# Human-AI Adoption Futures: A Foresight-Informed Reskilling Framework for Non-Technical Workforces in Emerging Economies

**Mehrdad Naderi**

University of Colorado Boulder, M.S. in Data Science
Edgewood University, EdD in Emerging Technologies
*mail@mehrdadnaderi.com*

**Abstract**

Debates on organizational artificial-intelligence adoption still center on technological readiness, treating the workforce as a downstream training problem. This paper argues that technical AI exposure does not become successful adoption automatically: in non-technical roles (administration and support, finance, education, health services, and management or human resources), whether exposure becomes productive augmentation and job resilience, or instead displacement and degraded job quality, is mediated by workforce readiness. The paper synthesizes recent foresight intelligence and labour-market evidence from the World Economic Forum, OECD, the International Labour Organization, and the IMF, together with peer-reviewed findings on reskilling effectiveness, to develop a conceptual, foresight-informed framework. Using a STEEP-structured signal scan and two critical uncertainties, namely the pace and depth of AI deployment and the speed and quality of reskilling and role redesign, it derives four plausible 2030 adoption futures and shows that workforce reskilling readiness is the human-capability layer that most consistently separates a desirable future from a damaging one across them, alongside conditioning factors such as governance, trust, and infrastructure. The framework links five elements (automation-exposure mapping, human-AI role redesign, future-skill development, adaptive organizational learning, and early-warning signal monitoring) into a single adoption-readiness pathway, accompanied by an illustrative 2025 to 2027 capability-building roadmap. It is presented as a conceptual artifact rather than an empirical study, and is especially relevant to emerging and resource-constrained economies, where automation pressure interacts with uneven digital infrastructure and fragmented training systems. The central claim is that reskilling readiness should be modelled as a mediating adoption capability, not a post-adoption labour-market response.

**Key words:** human-AI adoption, technology foresight, reskilling and upskilling, future of work, job resilience, emerging economies

## 1. Introduction

The diffusion of artificial intelligence (AI) into organizational work is most often framed as a question of technological readiness: which model to license, which platform to integrate, which workflow to re-architect. Yet in the large class of non-technical roles (administration and support, finance and accounting, education, health services, and management or human resources), the value and the risk of AI do not materialize at the level of the tool. They materialize at the level of the people whose roles are being reshaped and the tasks those people perform [1], [2]. A workflow can be re-platformed in a quarter; a workforce cannot be re-skilled on the same schedule.

The scale of the coming change is no longer in serious dispute. The World Economic Forum reports that a majority of employers expect AI and information processing to transform their business by 2030, that clerical and secretarial roles face the largest absolute decline of any occupational category, and that roughly two-fifths of workers' core skills will be transformed or outdated over the second half of this decade [10], [11]. The IMF estimates that about 40 percent of global employment is exposed to AI, rising to some 60 percent in advanced economies [9]. The International Labour Organization's task-based analysis finds clerical work to be the single occupational group with concentrated high exposure to generative AI, even as it stresses that the dominant near-term effect is more likely to be augmentation than full automation [6], [7].

These figures describe exposure and expectation, not destiny. The same technical capability can yield very different outcomes depending on whether organizations convert exposure into productive augmentation through reskilling, role redesign, and governance. This is visible in the failure mode that organizations report most often: capable systems are deployed and then quietly worked around, staff revert to manual routines, trust erodes, and the gap between training completion and real workflow use widens until the initiative stalls. If the workforce is where adoption succeeds or fails, the workforce cannot remain a problem to be solved after the technology decision has been made. The author's prior operational work on AI adoption treats such adoption-and-behaviour signals, including reversion to manual workarounds, disengaging champions, and employee concern about role and job security, as first-order indicators of whether a deployment will hold [41].

Three literatures speak to this problem but rarely meet. Technology-foresight research anticipates the trajectory of AI and structures decisions under uncertainty [26], [27]. The reskilling and future-skills literature documents which competencies a changing labour market will demand and how reskilling affects adaptability and resilience [17], [18], [20]. And the adoption literature concentrates on organizational and technological readiness. What is missing is a connection: a way to translate plausible near-term futures of AI in non-technical work into a concrete, foresight-driven pathway for building the workforce capability on which adoption depends.

This paper addresses that gap. Its research question is: given uncertain near-term futures of AI in non-technical work, what reskilling and resilience capabilities must organizations build today to make human-AI adoption succeed across those futures? Its contribution is threefold. First, it reframes reskilling readiness from a human-resource afterthought into a mediating adoption capability, the human-capability layer through which technical AI exposure becomes durable augmentation rather than displacement, and argues that it should be modelled as part of the adoption decision rather than as a post-adoption labour-market response. Second, it proposes a foresight-informed reskilling framework of five linked elements forming a single adoption-readiness pathway, accompanied by an illustrative near-term capability roadmap. Third, it situates the framework in emerging, transition, and resource-constrained economies, where the argument has the sharpest practical bite. The framework is offered as a conceptual, foresight-informed artifact in the sense recognized by the conceptual-article and design-science literatures [42], [43]; it is not an empirical study, and an agenda for empirical instantiation is identified in Section 8.

