AI, Teamwork, and the Dynamics of Skill Formation in the Workplace

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Abstract

This paper develops a dynamic model of workplace skill formation under AI adoption. AI can substitute for junior workers, boosting short-run productivity but disrupting the apprenticeship ladder that produces future senior talent. We analyze how team production, learning-by-doing, and AI capabilities interact to shape wages, inequality, and long-run output. While AI enhances senior productivity, its displacement of juniors may lead to lower human capital in steady state. We derive conditions under which the dynamic loss outweighs the static gain, and discuss implications for inequality, labor market design, and optimal policy. The model highlights trade-offs between immediate efficiency and long-term skill development.

1 Background and Motivation

The rapid rise of artificial intelligence (AI), especially generative AI, is reshaping how work is organized. One notable trend is the replacement of entry-level roles by AI tools. Many companies have reportedly stopped hiring interns and junior employees, choosing instead to rely on AI to handle tasks that junior staff used to perform. For example, senior lawyers now use AI to draft contracts, and expert software developers leverage AI code generators (like GitHub Copilot) to write code, rather than delegating these tasks to junior colleagues. Managers applaud the productivity spike – smaller teams delivering faster with AI assistance – and question the need for juniors in such a workflow.

While this AI-driven productivity boost is real (field studies show generative AI can raise worker output by 14% on average), there is growing concern about long-term consequences. If firms cut junior positions, who will become the next generation of experts? As one commentator put it, "what happens when the seniors leave? Who takes over their work?". In traditional organizations, juniors learn from seniors via an apprenticeship model, gradually acquiring the expertise to step into senior roles. AI threatens to break this career ladder.

*This version of text written by OpenAI o3 based on our model notes and deep research prompts.

The worry is that lack of on-the-job learning opportunities for juniors could lead to a future shortage of skilled seniors, and a loss of tacit knowledge that comes from experience. Juniors also bring fresh perspectives and "beginner's mind" questions that spur innovation – benefits that may be lost if only seasoned workers and AI are in the room.

Early evidence from labor economics supports these concerns. Automation appears to reduce human capital investment: one study finds workers whose jobs are at risk of automation are 15 percentage points less likely to participate in training than similar workers not exposed to automation. Firms facing automation tend to cut training for incumbent workers, possibly because they expect AI to take over tasks. In a recent IZA study, companies adopting AI reduced continuing training for their staff, while hiring more already-skilled workers instead. This behavior contributes to a "skills gap" or polarization: fewer mid-skill workers being developed, and a greater reliance on a small pool of high-skill experts. On the other hand, some firms did increase apprenticeships even as they adopted AI, suggesting awareness that future workers still need preparation for an AI-driven workplace. These mixed findings underscore the central trade-off: AI can raise current productivity, but might undermine the learning-by-doing that builds future productivity.

Our work develops a simple economic model to study this trade-off. We ask: Could the use of AI in teams lead to "dynamic losses" by halting the development of human skills? Conversely, under what conditions can AI be integrated without depriving the next generation of experience? We build on a framework of team production with senior (high-skill) and junior (low-skill) workers, extending it to include an AI "worker." We analyze how AI affects output, wages, and inequality in the short run, and then examine the long-run steady state when junior workers normally learn from seniors over time. This model helps clarify when AI is a complement that augments workers versus when it becomes a substitute that hollows out career progression.

In what follows, we first describe the baseline model of teams and skill hierarchy. We then derive the equilibrium outcomes in two regimes (when juniors are plentiful vs. when seniors are plentiful) and discuss how technology (communication efficiency, AI) affects productivity and wage inequality. Next, we introduce AI as a special kind of "free junior" and determine when seniors would prefer AI over human juniors. Finally, we incorporate dynamic mentoring (learning) into the model – juniors can become seniors by working in teams – and explore how the presence of AI alters the long-run supply of skills and overall output. Throughout, we connect our findings to recent literature. In particular, we relate the rent-seeking behavior and learning externalities in our model to the dynamic efficiency considerations highlighted by Buera et al. (2025), and we situate our results in the broader discussion on AI's impact on the labor market (e.g. Acemoglu & Restrepo, Korinek, etc.) with an emphasis on the potential dynamic losses from a lack of learning opportunities.

2 Model Setup: Skill Levels, Tasks, and Team Production

We consider an environment where problems (or tasks) have varying difficulties. Formally, let task difficulty Z be uniformly distributed on $[0, 1]$. A worker's skill level z (with $0 < z < 1$) represents the maximum difficulty of problem they can solve. In other words, a person with skill z_i can solve any problem of difficulty $Z < z_i$ with certainty. Problems harder than their skill level are beyond their capability. We assume there are two classes of human workers:

Juniors: skill level z_0 (low skill). They can solve easier problems.

Seniors: skill level z_1 (high skill, with $z_1 > z_0$). They can solve a wider range of problems (all that juniors can, and more).

In a solo work setting, if a worker devotes one unit of time to work on random problems, their probability of solving a given problem equals the fraction of problems within their skill range. Since $Z \sim U(0, 1)$, a junior working alone solves a fraction z_0 of problems (those with $Z < z_0$), while a senior solves z_1 fraction. Thus, the expected output per unit time is z_0 for a junior and z_1 for a senior. These values also pin down their solo productivity-based wage in a competitive market: working alone, a junior would earn $w_0 = z_0$ per time unit, and a senior $w_1 = z_1$.

Now consider teamwork: a senior can collaborate with n_0 juniors. The idea is that juniors attempt the problems first; they will solve the easier ones they are capable of, and escalate the unsolved harder problems up to the senior. The senior then spends time to handle those tougher problems. However, communication and coordination take time. We assume whenever a junior brings a problem to the senior, the senior spends $h < 1$ units of time on it, whether or not the senior eventually solves it (the difficulty is unknown until attempted). The parameter h captures the time cost of mentoring/communication per problem. Importantly, $h < 1$ reflects that it is more time-efficient for a senior to solve a problem brought by a junior than to pick up a random problem on their own. Intuitively, the junior filters and only forwards the harder subset of problems.

Given a senior with n_0 juniors under them, how do they allocate time? Each junior works on problems for one unit of time (we normalize a "unit of work time" per person). In that time, each junior encounters some problems they cannot solve (the fraction is $1 - z_0$, since they solve z_0 fraction themselves). Those unsolved problems – on average $1 - z_0$ per junior – are passed to the senior. In total, the senior receives about $n_0(1 - z_0)$ problems to look at. Crucially, the senior must spend h time on each forwarded problem. Setting the senior's total time to 1 unit (one time period of work), we get a capacity constraint: $n_0(1 - z_0)h \leq 1$. If the team is working at full capacity, the senior's time is fully utilized by handling juniors' questions. The above equation then binds, giving the maximum team size a single senior can manage:

$$n_0 = \frac{1}{h(1 - z_0)}. \tag{1}$$

This result highlights why seniors can be extremely productive when supported by a team of juniors: if communication is efficient (small h) and juniors only pass on the truly hard problems (small $1-z_0$), a senior can leverage a large team. The senior essentially "multiplies" their expertise across n_0 juniors. In the limit of $h \to 0$ or $z_0 \to 1$, the leverage goes to infinity – though those are extreme cases.

