



AIGW Policy Observatory
Global AI Governance & Workforce Transformation

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AIGW POLICY ANALYSIS

Designing the First Rung

How Employers Can Rebuild Early-Career Work
in the AI Era

October 2026

An abstract graphic in the bottom right corner consisting of several concentric, curved lines in shades of blue and purple, creating a sense of motion and depth.

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EXECUTIVE SUMMARY

Executive Summary

Artificial intelligence is changing the economics of entry-level work.

The traditional first rung of many careers was built around a bargain that was rarely stated explicitly. Organizations hired inexperienced people to perform relatively structured work. The work created value for the employer, but it also created experience for the worker. Repetition produced pattern recognition. Writing produced reasoning. Research produced domain fluency. Client exposure produced judgment. Review produced standards. Over time, junior employees became people who could be trusted with more complex work. AI can break that bargain in two different ways. First, it can automate or compress the tasks that historically justified hiring large cohorts of inexperienced workers. Second, it can help a junior employee produce work that looks more advanced before the employee has developed ownership of the reasoning behind it. The result is not simply an employment problem. It is a capability-formation problem.

The World Economic Forum reported in June 2026 that more than one in three young workers globally are in occupations with medium-to-high exposure to AI-driven task change.[1] Using payroll data covering millions of U.S. workers through June 2026, Stanford Digital Economy Lab researchers found no widespread economy-wide AI displacement, but a growing employment gap for workers aged 22–25 in highly exposed occupations. Employment was about 19% below the path implied by less-exposed peers, with

adjustment appearing primarily through reduced hiring rather than increased separations.[2]

At the same time, entry-level roles are not simply becoming fewer. In some areas they are becoming more demanding. PwC's 2026 Global AI Jobs Barometer, analysing 2.4 million U.S. entry-level job postings, found that highly AI-exposed entry roles were seven times more likely to require skills traditionally associated with more senior workers, such as leadership, creativity and face-to-face interaction. Those "seniorised" entry roles grew while other entry-level roles contracted over the study period.[3] These findings point to a double pressure:

fewer traditional entry tasks + higher expectations for the people who remain.

That is the first-rung problem. AIGW's earlier research note, *The Missing First Rung*, identified three emerging signals from exploratory early-career interviews:

- 1. Task misallocation: organizations may automate work that is developmentally valuable while leaving low-learning administrative work untouched.
- 2. The output–capability gap: AI can help a junior employee produce an artifact faster than the employee develops the ability to explain, defend or modify the underlying reasoning.
- 3. Developmental reciprocity: demanding work can be developmental when it builds capability, ownership and future options; it becomes extractive when responsibility grows without a coherent pathway.

EXECUTIVE SUMMARY

Those signals were based on five structured early-career conversations and one strategic peer conversation. The sample was intentionally treated as exploratory and non-representative. It overrepresented internationally exposed, ambitious and relatively high-agency young people and was not used to make percentage-based claims about Gen Z.[23] Since then, the enterprise evidence has become stronger.

PwC US offers a clear example of the old first rung under compression. AI and automation are moving into research, data preparation, walkthroughs, documentation and other parts of audit work. PwC is simultaneously teaching junior auditors to use AI while placing earlier emphasis on review, professional skepticism and judgment. Its own workforce strategy warns that shrinking the base of the traditional professional-services pyramid too aggressively can damage the pipeline that produces future experts. Reported internal planning also points to a smaller U.S. entry-level Audit and Tax intake, although the change is multi-causal and cannot be attributed to AI alone.[4][5][6][19]

SimplifyNext offers the opposite perspective: a new first rung being built around AI-enabled work from the beginning. Through Singapore's Company-Led Training programme, successful participants become employees, receive salary, follow structured training, work on real projects and receive mentorship. IMDA reported that SimplifyNext had hired close to 50 trainees by January 2026, involved trainees in nearly half of more than 35 AI-powered client projects, and

reported that more than 90% had progressed into some form of project-leading responsibility.[7][8] The contrast is instructive. PwC asks:

How do we preserve capability formation when the old learning tasks disappear?

SimplifyNext asks:

How do we build capability when AI is already part of the job on day one?

This brief argues that the answer is not to preserve every legacy junior task. It is to preserve — and deliberately redesign — the developmental functions those tasks served. A strong first rung in the AI era should do six things: Access → Employment → Capability → Production → Ownership → Progression And it should be supported by three integrated design systems: Work Design → Learning Design → Career Design Work Design determines which tasks should be automated, augmented, protected or redesigned. Learning Design ensures that AI-assisted work still requires workers to verify, explain, judge and eventually modify what they produce. Career Design makes clear what capability is being built, how responsibility increases, and what future opportunities become possible. The core policy proposition is therefore simple:

Do not ask whether junior work should survive. Ask whether the organization still has a reliable system for turning inexperienced people into capable professionals.

That system must be redesigned deliberately.

RECOMMENDATIONS

Key Recommendations

01

Key Recommendations — 1. Redesign from developmental function, not legacy task

Before automating a junior task, identify both:

- the production value of the task; • the learning value of the task. If AI removes the task, replace the learning function intentionally.

02

2. Automate low-learning work first

Prioritize repetitive work that creates little developmental value:

- formatting; • basic reconciliation; • administrative transfer; • routine reporting. Be more careful with tasks that build: • pattern recognition; • domain context; • judgment; • accountability.

03

3. Require verification before independence

A junior worker who can produce with AI but cannot verify, explain or modify the output is not yet independently capable. Use a capability ladder:

Access → Use → Verify → Explain → Judge → Modify Independently

04

4. Give early-career workers real work with bounded responsibility

The alternative to obsolete junior tasks is not observation. Use real projects, clients and production constraints — but with explicit review, escalation and senior accountability.