## 2. Background and Conceptual Foundations

### 2.1 From job-level to task-level analysis

Labour economics has long held that the effect of new technology is best analyzed not at the level of whole jobs but at the level of the tasks that compose them [1], [2]. The task-technology-fit tradition in information systems established three decades ago that technology improves performance only when its functionality fits task characteristics [3]. Recent field-experimental evidence reinforces the point at finer grain: AI performance varies sharply from one task to the next, producing a jagged frontier on which systems are excellent on some tasks and confidently wrong on adjacent ones. In one controlled study, consultants gained markedly in speed and quality on tasks inside the frontier but lost accuracy on tasks outside it [4]. Adoption, in this view, is not a single organizational choice but a structured pattern of task-level decisions, and the unit at which value and risk concentrate is the task, not the platform.

### 2.2 Exposure of non-technical work

The clearest cross-country evidence places clerical and administrative work at the near-term epicentre of exposure. In the ILO's task-based global analysis, clerical occupations are the only broad group with concentrated high exposure to generative AI: roughly a quarter of clerical tasks are classified as highly exposed and over half as medium-exposure, whereas for other broad groups highly exposed tasks typically range only from a few percent [6], [7]. A U.S.-based task-exposure study reaches a complementary conclusion: about four-fifths of the workforce could have at least a tenth of their tasks affected by large language models, and the share of tasks that can be done much faster rises substantially once complementary software and tooling are added [5]. That last result matters for adoption: realized impact is driven not by raw model capability alone but by the complementary workflow tools, training, and redesign that surround it.

OECD evidence adds an essential nuance. High-skill white-collar occupations, including business professionals, managers, and senior executives, are among the most exposed to recent AI progress, yet they remain among the least at risk of full automation because many of their required skills are bottlenecks to machine substitution [8]. The occupations at highest automation risk account for roughly a quarter of OECD employment, but they are not the same as those most exposed to AI progress. For the present argument this distinction is crucial: finance professionals, managers, and similar non-technical roles can be AI-exposed without being automatable, which is precisely the conceptual space in which reskilling and role redesign matter most. At occupation level, the roles that recur near the top of exposure rankings are information-processing jobs: correspondence and data-entry clerks, accountants and auditors, administrative assistants and secretaries, and bank tellers. These are also the categories WEF expects to decline most by 2030 [10]. Evidence for non-technical education and health work is thinner and more heterogeneous; the honest reading is selective task augmentation rather than broad near-term substitution, with relational and embodied tasks remaining least automatable, and with care and teaching roles often projected to grow [6], [10], [39].

### 2.3 Augmentation versus substitution

The best-supported synthesis is that the near-term effect for most non-technical work is task recomposition, not job disappearance. The ILO argues explicitly that generative AI is more likely to augment work, automating some tasks within an occupation and freeing time for others, than to automate whole occupations [6]. Causal evidence supports conditional complementarity. In a large field study of customer-support agents, generative-AI assistance raised productivity on average, with the largest gains for less experienced and lower-skilled workers and improved customer sentiment [12]. In professional writing, experimental evidence shows reduced task time and improved output quality, with the weakest writers benefiting most [13]. In preprint evidence that should be labelled as such, an analysis of millions of vacancy postings finds that AI demand raises the value of complementary human skills such as resilience, analytical thinking, and adaptability, with complementary effects materially larger than substitution effects [14].

The substitution side cannot be minimized. A substantial share of employers expect to reduce headcount where AI can automate tasks, and clerical roles remain the clearest projected decline category [10]. The OECD warns that workers can be squeezed into a shrinking set of tasks and that algorithmic management can erode autonomy, privacy, and increase work intensity [8]. The defensible conclusion is therefore not a binary verdict but a conditional proposition: AI tends toward augmentation where organizations invest in complementary skills and redesign work around human judgment, and toward substitution where firms pursue cost-cutting in routine-heavy processes without building reskilling capacity. This conditionality is the hinge on which the rest of the paper turns.

### 2.4 Reskilling, resilience, and the moderating role of organizational support

A converging body of recent work supports the proposition that reskilling and continuous, competency-oriented learning underpin workforce adaptability and job resilience in AI-intensive labour markets, although direct causal evidence specifically on job resilience is still emerging [17], [18], [19], [20], [23]. Three regularities are relevant here. First, structured upskilling and reskilling are associated with greater workforce agility, adaptability, and performance in non-technical roles, and reviews increasingly describe reskilling as a precondition for job security rather than an optional addition [17], [18], [20]. Second, organizational support, in the form of leadership sponsorship, resources, and a growth-oriented learning culture, significantly moderates reskilling effectiveness; programmes misaligned with strategy or lacking leadership buy-in underperform, and a continuous learning culture is a stronger predictor of adaptability than one-off reskilling events [20], [22], [23]. Third, competency-centric education, organized around observable, task-aligned competencies, is repeatedly associated with stronger transfer of learning and workforce preparedness than content-centric, time-based training, a pattern reported particularly in clinical and community-health workforce reviews and best read as indicative rather than universally established [21], [24]. These regularities matter for the framework in Section 4: they identify learning culture and competency focus as conditions of effect, not optional refinements.

