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Generative AI and Employment Concerns among AI Aware Respondents in Bangladesh

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ABSTRACT

Generative artificial intelligence (AI) may change professional tasks, but the implications for workers depend on how technology is introduced and how people adapt. This study examines stated perceptions of task change, concern about routine work and AI-related learning in 385 adult, AI-aware questionnaire records from Bangladesh. Most respondents were recorded as law students, and the dataset does not establish that all participants were employed or young professionals. The questions do not directly measure current job security or the effects of AI exposure on employment. Individual items are therefore analysed separately using response distributions, paired endorsement comparisons and exploratory rank correlations. Of 385 respondents, 232 (60.3%) agreed that AI may reduce demand for some routine professional tasks; 307 (79.7%) agreed that learning to work effectively with AI could reduce their future job-security concerns; and 211 (54.8%) anticipated new tasks requiring human judgement and oversight. A total of 184 respondents endorsed both the routine-task concern and the potential reassurance of learning. These statements differ in meaning and do not establish whether training actually reduces insecurity. Exploratory correlations were small and should not be interpreted causally. Job demands-resources theory, psychological contract theory and career construction provide complementary lenses rather than validated models. The study distinguishes concern about tasks from concern about losing a job and identifies the need for independently verified employment status, recruitment documentation and direct measures of perceived job security in future research.

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1. Introduction

Generative AI can draft text, summarise information and assist analysis across a wide range of occupational activities. The International Labour Organization's 2025 occupational index estimates potential exposure to the technology, while distinguishing exposure from actual job loss. Its 2026 review further stresses that observed effects on employment, earnings and work organisation require evidence beyond technical capability.[1] These distinctions matter for students preparing for professional work as well as those already employed.

Task change can be experienced as an opportunity, a requirement to learn, or a source of uncertainty. The relevant question is not only which tasks a system can perform but also how organisations redesign jobs, distribute benefits, support workers and maintain accountability. Research on automation and new tasks shows that technological substitution and the creation of complementary activities can occur together.[2] AI-related expectations may consequently differ from experience of an actual workplace transition.

The original manuscript framed the study around generative AI exposure and perceived job security among young professionals. The supplied instrument, however, does not ask a direct question about the security of a respondent's current job or establish employment status for the entire sample. It includes a statement that learning AI can reduce future job-security concerns; agreeing with that statement does not establish the respondent's level of insecurity or whether training worked. Other items address perceived task change, routine-task demand, new tasks and anticipated adaptation.

The sample includes law students, graduates, legal professionals and other respondents, including adults aged 31 or older. It should not be described as a verified sample of young employees. This article therefore focuses on observed questionnaire responses about employment-related task change and learning. Its distinctive contribution is to examine the coexistence of routine-task concern and support for learning, rather than combine heterogeneous items into a purported job-security scale.

The objectives are to describe respondents' views about task change; examine whether routine-task concern coexists with perceived reassurance from learning; and explore whether concern is associated with selected statements about judgement, adaptation and AI understanding. The research questions are: How frequently are these statements endorsed? How many respondents endorse both concern and potential reassurance? What are the magnitudes and uncertainty of associations among selected responses? The results describe this dataset and do not establish occupational displacement, training

[1] International Labour Organization and NASK, Generative AI and Jobs: A 2025 Update (ILO 2025) <https://www.ilo.org/publications/generative-ai-and-jobs-2025-update>; International Labour Organization, The Impact of GenAI on Jobs, Productivity and Work Organization: A Review of the Empirical Evidence (ILO 2026) <https://www.ilo.org/publications/impact-genai-jobs-productivity-and-work-organization-review-empirical>.

[2] Daron Acemoglu and Pascual Restrepo, 'Automation and New Tasks: How Technology Displaces and Reinstates Labor' (2019) 33 Journal of Economic Perspectives 3.

effectiveness or population prevalence.

2. Literature Review and Theoretical Foundation

This section connects research on automation, work design and career adaptation to the precise concepts the questionnaire can address. The frameworks guide interpretation, but the available items do not constitute full measures of their constructs.