05

5. Treat mentorship as production infrastructure

If organizations expect juniors to take on higher-context work earlier, senior review capacity must be planned into delivery economics. Mentorship cannot remain an informal extra.

06

6. Connect training to a real destination

Generic AI learning is not workforce transition. A credible pathway should answer:

current role / entry point → capability gap → real work → destination role → next rung.

07

7. Preserve access while roles become more demanding

If entry roles require more senior-like capabilities, employers risk creating an experience trap:

no experience → no job → no way to gain experience.

Design hiring and apprenticeship mechanisms that allow capability to be built inside employment.

08

8. Measure progression, not only entry

The first rung succeeds only if it creates the second rung. Track:

- retention; • promotion; • pay progression; • increasing responsibility; • skill portability.

FIRST-RUNG DESIGN

The First Rung and the Changing Entry Market

01

1. The First Rung Is a System, Not a Job Title

The phrase "entry-level job" can hide what the first rung actually does. A first rung performs at least three institutional functions.

03

It creates capability

It exposes the worker to:

- repetition; • mistakes; • feedback; • expert judgment; • real constraints.

02

It creates access

It gives someone without a long track record a legitimate way into the labor market or profession.

04

It creates progression

It produces evidence that the worker can take on more responsibility. Historically, these functions were bundled inside relatively junior work. A new accountant reconciled and documented. A junior consultant researched and drafted. A support employee solved recurring customer problems. A production inspector repeatedly saw defects. A young technologist completed implementation tasks. The work itself served as a curriculum. AI is beginning to unbundle that system. An organization may no longer need as many people to perform the entry task. But it still needs future:

- reviewers; • managers; • experts; • relationship leaders; • decision-makers. This creates the central institutional tension:

The organization can need less novice labor today while still needing experienced human capability tomorrow.

The first rung is therefore not synonymous with preserving a particular set of manual tasks. It is the system that turns work into capability.

FIRST-RUNG DESIGN

01

2. Why the Problem Is Becoming Urgent

Three evidence streams now point in the same direction, while still leaving substantial uncertainty about magnitude and causality.

03

Entry-level work is becoming more "senior"

PwC's 2026 AI Jobs Barometer finds that highly AI-exposed U.S. entry-level roles are seven times more likely to require traditionally senior human-intensive capabilities.[3] This suggests a shift in role architecture. Employers may expect early-career workers to demonstrate sooner:

- judgment; • leadership; • creativity; • communication; • client-facing ability.

The evidence is based on job postings, not observed workplace performance. It shows what employers are asking for, not what every junior worker actually does.

02

Young-worker hiring is under pressure in highly AI-exposed work

The Stanford Digital Economy Lab's August 2026 revision of *Canaries in the Coal Mine* uses high-frequency ADP payroll data covering millions of U.S. workers.[2] The researchers report:

- no widespread economy-wide employment displacement linked to AI; • a widening employment gap for workers aged 22–25 in highly AI-exposed occupations; • an estimated 19% shortfall relative to the path those workers would have followed had their employment kept pace with similarly aged workers in less-exposed occupations; • adjustment operating primarily through reduced hiring rather than higher separations; • larger declines in occupations where AI use is more substitutive than complementary.

The authors are careful about causal interpretation, and the evidence is U.S.-specific. The result should not be generalized mechanically to every labor market. It does, however, reinforce a critical point:

Entry-level disruption can appear through fewer doors opening, not only through layoffs of people already inside.

04

The majority of exposed jobs are still more likely to transform than disappear

The ILO's 2025 refined global index estimates that one in four workers globally is in an occupation with some degree of GenAI exposure, while emphasizing that continued human input means transformation is more likely than wholesale redundancy for most exposed jobs.[9] This is a useful counterweight to simplistic replacement narratives. But "transformation" is not automatically positive. A transformed job can involve:

- better tools; • fewer openings; • higher expectations; • weaker apprenticeship; • better productivity; • more surveillance; • better career paths; • poorer career paths.

The quality of the transition depends on design.

WORK AND LEARNING

The Three Failure Modes of the Old First Rung

01

3. The Three Failure Modes of the Old First Rung

AIGW's exploratory Missing First Rung research identified three failure modes that remain useful as a diagnostic framework.

02

Failure Mode 1 — Task Misallocation

The problem is not that every junior task should be preserved. Some work is low-learning and low-value. An early-career consultant in AIGW's field research described using AI to process large document sets, support research and accelerate drafting, while a tedious manual task — checking whether files were missing across folders — remained untouched. At the same time, the participant worried that accelerating more developmental work could reduce the repeated exposure through which a junior learns to recognize when something is wrong.[24] The design error is therefore not:

too much automation.

It is:

automating the wrong developmental functions while leaving low-learning friction intact.

03

AIGW Task Decision

AUTOMATE Repetitive work with little perceived learning value. AUGMENT WITH SAFEGUARDS Work where AI creates speed but the employee must still verify and explain. PROTECT OR REDESIGN Experiences that build future judgment, context and accountability. The goal is not to preserve inefficiency. It is to protect learning value.

04

Failure Mode 2 — The Output–Capability Gap

A second participant described building a complex financial model for an enterprise AI platform with substantial AI assistance. The tool helped the worker move rapidly from no prior experience to a usable first version. But when a senior colleague challenged the assumptions and logic, the junior could not fully defend the reasoning.[25] The artifact advanced faster than the capability. This is a new performance-management risk. Organizations can observe:

- faster output; • better formatting; • more complete first drafts. But they may fail to observe whether the worker can: • verify; • explain; • judge; • modify. The output can look senior before the worker is senior.