### 2.5 Localization and the emerging-economy condition

A consistent finding across reviews of national AI-skills strategies and vocational-education transfer is that ready-made training models, moved directly across contexts, transfer poorly. AI-skills and reskilling policies are highly context-dependent, with comprehensive frameworks concentrated in a minority of high-income countries; exported vocational-education models must be adapted in their content and implementation even when their core principles are preserved; and imported programmes lack traction without deep localization, stakeholder engagement, and sensitivity to local culture and resources [23], [24]. In emerging and transition economies this is compounded by structural constraints, including uneven connectivity, limited compute, fragmented adult-learning systems, and short-horizon organizational planning, captured in the widening gap across what one foresight source frames as connectivity, compute, context, and competency. The result is an asymmetric risk of disruption before benefit: automation-exposed jobs such as business-process outsourcing and clerical export work are already online and can be displaced rapidly, while augmentation-eligible jobs often lack the infrastructure to capture the productivity premium [9], [36]. Localization is therefore not a stylistic choice but a success condition for adoption in these settings.

### 2.6 Five non-technical clusters

The framework targets five clusters in which exposure, augmentation potential, and the appropriate reskilling response differ, and conflating them obscures the adoption problem. In administration and support, the near-term epicentre, concentrated high exposure of clerical tasks and the largest projected occupational decline mean the reskilling task is to re-specify roles around verification, exception handling, escalation, and relational service rather than throughput, while moving displaced capacity into adjacent work [6], [10]. In finance and accounting, analysts, auditors, and tax-preparation roles rank high on exposure, yet accountability, interpretation, and compliance keep judgment with the human; here AI is best framed as a drafting and analysis layer, and the reskilling target is disciplined oversight: knowing when to trust, verify, override, and document AI output [8]. In education, the evidence base is thinner: lesson planning and parts of assessment receive moderate exposure, but classroom relational work, supervision, and contextual adaptation remain much less automatable, and teaching roles are often projected to grow, so the reskilling task is selective AI fluency layered onto retained pedagogical and relational expertise [6], [10]. In health services, the strongest near-term effect for non-clinical and clinical-administrative work is documentation and administrative time savings, freeing capacity for higher-value and relational tasks, while clinical judgment is retained [39]. In management and human resources, managers and business professionals are among the most AI-exposed yet least automatable groups, AI is already widely used in people decisions, and such decisions are classified as high-risk under emerging regulation, so the reskilling target combines analytical AI fluency with governance literacy, fairness awareness, and oversight competence [8], [37]. Across all five, the recurring lesson is that exposure is not automatability, and the reskilling response must be designed cluster by cluster.

## 3. A Foresight Lens on Human-AI Adoption

Foresight is used here not to forecast a single outcome but to structure decisions under uncertainty, that is, to identify drivers, name critical uncertainties, and reason across plausible futures so that organizations can derive strategies that are robust whichever future arrives [26], [27]. Workforce futures are already studied through three overlapping methods, all of which inform this section: anticipatory employer surveys, task-exposure modelling, and explicit scenario analysis. WEF's employer survey is anticipatory intelligence rather than econometric forecast, gathering the expectations of more than a thousand employers across dozens of economies [10]. The ILO's task-exposure modelling derives technical-feasibility bounds, not realized-adoption forecasts, and explicitly warns that infrastructure, connectivity, digital literacy, and local labour costs condition what actually diffuses [6]. And explicit scenario analysis, in the established strategic-foresight tradition, treats its futures as tools to stress-test assumptions and derive strategies that are robust across them, rather than as predictions [25], [26]. The methodological lesson is that a foresight-informed framework need not predict a single future; it must identify the uncertainties, pathways, and workforce conditions that make different adoption futures more or less likely. The synthesis here follows a transparent sequence: signals to 2030 were drawn from primary institutional foresight and peer-reviewed labour-market evidence and grouped using a STEEP lens (social, technological, economic, environmental, and political-regulatory); recurring signals were clustered into drivers and ranked by impact and uncertainty; the two drivers scoring highest on the combined criterion were taken as the scenario axes; and the resulting two-by-two matrix was developed into four futures and an illustrative backcasting roadmap. The scenario axes are deliberately chosen to foreground workforce readiness rather than to reproduce a generic capability-versus-readiness grid.

### 3.1 A signal scan of non-technical work

Table 1 summarizes a selection of dated signals of change affecting non-technical work, drawn from primary institutional and peer-reviewed sources. The signals are tagged as trends (T) or weak signals (WS) and span the horizon to 2030. They are not exhaustive; they are chosen to expose the structural tension the framework addresses.

### 3.2 Critical uncertainties and ranked drivers

Clustering the signals yields a small set of drivers that can be ranked by impact and uncertainty (Table 2). Two drivers dominate on both dimensions and serve as the scenario axes: the pace and depth of AI capability and complementary software (because complementary tooling, not model capability alone, scales realized task impact), and the capacity and speed of reskilling and role redesign (because a large share of skills will turn over within the decade while training access remains uneven) [5], [10]. Governance and worker voice, worker trust and adoption choice, and digital-infrastructure parity are high-impact conditioning factors that the framework also tracks [8], [35], [37].

### 3.3 Four adoption futures to 2030

Crossing the two scenario axes, AI deployment depth (incremental to pervasive) against reskilling and role-redesign delivery (lagging to adaptive), yields four plausible 2030 futures (Table 3). They are composites for stress-testing, not predictions. Read together they expose a single structural fact: across all four, the variable that separates a durable, humane adoption from a brittle or failed one is the reskilling readiness and resilience of the non-technical workforce.