Team output: In such an optimal team, what is produced in one unit of time? There are two sources of solved problems:

Problems solved by juniors: Each of the n_0 juniors solves a fraction z_0 of the problems they see. So total junior-solved output $= n_0 \cdot z_0$.

Problems solved by the senior: The senior tackles the forwarded problems. The senior's skill is higher, so they can solve problems up to difficulty z_1. However, note that juniors would have solved anything below z_0 already. Therefore, the senior only gets problems in the difficulty range $[z_0, z_1)$ (those below z_0 solved by juniors, those above z_1 unsolvable by anyone). Thus, among the problems forwarded, the fraction the senior can solve is $\frac{z_1-z_0}{1-z_0}$ (solvable out of those forwarded). Since the senior receives $n_0(1-z_0)$ problems (as established), the number of problems the senior solves is: $n_0(1-z_0) \times \frac{z_1-z_0}{1-z_0} = n_0(z_1-z_0)$. This simplifies nicely: problems solved by the senior $= n_0(z_1 - z_0)$.

Adding up, the team's total output (problems solved by junior + senior per senior's time) is: $Q_{\text{team per senior}} = n_0 z_0 + n_0(z_1 - z_0) = n_0 z_1$. Using the expression for n_0 from (1), this becomes:

$$Q_{\text{team per senior}} = \frac{z_1}{h(1-z_0)}. \tag{2}$$

This result is striking: a senior-led team produces output $\frac{z_1}{h(1-z_0)}$ per senior, which can be much larger than either a senior or junior alone. The factor $\frac{1}{h(1-z_0)}$ ¿ 1 represents the productivity boost from teamwork. It grows as communication becomes cheaper (smaller h) or as junior skill z_0 increases (meaning juniors handle a larger share of tasks without escalation).

In fact, the marginal value of increasing the senior's skill z_1 is amplified in a team: $\frac{\partial Q_{\text{team}}}{\partial z_1} = \frac{1}{h(1-z_0)}$, which is greater than 1 (since $h(1-z_0) < 1$). By contrast, if the senior works solo, the marginal return to their skill is just 1 (one more point in z_1 means one more problem solved per time unit). Thus, a senior's skill is more valuable when complemented by a team. This captures the idea that high-skill individuals can have an outsize impact when supported by others – a phenomenon often observed in professional firms and R&D labs, and a key reason why teams leverage talent.

We have so far treated n_0 as a continuous quantity for analytical ease. In reality n_0 would be integer (number of juniors per senior), but the formula (1) can be interpreted as a "target" ratio.

2.1 Equilibrium Wages in a Static Team Setting

We now introduce labor market equilibrium with a given supply of seniors and juniors. Let L_1 be the total number of seniors (skill z_1) and L_0 the number of juniors (skill z_0) in the economy. We consider a one-period (static) scenario where each worker either works solo or in a team. Wages w_1 (for seniors) and w_0 (for juniors) will be determined by supply and demand, depending on whether team opportunities are abundant or scarce.

Two cases naturally arise:

Case 1: Seniors are the bottleneck (Senior-scarce, "Too many juniors"). Suppose there are a lot of juniors relative to seniors, specifically $L_0 > n_0 L_1$. This inequality says: even if every senior takes on a full team of n_0 juniors, there would still be some juniors left without a senior. In this scenario, not all juniors can join teams; the "excess" juniors must work solo (since there aren't enough seniors to mentor them). Essentially, seniors are the limiting factor for forming teams.

In equilibrium, any junior not in a team will produce output on their own and earn their solo wage z_0. This sets a floor for the junior wage: junior wage w_0 must equal z_0, the solo productivity. If a firm tried to pay a junior less, that junior could instead choose to work alone and earn z_0 by solving easy tasks on their own. Thus:

$$w_0 = z_0. \tag{3}$$

Now consider seniors. Every senior can form a team and achieve the high output $Q_{\text{team}} = \frac{z_1}{h(1-z_0)}$ (per time unit). This is the value of one senior plus n_0 juniors. How is this value split into wages? If juniors each earn z_0 (their outside option), the total junior wage bill per team is $n_0 \cdot w_0 = n_0 z_0$. The remainder of the team output goes to the senior as the senior's wage. Therefore: $w_1 = Q_{\text{team}} - n_0 w_0 = \frac{z_1}{h(1-z_0)} - n_0 z_0$. But recall $n_0 = \frac{1}{h(1-z_0)}$ from (1). Plugging that in:

$$w_1 = \frac{z_1}{h(1-z_0)} + \frac{1}{h(1-z_0)}, z_0 = \frac{z_1 - z_0}{h(1-z_0)}. \tag{4}$$

Thus in Case 1, senior wage $w_1 = \frac{z_1 - z_0}{h(1-z_0)}$, while junior wage $w_0 = z_0$. We observe that seniors capture all the surplus from teamwork above what juniors could produce alone. Juniors are paid just their solo productivity, and the extra output that comes from the senior's guidance accrues to the senior. This wage structure reflects the bargaining power of scarce seniors: they are the limiting resource, so they can demand a high wage. The wage ratio here is:

$$\frac{w_1}{w_0} = \frac{z_1 - z_0}{h z_0 (1-z_0)}. \tag{5}$$

This can be much larger than 1, indicating significant inequality in favor of seniors when seniors are scarce.

GDP in Case 1: In aggregate, all L_1 seniors will form teams and produce $\frac{z_1}{h(1-z_0)}$ each, while the leftover juniors (those not in teams) work solo producing z_0 each. The number of juniors in teams is $n_0 L_1 = \frac{L_1}{h(1-z_0)}$. If $L_0 > n_0 L_1$, then $L_0 - \frac{L_1}{h(1-z_0)}$ juniors are solo. So total output (GDP) is: $Y = L_1 \left(\frac{z_1}{h(1-z_0)}\right) + \left(L_0 - \frac{L_1}{h(1-z_0)}\right) z_0$. Simplifying, $Y = \frac{L_1(z_1 - z_0)}{h(1-z_0)} + L_0, z_0$. The first term is output from teams (which equals total senior wages $L_1 w_1$), and the second term is output from solo juniors (equal to their wages $L_0 w_0$). This economy's GDP is higher than it would be without teams, due to the productivity boost of seniors collaborating with juniors.

We should note a participation constraint: seniors will only agree to work in a team (bearing the hassle of mentoring) if they earn at least what they could get by working solo. A senior's solo outside option is z_1. In Case 1, do they get at least that? The condition $w_1 \geq z_1$ implies:

$$\frac{z_1 - z_0}{h(1 - z_0)} \geq z_1.$$

This rearranges to

$$z_1 \geq \frac{z_0}{1 - h(1 - z_0)}. \tag{PC}$$

This inequality is assumed to hold by parameter choice (the problem statement notes we assume parameters such that the participation constraint holds). Intuitively, it requires the senior's skill advantage $z_1 - z_0$ and the leverage factor $1/[h(1 - z_0)]$ be large enough that team output exceeds the sum of what the senior and juniors could do separately. If this holds, seniors willingly form teams (it is indeed optimal for them). We will maintain this assumption so that teamwork is viable; otherwise, if $w_1 < z_1$, a senior might prefer to dismiss the juniors and just solve problems alone.