WORK AND LEARNING

01

Failure Mode 3 — Developmental Reciprocity Breaks

A third participant described an initially valuable stretch role spanning programming, coordination, reporting and stakeholder work. The breadth was developmental because it exposed the worker to much of the project lifecycle. Later, overlapping authority relationships and disconnected assignments turned the role into fragmentation. The worker could no longer see what capability or ownership the work was building and eventually left. [26] This suggests a simple exchange.

effort + adaptability + responsibility

capability + ownership + credible future options

When the second side disappears, responsibility becomes overload rather than development. AI can intensify this risk by allowing organizations to give fewer juniors more output responsibility without necessarily investing in the developmental system around them.

03

Harmful experience compression

The worker skips the experience needed to understand the work. Symptoms include:

- strong output, weak reasoning;
- dependence on AI when conditions change;
- poor error detection;
- shallow domain knowledge.

02

4. AI Can Also Accelerate Learning — If Work Is Designed for It

The first-rung problem should not be interpreted as an argument against giving junior employees AI. There is credible evidence that AI can accelerate capability formation under the right conditions.

In *Generative AI at Work*, Erik Brynjolfsson, Danielle Li and Lindsey Raymond studied the deployment of a generative-AI conversational assistant to 5,179 customer-support agents. Access to the tool increased productivity by 14% on average, with a much larger 34% gain for novice and lower-skilled workers. The authors found suggestive evidence that the system helped disseminate the practices of more capable workers and helped newer workers move down the experience curve faster.[10] This is important because it reveals a different possible future. AI can create: experience compression in two very different senses.

04

Productive Experience Compression and Design Implication

The worker gains expert examples, guidance and feedback earlier. This can speed pattern recognition, increase access to expert practice, lower the cost of questions and expose juniors to higher-quality work. Managers should distinguish faster removal of low-learning friction from compression of learning itself. Use AI as a scaffold that reveals expert reasoning rather than bypassing it. Require workers to compare outputs with sources, identify assumptions, explain answers, propose alternatives, diagnose failures and reconstruct work when context changes.

EMPLOYER EVIDENCE

From Learning Design to Employer Practice

01

AI Reshapes Audit Work

PwC US provides a useful example of what happens when the old first rung begins to lose its production logic. Audit historically relied on a pyramid model. Large cohorts of junior professionals performed relatively structured tasks while developing:

02

The Apprenticeship and Access Problem

- technical fluency; • pattern recognition; • client understanding; • professional skepticism; • confidence in applying standards. AI now enters precisely those workflows. PwC has deployed GenAI and other technologies across: • technical research; • data acquisition; • data preparation; • documentation; • walkthroughs; • evidence validation; • selected audit procedures.[4][5] The firm's ChatNational tool supported more than 17,000 assurance professionals and answered more than 350,000 questions in its first year.[11] PwC's 2025 Audit Quality Report says Audit and Digital Assurance & Technology professionals completed more than 50,000 hours of AI-use training in FY25. The firm also expanded first-year development, small-group training for new reviewers, in-person learning and coaching.[5] The role direction is clear. PwC says entry-level auditors are being taught not only to use AI but to: • think critically; • maintain professional skepticism; • understand broader client needs; • review and supervise AI-supported work.[4]

Reported internal PwC planning adds another tension. Business Insider reported that PwC planned to reduce annual U.S. Tax and Assurance associate hiring from 3,242 in FY25 to 2,197 in FY28, with audit hiring reportedly planned to fall from 1,676 to 1,015. PwC confirmed that campus hiring goals were decreasing, but did not confirm the specific figures. The reported drivers include technology, low attrition and greater use of Acceleration Centers.[19] The evidence does not support:

AI caused a 39% reduction in PwC audit hiring.

It does support:

the entry pathway is becoming smaller at the same time that the role is becoming more demanding.

That is exactly the first-rung challenge.

EMPLOYER EVIDENCE

Building an AI-Native First Rung

01

6. Case Two: SimplifyNext and the Construction of an AI-Native First Rung

SimplifyNext starts from a different position. It does not need to preserve a decades-old apprenticeship architecture. It can design an entry pathway around AI-enabled work from the beginning. Through Singapore's Company-Led Training programme, successful participants enter an employment relationship before training begins. They receive salary, structured on-the-job development, practical project exposure and mentor support. Participating employers are expected to commit real projects and structured career progression. [7] By January 2026, IMDA reported that SimplifyNext had: • hired close to 50 trainees; • delivered more than 35 AI-powered client projects; • involved CLT trainees in nearly half of those projects; • reported more than 90% of trainees progressing into some form of project-leading responsibility.[8] The exact meaning of "leading" is not publicly defined. It should not be translated into: 90% became project managers. But the evidence is still valuable because it shows movement beyond classroom participation.

02

The architecture of the pathway

The SimplifyNext model can be summarized as: employment → structured learning → mentored production work → increasing responsibility Current graduate roles show what that first rung contains. The AI Engineer (Graduate) role includes:

- model development; • LLM/RAG/agenic work; • data preparation; • solution architecture participation; • integration; • testing; • deployment; • client/domain collaboration.[12] The Technology Analyst (Graduate) role includes: • client problem analysis; • requirements gathering; • solution design; • implementation; • user-acceptance testing; • rollout; • post-implementation support.[13] The role is not built around low difficulty. It is built around bounded responsibility. The entrant participates in meaningful work, while experienced data scientists, architects and other practitioners provide the support layer.[8]

03

The key institutional difference

A conventional skills programme says:

learn first → compete for work later.

A demand-backed apprenticeship says:

real employer demand → employment → learning → work → increasing ownership.

This shifts part of the capability-formation risk from the worker to the employer. It also gives the employer a stronger incentive to make training relevant because the employee is already part of the delivery system.

EMPLOYER EVIDENCE

01

7. The Core Principle: Preserve Developmental Functions, Not Legacy Tasks

The debate is often framed as a false choice. Either: preserve junior tasks to protect learning or: automate them to improve productivity. A better question is: What developmental function did this task serve, and how will that function survive after automation? Consider four examples.