2.1 Task exposure, employment and perceived security

Occupational exposure estimates describe the potential relevance of AI to tasks, whereas direct exposure might be measured by observed use, task-level interaction, or changes in work processes. Self-reported frequency of AI use does not by itself indicate exposure within paid employment. The ILO's estimates are not forecasts of individual job losses, and cannot validate an individual respondent's employment expectations.[3]

Perceived job insecurity concerns anticipated threats to continuity or valued aspects of employment. A belief that AI may affect routine tasks is related but is not equivalent: a task can change without a job disappearing, and job concerns can arise from many sources. Studies of employees' perceptions of smart technology illustrate why technological change may affect expectations, but findings from employees cannot automatically be transferred to a mixed sample that includes students.[4]

2.2 Theoretical foundation

Job demands-resources theory distinguishes work demands that require effort from resources that support goal achievement and coping.[5] Applied cautiously, learning new AI practices may be experienced as a demand, while access to effective training could operate as a resource. The present questionnaire asks whether learning might reduce concern, not whether suitable training was supplied or effective; it cannot test a demand-resource mechanism.

Psychological contract theory concerns perceived obligations in an employment relationship.[6] It highlights the role of expectations about consultation, development and fair treatment when employers adopt technologies. However, the dataset does not measure a particular employer's promises or their fulfilment. The theory therefore motivates future questions about communication and support, rather than an inference that a psychological contract was breached.

Career construction approaches emphasise adaptation to changing vocational tasks. The Career Adapt-Abilities Scale operationalises career adaptability using multiple dimensions.[7] The questionnaire's individual confidence and skill-development statements

[3] ILO and NASK (n 1).

[4] David Brougham and Jarrod Haar, 'Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' Perceptions of Our Future Workplace' (2018) 29 Journal of Management & Organization 239.

[5] Evangelia Demerouti and others, 'The Job Demands–Resources Model of Burnout' (2001) 86 Journal of Applied Psychology 499.

[6] Denise M Rousseau, 'Psychological and Implied Contracts in Organizations' (1989) 2 Employee Responsibilities and Rights Journal 121.

[7] Mark L Savickas and Erik J Porfeli, 'Career Adapt-Abilities Scale: Construction, Reliability, and Measurement Equivalence across 13 Countries' (2012) 80 Journal of Vocational Behavior 661.

are useful starting points, but they are not that validated scale and cannot establish a career-adaptability mechanism.

2.3 AI literacy, reassurance and work organisation

The ability to identify errors, verify outputs and use AI appropriately can support responsible professional practice. Conceptual work on AI literacy describes competencies that exceed a single self-reported understanding item.[8] Stated confidence or agreement with verification is therefore not a direct test of objective ability.

Algorithmic management scholarship explains how automated monitoring and data use can alter workplace control.[9] Yet endorsement of a principle such as informing workers about monitoring does not prove that any respondent's employer actually provides such a safeguard. These matters are distinct from this article's focal task-change questions and are treated as contextual rather than as predictors in a latent model.

2.4 Analytical expectations

Three comparisons selected for this exploratory analysis, not claims about causal pathways: routine-task concern versus perceived reassurance from learning; concern versus expected new tasks requiring judgement; and concern versus confidence in adapting career plans. Respondents can agree with both sides because the statements refer to different processes. Four exploratory correlations compare the ordinal concern item with perceived reassurance, anticipated new tasks, career confidence and awareness of plausible AI inaccuracies. The questionnaire does not justify formal directional hypotheses that require a directly measured job-security outcome.

3. Methodology

This section describes the supplied records, analytical choices and safeguards, including the distinction between the study's stated aims and the measures available in the workbook.

[8] Duri Long and Brian Magerko, 'What Is AI Literacy? Competencies and Design Considerations' in Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (ACM 2020).

[9] Katherine C Kellogg, Melissa A Valentine and Angèle Christin, 'Algorithms at Work: The New Contested Terrain of Control' (2020) 14 Academy of Management Annals 366.

3.1 Design and population

The analysis uses a cross-sectional, item-level questionnaire dataset with 385 records. The workbook includes only consenting, adult-eligible and AI-aware records. The status categories identify law students, law graduates, advocates or legal professionals, and other relevant respondents. They do not document whether all respondents were currently employed, their industry or their professional tenure. The unit of analysis is the individual recorded response.

3.2 Sample and provenance

The workbook provides unique respondent identifiers and recorded demographic categories. The supplied materials do not establish recruitment dates, a sampling frame, response rate, administration method, independent duplicate checks or probability selection. Therefore the sample is not presented as nationally representative. A size of 385 alone does not establish random sampling or a population margin of error.[10]

The researcher identifies the numerical responses as real survey data. The workbook Codebook nevertheless labels the respondent sequence and optional contextual comments as synthetic. Those labels do not independently establish that the numerical responses are synthetic; the creation and provenance of the identifiers and text should be documented against source records. The optional contextual text was excluded from the analysis. Fieldwork records and the relationship between the workbook and original responses remain necessary for reproducibility.