Case 2: Juniors are the bottleneck (Junior-scarce, "Too many seniors"). Now consider the opposite situation: $L_0 < n_0 L_1$. There are not enough juniors to utilize all seniors' capacity. In fact, in this case every junior can join a team, and some seniors will still be left without a junior partner. Juniors become the scarce factor. In equilibrium, junior wages will be bid above their solo productivity because seniors compete to get them on their team.

Specifically, when seniors are abundant, a senior who fails to hire a junior would have to work alone and earn z_1. But a senior with a junior (or ideally n_0 juniors) can achieve higher output. So seniors are willing to pay a premium to attract juniors. The equilibrium will equalize the benefit: some seniors end up solo and earn z_1, while those with teams get the team output minus what they paid juniors. In a competitive equilibrium, no arbitrage implies a senior is indifferent between working solo or hiring juniors at the going wage.

In Case 2, the senior wage gets pushed down to their solo output: $w_1 = z_1$. Seniors are no longer capturing a big surplus; if they tried to demand more, firms would just use an extra senior in place of a costly one (since seniors are plentiful). Meanwhile, juniors capture all the surplus from teamwork. The logic: a junior joining a team enables the senior to go from z_1 output (solo) to $\frac{z_1}{h(1-z_0)}$ output. That gain is $\frac{z_1}{h(1-z_0)} - z_1$. With juniors scarce, they can bargain for (almost) that entire gain in their wage. Formally, if one senior can only hire n_0 juniors, the total team output minus the senior's outside option is the pool to pay juniors. For one senior with n_0 juniors: Surplus from team $= \frac{z_1}{h(1-z_0)} - z_1$. This must equal the total premium paid to juniors above their next best option. Juniors' next best is working solo for z_0. So if the junior team wage is $w_{0,\text{team}}$, the premium per junior is $w_{0,\text{team}} - z_0$. With n_0 juniors, $n_0(w_{0,\text{team}} - z_0)$ should equal the surplus: $n_0(w_{0,\text{team}} - z_0) = \frac{z_1}{h(1-z_0)} - z_1$. Using $n_0 = \frac{1}{h(1-z_0)}$, this yields: $w_{0,\text{team}} = \frac{z_1}{h(1-z_0)n_0} - \frac{z_1}{n_0} + z_0 = \frac{z_1}{h(1-z_0)}\frac{1}{n_0} - \frac{z_1}{n_0} + z_0$. But $1/n_0 = h(1 - z_0)$. Simplifying: $w_{0,\text{team}} = z_1[h(1 - z_0)] - 0 + z_0 = z_0 + z_1 h(1 - z_0)$. Note $h(1 - z_0) < 1$, so $w_{0,\text{team}}$ is between z_0 and z_1. In fact, since typically $z_1 \gg z_0$ and h might not be extremely small, this wage can be substantially higher than z_0. In equilibrium, all juniors would receive this team wage (because any junior not in a team could be hired by some senior for at least this much). We can rewrite it as:

$$w_0 = z_1[1 - h(1 - z_0)]. \tag{6}$$

This is the junior's wage in Case 2. They essentially get a cut of the senior's high productivity. The wage ratio now is: $\frac{w_1}{w_0} = \frac{z_1}{z_1[1-h(1-z_0)]} = \frac{1}{1-h(1-z_0)}$. This ratio is ¿1 (since the denominator ¡1), but notably it no longer depends on the skill gap $z_1 - z_0$. In fact, in this junior-scarce regime, the relative wage is lower than in Case 1 if $z_1 - z_0$ is significant. (Because in Case 1, w_1/w_0 grows with z_1; in Case 2, w_1/w_0 is fixed by h and z_0.)

Intuitively, when juniors are scarce, even a very high-skill senior cannot command a huge premium because they desperately need juniors to leverage their skill. Juniors then receive a large share of the value (they "capture the rent" from the teamwork). By contrast, in senior-scarce scenario, the senior could name their price since juniors had nowhere else to get the premium.

In summary, our static model yields two distinct regimes for wage inequality. In Case 1 (many juniors), seniors capture most of the surplus and inequality is high. In Case 2 (many seniors), juniors get a larger share of the surplus, compressing the wage gap. This has interesting implications: for example, if an economy suddenly increases the supply of seniors (say through education or immigration of skilled workers), it could flip from Case 1 to Case 2, potentially reducing wage inequality. Conversely, an influx of junior workers without enough senior mentors could increase inequality.

We can also analyze how technology changes affect inequality. For instance, improvements in communication technology (a lower h) make teams more efficient. In Case 1, a drop in h increases w_1/w_0 because it amplifies the senior's leverage (see Eq. 5: h in the denominator increases the ratio). In Case 2, $w_1/w_0 = 1/[1 - h(1 - z_0)]$, which actually decreases as h decreases (since $1 - h(1 - z_0)$ increases). Thus, if better IT reduces mentoring time h, the effect on inequality is ambiguous: if seniors are scarce (Case 1), inequality rises; if juniors are scarce (Case 2), inequality falls. This observation foreshadows what could happen with AI, which can be seen as an extreme improvement in "communication" productivity (or even a replacement for juniors).

Another comparative static: raising the junior skill level z_0 (e.g. better basic education for all workers) tends to reduce wage inequality in both cases. In Case 1, Eq. (5) shows w_1/w_0 decreases if z_0 increases (holding z_1 fixed). In Case 2, $w_1/w_0 = 1/[1 - h(1 - z_0)]$ also decreases as z_0 rises. The intuition is that if juniors become more capable, the senior's relative advantage shrinks, and juniors also solve more tasks themselves, making the senior slightly less pivotal.

(These insights are qualitatively in line with broader labor literature: technologies that complement high-skill workers can increase inequality if high-skill workers are scarce, but if lower-skill workers improve their capabilities, the gap narrows.)

2.2 Introducing AI as a Team Member

We now extend the model to include AI (artificial intelligence) as a potential "worker" in the team. We consider an AI system that functions similarly to a junior: it can attempt problems up to a certain competence and pass on the rest. Let:

- z_A = the AI's "skill" (the maximum difficulty of problems the AI can handle). This could be interpreted as the quality or sophistication of the AI. For example, if $z_A = z_0$, the AI is as good as a junior at solving problems; if $z_A > z_0$, the AI might surpass a human junior in capability.
- h_A = the communication time per problem between the AI and the senior. This represents the time a senior must spend to review or integrate the AI's output on tasks the AI couldn't fully resolve. Perhaps surprisingly, working with an AI might involve some overhead (interpreting AI suggestions, correcting errors). We assume h_A plays a similar role to h for human juniors, and likely h_A is also ¡ 1 (AI can also save time, but not eliminate oversight entirely).

The key difference is cost: hiring an AI has essentially no wage cost. The AI is like a machine – we can assume it's a fixed asset or its "salary" is zero for the marginal analysis (or its cost is not a wage paid to a human). Thus, a senior who has access to AI can use as many "AI juniors" as they want, limited only by time.