Each future implies a different reskilling posture. Prepared Augmentation invests ahead of deployment in AI-fluent process work, covering prompt design, exception handling, oversight, and ethics, paired with maintained domain expertise. Managed Co-Piloting rewards broad literacy and continued public and institutional investment as the urgency narrative cools. Capability Drift is the failure of under-investment, where voluntary, costly, fragmented reskilling is unevenly taken up. Automation-Led Hollowing is the failure of speed, where crisis-mode transition support arrives too late for the first displaced cohort. Naming the futures around workforce readiness rather than around AI capability alone is deliberate: it foregrounds the variable this paper argues is decisive and distinguishes the set from generic capability-centred scenario exercises. In every case, the determining factor is whether reskilling readiness was built in advance, which is the warrant for treating it as a mediating adoption capability rather than a downstream response.

Table 1. Selected dated signals of change in non-technical work (to 2030)

| Signal | Evidence (source, year) | Tag |
|---|---|---|
| AI is the leading disruptor employers expect; most plan reskilling | Majority of employers expect AI to transform business by 2030; a large share plan workforce reskilling, while about 40% anticipate reductions where tasks can be automated. WEF, 2025 [10] | T |
| Clerical/secretarial is the largest declining category | Largest projected absolute decline 2025 to 2030: data-entry, admin assistants, bank tellers, cashiers. WEF, 2025 / 2023 [10], [11] | T |
| About 40% of workers' core skills transformed by 2030 | WEF, 2025 [10] | T |
| About 40% of global employment exposed to AI (60% AE) | IMF, Cazzaniga et al., 2024 [9] | T |
| Clerical work is the concentrated high-exposure group | About 24% of clerical tasks highly exposed, about 58% medium; augmentation greater than automation overall. ILO, 2023 to 2024 [6], [7] | T |
| Productivity premium concentrates on novice/low-skill workers | Customer support +15% on average, larger for novices. Brynjolfsson, Li & Raymond, 2025 [12] | T |
| GenAI compresses skill gaps in professional writing | Reduced task time, improved quality; weaker writers gain most. Noy & Zhang, 2023 [13] | T |
| Complementary software scales task impact | Share of tasks done much faster rises sharply once tooling is added. Eloundou et al., 2023 to 2024 [5] | T |
| Workplace AI classified high-risk; oversight duties | Employment and worker-management AI is high-risk; human oversight and worker information required. EU AI Act, 2024 [37] | T |
| Worker sentiment is anxious | Around half of workers worried; few expect more opportunity. Pew, 2025 [35] | WS |
| 'Disruption before benefit' risk in developing economies | Exposed jobs already online; augmentation-eligible jobs lack connectivity. IMF / World Bank, 2024 to 2025 [9], [36] | T |

Table 2. Ranked drivers of human-AI adoption in non-technical work (Impact × Uncertainty)

| Driver | Impact (1 to 5) | Uncertainty (1 to 5) | Basis |
|---|---|---|---|
| Pace and depth of AI capability plus complementary software | 5 | 4 | Complementary tooling scales task impact; biggest swing in forecasts [5], [10] |
| Reskilling capacity and speed of role redesign | 5 | 4 | About 40% skill turnover by 2030; uneven training access [10] |
| Governance, regulation and worker voice | 4 | 4 | Workplace AI high-risk; oversight and consultation duties [37] |
| Worker trust, sentiment and adoption choice | 4 | 4 | Anxious sentiment; fragile trust conditions real use [35] |
| Digital infrastructure and access parity | 4 | 3 | Decisive for emerging-economy outcomes [9], [36] |

Table 3. Four 2030 futures for human-AI adoption in non-technical work

| Future | Configuration | Decisive workforce condition |
|---|---|---|
| Prepared Augmentation (desirable) | Pervasive AI $\times$ high readiness | Institutional, employer-funded reskilling plus redesigned role architectures; novices capture the productivity premium; worker voice embedded. |
| Managed Co-Piloting | Incremental AI $\times$ high readiness | Broad AI literacy and socio-emotional skills; clerical decline absorbed through attrition and lateral moves. |
| Capability Drift | Incremental AI $\times$ low readiness | Weak institutions leave reskilling to individuals; gains never arrive and AI-fluency inequality compounds. |
| Automation-Led Hollowing (most damaging) | Pervasive AI $\times$ low readiness | Deployment outruns adjustment capacity; partial automation erodes job quality and wages; gendered clerical shock; trust collapses. |

## 4. A Foresight-Informed Reskilling Framework

The framework treats reskilling as an adoption-readiness pathway composed of five linked elements (Table 4). The elements are sequential in logic but cyclical in operation: the fifth feeds the first, so the pathway is refreshed as the external environment and internal practice change. Each element is paired with the signal it monitors, which turns foresight from a one-time exercise into an operating discipline.

### 4.1 Automation-exposure mapping

The pathway begins by establishing, at task and role grain, which parts of non-technical work are exposed to current and near-term AI. Mapping draws on task-exposure evidence rather than tool-level intuition, and its central discipline is to separate exposure from automatability: a task may be highly exposed yet retain a human bottleneck of judgment, accountability, or relational content [5], [6], [8]. The output is a living exposure profile per role and cluster, refreshed as the frontier moves, which becomes the substrate for every subsequent decision.