3.3 Measures and screening

The questionnaire has five response options from strongly disagree to strongly agree. The focal JS items concern perceived task change (JS1), concern about routine-task demand (JS2), new tasks requiring human judgement (JS3), the possibility that learning can reduce future job-security concerns (JS4), and expected adaptation to AI-enabled work (JS5). LCA4 concerns confidence in adapting career plans; AIL1 concerns awareness that AI can produce plausible but inaccurate information. Exact item wording appears in Appendix A.

All focal numerical items contain valid responses for the 385 records. Strongly agree and agree are combined as endorsement; neutral and disagreement responses are retained separately in the distributions and jointly classified as non-endorsement only for the paired comparisons. A neutral answer is not treated as opposition. JS1-JS5 are not averaged into a job-security score: their different objects and directions preclude assuming a unidimensional, validated measure.[11] Pilot testing, item-source adaptation, objective ability and validated construct structure are not established by the supplied material.

[10] William G Cochran, Sampling Techniques (3rd edn, John Wiley & Sons 1977).
[11] Klaas Sijtsma, ‘On the Use, the Misuse, and the Very Limited Usefulness of Cronbach’s Alpha’ (2009) 74 Psychometrika 107.

3.4 Statistical analysis

Counts, proportions and pointwise Wilson intervals summarise each statement. Three paired contrasts use the same individuals and compare endorsement proportions. Exact McNemar tests evaluate discordant pairs, with Holm adjustment across the three tests. Differences are accompanied by percentile bootstrap intervals from 10,000 respondent-level resamples. Different wording and response contexts mean that these contrasts do not rank priorities or estimate the effectiveness of training.[12]

Four Spearman correlations use the original five-category responses and examine JS2 against JS3, JS4, LCA4 and AIL1. Holm adjustment covers this four-test family; percentile bootstrap intervals are pointwise and do not adjust for multiplicity. The analysis is exploratory and cross-sectional. Statistical non-significance does not establish the absence of an association.[13] No structural model or causal effect is claimed.

3.5 Research context and measurement boundaries

Questionnaire respondents may be preparing for employment or already working. The career implications of AI can differ across these situations, but the available status variable does not consistently distinguish paid work from study. In particular, expected adaptation is not observed adaptation; believing learning could reduce concern is not evidence that a training intervention reduced it. The questionnaire does not measure firm adoption or actual changes in wages, work tasks or employment.

3.6 Data handling

Analyses used the numerical workbook fields, retained all 385 eligible records and did not analyse the optional comments. Reported results are aggregated. No sampling weights or missing-data imputation were applied. Sampling uncertainty intervals rely on conventional assumptions that cannot be verified from the undocumented recruitment design and should not be interpreted as nationally representative estimates.

[12] Quinn McNemar, ‘Note on the Sampling Error of the Difference between Correlated Proportions or Percentages’ (1947) 12 Psychometrika 153; Sture Holm, ‘A Simple Sequentially Rejective Multiple Test Procedure’ (1979) 6 Scandinavian Journal of Statistics 65; Bradley Efron and Robert J Tibshirani, An Introduction to the Bootstrap (Chapman & Hall 1993).

[13] Douglas G Altman and J Martin Bland, ‘Absence of Evidence Is Not Evidence of Absence’ (1995) 311 BMJ 485; Ronald L Wasserstein and Nicole A Lazar, ‘The ASA Statement on p-Values: Context, Process, and Purpose’ (2016) 70 American Statistician 129.

3.7 Ethical considerations

The authors state that formal ethical approval was not obtained because an accessible formal review mechanism for this study was unavailable in their institutional setting. They report informed consent, adult eligibility, voluntary participation, an anonymous questionnaire, the opportunity to discontinue and aggregate reporting. These protections and responsibility for ethical conduct are stated in the Declarations. The consent and eligibility fields contain affirmative responses for the analysed records; the workbook alone cannot independently verify the consent process or institutional context.

4. Results

The results are presented as individual responses and paired patterns. They concern stated expectations and do not establish respondents' current employment security or actual outcomes of AI adoption.

4.1 Respondent profile

Table 1 describes recorded age and status. These categories help interpret the sample but do not independently establish employment or professional experience.

