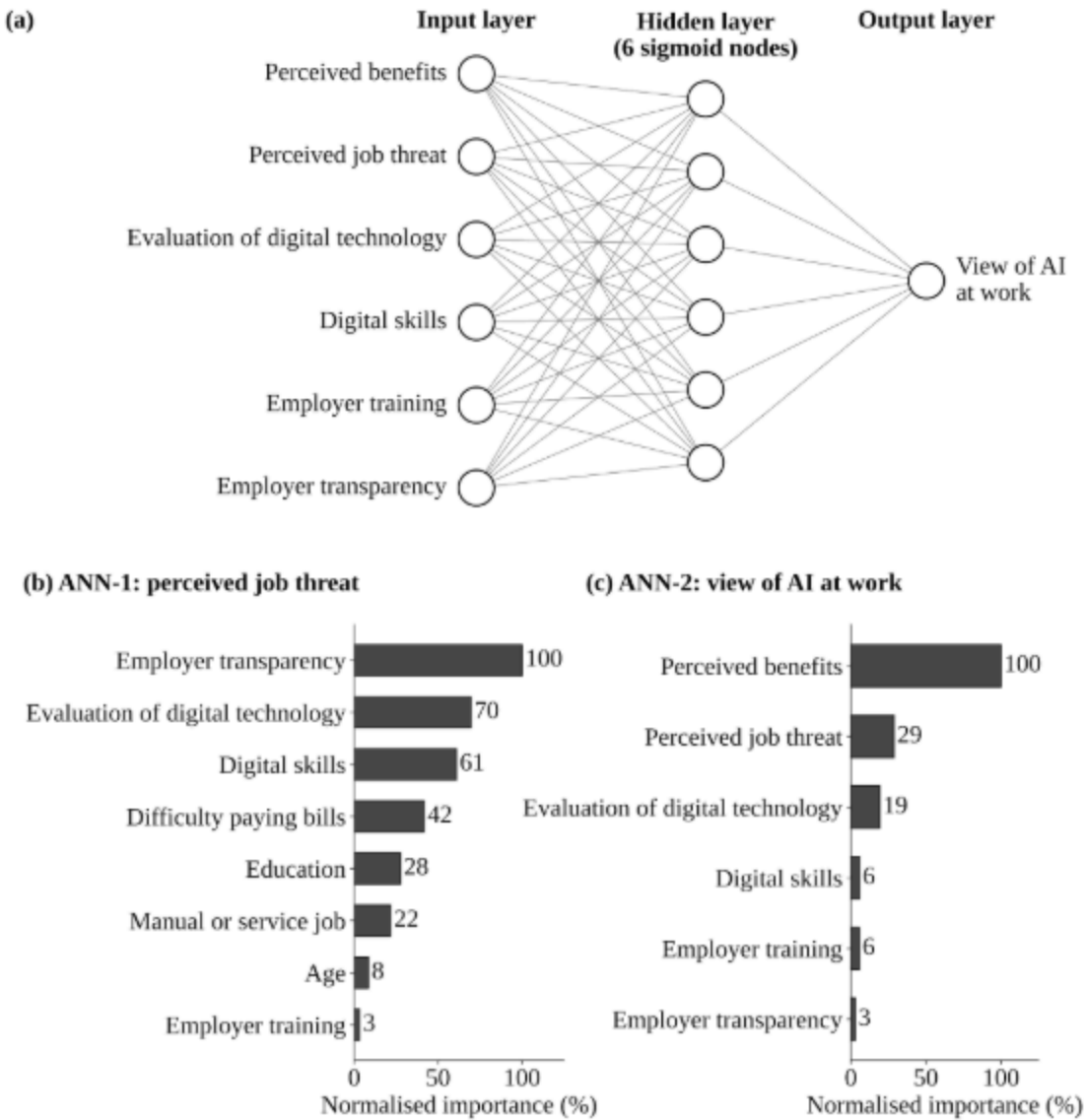


Figure 6

ANN results: (a) architecture of ANN-2 (one hidden layer of six sigmoid nodes); (b, c) normalised predictor importance from permutation on test folds (10-fold cross-validation × 3 seeds)