03

Example 2 — Audit documentation

Legacy task:

- create first-pass documentation manually. Possible learning value: • learn audit logic; • understand evidence chains; • learn what must be documented.
- AI redesign: • AI drafts; • junior reconstructs rationale; • junior identifies unsupported assertions; • senior reviews the reasoning.

05

Example 4 — Data preparation

Legacy task:

- clean and transform data manually. Possible learning value: • learn data quality problems; • understand assumptions; • see how upstream data affects models.
- AI redesign: • automation handles repetitive transformation; • junior inspects anomalies; • junior documents assumptions; • junior traces model failures back to data.

02

Example 1 — Technical research

Legacy task:

- manually search standards and guidance. Possible learning value: • vocabulary; • source familiarity; • pattern recognition; • understanding exceptions.
- AI redesign: • AI retrieves and synthesizes; • junior verifies source authority; • junior explains applicability; • junior defends the conclusion.

04

Example 3 — Customer support

Legacy task:

- answer recurring customer questions. Possible learning value: • product knowledge; • customer pattern recognition; • exception familiarity.
- AI redesign: • AI handles routine demand; • junior reviews escalations; • junior studies failure cases; • junior contributes to knowledge and AI evaluation.

06

The design rule

The organization should be able to state:

This task is being automated, and this is the mechanism that will replace the learning previously embedded in it.

If it cannot, the productivity programme is accumulating learning debt.

DESIGN SYSTEMS

The Three Design Systems

FIGURE 1

AIGW analytical framework

Four task-design responses

Work type	Default design response	Why
Low-learning / repetitive	Automate	Remove friction without sacrificing meaningful learning [4] [5] [10]
High-volume but diagnostic	Augment	Let AI accelerate while workers inspect patterns and errors [5] [10]
Developmentally important	Protect or redesign	Preserve exposure to judgment, context and accountability [20] [23]
High-stakes / consequential	Human-led with explicit controls	Capability and accountability matter more than raw speed [5] [20]

Source: AIGW synthesis, informed by [\[1\]](#) [\[4\]](#) [\[5\]](#) [\[10\]](#) [\[20\]](#) [\[23\]](#)

Note: Decision defaults from AIGW synthesis; the framework is not a measured ranking.

ROLE ARCHITECTURE

Six-Stage First-Rung Architecture

FIGURE 2

AIGW analytical framework

From access to progression

Stage	Design question	Signals, mechanisms or risk
Stage 1 — Access	Can a person without years of experience get in?	Mechanisms: ; graduate hiring; • apprenticeships; • structured career conversion; • internships; • applied challenges; • skills-based hiring. Failure mode: ; roles become "entry level" in title but require prior professional experience. [1] [7] [21]
Stage 2 — Employment	Is there actual labor demand behind the training?	Strong signal: ; paid employment; • defined role; • clear contract status. Weak signal: • course completion with no employment destination. [7] [8] [12] [13]
Stage 3 — Capability	What must the person be able to do?	Move beyond generic AI literacy toward;; domain knowledge; • AI use; • verification; • communication; • judgment; • workflow understanding. [5] [8] [10]
Stage 4 — Production	Does the worker encounter real constraints?	Useful exposure includes;; real projects; • production systems; • clients; • data quality; • deadlines; • integration; • post-deployment problems. [8] [12] [13]
Stage 5 — Ownership	Does responsibility increase?	Possible progression: observe → contribute → own bounded task → own workstream → lead project → mentor others This stage should be calibrated to capability. [5] [6] [8]
Stage 6 — Progression	Does the first rung create the second rung?	Measure;; retention; • promotion; • pay growth; • responsibility; • mobility; • skill portability. [7] [8] [14] [15]

Source: AIGW synthesis, informed by [\[1\]](#) [\[7\]](#) [\[8\]](#) [\[20\]](#) [\[21\]](#)

Note: AIGW analytical framework; stages describe design functions, not quantified outcomes.

CAPABILITY

The Capability Ladder

FIGURE 3

AIGW analytical framework

From AI access to independent judgment

Level	Expected capability
1. ACCESS	Can the employee access an appropriate AI tool? This is the lowest threshold. It says little about professional capability. [10] [12] [13]
2. USE	Can the employee produce something useful with it? Examples:; prepare a first-pass memo; • generate code; • summarize research; • build a first-pass model. Many performance systems stop here because the output is visible. [10] [12] [13]
3. VERIFY	Can the employee identify:; unsupported claims; • wrong assumptions; • missing evidence; • model failure; • inappropriate use? Verification marks the beginning of real professional control. [5] [10] [20]
4. EXPLAIN	Can the employee explain:; why the output is correct; • what assumptions drive it; • what sources matter; • where uncertainty remains? A worker who cannot explain the reasoning does not yet own the work. [5] [6] [8]
5. JUDGE	Can the employee decide:; whether the output is appropriate; • whether more evidence is needed; • when not to use the AI; • when to escalate? Judgment requires both domain knowledge and context. [3] [5] [6]
6. MODIFY INDEPENDENTLY	Can the employee revise or rebuild the work when:; the situation changes; • the model fails; • the assumptions no longer hold? This is a stronger test of transferable capability than producing a polished artifact once. [12] [13] [20]

Source: AIGW synthesis, informed by [\[3\]](#) [\[5\]](#) [\[6\]](#) [\[8\]](#) [\[10\]](#) [\[20\]](#)

SYSTEMS INTO PRACTICE

Putting the First-Rung Systems into Practice

01

Work Design and Learning Design

8. The Three Design Systems. A first rung cannot be rebuilt by L&D alone. It requires three connected systems. System 1 — Work Design. Work Design answers: Which tasks should be automated, AI-assisted, preserved or redesigned? A useful four-way classification is: The crucial change is to add learning value to automation assessment. Traditional automation cases often ask: • cost; • time; • quality; • volume. The redesigned business case should also ask: What capability disappears if humans stop doing this? System 2 — Learning Design. Learning Design answers: How does the worker move from AI user to independent professional? The learning system should include: • explanation; • verification; • feedback; • reflection; • supervised practice; • increasing autonomy. The goal is not to force the junior to reproduce work AI can already do efficiently. The goal is to ensure the worker understands enough to challenge and redirect the AI.