Table 1. Recorded age and respondent status

Measure	Category	Count (%)
Age	21-23	159 (41.3%)
	18-20	74 (19.2%)
	24-26	69 (17.9%)
	27-30	47 (12.2%)
	31+	36 (9.4%)
Status	Law student	238 (61.8%)
	Law graduate	61 (15.8%)
	Advocate or legal professional	53 (13.8%)
	Other relevant respondent	33 (8.6%)

N = 385. Recorded categories do not establish current employment or professional tenure.

Law students account for 238 records (61.8%), followed by 61 law graduates (15.8%), 53 advocates or legal professionals (13.8%) and 33 other respondents (8.6%). In total, 159 respondents were aged 21-23 and 36 were aged 31 or older. These distributions limit claims about a defined population of young employees.

4.2 Employment-related statements

Table 2 presents all five JS statements without combining them into a scale. The proportions refer to agreement with each statement, not to the prevalence of job insecurity.

Table 2. Responses to employment-related statements

Item	Counts 1 / 2 / 3 / 4 / 5	Endorsed n (%)	95% CI (%)
JS1	0 / 20 / 126 / 181 / 58	239 (62.1%)	57.1-66.8
JS2	2 / 16 / 135 / 164 / 68	232 (60.3%)	55.3-65.0
JS3	2 / 25 / 147 / 160 / 51	211 (54.8%)	49.8-59.7
JS4	0 / 7 / 71 / 184 / 123	307 (79.7%)	75.4-83.5
JS5	1 / 32 / 151 / 156 / 45	201 (52.2%)	47.2-57.2

N = 385. Endorsement means agree or strongly agree; neutral answers are not opposition. Wilson intervals are pointwise;

exact wording is in Appendix A.

The strongest endorsement was for the proposition that learning to work effectively with AI could reduce future job-security concerns: 307 respondents (79.7%). Routine-task concern was endorsed by 232 (60.3%), and 211 (54.8%) anticipated new tasks requiring human judgement. These responses can coexist; their differing wording makes direct comparisons descriptive.

4.3 Coexisting concern and potential reassurance

Table 3 cross-tabulates routine-task concern and the belief that learning could reduce future job-security concerns. Each person appears in one category.

Table 3. Joint endorsement of concern and learning

Response configuration	Count (%)
Both endorsed	184 (47.8%)
Concern only	48 (12.5%)
Learning statement only	123 (31.9%)
Neither endorsed	30 (7.8%)

N = 385. Neither includes neutral answers; categories describe responses, not fixed types of people.

A total of 184 respondents (47.8%) endorsed both statements. A further 123 endorsed learning-related reassurance without endorsing routine-task concern. These are response combinations, not stable worker types. They do not show that training was received, that concern was severe, or that learning caused a change in concern.

4.4 Paired endorsement comparisons

Table 4 compares selected statements within respondents. Pointwise confidence intervals and adjusted p-values are included to show uncertainty and the scope of the exploratory comparisons.

Table 4. Paired endorsement comparisons

Contrast	First only / second only	Difference pp	95% CI pp	Holm p
JS2 – JS4	48 / 123	-19.5	-25.7 to -13.0	<.001
JS2 – JS3	101 / 80	5.5	-1.3 to 12.2	0.137
JS2 – LCA4	111 / 67	11.4	4.7 to 17.9	0.002

N = 385; pp = percentage points. Exact McNemar tests, Holm adjusted across three tests. Bootstrap intervals are pointwise. Items have different wording.

The comparisons describe differences in agreement with differently worded questions. A higher percentage for one item does not demonstrate that the underlying concern is more important or that one policy is more effective than another.

4.5 Exploratory associations

Table 5 examines whether responses to the routine-task concern item vary with responses to four selected items. Correlations use the full ordinal response scale.

Table 5. Exploratory associations with routine-task concern

Items	Spearman ρ	95% CI	p	Holm p
JS2 / JS3	0.058	-0.038 to 0.151	0.254	1.000
JS2 / JS4	0.048	-0.047 to 0.144	0.351	1.000
JS2 / LCA4	0.030	-0.069 to 0.131	0.557	1.000
JS2 / AIL1	0.008	-0.099 to 0.106	0.878	1.000

N = 385. Holm adjustment covers four tests; 95% percentile bootstrap intervals are pointwise, based on 2,000 resamples.