### 4.2 Human-AI role redesign

Mapping is followed by redesign. Roles are reconfigured around augmentation: each constituent task is marked as human-retained, AI-assisted, or delegated, so that reskilling targets redesigned roles rather than legacy job descriptions. In information-processing roles this typically shifts the human centre of gravity from throughput toward verification, exception handling, escalation, coordination, and relational service recovery. Redesign is the step most often skipped: organizations procure tools and train staff on them without re-specifying the role, which is a common path into stalled adoption.

### 4.3 Future-skill development

Redesigned roles define the competency basket to be built. It is hybrid by construction: applied data and AI literacy, covering prompting, oversight, hallucination spotting, data sensitivity, and awareness of model limitations, paired with the higher-order human capabilities that the evidence shows rising in value, including analytical thinking, resilience, adaptability, communication, and ethical judgment [10], [14]. The competency map is occupation-specific rather than generic, because the same nominal skill carries different content in finance oversight than in classroom practice or clinical administration.

### 4.4 Adaptive organizational learning

Competencies are built through continuous, competency-centric, data-informed learning rather than one-off content delivery. The evidence indicates that competency-based approaches are often associated with stronger transfer and preparedness, particularly when aligned with observable, role-specific capabilities; that a continuous learning culture predicts adaptability more strongly than discrete reskilling events; and that leadership sponsorship and a supportive environment significantly moderate effectiveness [20], [21],

[22], [23]. These are therefore treated as design conditions of the element, not optional enhancements, and learning is instrumented so that effect can be observed rather than assumed.

### 4.5 Early-warning signal monitoring

The fifth element closes the loop and makes foresight continuous. The organization watches the AI frontier, the drift of role boundaries, and adoption behaviour, including reversion to manual workarounds, disengaging champions, and worker concern about role and security, and feeds material change back into exposure mapping, restarting the cycle. This logic draws on the continuous signal-and-drift monitoring proposed in the author's prior conceptual work [41], and it is what distinguishes a foresight-informed pathway from a one-time reskilling project: the pathway is designed to be revised as the futures of Section 3 resolve in one direction or another.

Table 4. The five elements of the foresight-informed reskilling pathway

| Element | Guiding question | Signal monitored / output |
|---|---|---|
| 1. Automation-exposure mapping | Which non-technical tasks and roles are exposed, and which are exposed but not automatable? | Task/role exposure profile, refreshed as the frontier moves [5], [6], [8] |
| 2. Human-AI role redesign | Which tasks stay human, become AI-assisted, or are delegated? | Redesigned roles and augmentation boundaries |
| 3. Future-skill development | What hybrid competencies do redesigned roles require? | Competency map: AI literacy plus higher-order human skills [10], [14] |
| 4. Adaptive organizational learning | How is learning made continuous, measured, and competency-centric? | Adaptive learning pathway; resilience and skill indicators [21], [22] |
| 5. Early-warning signal monitoring | What internal and external signals warrant updating the pathway? | Watch on frontier, role drift, adoption behaviour; loop back to (1) [41] |

Because foresight is most useful when it is actionable, the framework includes an illustrative backcasting roadmap (Table 5) that works backwards from the desirable Prepared Augmentation future to the capabilities an organization would build in the near term. The roadmap is illustrative rather than prescriptive; its sequencing reflects the logic that compliance and literacy foundations precede scaled reskilling, which in turn precedes institutionalization.

Table 5. Illustrative near-term (2025 to 2027) capability-building roadmap

| Phase | Capability to build | Rationale / anchor |
|---|---|---|
| Foundations | Task-level role-redesign function; AI-literacy floor for the whole non-technical workforce; jagged-frontier risk controls (human-in-the-loop checkpoints, decision logs) | Complementary tooling and exposure evidence; AI-literacy obligations [4], [5], [37] |
| Scaling and equity | Reskilling pipeline that front-loads low-skill and novice workers; equity-targeted programmes for clerical/admin (often female-dominated) | Novice productivity premium; gendered clerical exposure [12], [13] |
| Institutionalization | Continuous early-warning monitoring at leadership level; productivity-share governance; cross-functional 'AI process steward' roles | Sustained adoption depends on monitoring and shared gains [10], [41] |

### 4.6 Making the pathway measurable

A design intention runs through all five elements: each should be made measurable, so that reskilling decisions rest on evidence rather than assertion. Several instrument families are candidates without committing the framework to any single one. Competency can be assessed directly against the role-specific maps produced in element three, rather than inferred from course completion. Adaptability and resilience can be tracked with validated psychometric instruments, for example career-adaptability and workforce-resilience scales, provided they are translated and locally validated rather than transplanted, consistent with the localization condition of Section 2.5. Adoption itself can be instrumented through behavioural indicators such as the rate of reversion to manual workarounds and the elapsed time between training completion and real workflow use, which serve as early-warning signals in element five. And attribution can be strengthened through multi-wave, pre- and post-intervention designs with comparison groups, so that change can be linked to the reskilling pathway rather than to background trend.

The selection and validation of specific instruments is deliberately left open here, consistent with the conceptual status of the artifact, and is identified as future work in Section 8. The point of this subsection is narrower but important: a foresight-informed reskilling pathway is only as good as its feedback, and feedback requires measurement that is designed in from the start rather than retrofitted after a programme has run.