02

Career Design and Progression

System 3 — Career Design. Career Design answers: What future capability and opportunity is this work building? A good entry role should make clear: • what skill is being built; • how responsibility grows; • how progress is evaluated; • what next role becomes possible; • whether the capability is portable. The young worker needs to see a relationship between today's effort and tomorrow's option set. Integrated proposition. AI-era productivity becomes sustainable only when Work Design, Learning Design and Career Design are rebuilt together.

CAPABILITY AND MANAGEMENT

Capability and Guided Autonomy

01

The Six-Stage Worker Journey

The worker journey can be represented as six stages.
Access → Employment → Capability → Production → Ownership → Progression

Each stage solves a different failure mode.

Many programmes stop at Stage 3. They create trained people. Employers need Stage 4 and Stage 5. Workers need Stage 6. A functioning first rung requires the complete chain.

02

Evaluating Independent Judgment

One of the biggest risks in AI-enabled early-career work is confusing tool access with professional capability. AIGW proposes a six-stage capability ladder.

Automate the low-learning task. Interrogate the high-stakes output.

Organizations should deliberately evaluate workers above the line between USE and VERIFY. That is where capability becomes more than assisted production.

This is an AIGW analytical framework, not a proficiency rate or timed curriculum.

03

Guided Autonomy: Bounded Responsibility

11. Guided Autonomy: The Missing Operating Model for Early Responsibility. If entry-level roles are becoming more demanding, organizations face a design problem. They can respond in two bad ways. Bad response A — protect juniors from meaningful work. The employee watches, completes administrative tasks and waits. This preserves safety but slows capability formation.

Bad response B — hand over responsibility too quickly. The employee receives consequential work because AI makes execution easier, but lacks the experience to recognize failure. This increases operational risk. The better model is guided autonomy. Guided autonomy means: • real work; • bounded scope; • explicit review; • clear escalation; • feedback; • gradually increasing independence. SimplifyNext's model provides a useful example: trainees contribute to real AI and automation projects under in-house data scientists and AI architects.[8] PwC's strengthened reviewer training and apprenticeship architecture point in the same direction from a different sector.[5]

04

Mentorship as Production Infrastructure

Why mentorship becomes infrastructure. Traditional apprenticeship could rely heavily on ambient learning. The junior sat near experienced workers, performed repeated tasks and absorbed standards over time. AI can reduce that ambient learning. Mentoring therefore becomes more deliberate. Organizations need to budget for: • reviewer time; • coaching; • structured debriefs; • model-error discussions; • scenario practice; • feedback loops. This is not soft culture work. It is part of the production cost of an AI-enabled workforce. AIGW management test. For every early-career AI-enabled assignment, leaders should be able to answer: • Who reviews the work? • What can the junior decide independently? • What requires escalation? • What capability should be stronger at the end? If those answers are unclear, the assignment is not yet designed as developmental work.

EMPLOYER PATHWAYS

Transition Evidence Across Cases

01

Salesforce and DBS: Design the Destination

12. What the Wider Case Library Adds. PwC and SimplifyNext are the central paired cases, but the wider AIGW Case Library adds several lessons about what happens after the first rung.

Salesforce — mobility works better when destination roles are real. Salesforce reported hundreds of support engineers redeployed into roles including Success, Renewals and Forward Deployed Engineering as Agentforce changed customer-support work.[14] The lesson for early-career design is not simply that workers can be reskilled. It is that transition becomes credible when the organization can name: • the destination role; • the retained expertise; • the new capability gap. A first rung should be built with that same clarity. DBS — define future roles before training. DBS says units where AI is expected to materially change job roles assess the impact on existing job functions, identify affected roles and define new or enhanced roles before deeper reskilling is designed.[15] This sequencing matters. It reverses a common mistake: train broadly → hope skills become useful. A better sequence is: future work → future role → capability gap → learning pathway.

02

LONGi and JD.com: Domain Expertise as Transition Capital

LONGi — old domain expertise can become AI expertise. Xinhua documented a LONGi quality inspector moving into an AI-trainer role as machine vision automated more visual inspection.[16] The retained asset was production knowledge. The case suggests that young workers still need opportunities to accumulate domain expertise even when AI performs more execution. If no one learns the domain deeply, future AI trainers, verifiers and process improvers have no expertise to draw on.

JD.com — the destination role can move again. JD documented an experienced customer-service worker moving into an AI-trainer role and later reported thousands of job transformations or upgrades around the service system.[17][18] But JD's current AI-service products are themselves automating parts of knowledge-base configuration. This produces a warning for first-rung design: do not train people only for the next routine AI task. Build capabilities that become more valuable as the technology advances: • judgment; • error analysis; • domain expertise; • workflow design; • evaluation; • governance.

QUALITY TEST

The First-Rung Quality Test

FIGURE 4

AIGW analytical framework

Six tests of a credible first rung

Test	Core question	Evidence of quality	Failure signal
Demand	Is there a real job?	actual hiring, defined role, business demand	course with no destination [1] [7] [8] [20] [21]
Work	Does the entrant do real work?	production/client exposure, meaningful constraints	observation-only role [1] [7] [8] [20] [21]
Support	Can the entrant learn safely?	mentors, review, escalation, structured learning	unsupported responsibility [1] [7] [8] [20] [21]
Ownership	Does responsibility increase?	bounded task ownership, workstream leadership	endless junior assistance [1] [7] [8] [20] [21]
Progression	Is there a second rung?	promotion, pay growth, advanced role	temporary trainee plateau [1] [7] [8] [20] [21]
Portability	Will the capability travel?	recognized skills, external mobility, durable expertise	firm-specific dependency [1] [7] [8] [20] [21]

Source: AIGW synthesis, informed by [\[1\]](#) [\[7\]](#) [\[8\]](#) [\[20\]](#) [\[21\]](#)

Note: AIGW proposed diagnostic; not a validated score or outcome measure.