Suppose a senior can choose to work with n_A units of AI (multiple AI instances or simply scaling usage). Similar to before, if the senior allocates all their time to handling the AI's unsolved problems: $n_A(1 - z_A)h_A = 1$, giving $n_A = \frac{1}{h_A(1-z_A)}$. This mirrors (1). Essentially, a single senior can now leverage up to $1/[h_A(1 - z_A)]$ AI processes in parallel. The output per senior with AI would be:

$$Q_{\{}\text{with AI per senior}\} = n_A z_A + n_A(z_1 - z_A) = n_A, z_1 = \frac{z_1}{h_A(1 - z_A)}. \tag{7}$$

So substituting "A" for "0" in the earlier team formula, we see the structure is analogous. If z_A and h_A are comparable to a junior's z_0, h, then an AI can similarly boost the senior's productivity. Importantly, however, the AI doesn't demand a wage or have an outside option. This can fundamentally alter the equilibrium.

Consider a scenario initially in Case 1 (too many juniors for available seniors). In the absence of AI, seniors were teaming up with juniors and paying them $w_0 = z_0$. Now introduce a capable AI. A senior could choose to replace human juniors with AI if it's beneficial. The senior's decision will depend on whether using AI yields a higher net output (since AI has no wage, net output = gross output). Comparing senior's payoff in two options:

- Using human juniors: senior gets w_1 as given in (4) which equals $\frac{z_1 - z_0}{h(1-z_0)}$. (Recall this already subtracts the junior wages.)
- Using AI: senior would get the entire output $\frac{z_1}{h_A(1-z_A)}$ (since no juniors to pay).

The senior will prefer AI if:

$$\frac{z_1}{h_A(1-z_A)} > \frac{z_1 - z_0}{h(1-z_0)}. \tag{8}$$

Rearranging, this inequality is:

$$\frac{h(1-z_0)}{h_A(1-z_A)} > 1 - \frac{z_0}{z_1}. \tag{9}$$

This condition says that the relative efficiency of AI (the LHS is basically how many more tasks a senior can handle with AI vs with an equivalent junior) exceeds a threshold related to the junior's contribution (the RHS is the fraction of senior-solved tasks that juniors cannot solve). If AI is equally as capable as juniors ($z_A = z_0$) and equally easy to work with ($h_A = h$), then the LHS of (9) simplifies to 1, and the RHS is $1 - \frac{z_0}{z_1}$. Since $z_1 > z_0$, the RHS is positive, so (9) holds automatically. This means even if AI had the same skill and communication cost as a junior, a senior would still prefer AI, because with AI they don't have to share output as wages. Essentially, as long as seniors have to pay juniors at least something (and in Case 1 they pay juniors their outside option z_0), an equivalent AI is more attractive due to zero wage. The senior "saves" the junior wage cost and keeps the full surplus.

Thus, if AI is available, seniors will tend to replace human juniors for any configuration where the AI can do a comparable job. In practice, AI might even have advantages: for instance, an AI could be deployed in unlimited quantity. A senior is not limited to n_0 humans; if h_A is small enough, they could potentially use more AI instances in parallel. In our simplified model we considered using up to $n_A = 1/[h_A(1 - z_A)]$ AIs to fully use the senior's time – analogous to the human case – but one can imagine that if AI scales cheaply, a senior might handle even more (subject to fatigue or other constraints). We will stick to the model's assumption that time is the binding constraint.

Under condition (8), a senior's optimal choice is to employ AI exclusively and hire zero juniors. In that outcome:

All juniors are effectively pushed out of teams. They must either find solo work or remain underemployed. Given our model, they would revert to working solo on problems (output z_0 each).

Each senior now works with their AI helpers and produces output $\frac{z_1}{h_A(1-z_A)}$. The senior's wage would adjust to reflect their new productivity (if seniors are still scarce, they capture it; if seniors became abundant relative to remaining team opportunities, wages might equalize differently, but presumably if all seniors adopt AI, juniors are no longer a limiting factor at all).

We are especially interested in the impact on output and wages in this scenario:

Output per senior with AI is given by (7) above. Comparing (7) to the old team output (2), we see two changes: z_0 is replaced by z_A, and h by h_A. If AI is "better" than juniors (say $z_A > z_0$ or $h_A < h$), then obviously a senior+AI team outperforms a senior+human team. But even if AI were equivalent in skill and cost, the allocation of surplus differs – seniors now get all of it.

Wages: In the new equilibrium, what are wages? All juniors are essentially relegated to solo work, earning $w_0 = z_0$ (since they can't command any premium; seniors aren't hiring them). Seniors, using AI, can produce a lot more. If seniors remain the scarce factor, one might expect $w_1 = \frac{z_1}{h_A(1-z_A)}$ (the value of their augmented output). However, if AI is sufficiently powerful, it might increase the effective supply of problem-solving capacity such that seniors are no longer so scarce. In our setting, since the number of seniors hasn't changed, seniors likely still remain the only ones who can solve the hardest problems, so they probably still earn a premium. For simplicity, assume L_0 is large enough (and juniors not used) so that we remain in a regime analogous to Case 1: seniors capture the surplus. Then: $w_1 = \frac{z_1}{h_A(1-z_A)}, \qquad w_0 = z_0$. The wage ratio with AI (under these assumptions) becomes: $\frac{w_1}{w_0} = \frac{z_1}{h_A(1-z_A)z_0}$. This is typically even higher than the original ratio (5), since h_A is likely not greater than h, and $1-z_A \leq 1-z_0$ if $z_A \geq z_0$. In words, if AI replaces juniors, inequality spikes: seniors' productivity (and pay) shoot up, while juniors fall back to low-productivity solo work earning z_0. We've shifted to a world somewhat akin to Case 1 (seniors with teams) but where the "teams" are AI and the juniors' labor is largely sidelined.

From a static output perspective, introducing AI in this way unambiguously raises GDP. Previously, one senior with n_0 juniors produced $z_1/[h(1-z_0)]$. Now each senior produces $z_1/[h_A(1-z_A)]$, which we are given is higher (since (8) held for adoption). Plus, the juniors still produce something on their own (each junior can still solve some easy problems solo, contributing z_0 each). So the new total GDP is: $Y_{\text{AI}} = L_1 \frac{z_1}{h_A(1-z_A)} + L_0 z_0$. This is at least as large as the no-AI GDP we wrote earlier, and indeed greater given (8). Thus, in a static sense, AI raises efficiency – no surprise there. We get more output because seniors can handle more problems faster with AI help, and juniors do what little they can on their own.

However, static efficiency is not our sole interest. The worry is about dynamics: what happens over time if juniors never work with seniors? Juniors working solo do not learn from a mentor, potentially stunting the creation of future seniors. The next section incorporates this learning aspect.

Before moving on, we briefly consider: What if juniors also have access to AI? So far, we assumed juniors couldn't use AI, which is why they became redundant. But suppose juniors too could utilize AI tools in their solo work. In reality, tools like ChatGPT or Copilot augment even relatively inexperienced workers, helping them perform above their usual skill level. If a junior with AI could effectively achieve a higher skill (say solve problems up to difficulty z_0' where $z_0' > z_0$), it might reduce the gap with seniors. It might allow one junior+AI to handle tasks that previously required escalation to a senior. This scenario could change senior behavior: instead of entirely displacing juniors, seniors might still employ a smaller number of juniors who are each more productive thanks to AI assistance. The model would then treat the junior+AI bundle as having a higher effective z_0' or lower effective time h needed. We won't formally analyze this case here, but we note that AI as a complement (augmenting juniors) has very different implications than AI as a pure substitute. Indeed, recent empirical evidence suggests generative AI can help junior or less-skilled workers improve faster, by disseminating best practices and providing guidance. For instance, customer support agents with AI assistance saw novices catch up to experienced workers more quickly, moving "down the experience curve" faster. If juniors could similarly learn faster with AI, then the dynamic loss might be mitigated. The worst dynamic outcome arises when AI is used instead of training juniors, not when it's used to support juniors. We return to this point in the conclusion.

