

# The Impact of Generative AI on Knowledge Workers' Skills, Productivity and Career Development

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## Abstract

Generative AI raises the productivity of knowledge workers, most for those with the least skill, and this compression of performance differences has been widely reported. Less attention has been paid to what happens to the underlying skills of workers who rely on the tools, and to the careers that depend on those skills. This paper develops a dynamic model in which generative AI lifts output in proportion to the gap between a worker's skill and the frontier, while its effect on skill development depends on how the worker uses it: novices who substitute the tool for practice develop skill more slowly, experts who use it to extend their reach develop faster. A simulation over eight years for novice, intermediate and expert workers shows that novices gain 93% in productivity in year one but only 36% by year eight, and end with lower underlying skill (0.42) than novices without the tool (0.50); intermediates gain 27% falling to 20% with slightly higher skill; experts gain 4% with slightly higher skill. Because career progression depends on skill rather than on tool-assisted output, novices face a career penalty masked by their productivity. The paper draws implications for individual workers, for organisations designing roles and development, and for the structure of knowledge-work careers in which the apprenticeship stage is eroded.

**Keywords:** Generative AI; knowledge workers; skill development; productivity; career development; deskilling.

## Introduction

Field experiments on generative AI in writing, customer support, programming and consulting report large productivity gains and a consistent pattern: workers with the lowest prior performance gain most, and the distribution of output compresses [1-3]. The findings have been read as good news for inclusion and for organisations seeking to raise average performance. They leave a question unanswered. Productivity with the tool is not the same as skill without it, and knowledge-work careers advance on the basis of judgement, expertise and reputation that are built through practice. If generative AI substitutes for the practice through which novices become experts, then the workers who gain most in the short run may lose most in the long run.

The concern has precedent. Automation research has long identified deskilling, in which tools that perform a task remove the opportunity to learn it, and the irony that automation leaves humans responsible

for what the automation cannot do while depriving them of the practice to do it [4]. Generative AI differs from earlier automation in being general, in producing outputs that require judgement to evaluate, and in being used most heavily by those least able to evaluate it.

This paper models the dynamics. Productivity and skill are treated as distinct state variables, generative AI affects each differently depending on the worker's starting skill and usage pattern, and career progression depends on skill. The simulation traces the trajectories over eight years and the paper derives implications for workers, organisations and the structure of careers.

## Background

### Productivity evidence

Brynjolfsson, Li and Raymond [1] found that a generative AI assistant raised customer-support productivity by 14% on average and by 34% for the least experienced agents. Noy and Zhang [2] found

similar compression in writing tasks. Dell'Acqua et al. [3] found large gains for consultants on tasks within the tool's capability and losses on tasks beyond it. The compression pattern is robust across these settings.

### Skill development

Expertise develops through deliberate practice with feedback [5]. Knowledge-work careers institutionalise this through apprenticeship-like stages in which juniors perform routine tasks under supervision, receive correction and progressively take on judgement. Tasks that generative AI performs well are disproportionately the routine tasks of these early stages.

### Deskilling and augmentation

Bainbridge's ironies of automation [4] describe how automated systems erode the skills operators need when the automation fails. Augmentation research argues that tools can instead extend skill if used to attempt harder tasks with the tool's support [6]. Which outcome occurs depends on the usage pattern, which depends on the worker's ability to evaluate the tool's output, which depends on skill.

### Why the usage pattern depends on skill

The asymmetry at the centre of the model, that the same tool erodes novice skill and extends expert skill, follows from the evaluation problem. Generative AI produces plausible output whose errors are visible only to those who could have produced the output themselves. An expert can see where the output falls short, correct it and in doing so attempt tasks at the edge of their competence; the tool becomes a collaborator whose failures are instructive. A novice cannot evaluate the output reliably, accepts it, and loses both the practice of producing it and the feedback of having it corrected; the tool becomes a substitute whose successes teach nothing. The pattern is not a matter of motivation but of capability: using the tool for extension requires the skill the novice is trying to acquire.

