Risk Index – Job Loss Model

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1. Exposure, employment pressure and job loss

An exposure score describes the technical potential for AI to affect tasks. Employment pressure is a calculated reduction in required work under stated assumptions. Job loss is the observed loss of a job or position over a defined period. JLM links exposure to employment pressure. It does not measure job loss. The ILO also distinguishes exposure from an employment forecast. [ilo-explorer]

The model uses full-time equivalents, abbreviated as FTEs. One FTE is the amount of work assigned to one full-time position. FTEs measure work capacity, not a count of identified people. A result can therefore include a fraction of an FTE.

The calculator shows how each assumption affects the result. Employers, workers and public agencies can use it to identify the evidence needed for a local study. Local measurements can replace the assumed values after validation.

2. What the occupation data show

The source is the supplementary workbook for the ILO’s 2025 occupational-exposure study. It contains 3,265 task rows linked to 427 four-digit ISCO-08 occupation groups. ISCO-08 is the International Standard Classification of Occupations. [ilo25] [ilo-data]

The workbook repeats occupation means and standard deviations across task rows. CAIA checked these repeated values for consistency and kept one record per occupation code. Thus, an occupation with more listed tasks does not receive more weight in the occupation statistics.

The median exposure score is 0.27, and the mean is 0.2965. These statistics give each occupation group equal weight. Thirteen groups are in the source’s highest exposure category. Data Entry Clerks score 0.70. Typists and Word Processing Operators score 0.65. These are exposure scores, not percentages of Caribbean workers who will lose their jobs.

The source classifies 231 groups as Not Exposed and 84 as Minimal Exposure. Another 112 groups fall across Gradients 1–4. The 112 groups represent 26.2% of the 427 occupation groups, with each group counted once. This percentage does not describe the share of workers. This release has no national employment counts for these groups.

The assessment retains the source category and the standard deviation of task scores within each occupation. The standard deviation describes the spread of those task scores. It is not a probability of job loss.

3. Model terms and calculation

The model calculates employment pressure for each occupation group o. Its terms have these meanings:

Term	Meaning
No	Initial workforce in FTEs.
eo	Exposure score used as a substitute for the affected share of work capacity.
ao	Adoption: the fraction of exposed capacity for which AI is used during the selected period.

Term	Meaning
so	Substitution: the fraction of adopted exposed capacity that replaces labour.
ro	Redeployment: the fraction of gross pressure absorbed through work in other roles.
G	New FTE positions during the same period.

Gross employment pressure is D = Σ Noeoaoso. Pressure after redeployment is U = Σ Noeoaoso(1 – ro). Net employment pressure is L = U – G. The symbol Σ means the sum across occupation groups.

A negative L means net expansion under the selected assumptions. The model retains negative results. The percentage pressure index is 100 × L / ΣNo. The total initial workforce must be greater than zero.

The exposure score is not a measured share of hours that AI can automate. Its use as a work-capacity fraction is an extra model assumption. Local task-time studies must test this conversion. The calculator limits e, a, s and r to values from zero to one. Users enter new positions as a percentage of the same initial workforce.

The default example covers three years and uses 10,000 FTEs. It assumes exposure of 0.29, adoption of 50%, substitution of 30%, redeployment of 50%, and new positions equal to 1%. The exposure assumption differs from the source median of 0.27.

The example gives 435 FTEs of gross pressure. Redeployment absorbs 217.5 FTEs, and the example assumes 100 new FTEs. Net pressure is 117.5 FTEs, or 1.175% of the initial workforce. These values describe a calculation, not observed layoffs.

4. How to read the charts

The animated line chart changes adoption from zero to 100%. It holds the other inputs fixed. The animation tests sensitivity to adoption. It does not predict annual changes.

The 3D chart changes adoption and substitution. Its height shows net FTE pressure at the selected exposure, redeployment and new-position values. Orange shows positive pressure. Blue shows net expansion. Rotation changes the view, not the calculation.

At zero adoption, gross AI-related pressure is zero. Separately assumed new positions can still produce net expansion. At 100% redeployment, pressure after redeployment is zero. If no new positions are assumed, net pressure cannot be negative. Calculation tests check these limits.

The model treats G as a separate input. It does not require new positions to increase with adoption. This assumption matters when a user changes the adoption rate.

For one occupation group, the sensitivity to adoption is N × e × s × (1 – r). A larger workforce or substitution rate increases this sensitivity. More redeployment reduces it. The equation gives this relationship directly.

The model does not assign probabilities to the input values. A chart surface or slider range is therefore not a confidence interval. JRC guidance supports the explicit examination of these design choices. [jrc]

5. Evidence and limits

The World Bank and ILO study identifies potential for both AI assistance and automation in Latin America and the Caribbean. Digital access affects who can use that assistance. Some labour microdata in its reproduction package are restricted. JLM does not reproduce its national employment estimates or replace missing records with invented data. [wb-lac] [wb-repro]

Task-based economic theory separates displacement, productivity gains and new tasks. JLM uses that distinction, but its equation is not a fitted model of the whole economy. It excludes prices, trade responses,

migration, fiscal transfers, job-search delays and feedback between demand and adoption. [automation]

Workplace studies do not supply a universal conversion from time saved to layoffs. Brynjolfsson, Li and Raymond report higher productivity in their support-agent setting. Becker and colleagues report slower completion in their early-2025 developer trial. These studies support task-specific measurement, not one effect for all Caribbean sectors. [work] [metr]

6. Evidence needed for a workforce estimate

Before deployment, an employer study needs a task list, paid hours, output quality, vacancies, new hires, departures and internal transfers. A phased introduction can support a comparison. The study must examine selection into adoption and whether comparison groups had similar earlier trends.

The study must measure both task-time changes and the use of any released work capacity. Redeployment requires a defined paid role and evidence of work in that role. Attendance at training does not establish successful redeployment.

A national estimate needs employment counts by occupation and industry, consistent FTE conversions, survey weights and adoption measures for the same period. Reports must identify missing occupations. Income and participation data provide context, but they do not replace employment counts or establish causation. [participation] [income] [api]

Before the analysis, the plan must fix the outcome, period, sampling frame and comparison method. Later periods or separate organisations must provide validation data. A future probabilistic model must report forecast error, probability calibration and coverage of worker groups.

The composite-indicator handbook can inform reporting. Governance and worker participation require a suitable local process. [composite] [ram] [ethics]

JLM currently helps users examine assumptions and plan data collection. The existing Jamaica economic study is a separate scenario analysis. Users must reconcile populations, periods and mechanisms before they combine outputs from different models. They must not add the losses from both models without that check.

Sources and references 15 sources

Sources checked on 10 November 2026. The notes state which material CAIA checked and how the study uses it.

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• World Bank. Indicators API documentation.Version 2 API; query URLs, response dates and hashes retained with the analysis.

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