The estimated associations are small. Their uncertainty and the Holm adjustment should be considered together. The findings do not establish that awareness, career confidence or learning is unrelated to concern, nor do they establish a causal direction.

5. Discussion

The central finding is that concern about routine-task demand can coexist with the belief that learning to work with AI may reduce future job-security concerns. This pattern illustrates the need to study perceived risk and possible resources separately.

5.1 Task concern and future job security

A majority endorsed the routine-task concern statement, but it concerns the demand for some tasks, not the probability that the respondent will lose a job. Research on automation describes both displacement and creation of tasks, so interpreting task concern as an estimate of job loss would overstate the evidence.[14] Similarly, agreement that AI will create new judgement-intensive work does not establish the number, quality or distribution of new jobs.

These distinctions matter for Bangladesh because the respondents' educational and occupational situations vary. A law student may anticipate future labour-market entry while a legal professional may evaluate existing work. The current status categories do not support a reliable comparison of employment insecurity across these groups. Future research should identify employment status, professional sector and AI use within paid tasks before analysing these differences.

5.2 Learning as a perceived resource

Endorsement of the learning statement is consistent with the possibility that participants regard learning as a resource for navigating uncertainty. In job demands-resources terms, however, an available, effective resource must be measured separately from a belief that it might help.[15] The survey does not record whether a particular training programme was relevant, accessible or effective, and the item cannot establish a reduction in anxiety or insecurity.

The joint distribution makes this distinction visible: 184 individuals endorsed both concern and possible reassurance from learning. This is not a contradiction. A person may expect routine tasks to change while also believing that new skills could improve their prospects. The design cannot determine whether the same individuals would report less concern after training. A prospective study with a direct security measure and a comparison group would be better suited to that question.

[14] Acemoglu and Restrepo (n 2); ILO and NASK (n 1).
[15] Demerouti and others (n 5).

5.3 New tasks and career adaptation

The judgment-oriented item expresses an expectation that AI will create some new tasks; it does not measure whether these tasks already exist, whether they are paid or whether respondents can access them. Career construction theory helps frame adaptation as an ongoing process involving resources and opportunities, rather than an outcome caused by personal willingness alone.[16] A validated multi-item measure would be needed to examine whether adaptability mediates a relationship between AI exposure and perceived job security.

Correlations in the present study are descriptive, and small estimates do not rule out relationships that differ by setting or subgroup. The common response scale, simultaneous measurement, unknown recruitment and heterogeneous respondents can all affect observed patterns. Neither a non-significant result nor a positive coefficient alone resolves these questions.[17]

5.4 Organisational expectations and worker safeguards

Psychological contract theory draws attention to the relationship between organisational change and perceived obligations, including training and transparent communication.[18] Those considerations cannot be tested here because the workbook does not identify an employer or document a promise. Employers designing AI transitions could nevertheless make responsibilities clear, explain how tasks are changing, consult workers and evaluate whether training helps in practice. These are prospective recommendations informed by theory, not effects demonstrated in the survey.

Automated monitoring may also introduce concerns over control and workplace data, as described in algorithmic management research.[19] The fact that the questionnaire includes monitoring items does not establish monitoring in respondents' workplaces, the existence of safeguards, or a link to measured job security. Treating endorsement of safeguards as evidence of their implementation would obscure an important practical distinction.

[16] Savickas and Porfeli (n 7).
[17] Wasserstein and Lazar (n 13); Altman and Bland (n 13).
[18] Rousseau (n 6).
[19] Kellogg, Valentine and Christin (n 9).

5.5 Integrated interpretation

The three perspectives illuminate different questions: demands and resources concern the conditions under which workers cope; psychological contracts concern employment expectations; and career construction concerns adaptation over time. Their joint use here is conceptual rather than an estimated integrated model. The survey provides a useful description of coexisting expectations but not a test of whether these mechanisms produce security. A stronger design would measure each mechanism with validated items, identify the relevant workplace and follow changes over time.

6. Theoretical and Practical Implications

The implications below distinguish what the observed responses show from actions and research designs proposed for evaluation. They do not imply that any intervention was tested.

6.1 Theoretical implications

First, routine-task concern, anticipated job insecurity and actual employment change should remain separate constructs. An instrument that averages concern, expected opportunity and reassurance risks producing a score whose interpretation is unclear. Construct development should begin with explicit definitions and validation in the intended population.[20]

Second, the coexistence of concern and possible reassurance supports examining resources and demands in parallel, while leaving open whether either changes security. Third, contextualising psychological contracts requires identifying a real employment relationship and its communication practices. Together these distinctions provide a measurement agenda for research on AI and work in Bangladesh.

