Broken Ladders: 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.

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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. 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

Problems and skills. 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 $z \in (0, 1)$ represents the hardest problem that they can solve. In other words, a person with skill z_i can solve any problem of difficulty $Z \leq z_i$ with certainty, but cannot solve any problem $Z > z_i$. We assume that there are two types of workers, who differ in their skill levels, denoted by $z_0 < z_1$. We call individuals with skill level z_0 'juniors', and individuals with skill level z_1 'seniors'.

Demographic structure. We assume that time is continuous, and at any given point in time, δL people are born. A fraction ϕ of them are born with senior skills z_1 , and fraction $1 - \phi$ with junior skills, z_0. They each die with a Poisson arrival rate of δ, independent of skill. The model allows for learning by juniors in some cases, meaning that their skill level changes to z_1 stochastically.

Working solo. Working on a problem requires time, committed before knowing the difficulty of the problem. One problem takes one unit of time to work on. (This is a normalization of units.) If a person is working alone on a problem (called 'solo work'), they can solve it with probability z_i, so their expected output per unit of time is z_i. 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 unit of time, and a senior would earn $w_1 = z_1$.

Working in teams. Now consider teamwork: a senior can collaborate with several juniors. The idea is that juniors attempt the problems first; they solve the easier ones that they are capable of, and escalate the unsolved harder problems up to the senior. The senior then spends time on handling those tougher problems. We assume that 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 manages to solve it (the difficulty is unknown until attempted). The parameter h captures the time cost per problem of communication, mentoring and solving the 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 to seniors. There is a constraint on the senior's time, in expectation, they have to be able to handle all the problems that juniors send to them.

2.1 Solution of baseline model

In our baseline model there is no learning, each individual spends their entire life with the skill they were born with. This is essentially a static model, where the measure of juniors in the economy is $L_0 = (1-\phi)L$ and the measure of seniors is $L_1 = \phi L$ at all times.

The time constraint of the senior pins down the measure of juniors they can work with, which we denote by n_0. As the probability that a single junior passes on the problem that they draw is $1 - z_0$, the measure of total problems passed on is given by $n_0(1 - z_0)$, which takes $hn_0(1 - z_0)$ time for the senior. Since seniors also have 1 unit of time, this implies that the optimal team size is given by

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

Team output. Team output is the sum of problems that the juniors solve and of those that the senior solves. The probability that the senior can solve a problem escalated to them is $(z_1 - z_0)/(1 - z_0)$. So total team output is

$$Q_{team} = n_0 z_0 + n_0(1 - z_0)\frac{z_1 - z_0}{1 - z_0} = n_0 z_1 = \frac{z_1}{h(1 - z_0)}. \tag{2}$$

The senior essentially 'multiplies' their expertise across n_0 juniors.[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. Note that the marginal value of increasing the senior's skill z_1 is amplified in a team relative to solo work as $1/h(1 - z_0) > 1$, which follows from our assumptions on h and on z_0.

[1]Thus the team output is simply the measure of problems encountered by the team (n_0) times the probability that the senior can solve a random problem (z_1).

Team work is better than solo work if team output is higher than the sum of individual outputs ($n_0 z_0 + z_1$), which boils down to the following:

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

This requires the senior's productivity to be sufficiently large relative to the junior's productivity. By how much depends on the efficiency of teamwork. If teamwork is more efficient, i.e., h is smaller and z_0 is larger, the senior's productivity does not have to be so large relative to the junior's for teamwork to be better than solo work. We refer to this condition as the participation constraint (the reason for this is described later), and we assume it holds.

Labor market equilibrium. If teamwork is better than solo work, then given the supply of seniors, L_1, and juniors, L_0, as many teams form as possible. Wages for seniors, w_1 and for juniors w_0 are determined by supply and demand, depending on whether team opportunities are abundant or scarce.

As in teamwork each senior wants to head a team of n_0 juniors, two cases naturally arise. Either there are too many juniors (case 1) or too few juniors (case 2) relative to seniors.

Case 1: Too many juniors. This case arises if $L_0 > n_0 L_1$, that is even if every senior takes on a full team of n_0 juniors, there would still be some juniors left without a senior. In the model without learning this condition boils down to $\phi = \frac{L_1}{L} < \frac{h(1-z_0)}{1+h(1-z_0)}$. In this scenario, not all juniors can join teams, and the excess juniors must work solo. All juniors not in a team produce output on their own and earn their solo wage $w_0 = z_0$. All juniors working in teams must also earn w_0; if they were offered less, they would choose to work on their own, and no senior would offer more, as any solo-working junior would join a team for wage $w_0 + \varepsilon$. If juniors are abundant, then seniors extract all the surplus generated by teamwork. The senior's wage is team output, as given by equation (2), minus the wage cost of juniors:

$$w_1 = Q_{team} - n_0 w_0 = \frac{z_1 - z_0}{h(1 - z_0)}. \tag{3}$$

The seniors are happy to head teams if their wage from teamwork exceeds their wage from solo work, z_1. This implies a participation constraint that is equivalent to equation (PC). If output from teamwork is larger than the sum of the solo output of team members, then the senior who extracts all the rent is better off heading a team than working solo.