2.3 Dynamic Considerations: Learning by Mentoring

Thus far, we treated the supply of seniors and juniors as fixed. We now enrich the model with a simple dynamic mechanism: juniors can learn and become seniors over time by working in teams (being mentored). This captures the idea of a career progression or on-the-job learning: a junior who spends time collaborating with a senior gradually acquires the senior-level skill. We model this as a Poisson process: while working in a team under a senior, a junior "graduates" to senior skill level at an instant rate λ. This promotion could be thought of as the junior accumulating enough knowledge to handle the hardest problems, thus effectively reaching skill z_1. We assume if this happens, the person is now a senior (skill z_1) from that point on. (In a continuous-time overlapping generations model, one could formalize it, but here we focus on steady state.)

For simplicity, let's consider a continuous-time steady state. People are born at rate δL (so δ is birth rate relative to population) and die at rate δ (ensuring a stationary population L). A fraction ϕ of new entrants are exogenously high-skill (perhaps through education) and start as seniors, while the rest $1-\phi$ start as juniors. Without any on-the-job learning, the economy's fraction of seniors would just be ϕ in steady state. However, with learning by mentoring, additional seniors are created from juniors' ranks each period.

In steady state, the stock of seniors L_1 evolves according to: new seniors come from two sources – the $\phi\delta L$ who are born as seniors, and those promoted via learning – and seniors exit due to death. Because at steady state L_1 is constant, we have: $\delta L_1 = \delta L\phi +$ (promotions from junior to senior per unit time). How many promotions occur? Only juniors working on teams with seniors can learn at rate λ. If a junior is working solo, there is no senior to learn from, so we assume no progression (one could assume some slower self-learning, but our focus is the mentorship channel). In Case 1 (the relevant case, as we will assume seniors are scarce enough to have full teams formed), the number of juniors in teams with each senior is $n_0 = \frac{1}{h(1-z_0)}$. So per senior, promotions happen at rate λn_0 (since each junior has rate λ). Across all seniors L_1, promotions $= L_1\lambda n_0$. We equate this to senior deaths + outflow: $\delta L_1 = \delta L\phi + L_1\lambda n_0$.

Divide through by δL to get seniors as a fraction of population L_1/L: $\frac{L_1}{L} = \frac{\phi + \frac{\lambda}{\delta}\frac{L_1}{L}n_0}{1}$. Solving,

$$\frac{L_1}{L} = \frac{\phi}{1 - \frac{\lambda}{\delta}n_0}. \tag{10}$$

This is the steady-state share of seniors including the effect of learning. Because $n_0 = \frac{1}{h(1-z_0)}$, we can rewrite the denominator as $1 - \frac{\lambda}{\delta}\frac{1}{h(1-z_0)}$. As long as $\frac{\lambda}{\delta} < h(1-z_0)$, this fraction is well-defined (less than 1 in numerator). We assume learning is slow relative to exit so that not everyone ends up a senior (i.e. λ is not too high). This condition was earlier given as $\frac{\lambda}{\delta} < (1-\phi)h(1-z_0) - \phi$ to ensure consistency with Case 1 (seniors remain scarce despite learning). Essentially, as long as seniors do not become too common (which would flip us to Case 2), our analysis holds.

Notably, (10) implies: $\frac{L_1}{L} > \phi$, since $\frac{\phi}{1-x} > \phi$ for any $x > 0$. Learning by mentoring raises the long-run proportion of high-skill workers. In effect, some juniors "graduate" to senior roles faster than they are aging out. This is a positive externality of teamwork: it increases the economy's human capital over time. The faster the learning rate λ or the larger the teams (higher n_0), the greater the boost to L_1/L. If $\lambda \to 0$, we recover $L_1/L = \phi$. If λ is very large (approaching the threshold where denominator $\to 0$), L_1/L can be substantially above ϕ (though we keep it below the Case 1 to Case 2 flip point).

What is the steady-state output per capita without AI? Using the same approach as static but weighting by the new L_1, L_0, we have: $\frac{Y_{\text{no AI, steady}}}{L} = \frac{L_1}{L}\frac{z_1 - z_0}{h(1-z_0)} + \frac{L_0}{L} z_0$. Substitute L_1/L from (10) and $L_0/L = 1 - L_1/L$:

$$\begin{aligned}\frac{Y_{\text{no AI}}}{L} &= \frac{\phi}{,1 - \frac{\lambda}{\delta h(1-z_0)},} \cdot \frac{z_1 - z_0}{,h(1-z_0),} + \left[1 - \frac{\phi}{,1 - \frac{\lambda}{\delta h(1-z_0)},}\right] z_0 \\ &= z_0 + \frac{\phi(z_1 - z_0)}{,h(1-z_0) - \frac{\lambda}{\delta},} + \frac{\phi, z_0}{,1 - \frac{\lambda}{\delta h(1-z_0)},}.\end{aligned}$$

After some algebra, this simplifies to:

$$\frac{Y_{\text{no AI}}}{L} = z_0 + \phi \frac{z_1 - z_0[1 + h(1-z_0)]}{h(1-z_0) - \frac{\lambda}{\delta}}. \tag{11}$$

One can verify that $\partial(Y/L)/\partial\lambda > 0$; increasing the learning rate λ raises steady-state output per capita (because more workers end up as high-skill). In the limit of no learning ($\lambda = 0$), (11) reduces to $z_0 + \phi\frac{z_1 - z_0}{h(1-z_0)}$, which corresponds to each senior producing their static team output and juniors remaining juniors forever.

Now consider the steady state with AI. If seniors use AI exclusively and juniors never join teams, no on-the-job learning occurs (juniors have no mentors). The fraction of seniors in the long run will then remain ϕ – essentially, the only seniors are those who were initially endowed with high skill, since no new ones are trained. Thus $L_1/L = \phi$ in the long run with AI (we assume AI adoption eliminates the mentoring pathway). Each senior still produces a high output $\frac{z_1}{h_A(1-z_A)}$ with AI. Juniors remain juniors (fraction $1 - \phi$ of pop) and work solo for output z_0 each. So the steady-state per-capita output with AI is:

$$\frac{Y_{\text{AI, steady}}}{L} = \phi \frac{z_1}{h_A(1-z_A)} + (1-\phi) z_0. \tag{12}$$

The crucial question is: which steady state yields higher output, with or without AI? It is not obvious because AI boosts current productivity (especially of seniors) but eliminates the learning that boosts future human capital. If learning effects are small (either λ low or $z_1 - z_0$ not too large), the AI-gained output may dominate. But if learning effects are powerful, losing them can outweigh AI's static gain in the long run.