Interpretation

AIGW's six tests ask more than how many people completed a programme. High completion can coexist with weak career outcomes. A strong first rung creates:

productive workers, stronger future capability and credible options.

IMPLEMENTATION

14. A 90-Day Employer Playbook

A focused 90-day pilot can redesign one role family without waiting for organization-wide transformation.

Days 1–30 — Map the developmental system

Choose an early-career role with meaningful AI exposure. Map its tasks, time use, AI use, error rates, learning value and progression path. Interview juniors, managers, recent promotees and senior experts: Which tasks taught you most? Which wasted time? Which experiences made you trustworthy?

Days 46–60 — Define the capability ladder

Define what a worker should do after 30 days, 90 days, six months and 12 months. Specify verification, explanation, judgment and independent modification; do not measure progression by output volume alone.

Days 76–90 — Connect to the next rung

Define what success unlocks, the next role or workstream, possible pay/grade progression and portable capability. Communicate the pathway. Success means one redesigned role where AI removes low-learning friction, workers gain production exposure, capability is measured beyond tool use, and progression is explicit.

Days 31–45 — Make the task decisions

Classify major tasks: automate; augment with safeguards; protect or redesign. For each task moved to AI, record the learning function removed and design a replacement where needed.

Days 61–75 — Build guided autonomy

Assign real work with bounded responsibility, an explicit mentor, review checkpoint, escalation rule and reflection. The junior owns meaningful work; the senior owns the risk while the junior is learning.

MEASUREMENT

The Measurement Dashboard

FIGURE 5

AIGW analytical framework

Indicators across six transition layers

Layer	Suggested measures
Layer 1 — Access	Track:; applicants; • offer rate; • acceptance; • prior-experience requirement; • demographic reach; • non-traditional entrants. [4] [5] [7] [8] [14] [15] [20]
Layer 2 — Employment	Track:; actual hires; • contract type; • salary; • time to start; • role family. [4] [5] [7] [8] [14] [15] [20]
Layer 3 — Learning	Track:; structured training; • mentor contact; • assessed capability; • verification quality; • ability to explain reasoning. [4] [5] [7] [8] [14] [15] [20]
Layer 4 — Production	Track:; real projects; • client exposure; • production deployments; • complexity; • error/rework; • review burden. [4] [5] [7] [8] [14] [15] [20]
Layer 5 — Ownership	Track:; bounded tasks owned; • workstreams led; • decisions made; • escalation frequency; • supervisor confidence. [4] [5] [7] [8] [14] [15] [20]
Layer 6 — Progression	Track:; 12-month retention; • 24-month retention; • promotion; • pay growth; • internal mobility; • external portability. [4] [5] [7] [8] [14] [15] [20]

Source: AIGW synthesis, informed by [\[4\]](#) [\[5\]](#) [\[7\]](#) [\[8\]](#) [\[14\]](#) [\[15\]](#) [\[20\]](#)

Note: Proposed indicators; the brief does not report values for these measures.

INSTITUTIONAL DESIGN

Public Policy, Education and Shared Responsibility

01

16. The Role of Public Policy: Build the Infrastructure Around the Rung

Employers cannot solve the early-career transition alone. The strongest institutional models reduce coordination failure between: • workers seeking experience; • employers seeking capability; • educators providing foundations; • governments funding transition; • skill systems defining what competence means.

02

Quality apprenticeship principles still matter in an AI economy

The International Labour Organization's Quality Apprenticeships Recommendation, 2023 (No. 208), defines apprenticeship around structured and remunerated or otherwise financially compensated learning that combines on-the-job and off-the-job development and leads toward recognized competence or qualification.[20] The recommendation also emphasizes:

- regulation; • inclusion; • adequate remuneration; • social protection; • qualified supervision; • involvement of employers and workers' organizations; • alignment with current and future skill demand.[20] These principles remain highly relevant even when the occupation is new and AI-enabled. The technology may be novel. The institutional question is familiar:

How do we make learning at work productive for the employer without making the learner disposable?

03

Policy should subsidize capability formation, not training volume

A poorly designed subsidy can reward:

- course seats; • completion certificates; • short-term enrollment. A stronger policy can reward: • actual employment; • mentor commitment; • real project exposure; • assessed capability; • retention; • progression. Singapore's CLT model is useful because employer participation is tied to real roles, employment and structured workplace learning.[7]

04

Policy needs to watch access

If AI-exposed entry roles demand more senior-like capabilities, the first-rung crisis can become an inequality problem. Candidates with:

- strong universities; • unpaid project time; • AI tool access; • professional networks; • prior internships; may be better positioned to satisfy the new expectations. Public policy should therefore track who is excluded before hiring, not only outcomes for those who enter programmes.

INSTITUTIONAL DESIGN

01

Portability matters

A new AI role can be valuable inside one company but weak in the broader labor market. Public skills frameworks and recognized credentials can help workers carry capability across employers. This becomes more important as AI roles themselves change quickly.

03

Bridge 1 — Foundation → application

Students should understand:

- domain fundamentals; • analytical reasoning; • data;
- AI limitations; before being evaluated only on tool fluency.

05

Bridge 3 — Output → defense

Assessment should increasingly require students to:

- explain assumptions; • cite evidence; • defend decisions; • identify AI contributions; • revise when challenged. A polished output should not be enough.

07

A university design rule

Do not try to make students look experienced. Give them structured opportunities to become experienced.