Wage inequality in this case is

$$\frac{w_1}{w_0} = \frac{z_1 - z_0}{z_0 h(1 - z_0)}, \tag{4}$$

which exceeds wage inequality from solo work, z_1/z_0, as long as seniors are willing to lead teams, that is as long as the participation constraint, equation (PC), is satisfied.

Output per capita in the economy is the sum of team output and solo output of all juniors who could not join a team divided by population

$$Y_{base1} = \frac{L_1}{L} Q_{team} + \frac{L_0 - L_1 n_0}{L} z_0 = (1 - \phi) z_0 + \phi \frac{z_1 - z_0}{h(1 - z_0)}. \tag{5}$$

This exceeds autarky GDP, i.e., output per capita if everyone works solo, given by $Y_{solo} = (1 - \phi) z_0 + \phi z_1$ if the participation constraint in (PC) is satisfied.

Case 2: Juniors are scarce. This case arises if $L_0 \leq n_0 L_1$, which means that there are not enough juniors to utilize all seniors' capacity. In this case every junior joins a team, and some seniors will be left without any junior partners. Juniors become the scarce factor, and seniors are abundant. Seniors who fail to hire a junior would have to work alone and earn $w_1 = z_1$. This implies that also those seniors who work in teams will earn the same wage, and juniors capture all the surplus generated in teamwork. Each junior's wage in this case is their share of output minus the senior's wage:

$$w_0 = \frac{Q_{team} - z_1}{n_0} = \frac{\frac{z_1}{h(1-z_0)} - z_1}{\frac{1}{h(1-z_0)}} = z_1[1 - h(1 - z_0)]. \tag{6}$$

Juniors are willing to be part of a team if their wage in teams exceeds their solo wage, $w_0 > z_0$. This participation constraint is satisfied if equation (PC) holds, that is if team output is higher than the sum of individual outputs. Junior wages will be higher if teamwork is more efficient, i.e. if h is small and if z_0 is large. Wage inequality in this case is

$$\frac{w_1}{w_0} = \frac{z_1}{z_1[1 - h(1 - z_0)]} = \frac{1}{1 - h(1 - z_0)}, \tag{7}$$

which is below wage inequality from solo work, z_1/z_0, as long as juniors are willing to participate in teams, that is the participation constraint in equation (PC) is satisfied. Note that $w_1 > w_0$ even in this case, so seniors prefer to work either solo or as team leaders, rather than joining a team as a junior.

Output per worker in case 2 is given by the measure of teams L_0/n_0 times team output, plus the measure of seniors working solo times z_1 divided by population:

$$Y_{base2} = \frac{L_0/n_0}{L} Q_{team} + \frac{L_1 - L_0/n_0}{L} z_1 = [1 - (1 - \phi)h(1 - z_0)]z_1. \tag{8}$$

In summary, our baseline static model yields two distinct regimes for wage inequality. In case 1, when there are too many juniors, seniors capture most of the surplus and inequality is high. In case 2, when there are too 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 technological changes affect inequality. For instance, improvements in communication technology (a lower h) make teams more efficient. In case 1, a reduction in h increases w_1/w_0 because it amplifies the senior's leverage (see (4)). In case 2, inequality actually decreases as h falls (see (7)). 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.

Other interesting comparative statics are with respect to the skill level of juniors and seniors. An increase in the juniors' skill level z_0 (e.g. better basic education for all workers) reduces wage inequality in both cases (see (4) and (7)). The intuition is that if juniors become more capable, the senior's relative advantage shrinks, and juniors also solve more tasks themselves, making seniors slightly less important. An increase in the seniors' skill level z_1 increases wage inequality in case 1, but does not impact wage inequality in case 2.

In what follows our analysis will consider economies in case 1, where juniors are abundant.

2.2 Introducing AI as a team member

We now extend the model to include AI as a potential 'worker' in the team. We consider an AI system that functions similarly to a junior: it attempts to solve all problems, it can solve problems up to a certain difficulty, z_A, and it passes on the rest. Thus, z_A for AI is similar to the junior's skill z_0. Let h_A denote 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 $h_A \in (0, 1)$, implying that AI can also save time, but does not eliminate oversight entirely.