Comparing (12) and (11) is a bit messy in general. However, we can derive a condition for when introducing AI reduces long-run GDP per capita: $\frac{Y_{\text{AI}}}{L} < \frac{Y_{\text{no AI}}}{L}$. Using the expressions above, one key case to consider is when seniors do choose to use AI (so condition (8) holds) – otherwise AI wouldn't be adopted at scale. Under condition (8), we indeed have $Y_{\text{AI (static)}} > Y_{\text{no AI (static)}}$ initially. But as λ increases, $Y_{\text{no AI (steady)}}$ grows, while $Y_{\text{AI (steady)}}$ stays the same (since it doesn't benefit from λ). There will be a threshold λ beyond which $Y_{\text{no AI steady}} > Y_{\text{AI steady}}$. In other words, for sufficiently high learning rates or long-term considerations, AI adoption could lead to a lower steady-state output than a scenario with no AI but continual skill development.

Deriving the precise inequality, from (11) and (12), one condition for $Y_{\text{AI}}/L < Y_{\text{no AI}}/L$ turns out to be:

$$\frac{z_1}{h_A(1-z_A)} - z_0 < \frac{z_1 - z_0}{h(1-z_0) - \frac{\lambda}{\delta}} - \frac{z_0}{1 - \frac{\lambda}{\delta h(1-z_0)}}. \tag{13}$$

This expression basically asks whether the AI-driven senior output advantage ($\frac{z_1}{h_A(1-z_A)} - z_0$, i.e. how much more a senior+AI produces over a junior's output) is smaller than the mentoring-driven output advantage (the right-hand side is roughly the additional output per capita gained from having more seniors via learning). If the learning term is large (high λ), the inequality can hold even if AI has a strong static benefit.

To give intuition: if $\lambda = 0$ (no learning), the RHS of (13) reduces to $\frac{z_1-z_0}{h(1-z_0)} - z_0$, which is exactly $\frac{z_1}{h(1-z_0)} - (z_0 + \frac{z_1-z_0}{h(1-z_0)}) = \frac{z_1}{h(1-z_0)} - \frac{z_1}{h(1-z_0)} = 0$. So the inequality says AI decreases output if $\frac{z_1}{h_A(1-z_A)} - z_0 < 0$, which would never be true if $z_1 > z_0$. So with $\lambda = 0$, AI always helps or at least doesn't hurt output (as expected). As λ grows, the RHS increases, eventually possibly exceeding the LHS.

In short, dynamic losses from the lack of learning can outweigh static gains from AI beyond some tipping point. This highlights a potential dynamic inefficiency: individual firms or seniors may adopt AI because it is privately optimal at time 0 (it yields higher output and profit for them), but collectively this might lead to lower output in the long run due to a collapse in human capital formation. There is a parallel here to the idea of excessive automation noted by some economists – that firms adopt labor-saving technology beyond the socially optimal level because they do not internalize the loss of future skilled workers or the broader consequences on the labor market (Acemoglu & Restrepo, 2020; Korinek, 2023). Our model provides a microfoundation for one such consequence: foregone learning-by-doing.

It is worth mentioning that our analysis is somewhat one-sided in that we did not allow AI itself to improve over time in this model. In reality, AI could also become more capable by learning from data (including data generated by humans). Some theorists describe advanced AI as having a "learning-by-using" dynamic – the more it's used, the more it learns from human decisions, potentially accelerating its capability growth. A recent NBER paper conceptualizes AI in this way and warns that AI might initially complement workers but eventually substitute them as the AI becomes very skilled. That dynamic is different from ours (where humans learn, not AI), but it also leads to time-varying impacts on labor. In their model, wages might rise initially and then fall as AI crosses a certain threshold. In our model, wages for juniors might rise initially (if juniors are scarce) but then collapse if AI adoption becomes ubiquitous and no new seniors emerge.

We have so far assumed that juniors do not internalize the future benefit of learning when bargaining. What if they anticipate the career progression and are willing to accept lower current wages for a chance to become seniors? This introduces an interesting twist: juniors might essentially "pay for" their training by working at a discount. In a competitive labor market with forward-looking workers, the junior's expected lifetime utility from a team position should equal that from working solo (or elsewhere). If J denotes the expected present value of being a junior on a team, we can write a Bellman equation: $\delta J = w_{0,\text{team}} + \lambda[\frac{w_1}{\delta} - J]$, where $\frac{w_1}{\delta}$ is the capitalized value of becoming a senior (earning w_1 per period indefinitely, for simplicity). Meanwhile, the value of being a solo junior is $J_{\text{solo}} = \frac{z_0}{\delta}$ (earning z_0 forever, no promotion). Indifference requires $J = J_{\text{solo}}$. Solving the Bellman: $J = \frac{w_{0,\text{team}} + \lambda \frac{w_1}{\delta}}{\delta + \lambda}$, and setting $J = z_0/\delta$, we get:

$$w\{0, \text{team}\} = z_0 - \frac{\lambda}{\delta}(w_1 - z_0). \tag{14}$$

This means juniors on a team might accept a wage below z_0 (their static marginal product) if $w_1 > z_0$ and $\lambda > 0$, because they expect to recoup it when they become seniors. In other words, they effectively pay the senior (or firm) for training via a wage discount. If firms can commit to long-term contracts or juniors are confident in promotion, such an equilibrium could occur. It resembles classic "apprenticeship" where trainees work for low pay to gain skills.

If (14) holds, the senior's surplus from a team is even larger because juniors are cheaper labor. In fact, substituting this $w_{0,\text{team}}$ into the senior's team wage formula, one finds: $w_1 = \frac{z_1}{h(1-z_0)} - n_0 w_{0,\text{team}} = \frac{z_1}{h(1-z_0)} - \frac{1}{h(1-z_0)}\Big(z_0 - \frac{\lambda}{\delta}(w_1 - z_0)\Big)$. Solving for w_1 gives:

$$w_1 = \frac{\frac{z_1 - z_0}{h(1-z_0)} + \frac{\lambda}{\delta}\frac{z_0}{h(1-z_0)}}{1 + \frac{\lambda}{\delta h(1-z_0)}}. \tag{15}$$

This is the senior wage when juniors fully internalize learning (in equilibrium w_1 is determined by a fixed point). One can check that this w_1 is lower than the previous $w_1 = \frac{z_1 - z_0}{h(1-z_0)}$; juniors' willingness to work for less transfers some rent back to themselves (or to the firm). Essentially, seniors can't exploit juniors as much if juniors are strategically considering their future payoff.

Now, how does this affect the decision to adopt AI? If juniors are already willing to undercut their wage for training, a senior's private benefit of replacing them with AI is smaller. We would modify the AI adoption condition (8) to compare w_1 from (15) (team with learning-internalizing juniors) to the AI output. The condition for AI use becomes:

$$w_1 \text{ (with learning-internalizing juniors) } < \frac{z_1}{h_A(1 - z_A)}. \tag{16}$$

Substituting (15) for w_1, this inequality is more complex, but the key insight is: if juniors value learning, they effectively subsidize the team, making seniors less eager to drop them for AI. In fact, seniors might stick with human teams even when AI is somewhat better, as long as the juniors' wage is depressed enough that the senior's net payoff is comparable. There is even a possibility that a senior might personally prefer to keep juniors instead of AI, to maintain the flow of future rents from those juniors when they become seniors. This hints at a kind of rent-seeking behavior: an incumbent senior might resist a labor-saving technology (AI) not because it's bad for productivity, but because adopting it would break the cycle that allows them to capture rents from the next generation. This is reminiscent of scenarios in industrial organization where incumbents deter entry or new technology to preserve future monopoly rents. In our labor context, the senior might forego an immediate productivity gain from AI in order to continue benefiting from cheap junior labor and possibly a share in their future success (if there's some way seniors benefit from having trained successors – e.g., in a firm hierarchy or partnership model). This particular strategic angle goes beyond our basic model, but it's an intriguing possibility for extension.