## 5. Relevance to Emerging and Resource-Constrained Economies

The framework is presented at a general conceptual level, but its argument is sharpest where adoption pressure meets structural constraint. Re-examining the four futures of Section 3 through an emerging- and lower-income-economy lens makes the matrix asymmetric (Table 6). The desirable Prepared Augmentation future is structurally harder to reach where connectivity, compute, and institutional reskilling capacity are thin; Managed Co-Piloting is the realistic upside for many middle-income economies; Capability Drift is more likely in lower-income settings where fewer non-routine analytical tasks and lower computer use reduce the scope for productivity gains; and Automation-Led Hollowing carries more damaging consequences per unit of likelihood, because automation-exposed roles such as business-process outsourcing and clerical export work are already online and can be displaced before augmentation-eligible jobs acquire the infrastructure to benefit [9], [36].

Table 6. Emerging-economy stress test of the four futures

| Future | Likelihood in EM/LIC | Why (sourced) |
|---|---|---|
| Prepared Augmentation | Less likely; possible in leapfrog pockets | Low connectivity and compute parity; leapfrog plausible where mobile/cloud adoption is fast [36] |
| Managed Co-Piloting | More likely for middle-income economies | Lower immediate exposure than advanced economies, with upside if infrastructure keeps pace [9] |
| Capability Drift | More likely in lower-income economies | Fewer non-routine analytical tasks; large offline populations limit gains [6], [36] |
| Automation-Led Hollowing | Most damaging asymmetric risk | Exposed BPO/clerical-export jobs already online; gendered shock; thin institutions [9], [36] |

Several context-specific studies sharpen this picture. Firm-level evidence from transition economies in the Western Balkans shows that organizations recognize the need for digital and green skills, yet low participation in adult education and weak upskilling incentives undermine readiness; comparative analysis links higher shares of adults with digital skills to labour productivity and development in the same region [29], [30]. In the GCC countries, digitalization amplifies demand for higher-order skills while threatening routine clerical and service work, making targeted upskilling and education reform critical [31]. Systematic and framework work converges on continuous, competency-oriented upskilling for non-technical professionals as a determinant of job quality and well-being in mixed advanced and emerging samples [19], [32], and case evidence from Africa and Asia underscores that large-scale, locally designed reskilling is essential for employability and productivity in services-dominated economies [33], [34].

These dynamics are concrete rather than abstract. In emerging economies such as Iran, national strategies increasingly emphasize human-capital empowerment in the AI era, yet workforce development on the ground frequently remains content-centric rather than competency-centric, and mechanisms for measuring reskilling effect and learning return are underdeveloped. In such contexts the framework's emphases on localization, competency-centric and measurable learning, and continuous signal monitoring are precisely the features that distinguish a durable adoption pathway from a one-off training intervention. This relevance is argued from the author's ongoing research into AI-related reskilling for non-technical professionals; it is offered as motivating context, not as an empirical, multi-country claim.

## 6. Discussion

Two propositions follow from the synthesis. The first is empirical and conditional: in non-technical occupations, AI exposure is already high enough to force task redesign, but whether adoption produces augmentation, resilience, and productivity gains, or instead displacement, degraded job quality, and stalled implementation, depends heavily on workforce readiness, especially AI literacy, complementary human skills, organizational learning capacity, and internal mobility mechanisms [5], [6], [8], [12]. This proposition is better supported than any stronger claim that AI will simply replace or simply save non-technical work. The second is the paper's central reframing: reskilling should be modelled as an adoption variable, not a post-adoption labour-market response. The warrant is that firms already retrain in response to AI adoption, that complementary tooling and skills drive a large share of realized task impact, that skill gaps are the most frequently reported obstacle to transformation, and that the most exposed non-technical roles are precisely those where judgment, verification, and relational work remain critical after routine tasks are automated [10], [12], [14].

The practical implication for managers is that reskilling readiness should be planned before and alongside technology decisions, as adoption infrastructure rather than aftercare. For policymakers and training providers, the implication is a shift from content-centric programmes toward localized, competency-centric, and measurable learning pathways, with leadership sponsorship and supportive learning environments treated as conditions of effect [20], [21], [22], [23]. For responsible adoption, the framework keeps human oversight, dignity, and role reinvention in view, consistent with the oversight and worker-information duties now codified for high-risk workplace AI [37].

The framework's originality relative to the author's prior work is in its unit of analysis. Task-centric governance frameworks reason per task about whether to adopt, defer, or retain AI, and human-AI convergence work models how humans and systems hand tasks back and forth across a task chain. The present framework takes neither the task nor the hand-off as its primary object, but workforce capability over time under uncertain futures: the reskilling readiness, role architecture, and learning capacity that determine whether per-task adoption decisions can actually be executed and sustained. It is therefore complementary to task-level governance rather than a substitute for it: governance answers what an organization should adopt; this framework answers whether its people can.

For national skilling systems and training providers, particularly in emerging and transition economies, the design lessons are concrete. The evidence points away from one-off, content-centric provision and toward continuous, competency-centric learning that is locally designed rather than imported; toward explicit measurement of learning return rather than completion counts; and toward prioritizing the most exposed clusters and the workers, disproportionately in clerical and administrative roles and disproportionately women, who stand on the front line of the disruption-before-benefit risk [29], [30], [31], [34]. Treating reskilling capacity as part of the AI-adoption decision, rather than as a separate social-policy afterthought, is as relevant to ministries and public training systems as it is to individual firms.