The key difference between employing juniors or using AI is in costs: hiring an AI has essentially no wage cost. AI is like a machine – we can assume it is a fixed asset or its 'salary' is zero for the marginal analysis. Thus, a senior who has access to AI can use as many 'AI juniors' – or send as many problems to the AI – as they want, limited only by the senior's time.

Suppose a senior can choose to work with n_A units of AI (multiple AI instances or simply scaling usage). Similarly to before, if the senior allocates all their time to handling the AI's unsolved problems, then $n_A(1 - z_A)h_A = 1$, implying $n_A = \frac{1}{h_A(1-z_A)}$. 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:

$$Q_{AI} = n_A z_A + n_A(1 - z_A)\frac{z_1 - z_A}{1 - z_A} = n_A z_1 = \frac{z_1}{h_A(1 - z_A)}. \tag{9}$$

Comparing this to Q_{team} in (2), we see that the structure is analogous. If z_A and h_A are comparable to a junior's z_0 and h, then AI can similarly boost the senior's productivity. Importantly, however, the AI does not demand a wage or have an outside option. This can fundamentally alter the equilibrium.

Consider an economy initially in case 1, with too many juniors relative to 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 is beneficial. The senior's decision depends on whether their return is higher when using AI (they get the entire output) or when employing juniors, in which case they get w_1 as given by (3). Comparing the senior's earnings in the two cases, they will choose to use AI if:

$$\begin{aligned} \frac{z_1}{h_A(1 - z_A)} &> \frac{z_1 - z_0}{h(1 - z_0)} \\ \frac{h(1 - z_0)}{h_A(1 - z_A)} &> 1 - \frac{z_0}{z_1}. \end{aligned} \tag{10}$$

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 a junior) exceeds a threshold related to the junior's contribution (the RHS is the fraction of solved tasks that juniors cannot solve). If AI is equally capable as juniors ($z_A = z_0$) and equally easy to work with ($h_A = h$), then the LHS of (10) simplifies to 1, and the RHS is $1 - \frac{z_0}{z_1}$. Since $z_1 > z_0 > 0$, the RHS is less than one and so (10) holds automatically. This means that even if AI had the same skill and communication cost as a junior, a senior would still prefer AI, because with AI they do not have to share the output with anyone. 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.

Condition (10) can also be satisfied even if seniors are relatively less productive using AI, i.e. $h_A(1 - z_A) > h(1 - z_0)$, their earnings can still be higher as they do not need to share output with juniors.

Under condition (10), a senior's optimal choice is to employ AI exclusively and hire zero juniors. In equilibrium all juniors are effectively pushed out of teams. Juniors revert to working solo on problems generating output and income z_0 each. Each senior now works with AI and produces output $\frac{z_1}{h_A(1-z_A)}$, and receives all of it as wage. Output per capita in the economy is given by

$$Y_{AI} = \frac{L_1}{L} Q_{AI} + \frac{L_0}{L} z_0 = (1 - \phi) z_0 + \phi \frac{z_1}{h_A(1 - z_A)}. \tag{11}$$

Output per capita in (11) is larger than without AI given in (5) whenever it is beneficial for seniors to adopt AI instead of working with juniors. Introducing AI in this way thus unambiguously raises GDP. Thus, in a static sense, AI raises efficiency – no surprise there. We get more output because seniors can handle more problems with the help of AI, and juniors do what they can on their own.

In the new equilibrium wage inequality is given by

$$\frac{w_1}{w_0} = \frac{z_1}{z_0 h_A(1 - z_A)},$$

as all juniors are essentially relegated to solo work, earning $w_0 = z_0$, and seniors get all the rents from working with AI, $w_1 = \frac{z_1}{h_A(1-z_A)}$. This is larger than the original level of inequality given in (4) as long as it is beneficial to use AI, that is (10) holds. If AI replaces juniors, inequality increases: seniors' productivity and pay goes up, while juniors remain at low-productivity solo work earning z_0.

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.