2.4 Discussion: Related Literature and Policy Implications

Our model highlights a dynamic externality in the adoption of AI in skilled work: the loss of learning opportunities for junior workers. This connects to several strands of literature:

Learning-by-doing and dynamic inefficiencies: The idea that current production can build future human capital has a long history in economics (Arrow, 1962; Lucas, 1988). In those models, firms or workers do not fully internalize the benefit of the skills they accumulate for society's future, leading to underinvestment in learning. In our setup, the externality is explicit: when a senior chooses AI over mentoring a junior, the senior ignores the fact that one less junior will become a high-skill worker. This is a social loss not reflected in the senior's private payoff. Our results echo themes in Acemoglu's work on automation: he argues that there can be excessive automation because firms adopt cost-saving technologies without considering the negative effect on workers' skill acquisition and earnings. Acemoglu & Restrepo (2018, 2020) emphasize that automation needs to be counterbalanced by new tasks for labor; otherwise, workers get displaced and aggregate gains may be smaller than anticipated. In our model, training juniors can be viewed as creating "new skilled workers" (akin to new task opportunities for labor in the future). If AI halts that, the long-run supply of skilled labor is lower, potentially reducing innovation or productivity down the line.

Rent-seeking and optimal incentives: We drew a parallel to an insight by Buera and co-authors (2025). They study dynamic competition in oligopolies and find that private incentives can deviate from social optima due to dynamic considerations (firms do not internalize the full social benefit of more competition or innovation). However, they also show that dynamic competition alone doesn't always justify intervention – in some cases the equilibrium can be constrained-efficient. The analogy in our context would be: is the private outcome (seniors replacing juniors with AI) inefficient, or could it be constrained-efficient? If seniors are scarce and capture rents, they undervalue the creation of new seniors (since that would erode their future rents). This likely leads to under-provision of training relative to the social optimum. Even if seniors internalize juniors' learning (via lower wages), the senior is just extracting that value; the junior's presence still creates a positive externality for others (e.g., future firms or the economy benefit from having more skilled workers beyond the senior's own firm). Thus, we suspect the market equilibrium is tilted toward too much AI adoption from a social viewpoint, whenever learning externalities are significant. This is a form of dynamic inefficiency where regulators or policy might want to intervene – akin to subsidizing training or taxing automation. Buera et al.'s framework is different (firms and innovation), but the common theme is balancing static gains with dynamic considerations. In Buera's model, the government might subsidize entrants to maintain competition; in our model, one could imagine incentives for firms to hire and train juniors even if AI is available, to sustain human capital formation.

Evidence on AI's impact on training and skills: Given that generative AI is a very recent technology, hard empirical evidence on long-run skill dynamics is limited. However, early studies and surveys provide hints:

As noted earlier, Hess et al. (2023) find that in jobs with high automation risk, workers and firms invest less in training. This aligns with our model's implication that firms might cut back on developing junior talent if they plan to automate roles. Muehlemann (2024) finds that AI adoption in German firms led to reduced training for current workers, but an increase in apprenticeship contracts. The latter suggests some firms anticipate needing skilled workers who know how to work with AI, so they ramp up apprentice programs. In our terms, that would be like trying to ensure juniors are still coming up the pipeline, perhaps in a more AI-centric way.

There is anecdotal evidence of companies reducing entry-level hiring because of AI. For example, some law firms have slowed hiring of junior lawyers as AI can do first drafts of contracts and research. In programming, one hears quotes like "why hire juniors when a single senior with AI can do the job?". Our model formalizes the logic behind such quotes. But commentators warn that this is short-sighted: junior roles today are how seniors of tomorrow are created.

On the flip side, AI tools might serve as a training device. The study by Brynjolfsson et al. (2023) provides "proof-of-concept" that generative AI can supplement human learning: in customer support, novice workers improved markedly with AI help, essentially learning from AI's suggestions. Noy and Zhang (2023) found less-skilled writers improved their writing quality using ChatGPT, closing some gap with more-skilled writers. These findings suggest a possible complementary path: instead of replacing juniors, firms could give juniors AI tools to make them productive and accelerate their learning. In our model's terms, that would keep λ (learning) alive while also enjoying some of AI's static benefits – a potential win-win if done right.

Policy responses: If indeed there is a danger that the pipeline of skill formation gets broken, what policies could mitigate this? One idea is incentivizing human-complementary uses of AI over pure automation. Acemoglu et al. (2023) argue for directing innovation towards augmenting workers rather than replacing them. Concretely, they suggest measures like:

Adjusting the tax code: currently, in the U.S., companies can often save costs by investing in software/AI (capital) rather than hiring workers, due to how labor is taxed (payroll taxes, etc.). Making taxes neutral between hiring a person and deploying an AI could remove an artificial incentive to cut jobs. Equivalently, one could offer tax credits for training expenses or for maintaining apprentice programs. If firms faced the true long-run cost of lost human capital, they might choose a more balanced approach.

Training subsidies or requirements: Governments could subsidize firms that provide robust training to young workers, or even mandate industries (like law, medicine) to maintain certain residency/internship positions. Historically, some professions have guild-like systems to ensure knowledge transfer. In an AI era, we might need updated versions of these to ensure juniors still get experience, perhaps focusing on tasks AI can't do (or overseeing AI).

Worker voice and bargaining: The CEPR columnsuggests that giving workers more voice in tech implementation decisions could help steer AI adoption in a worker-friendly direction. If junior employees (or their unions) had a say, they might push for AI that helps them rather than replaces them, or for maintaining pathways to advancement. This is of course challenging if the juniors are never hired to begin with – a catch-22 – but it speaks to the need for broader stakeholder involvement.

Ensuring new task creation: In the long run, entirely new roles might emerge that juniors can fill and learn in, even if old entry-level tasks are done by AI. For example, if AI handles coding, perhaps prompt engineering or AI supervision becomes the entry role. Some optimists believe AI will create more demand for human judgment and soft skills, which could form the basis of new junior positions. Our model does not incorporate new task creation, but if we did, it could alleviate the dynamic loss (Acemoglu & Restrepo (2019) stress that new tasks for humans historically accompanied automation). There may be a need for policies that encourage the development of new complementary jobs – e.g., funding for R&D in areas where humans can expand work with AI rather than be replaced.