A final implication concerns trust and worker voice, which the driver analysis of Section 3 ranked among the most consequential and most uncertain factors. Adoption is ultimately a behavioural choice by the people asked to use the system, and worker sentiment toward workplace AI is anxious: surveys find a large share of workers worried and few expecting more opportunity, while workers subject to algorithmic management report systematically more negative views, citing work intensity, reduced autonomy, and privacy concerns [8], [35]. A reskilling pathway that builds capability while ignoring trust will still fail at the point of use. The framework therefore treats worker information, consultation, and transparency, obligations now codified for high-risk workplace AI [37], not as compliance overhead but as conditions of adoption, and its early-warning element explicitly monitors sentiment and reversion as leading indicators. Building capability and building trust are, in this sense, two facets of the same readiness.

## 7. Conclusion

This paper has argued that the future of human-AI adoption in non-technical work is not primarily a question of model capability but of workforce capability. Synthesizing foresight intelligence and labour-market evidence, it derived four plausible 2030 adoption futures and showed that reskilling readiness is the invariant that separates desirable from damaging outcomes across all of them. On that basis it proposed a foresight-informed reskilling framework, covering exposure mapping, role redesign, future-skill development, adaptive learning, and early-warning monitoring, and an illustrative near-term capability roadmap, situated with particular force in emerging and resource-constrained economies. The contribution is to reposition reskilling from a downstream human-resource response to an upstream, foresight-driven precondition for responsible and durable adoption. The future of AI in non-technical work, on this view, will be decided less by what the technology can do than by whether organizations and workers build, in advance, the capability to adopt it well.

## 8. Limitations and Future Research

This paper is a conceptual, foresight-informed artifact; it has not been empirically instantiated or tested against alternatives, and the four 2030 futures are illustrative composites rather than forecasts. Its evidentiary base also has known limits that the argument should not overstate. Much of the strongest quantified evidence measures technical exposure or employer expectations rather than realized long-run employment outcomes, and exposure is not automation [6], [8]. Several pivotal sources are not of the same evidentiary type: employer surveys are structured anticipatory intelligence rather than causal estimates [10]; some task-exposure and vacancy studies are working papers or preprints and are cited here as suggestive rather than settled, including the complementary-skills analysis [5], [14]. The evidence is also concentrated in OECD and U.S. contexts and is materially thinner for cross-country, occupation-wide estimates in non-technical health and education work, so claims there are deliberately cautious [6]. Finally, the relevance to emerging economies is argued rather than measured. These limitations define the agenda: future work should instantiate the pathway in specific organizations and sectors, select and validate measurement instruments for exposure, competency, and job resilience, design multi-wave evaluation with comparison groups, and test the framework's portability across distinct economic and institutional contexts.

***Author note.*** *This paper draws on the author's ongoing research into AI-related reskilling and job resilience for non-technical professionals, including work undertaken in the Executive Master programme at HEC Paris and a Post-DBA research program at ATU.*

## References

[1] Autor DH, Levy F, Murnane RJ. The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics; 118(4): 1279-1333, 2003.

[2] Acemoglu D, Restrepo P. Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives; 33(2): 3-30, 2019.

[3] Goodhue DL, Thompson RL. Task-technology fit and individual performance. MIS Quarterly; 19(2): 213-236, 1995.

[4] Dell'Acqua F, McFowland E III, Mollick E, Lifshitz-Assaf H, Kellogg KC, Rajendran S, Krayer L, Candelon F, Lakhani KR. Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. Harvard Business School Working Paper 24-013; 2023.

[5] Eloundou T, Manning S, Mishkin P, Rock D. GPTs are GPTs: An early look at the labor market impact potential of large language models. arXiv:2303.10130; 2023 (working paper).

[6] Gmyrek P, Berg J, Bescond D. Generative AI and jobs: A global analysis of potential effects on job quantity and quality. ILO Working Paper 96. Geneva: International Labour Organization; 2023. doi:10.54394/FHEM8239.

[7] International Labour Organization. A refined global index of occupational exposure to generative AI. ILO Working Paper 140. Geneva: ILO; 2024.

[8] OECD. OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market. Paris: OECD Publishing; 2023. doi:10.1787/08785bba-en.

[9] Cazzaniga M, et al. Gen-AI: Artificial intelligence and the future of work. IMF Staff Discussion Note SDN/2024/001. Washington (DC): International Monetary Fund; 2024.

[10] World Economic Forum. The Future of Jobs Report 2025. Geneva: WEF; 2025.

[11] World Economic Forum. The Future of Jobs Report 2023. Geneva: WEF; 2023.

[12] Brynjolfsson E, Li D, Raymond L. Generative AI at work. Quarterly Journal of Economics; 140(2): 889-942, 2025. doi:10.1093/qje/qjae044.

[13] Noy S, Zhang W. Experimental evidence on the productivity effects of generative artificial intelligence. Science; 381(6654): 187-192, 2023. doi:10.1126/science.adh2586.

[14] Makela E, Stephany F. Complement or substitute? How AI increases the demand for human skills. arXiv:2412.19754; 2024-2025 (working paper / preprint).

[15] Goldstein J, Lobig B, Fillare C, Nowak C. Augmented work for an automated, AI-driven world. IBM Institute for Business Value; 2023.

[16] McKinsey & Company. The economic potential of generative AI: The next productivity frontier. McKinsey; 2023.