### Two timescales

The productivity studies measure effects over weeks or months, on tasks the tool performs well. Skill development operates over years and is revealed

on tasks the tool performs badly. A finding of large short-run productivity gains for novices is therefore compatible with a long-run skill deficit, and the two can be observed only by following workers over time and assessing them without the tool. The model is built to represent both timescales.

## Model

Worker  $w$  has skill  $s_t \in [0, 1]$  in year  $t$ . Productivity with generative AI is

$$p_t^{\text{AI}} = s_t + 0.4(1 - s_t), p_t^{\text{no}} = s_t, \quad (1)$$

so that the tool closes 40% of the gap to the frontier. Skill evolves as

$$s_{t+1} = s_t + 0.04(1 - s_t) \times \lambda(s_0), \quad (2)$$

where  $\lambda = 1$  without the tool, 0.6 with the tool for workers starting below 0.5 (substitution for practice) and 1.4 for workers starting above 0.5 (extension of reach). Career progression is a function of skill. Hypotheses: H1, productivity gains are largest for novices and decline over time as skill converges; H2, novices using the tool develop skill more slowly than novices without it; H3, experts using the tool develop skill faster; H4, novices' career progression lags despite their productivity gain.

### Simulation Design

Three workers with initial skill 0.3 (novice), 0.6 (intermediate) and 0.9 (expert) are simulated over eight years with and without the tool. Productivity gain, skill at year eight and the gap between tool and no-tool skill are reported. The parameters are design values encoding the substitution–extension asymmetry; the harness traces its consequences over a career-relevant horizon.

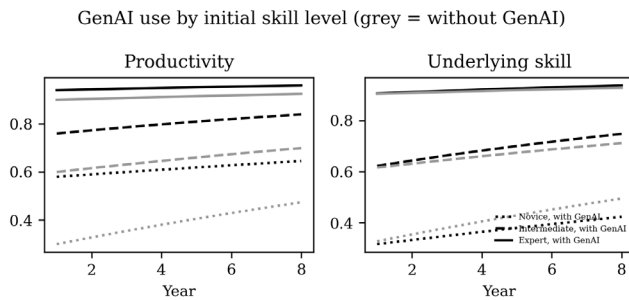
## Results

### Productivity and skill trajectories

Table 1 and Figure 1 report the trajectories. In year one, the tool raises productivity by 93% for the novice, 27% for the intermediate and 4% for the expert (H1), reproducing the compression pattern. By year eight, the novice's gain has fallen to 36%, because the gain is proportional to the skill gap and

**Table 1:** Productivity gain and skill at year eight by initial skill level, with and without generative AI (eight-year simulation)

| <i>Initial skill</i> | <i>Productivity gain, year 1</i> | <i>Productivity gain, year 8</i> | <i>Skill at year 8, with AI</i> | <i>Skill at year 8, without AI</i> |
|----------------------|----------------------------------|----------------------------------|---------------------------------|------------------------------------|
| Novice (0.3)         | +93%                             | +36%                             | 0.42                            | 0.50                               |
| Intermediate (0.6)   | +27%                             | +20%                             | 0.75                            | 0.71                               |
| Expert (0.9)         | +4%                              | +4%                              | 0.94                            | 0.93                               |

**Figure 1:** Productivity (left) and underlying skill (right) over eight years by initial skill level, with generative AI (black) and without (grey)

the no-tool novice has been closing that gap through practice. The novice's underlying skill at year eight is 0.42 with the tool against 0.50 without (H2): the tool-using novice is more productive than the practising novice throughout, yet less skilled at the end. The intermediate's skill is 0.75 with the tool against 0.71 without, and the expert's 0.94 against 0.93 (H3).

### The career penalty

If promotion depends on skill, the tool-using novice reaches any given skill threshold later than the practising novice: the 0.08 skill gap at year eight corresponds to roughly two years of development at the novice's practice rate. The penalty is masked, because the tool-using novice's output is higher throughout, and it becomes visible only when the worker is assessed on judgement rather than output, as at promotion to roles the tool cannot fill (H4).