The stock of seniors L_1 evolves according to

$$\dot{L_1} = \phi\delta L - \delta L_1 + \lambda \min\{L_1 n_0, L_0\},$$

where $\phi\delta L$ is the measure of individuals born with senior skills, δL_1 seniors exit due to death, and $\lambda \min\{L_1 n_0, L_0\}$ juniors become seniors. The $\min\{L_1 n_0, L_0\}$ is equal to $L_1 n_0$ in case 1 when seniors are scarce and determine the measure of juniors working in teams, and is equal to L_0 in case 2 when there are too many seniors, and all juniors work in teams. Let's consider a steady state of this system (L_1 constant) under the assumption that the economy starts and remains in case 1, i.e. seniors are always scarce. The steady state share of seniors is given by

$$\frac{L_1}{L} = \frac{\phi}{1 - \frac{\lambda}{\delta}\frac{1}{h(1-z_0)}}. \tag{12}$$

This is the steady-state share of seniors when there is learning. This fraction has to be between 0 and 1. As long as $\frac{\lambda}{\delta} < h(1 - z_0)$, this fraction is positive. Learning has to be sufficiently slow relative to exit, $\frac{\lambda}{\delta} < (1 - \phi)h(1 - z_0)$, for it to be also smaller than one, so that not everyone ends up a senior. To ensure that the economy remains in case 1, that is seniors remain scarce despite learning, the steady state share of seniors has to be smaller than $\frac{h(1-z_0)}{1+h(1-z_0)}$. This puts an even more stringent limit on the speed of learning: $\frac{\lambda}{\delta} < (1-\phi)h(1-z_0) - \phi$.

Not surprisingly, learning by mentoring raises the long-run proportion of high-skill workers as can be verified from (12) $\frac{L_1}{L} > \phi$. 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 $L_1/L = \phi$, and as λ increases, L_1/L can be substantially above ϕ.

Team output, junior and senior wages are all the same as in the model without learning. The steady-state output per capita with learning is given by

$$Y_{learning,steady} = \frac{L_1}{L}\frac{z_1 - z_0}{h(1-z_0)} + \frac{L_0}{L}z_0 = \phi\frac{z_1 - z_0}{h(1-z_0) - \frac{\lambda}{\delta}} + \left[1 - \phi\frac{h(1-z_0)}{h(1-z_0) - \frac{\lambda}{\delta}}\right]z_0. \quad (13)$$

It is easy to see that steady state output per worker is increasing in the speed of learning, λ, because more workers end up as high-skill. In the limit of no learning, $\lambda = 0$, (13) simplifies to $(1-\phi)z_0 + \phi\frac{z_1-z_0}{h(1-z_0)}$, which corresponds to output per capita without learning given in (5).

2.4 AI in the dynamic model with learning

Now imagine that the economy with learning is at its steady state, when AI technology arrives. If it is worth it for seniors to use AI, that is condition (10), repeated below, is satisfied

$$\frac{h(1-z_0)}{h_A(1-z_A)} > 1 - \frac{z_0}{z_1},$$

then all seniors use AI, no juniors work in teams, and hence no on-the-job learning occurs. At this point, the output of seniors increases, as well as overall GDP per capita. Hence AI is introduced only if it yields a static gain, holding the share of seniors and juniors constant. However, the fraction of seniors starts to fall (as a larger measure is dying than is born), until it reaches ϕ, its steady state without learning. Therefore, $L_1/L = \phi$ in the long run with AI and learning, as AI adoption eliminates the mentoring pathway. GDP per capita in the steady state is equal to that in the economy without learning and with AI as in (11), repeated below:

$$Y_{AI} = \frac{L_1}{L} Q_{AI} + \frac{L_0}{L} z_0 = (1-\phi) z_0 + \phi \frac{z_1}{h_A(1-z_A)}.$$

The crucial question is which steady state yields higher output, with or without AI? This is not obvious because AI boosts the current productivity 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), long run output with AI may dominate. But if learning effects are powerful, losing them can outweigh AI's static gain in the long run.

Comparing Y_{AI} (from (11)) and $Y_{learning,steady}$ (from (13)) we can derive a condition for AI to reduce long-run GDP per capita:

$$\frac{\lambda}{\delta} > \frac{z_1 \frac{h(1-z_0)}{h_A(1-z_A)} - (z_1 - z_0)}{\frac{z_1}{h_A(1-z_A)} - z_0}. \tag{14}$$

This condition requires the speed of learning to be sufficiently large relative to productivity gains from AI.[2] The right hand side is increasing in the productivity of an AI enhanced senior ($z_1/(h_A(1-z_A))$) and in the skill of juniors, while it is decreasing in the efficiency of teamwork ($1/(h(1-z_0))$) and in the skill difference between seniors and juniors. These results are all intuitive. The larger the productivity of an AI enhanced senior, the faster learning has to be to offset AI induced productivity gains. The higher is the skill of juniors, the better is the outside option for them when AI is adopted, and the smaller the economy's GDP loss from moving from teamwork to solo work. On the other hand, the more efficient teamwork is, the higher is GDP in the teamwork and no AI economy,

[2]The numerator on the right hand side is positive if (10) is satisfied and AI is implemented, the denominator is always positive.

and so learning does not have to be that fast for AI to generate dynamic losses. Similarly, the larger the skill gain from becoming a senior is, a lower learning speed can also lead to dynamic losses from AI. Note that the speed of learning cannot be too large either, otherwise eventually there would be too many seniors.