[17] Li L. Reskilling and upskilling the future-ready workforce for Industry 4.0 and beyond. Information Systems Frontiers; 24: 803-816, 2022. doi:10.1007/s10796-022-10308-y.

[18] Morandini S, Fraboni F, De Angelis M, Puzzo G, Giusino D, Pietrantoni L. The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. Informing Science; 26: 39-68, 2023. doi:10.28945/5078.

[19] Cramarenco RE, Burca-Voicu MI, Dabija D-C. The impact of artificial intelligence (AI) on employees' skills and well-being in global labor markets: A systematic review. Oeconomia Copernicana; 14(3): 731-767, 2023. doi:10.24136/oc.2023.022.

[20] Hasan M, Haque MA, Nishat SS, Hossain M. Upskilling and reskilling in a rapidly changing job market: Strategies for organizations to maintain workforce agility and adaptability. European Journal of Business and Management Research; 9(6), 2024. doi:10.24018/ejbmr.2024.9.6.2502.

[21] Sultan MA, Miller E, Tikkanen RS, Singh S, Kullu A, Cometto G, Fitzpatrick S, Ajuebor O, Gillon N, Edward A, Moleman YP, Pandya S, Park I, Shen JY, Yu Y, Perry H, Scott K, Closser S. Competency-based education and training for Community Health Workers: a scoping review. BMC Health Services Research; 25: art. 263, 2025. doi:10.1186/s12913-025-12217-7.

[22] Asiedu E, Tenakwah ES. Future-proofing your workforce: Upskilling and reskilling as HR's top priorities. Strategic HR Review; 24(4): 169-173, 2025. doi:10.1108/SHR-01-2025-0008.

[23] Shi L. Global perspectives on AI competence development: Analyzing national AI strategies in education and workforce policies. Human Resource Development Review; published online 2025 (OnlineFirst). doi:10.1177/15344843251332360.

[24] Fuchs M. MNCs' open international strategy-local dynamics: Transfer of German vocational education and training to emerging economies. Critical Perspectives on International Business; 2020. doi:10.1108/cpoib-12-2019-0106.

[25] Schoemaker PJH. Scenario planning: A tool for strategic thinking. Sloan Management Review; 36(2): 25-40, 1995.

[26] Amer M, Daim TU, Jetter A. A review of scenario planning. Futures; 46: 23-40, 2013. doi:10.1016/j.futures.2012.10.003.

[27] Rohrbeck R, Battistella C, Huizingh E. Corporate foresight: An emerging field with a rich tradition. Technological Forecasting and Social Change; 101: 1-9, 2015. doi:10.1016/j.techfore.2015.11.002.

[28] Das S, Steffen S, Clarke W, Reddy P, Brynjolfsson E, Fleming M. Learning occupational task-shares dynamics

for the future of work. arXiv:2002.05655; 2020 (working paper).

[29] Vidas-Bubanja M, Bogetic S, Besic C, Kalinic Z, Bubanja I. Managing the reskilling revolution for the digital age: Case study - Western Balkan countries. Journal of Engineering Management and Competitiveness; 13(1): 37-52, 2023. doi:10.5937/JEMC2301037V.

[30] Levkov N, Kitanovikj B. The importance of digital skills for the Western Balkans - Comparative analysis between the Western Balkans and the European Union. Economy, Business and Development; 5(1): 28-43, 2024. doi:10.47063/ebd.00016.

[31] Alhawarin I, et al. The labour market in the digital era: What matters for the Gulf Cooperation Council countries? Frontiers in Sociology; 7: 959091, 2022. doi:10.3389/fsoc.2022.959091.

[32] Bouwmans M, Lub X, Orlowski M, Nguyen T-V. Developing the digital transformation skills framework: A systematic literature review approach. PLOS ONE; 19(7): e0304127, 2024. doi:10.1371/journal.pone.0304127.

[33] Dinika A-AT. Preparing African youths for the future of work: The case of Rwanda. Digital Policy Studies; 1(2), 2022.

[34] Shah C (Ed.). Reskilling workers for enhancing labor productivity in Asia. Tokyo: Asian Productivity Organization; 2023. doi:10.61145/KFWK9459.

[35] Pew Research Center. US workers and workplace AI. Washington (DC): Pew Research Center; 2025.

[36] World Bank. Digital Progress and Trends Report 2025. Washington (DC): World Bank; 2025.

[37] European Union. Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union; 2024.

[38] UNESCO. Digital literacy global framework. Paris: UNESCO; 2018.

[39] Bhuyan SS, Sateesh V, Mukul N, Galvankar A, Mahmood A, Nauman M, Rai A, Bordoloi K, Basu U, Samuel J. Generative artificial intelligence use in healthcare: Opportunities for clinical excellence and administrative efficiency. Journal of Medical Systems; 49(1): art. 10, 2025. doi:10.1007/s10916-024-02136-1.

[40] OECD. OECD Skills Strategy 2019: Skills to shape a better future. Paris: OECD Publishing; 2019.

[41] Naderi M. TenXOps: The AI strategy for smarter teams. Independently published; 2024.

[42] Jaakkola E. Designing conceptual articles: Four approaches. AMS Review; 10(1): 18-26, 2020.

[43] Gregor S, Hevner AR. Positioning and presenting design science research for maximum impact. MIS Quarterly; 37(2): 337-355, 2013.