6.2 Practical and policy implications

Universities can offer AI-related learning that includes verification, domain-specific judgement and discussion of changing tasks. Employers can consult workers about implementation, explain how roles may change, and provide access to relevant training. Their effectiveness should be assessed with direct measures of knowledge, working conditions and perceived security, rather than assumed from agreement with a single statement.

Policy and professional bodies can support transparent evaluation of workplace AI and meaningful routes to human review where significant decisions are affected. These proposals should be adapted to the applicable legal context and tested with workers and employers. They do not imply that this survey identified unlawful practices or established compliance.

[20] Sijtsma (n 11); Savickas and Porfeli (n 7).

7. Conclusion, Limitations and Future Research

The 385 records show that many respondents endorsed both concern about demand for routine tasks and the possibility that learning to work with AI could reduce future job-security concerns. The data also indicate expectations of new tasks requiring human judgement. These findings describe perceptions within the recorded sample; they do not demonstrate job loss, employment security or training effectiveness.

The principal limitations are the mixed, predominantly law-student sample; the absence of a direct current job-security measure; cross-sectional self-report; undocumented sampling and fieldwork procedures; and uncertainty requiring documentation about the Codebook's synthetic identifier and optional-text labels. The researcher identifies the numerical records as real survey data. The recorded status categories do not establish that participants are all young professionals or employees, and the findings are not a national estimate.

Future work should record recruitment dates and methods, employment and occupational status, and the provenance of source records. Researchers should use a validated direct job-security measure, distinguish actual workplace AI exposure from general AI familiarity, and assess training participation and quality. Longitudinal or comparative intervention designs could examine whether changes in access to training precede changes in perceived security. Interviews with workers and employers could complement the survey by clarifying how task changes, consultation and workplace safeguards are experienced.

Declarations

Ethical approval and oversight

Formal ethical approval was not obtained because, at the time of the study, the authors' institutional setting did not provide an accessible formal review mechanism applicable to this non-interventional adult questionnaire research. The study nevertheless followed participant-protection safeguards, including informed consent, voluntary participation, the opportunity to discontinue, an anonymous questionnaire and aggregate reporting. The methodological safeguards are detailed in Section 3.7.

Informed consent

Informed consent was obtained from adult participants before questionnaire completion. The questionnaire explained the study purpose, voluntary participation, anonymity and the option to discontinue. All analysed records contain affirmative consent and adult-eligibility responses.

Data availability

The numerical data supporting the reported analyses are held by the research team. Requests for de-identified data and analytical specifications may be directed to the corresponding author. Any sharing is subject to participant confidentiality and applicable institutional requirements. The contextual-text field was excluded from the analysis.

Conflict of interest

The authors declare that they have no conflicts of interest.

Author contributions

Mst. Rafia Mahmuda Laboni: Lead student researcher; conceptualisation; preparation of study materials; organisation and curation of survey data; manuscript development. The project was conducted under the supervision of Prof. Dr Kazi Abdul Mannan.

Kazi Abdul Mannan: Conceptual and methodological guidance; supervision; interpretation of statistical findings; critical review and editing of the manuscript.

Generative AI disclosure

Generative AI assisted manuscript drafting, language editing, organisation and the development of analytical code. Statistical estimates were computed programmatically from the numerical survey data. Responsibility for the study's analysis, interpretation and reporting rests with the authors.

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Appendix A. Analytical questionnaire items

Table A1 reproduces the survey statements so that each estimate can be interpreted against its exact wording.

Table A1. Exact wording of analytical items

Code	Questionnaire statement
JS1	Generative AI is changing some tasks performed by legal and other young professionals.
JS2	I am concerned that AI may reduce demand for some routine professional tasks.
JS3	I believe AI will also create new tasks requiring human judgement and oversight.
JS4	Learning to work effectively with AI can reduce my concerns about future job security.
JS5	I expect my future role to require adaptation to AI-enabled work practices.
LCA4	I am confident that I can adapt my career plans as AI changes professional work.
AIL1	I understand that generative AI can produce plausible but inaccurate information.

Source: Group 9 Codebook. Response options range from strongly disagree to strongly agree.

Items are analysed separately and do not establish a single validated latent construct.