### Divergence between skill levels

The tool widens the skill gap between novices and experts over time: experts extend their reach and novices substitute for practice, so that the distribution of skill diverges even as the distribution of output compresses. The compression that the productivity studies report is, in this model, a transient that conceals a widening of the underlying capability on which careers depend.

### Sensitivity

The size of the novice skill deficit depends on the substitution multiplier; a value nearer one, representing novices who use the tool partly for extension, shrinks the deficit, and a value below 0.6 enlarges it. The threshold at which usage switches from substitution to extension, set at skill 0.5, is a simplification of a continuous relationship. The structural results, that output compresses while skill diverges and that the novice's productivity conceals a skill lag, follow from any multiplier below one for novices and above one for experts, which is the asymmetry the evaluation argument in Section 2.4 implies.

## Implications

### For workers

Workers early in their careers should use generative AI to attempt tasks beyond their current skill with the tool's support, and should retain practice on the routine tasks through which judgement is built, rather than delegating them entirely. The usage pattern, not the tool, determines whether skill develops. Workers should assess their own skill without the tool periodically, since productivity with it is an unreliable guide.

### For organisations

Organisations face a choice between maximising current output, which argues for giving novices the tool and the routine work, and developing future experts, which argues for preserving practice. The model suggests structured usage: tool-assisted work for output, with protected practice and evaluation tasks for development, and assessment of skill independent of tool-assisted output. Role design should preserve the apprenticeship stage that routine work previously provided.

### For the structure of careers

If entry-level routine work is absorbed by the tool, the pipeline from novice to expert thins, and organisations will find experts scarce a decade hence. Professions should consider how the apprenticeship stage is to be reconstructed: through deliberate practice programmes, through supervised evaluation of AI output as a learning task, and through credentials that certify unassisted competence.

### For research

The model's prediction, that tool-using novices show higher output and lower skill growth, is testable in longitudinal studies that measure both, using unassisted assessments to track skill. Experimental manipulation of usage patterns, substitution versus extension, would identify the mechanism.

### Rethinking entry-level roles

Entry-level roles have served two functions: producing routine output and training future experts. Generative AI performs the first function well and undermines the second. Organisations that eliminate entry-level roles because the tool performs their output will find that they have also eliminated their training pipeline. The alternative is to redefine entry-level roles around learning: fewer routine outputs, more supervised evaluation of AI-produced work, structured practice on tasks chosen for development rather than throughput, and explicit progression criteria based on unassisted competence. The cost is lower short-run output from juniors; the return is the expert workforce of a decade hence.

### Skills that gain in value

The model treats skill as one dimension, but generative AI changes which skills matter. The ability to specify tasks precisely, to evaluate output critically, to integrate AI-produced components into coherent work and to judge when the tool is unreliable become central, while fluency in routine production declines in value. Development programmes should target these evaluative and integrative skills explicitly, since they are the skills through which the extension pattern operates, and workers who possess them can use the tool to learn rather than to substitute.

### Measurement for organisations

Organisations should track three quantities separately: tool-assisted output, which is what productivity metrics capture; unassisted competence, assessed periodically through tasks performed without the tool; and progression readiness, judged on the judgement-intensive tasks the tool cannot perform. The gap between the first and the second is the deskilling signal, and its trend across cohorts shows whether the organisation's usage practices are building or eroding its future expertise.

### Limitations

The skill-development multipliers are design values encoding the substitution–extension asymmetry; evidence on their magnitudes is sparse. Skill is a single dimension, the tool's capability is static, and workers do not learn to use the tool better over time. Career progression is modelled only through skill. All reported values are simulation outputs.

### Conclusion

Generative AI raises knowledge workers' productivity most for novices and least for experts, and in a dynamic simulation it also slowed novices' skill development and accelerated experts', so that output compressed while skill diverged and novices faced a career penalty concealed by their productivity. The outcome depends on usage: substituting the tool for practice erodes skill, using it to extend reach builds it. Workers, organisations and professions should structure generative AI use so that the apprenticeship through which expertise is built survives the tools that make it seem unnecessary. The short-run compression of output is real and valuable; the long-run divergence of skill is the cost that organisations will pay if they mistake the one for the other.

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