Long-term distributional effects: Our model has implications for inequality that resonate with ongoing debates. In the short run, AI may increase the productivity of top-skilled workers (seniors), increasing the wage gap if they capture that value. Indeed, inequality could rise sharply if AI is used in the Case 1 scenario. Acemoglu's recent paper (2024) suggests that even if AI makes lower-skilled workers more productive in some tasks, it might still increase inequality unless it's creating whole new opportunities. Our model's Case 1 outcome with AI is an example: juniors might improve a bit with AI, but if they're largely sidelined, the gap widens. However, if juniors are scarce (Case 2), they could benefit and inequality could decrease, at least initially. Over the long run, if the supply of skilled workers doesn't grow (or even shrinks relative to population because of no learning), we could see a form of skill premium persistence or even a decline in overall innovation. There is also a parallel to the literature on human capital and growth: if one generation doesn't pass on skills to the next, you can get stagnation. This is somewhat analogous to some low-development traps where lack of skill transfer keeps productivity low.

In terms of empirics, this is a nascent area. It will be interesting to see in a decade whether industries that heavily adopted AI early (like perhaps software coding or customer service) have a missing cohort of mid-level professionals. Will companies regret not training people? Or will AI evolve so rapidly that many traditional senior roles themselves change or become obsolete, making the old "pyramid model" of organization unnecessary? Some have speculated about a future with very flat organizations: a few super-experts (plus AI) do all the work, and everyone else finds other things to do. Others argue that human oversight and creativity will remain in demand, preserving the need for career progression.

2.5 Conclusion

We developed a stylized model of an economy with high-skill "seniors" and low-skill "juniors" to investigate the impact of AI on productivity and skill formation. The model yields several insights. First, in a static setting, teams of juniors and seniors are highly productive, and the division of surplus depends on their relative supply. Seniors capture most gains when they are scarce, but if juniors are scarce, they can command higher wages. Second, AI can act like a super-efficient junior (requiring less time h_A and possibly having higher skill z_A), which makes it privately optimal for seniors to replace human juniors in many cases. This raises short-run output and can either increase or decrease wage inequality depending on the labor supply situation – though a likely outcome is increased inequality with seniors earning much more. Third, and most importantly, the removal of juniors from teams means the loss of a key learning channel. In our dynamic extension, junior-senior teams were the engine of creating new skilled workers (future seniors). If AI displaces this, the economy could suffer a lower steady-state level of human capital and output, despite the initial AI-induced boost. We derived conditions under which long-run GDP per capita falls with AI, even though short-run GDP rises.

These findings underscore a potential trade-off between present and future productivity. Our model is admittedly abstract – reality is more complex, with many tasks and continuous skill development – but it captures the essence of a concern raised by practitioners: "Where will the experts of tomorrow come from if nobody hires juniors today?". The model also resonates with historical anecdotes. For instance, in professions like crafts or medicine, when training pipelines broke down, it led to skill shortages until corrective measures were taken (sometimes through public intervention). We might be at risk of a similar phenomenon in modern knowledge industries with generative AI.

We should note some limitations and open questions in our analysis:

We treated z_1, z_0, z_A, h, h_A as exogenous. In reality, these could evolve. For example, z_A might improve over time as AI learns from data (as per Wang & Wong (2025) scenario). Also, human skills z_0, z_1 could respond to the presence of AI (educational systems might train people differently if certain tasks are automated). Incorporating such feedback is an important extension.

We assumed learning λ happens only through mentoring. Could there be alternative pathways? Perhaps juniors could learn from AI (a form of AI-driven training). If an AI can codify expert knowledge, maybe juniors could acquire skills faster on their own. This would mitigate the dynamic loss. Preliminary evidence (e.g., improved novice performance with AI tools) gives credence to this possibility. However, skeptics counter that true expertise often requires rich tacit knowledge that comes from experience, not just AI advice. More research (empirical and theoretical) is needed to understand AI's role as a teacher vs. as a crutch that prevents learning (as seen in education contexts where students over-rely on AI and don't learn the material).

Our equilibrium analysis with learning didn't delve into strategic behavior much (except a brief mention of juniors internalizing learning). In a dynamic game, one could ask: will seniors under-invest in training juniors or even intentionally not pass on knowledge to remain valuable (the classic "knowledge hoarding" problem)? How might that interact with AI adoption (since an alternative to hoarding is just not having juniors at all)? These nuances could be important in assessing whether the market under-provides learning opportunities.

Finally, there's the question of policy and welfare: if we determined that AI adoption is dynamically inefficient (i.e., society would be better off in the long run if some juniors were trained), what is the best way to achieve that? A blunt ban on AI in certain tasks seems unlikely and inefficient. Incentive-based approaches (like training subsidies or tax adjustments) are more promising and were discussed above. One could formally model a social planner or government that values future productivity and see what the optimal intervention would be. This intersects with the literature on R&D policy and human capital externalities.

To conclude, our model provides a theoretical framework to think about the long-term consequences of AI on the labor force's skill composition. It suggests that even if AI brings immediate gains, we should be vigilant about its impact on career dynamics and learning. The full impact of generative AI on the workforce will play out over decades; by combining insights from models like ours with empirical monitoring, policymakers and firms can hopefully steer toward outcomes where AI technologies augment human capabilities and sustain growth, rather than create a short-lived spike in productivity followed by stagnation due to missing human expertise. The evolving literature – from Buera et al.'s work on dynamic competition to Acemoglu et al.'s calls for human-centric AI deployment – all point to a common message: do not ignore the dynamic effects. Our contribution is to highlight the apprenticeship dimension of those dynamic effects in the age of AI, an area that will surely benefit from further research and data in the coming years.

References

- Buera, F. et al. (2025). The Life-cycle of Concentrated Industries. (EFG Draft). [We refer to dynamic efficiency analysis in this paper.]

- Heß, P., Janssen, S., & Leber, U. (2023). The effect of automation technology on workers' training participation. Economics of Education Review, 96, 102438. [Finds workers exposed to automation are significantly less likely to receive training.]

- Mühlemann, S. (2024). AI Adoption and Workplace Training. IZA Discussion Paper No. 17367. [Shows AI-adopting firms cut training for current workers and hire more skilled workers, but also increase apprenticeships in SMEs.]

- Brynjolfsson, E., Li, D., & Raymond, L. (2023). Generative AI at Work. NBER Working Paper 31161 (rev. Nov 2023). [Field experiment with customer support agents;

AI boosted productivity 14%, especially for novice workers, and helped disseminate expert best practices.]

- Acemoglu, D. (2024). The Simple Macroeconomics of AI. (Working Paper, April 2024). [Argues modest productivity gains from AI and that AI could increase capital share; also notes AI can increase inequality even if it improves some low-skill productivity.]
- Acemoglu, D., Johnson, S., & others (2023). Human-Centric AI (CEPR Policy Insight No. 124). [Advocates for AI that complements workers; discusses policy changes like tax reform to encourage hiring/training over pure automation.]
- Wang, P., & Wong, T.N. (2025). Artificial Intelligence and Technological Unemployment. NBER Working Paper 33867. [Model of AI as learning-by-using; scenarios of AI initially complementing then substituting labor.]
- Appelo, J. (2025). "AI Wrecks the Corporate Career Ladder. Give Juniors the Steering Wheel!" The Maverick Mapmaker (Medium, Mar 26, 2025). [Discusses how firms dropping junior hiring due to AI threatens apprenticeship and innovation; provides a practitioner perspective.]