02

17. The Role of Universities: Move from Exposure to Evidence of Capability

Universities do not need to reproduce the workplace. They do need to reduce the gap between academic learning and evidence of real capability. OECD research on internships emphasizes the value of supervised tasks in authentic workplaces for career development and school-to-work transition, while also stressing the importance of quality design.[21] In the AI era, universities can strengthen four bridges.

04

Bridge 2 — Classroom → authentic problem

Use:

- real datasets; • real institutional constraints; • external mentors; • ambiguous problems. The objective is not to simulate employment perfectly. It is to expose students to the fact that professional problems are rarely clean prompts.

06

Bridge 4 — Course → opportunity

Create credible transitions into:

- internships; • apprenticeships; • employer projects; • graduate roles. SimplifyNext's university hackathon-to-internship example is small but useful because it demonstrates how applied evidence can create a bridge into work.[22]

ACCOUNTABILITY

The First-Rung Compact

A sustainable first rung is a reciprocal institutional arrangement.

01

The early-career worker contributes

- effort; • curiosity; • adaptability; • responsibility; • willingness to learn; • accountability for using AI well.

02

The employer contributes

- access; • paid work; • meaningful tasks; • mentorship; • feedback; • increasing ownership; • a credible future path.

03

The education system contributes

- fundamentals; • reasoning; • domain foundations; • authentic practice; • evidence of capability.

04

The public system contributes

- skill standards; • co-funding where justified; • portability; • labor-market information; • protections; • quality assurance. This compact is useful because it reframes the early-career problem. The worker is not asking the employer to preserve obsolete work. The employer is not promising a lifetime job. The exchange is:

real contribution in return for real capability formation and credible opportunity.

That is developmental reciprocity at institutional scale.

05

Learning integrity

Ask periodically:

Can the worker perform the reasoning when the AI output is wrong?

This protects against a workforce that looks productive but becomes progressively less capable of independent judgment.

ACCOUNTABILITY

Failure Modes to Avoid

A redesign programme can sound progressive while recreating old problems in new language.

01

Failure Mode 1 — AI course without a job

The organization offers learning but no destination. Result: skills supply without demand.

02

Failure Mode 2 — Senior expectations without apprenticeship

Entry roles require judgment, client readiness and leadership, but the organization removes the experiences through which those capabilities are built. Result: experience trap.

03

Failure Mode 3 — Faster output mistaken for faster development

AI-assisted juniors produce polished work, and managers infer competence. Result: output–capability gap.

04

Failure Mode 4 — Real work without safe boundaries

Juniors are placed into consequential work with inadequate review. Result: accelerated responsibility without guided autonomy.

05

Failure Mode 5 — Mentorship without capacity

Senior staff are told to mentor but are still measured entirely on delivery. Result: mentoring becomes optional and disappears under pressure.

06

Failure Mode 6 — Project participation without progression

Young workers collect projects but remain permanently in support roles. Result: experience without ownership.

07

Failure Mode 7 — AI role as temporary safe harbor

Workers are reskilled into a new role whose routine tasks are themselves rapidly automated. Result: repeated displacement.

08

Failure Mode 8 — High-quality programme, narrow access

The pathway works for people who get in, but selection heavily favors already advantaged candidates. Result: capability development without mobility.

EVIDENCE BOUNDARIES

Failure Modes and Evidence Boundaries

01

Failure Mode 9 — Employer-specific competence

Workers become highly effective inside one stack but acquire little portable capability. Result: dependence without resilience.

02

Failure Mode 10 — Preservation for preservation's sake

Organizations retain low-value manual work only because it is traditional. Result: inefficient apprenticeship instead of redesigned apprenticeship. The goal is not nostalgia. It is capability.

03

The evidence establishes that:

- AI is materially changing entry-level task composition in professional and service work.
- young-worker hiring pressure is visible in some highly AI-exposed U.S. occupations, although there is no evidence of broad economy-wide AI displacement at present.[2]
- employers are asking for more traditionally senior human capabilities in many highly AI-exposed entry roles.[3]
- AI can improve novice productivity and may accelerate access to expert practice under some conditions.[10]
- traditional apprenticeship models can be weakened when routine developmental work is compressed.
- PwC is explicitly redesigning junior audit capability and strengthening apprenticeship as AI enters the workflow.[4][5]
- employment-based AI pathways can combine hiring, structured learning, real projects and increasing responsibility, as illustrated by SimplifyNext.[7][8]
- domain expertise can remain valuable after task automation and can support movement into AI-enabled roles, as shown across Salesforce, LONGi and JD.[14][16][17]
- defining future roles before designing training can strengthen workforce transition, as shown by DBS.[15]
- quality apprenticeship principles — employment connection, supervision, remuneration, structured learning and progression — remain relevant to emerging AI work.[20]

04

21. What the Evidence Does Not Establish

The combined evidence supports several conclusions.

21. What the Evidence Does Not Establish. The evidence does not establish that:.

- AI is the primary cause of all current weakness in graduate hiring;
- entry-level jobs are disappearing economy-wide;
- every AI-exposed occupation will require fewer young workers;
- AI-assisted early responsibility automatically produces faster professional development;
- preserving junior work is always the correct response;
- eliminating routine work is always harmful to learning;
- employer-led training guarantees long-term retention or wage growth;
- SimplifyNext's pathway is representative of Singapore employers or scalable to all sectors;
- PwC's future hiring plans will necessarily be realized;
- the reported PwC hiring change is caused by AI alone;
- AI reskilling guarantees better jobs;
- a worker who enters an AI-labeled role has reached a durable career destination;
- AIGW's exploratory interview evidence is representative of Gen Z. The brief therefore proposes a design framework, not a universal forecast.