If this condition is satisfied, then the dynamic losses from the lack of learning outweigh the static gains from AI. This highlights a potential dynamic inefficiency: seniors may adopt AI because it is privately optimal, as it yields higher earnings for them, but collectively this might lead to lower output in the long run due to the collapse of human capital formation.

There is a parallel here to the idea of excessive automation, i.e., 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-mentoring.

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.

2.5 Internalized gains from learning and AI

We have so far assumed that juniors do not internalize the future benefit of learning when deciding on jobs. 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 lower wage in teams than what they would earn solo. In a competitive labor market with forward-looking workers and where juniors are abundant, the junior's expected lifetime utility from a team position should equal that from working solo. Let $J_{0,team}$ denote the expected present value of being a junior in a team, given by the following Bellman equation:

$$\delta J_{0,team} = w_{0,team} + \lambda \left[\frac{w_{1,team}}{\delta} - J_{0,team} \right],$$

where $\frac{w_{1,team}}{\delta}$ is the present value of a senior earning $w_{1,team}$ per period until death. We can express $J_{0,team}$ as

$$J_{0,team} = \frac{w_{0,\text{team}} + \lambda \frac{w_{1,team}}{\delta}}{\delta + \lambda},$$

The value of being a solo junior is $J_{0,solo} = \frac{z_0}{\delta}$, as solo juniors don't learn and earn z_0 until death. As there is an abundance of juniors, they need to be indifferent between the two options, $J_{0,team} = J_{0,solo}$, which implies:

$$w_{0,team} = z_0 - \frac{\lambda}{\delta}(w_{1,team} - z_0). \tag{15}$$

This means that juniors in a team accept a wage below their solo marginal product z_0, because they expect to recoup it when they become seniors.[3] In other words, they effectively pay the senior (or firm) for training via a wage discount. If juniors are confident in promotion, such an equilibrium could occur. It resembles classic 'apprenticeship' where trainees work for low pay to gain skills.

[3] To see that $w_{0,team} < z_0$, note that $\lambda > 0$, and $w_{1,team} > z_0$, because for seniors to participate $w_{1,team} > z_1 > z_0$.

The senior's surplus from a team when juniors internalize gains from learning is even larger because juniors wages are lower. The senior's wage is determined as

$$w_{1,team} = n_0(z_1 - w_{0,team}) = \frac{z_1 - w_{0,team}}{h(1-z_0)}.$$

Using the expression for $w_{0,team}$ and re-arranging we get that

$$w_{1,team} = \frac{z_1 - z_0(1+\frac{\lambda}{\delta})}{h(1-z_0)(1-\frac{\lambda}{\delta}\frac{1}{h(1-z_0)})} = \frac{z_1 - z_0(1+\frac{\lambda}{\delta})}{h(1-z_0) - \frac{\lambda}{\delta}}.$$

This is the senior wage when juniors fully internalize learning. If there is no learning ($\lambda = 0$) then this is equal to the senior wage in case 1 of the baseline model. It is straightforward to check that $w_{1,team}$ is increasing in the speed of learning, λ/δ, and is larger than the senior wage when juniors do not internalize learning.[4] This is intuitive, as when juniors internalize learning, they accept lower wages than z_0, and hence the senior retains more of the same team output.

Wage inequality is higher in this economy than in the economy without (internalized) learning, as the lowest paid workers earn less than z_0, while the highest paid workers earn more than $(z_1 - z_0)/(h(1-z_0))$.

The fact that senior wages are higher with internalized learning means that the requirement on the productivity of AI is more stringent. The condition for AI use becomes

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

The key insight is that 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.

Team output and the long run share of seniors are the same as in the economy with

[4] Take the partial derivative of $w_{1,team}$ with respect to λ/δ and note that if (PC) is satisfied, then the derivative is positive.

learning that is not internalized, and hence GDP is also the same. The condition for the dynamic inefficiency of AI is therefore the same as before, given in (14) and repeated here:

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

As $z_1/(h_A(1-z_A))$ needs to be larger for AI to be implemented, the right hand side of the above expression will be higher, implying a ceteris paribus that the above inequality is less likely to hold. While internalized learning makes dynamically inefficient AI less likely to happen, it is still a possibility.

2.6 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.

2.7 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.]