RESEARCH AGENDA

Research Agenda and the AIGW Framework

01

22. Research Agenda

22. Research Agenda. The next stage of first-rung research should move from problem diagnosis to longitudinal worker outcomes. The highest-priority questions are: Access. • How are entry-level vacancy numbers changing by occupation and sector? • Which roles are reducing hiring rather than reducing incumbents? • Are prior-experience requirements increasing? • Which groups lose access first? Work Design. • Which junior tasks are being automated? • Which are being augmented? • Which tasks have high learning value despite low short-term productivity value? • What replacement learning mechanisms are used? Capability. • Can AI-enabled juniors verify and explain work at the same level as previous cohorts? • Does AI accelerate or weaken domain learning? • Which forms of AI assistance improve novice learning most?

Mentorship. • How much senior time is required in AI-native apprenticeship models? • Does review burden fall or rise when juniors use AI? • Which feedback practices best develop independent judgment? Progression. • Are early-career workers promoted faster or more slowly? • Are pay and responsibility increasing together? • Do AI-native apprenticeships produce durable second and third rungs? Portability. • Which capabilities remain valuable across employers? • Which new AI roles are temporary transition jobs? • How do occupational standards need to evolve? Worker experience. • Do young employees experience redesigned work as more developmental or more stressful? • Do they have meaningful choice over AI use and work allocation? • When does stretch responsibility become overload? Distribution. • Who gets access to the redesigned first rung? • Who bears the cost of capability formation? • Are employers using AI to widen opportunity or narrow selection?

02

23. AIGW's First-Rung Design Framework

23. AIGW's First-Rung Design Framework. The policy brief can be reduced to one integrated model. Three design systems. WORK DESIGN Automate · Augment · Protect · Redesign LEARNING DESIGN Access · Use · Verify · Explain · Judge · Modify CAREER DESIGN Access · Employment · Production · Ownership · Progression · Portability One operating principle. Do not preserve the old task. Preserve the developmental function. One management question. After completing this assignment, what will the employee be capable of doing that they could not do before? One institutional test. Does this first rung create a credible second rung? If the answer to the final question is no, the organization has not rebuilt the pathway. It has only redesigned the work.

CONCLUSION

Conclusion

01

Conclusion

Conclusion. The early-career problem created by AI is often described as a shortage of jobs. That is part of the story. The deeper problem is a shortage of developmental architecture. For decades, many organizations could rely on the work itself to train the worker. Junior employees performed repetitive tasks, saw hundreds of examples, received correction and gradually accumulated judgment. AI changes that process. It can remove low-value friction. It can make beginners more productive. It can expose workers to expert practice faster. But it can also remove the experiences that created expertise, make outputs look more mature than the people producing them, and raise entry expectations faster than institutions redesign learning. The response should not be to freeze the old apprenticeship in place. Nor should it be to assume that an AI course is a substitute for work experience. The task is more demanding: rebuild the mechanism that turns inexperienced people into capable professionals. PwC shows why the old mechanism is under pressure. SimplifyNext shows one possible architecture for the new one. The strongest model combines: real access with real employment with structured capability building with real production work with guided ownership with credible progression. That is the first rung the AI economy needs. It is not a protected collection of junior tasks. It is an institutional promise that productive work will still create future capability.

SOURCES

Method and Evidence Boundaries

This Policy Brief combines four evidence layers.

01

1. AIGW exploratory field evidence

The original Missing First Rung research note was informed by five structured conversations with early-career professionals and one additional strategic peer conversation used to challenge the framing and identify possible sample bias.[23] The sample was exploratory and non-representative. It overrepresented internationally exposed, ambitious and relatively high-agency participants. AIGW does not use those interviews to make percentage claims about Gen Z. The three anonymized cases used here are coded an anonymized participant, an anonymized participant and an anonymized participant.

03

3. External empirical research

Stanford Digital Economy Lab and NBER research provide empirical evidence on employment and worker productivity/learning. The studies have specific populations and contexts and are not generalized beyond what their methods support.

05

Causal discipline

The brief does not infer:

- job loss from task automation;
- capability from training attendance;
- promotion from project participation;
- AI causality from a coincident hiring decline.

Where sources are forward-looking, company-attributed or incomplete, those boundaries are stated explicitly.

02

2. Enterprise case evidence

PwC and SimplifyNext are the primary paired cases. Salesforce, DBS, LONGi and JD provide supporting transition mechanisms from the wider AIGW Case Library. Company-reported evidence is treated as first-party evidence, not independent validation.

04

4. Institutional and policy benchmarks

WEF, ILO, IMDA and OECD materials provide frameworks and institutional context. They are not used to prove enterprise-specific outcomes.

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Notes and References

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Supports: more than one in three young workers globally in occupations with medium/high AI-driven task exposure; framework covering job access, job design, talent pipelines and education-system alignment.
<https://www.weforum.org/publications/artificial-intelligence-and-the-future-of-entry-level-work-a-framework-for-safeguarding-and-reinventing-early-career-pathways>
2. Stanford Digital Economy Lab. *Canaries in the Coal Mine? Six Facts about the Recent Employment Effects of Artificial Intelligence*. Revision: 12 August 2026. Working paper using high-frequency ADP payroll data Authors: Erik Brynjolfsson, Bharat Chandar, Ruyu Chen..
Supports: no widespread economy-wide AI displacement; 22–25-year-old employment gap in highly AI-exposed occupations; 19% shortfall relative to less-exposed-peer trend; reduced hiring as the primary adjustment mechanism; difference between more substitutive and complementary AI use.
Boundary: U.S.-specific evidence; causal interpretation remains subject to research uncertainty.
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Supports: fresh-graduate role spanning model development, LLM/RAG/agent workflows, data preparation, validation, deployment and client/domain collaboration.
<https://job-boards.greenhouse.io/simplifynext/jobs/4996764007>
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Supports: fresh-graduate role spanning client problem analysis, requirements, solution design, implementation, UAT, rollout and post-implementation support.
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