Technology Bottlenecks: Measuring Where AI Could Raise the Value of Work It Cannot Yet Do*

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Abstract

AI exposure measures ask what work AI can do. We ask where the marginal value of work AI cannot yet do may rise as AI speeds up the rest of the job. Such work can become a bottleneck, especially where more of the surrounding tasks in a job can be done by AI. We call this bottleneck pressure. Using a task-based framework, we show that for an AI-infeasible task, pressure is the exposure of the occupation posting it: the same task faces different pressure across jobs. Occupation-level pressure is exposure times the AI-infeasible share of advertised work. To take this measure to the data, we map 288 million U.S. job postings from 2018 to mid-2026 to O*NET tasks and use their GPT-4 feasibility ratings from Eloundou et al. (2024). We measure both exposure and pressure from postings, where about 90 percent of labeled matched task mentions lie outside the occupation's O*NET task list. About half of mention-weighted variation in pressure on AI-infeasible work lies within tasks, across occupations. In every year, AI-infeasible tasks within occupations faced more pressure in senior than junior postings, about 6.5 percent more in the first half of 2026. Over the full sample, mean occupation pressure rose from 17.6 to 18.7, or by 6 percent, about three quarters from task mentions shifting toward higher-pressure occupations. Reporting pressure alongside exposure shows where improving the work AI cannot do may pay off more as capabilities expand.

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1 Introduction

Measures of AI exposure, which assess the tasks AI can perform, have become the standard tool for describing which occupations AI is likely to affect (Brynjolfsson, Chandar and Chen, 2025; Brynjolfsson, Mitchell and Rock, 2018; Eloundou et al., 2024; Felten, Raj and Seamans, 2021; Webb, 2020), and they align with measures constructed from observed AI use (Tomlinson et al., 2025). But what AI cannot do also matters. As capabilities expand (Kwa et al., 2025; Patwardhan et al., 2025) and AI speeds up the tasks it can do, the tasks it cannot do may take up a growing share of labor within jobs, a potential "mini Baumol" effect (Aghion, Jones and Jones, 2019; Baumol, 1967), suggesting that improving those tasks may become more valuable. Those tasks can become binding: they limit how far gains on the feasible tasks translate into output (Codreanu et al., 2026; Gans and Goldfarb, 2026; Jones and Tonetti, 2026; Kording and Marinescu, 2025; Kremer, 1993), and complementarity can raise the value of the labor that performs them (Agrawal, Gans and Goldfarb, 2019, 2024; Autor, 2024; Autor and Thompson, 2025; Imas and Shukla, 2026*a*).

A single task illustrates the core idea of the paper. "Greet customers and make them feel welcome" is a task rated AI-infeasible: it falls below the feasibility threshold, meaning that, by the GPT-4 rating in Eloundou et al. (2024), a language model could not reduce the time it takes to complete the task by at least half at the same quality, even with the assistance of complementary software. The task appears in the job postings of 667 of the 708 occupations we study. In occupations where a smaller share of advertised work is rated AI-feasible, such as fast food workers, the task faces lower "bottleneck pressure," as we call it: 23 on a scale from 0 to 100. In occupations where a larger share is rated AI-feasible, such as customer service representatives, it faces pressure of 83. Under the theoretical framework we develop en route, speeding up the surrounding AI-feasible work therefore raises the marginal value of greeting customers proportionally more in customer service than in fast food. Bottleneck pressure is therefore a property of a task inside its job, not of the task alone, and this paper proposes a novel, theoretically grounded empirical measure around that basic observation.

We derive the measure from a standard task-based model (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; Autor, Levy and Murnane, 2003) in which tasks are stronger complements within occupations than occupations are across the economy. This relative condition allows tasks to be gross substitutes within jobs. The growing share of labor and the binding constraint described above arise when tasks are gross complements, whereas the ranking of AI-infeasible tasks that we derive with labor fixed holds in either case. Holding labor fixed, AI raises, in proportional terms, the marginal value of labor in a task it

cannot perform through two channels: a scale effect common to all tasks, and a bottleneck effect that is, to first order, proportional to the AI exposure of the task's own occupation. When the elasticities and the size of the AI gain are common across occupations, this first-order effect ranks AI-infeasible tasks by an index of bottleneck pressure that is simply the product of a task's infeasibility and its occupation's exposure. *Infeasibility alone does not create pressure:* the occupation must also contain work rated AI-feasible. When labor can *move* across tasks and occupations, adjustment can instead occur through reallocating work toward AI-infeasible tasks. Even when we relax the assumption of keeping labor fixed, we show that, under the relevant elasticity conditions, the *same pressure index* still ranks, to first order, the proportional changes in those tasks' shares of aggregate income and the returns to speeding them up. Averaged over a job's work, the index becomes the occupation's exposure times the share of its work that AI cannot do. When both shares are measured on the same tasks, ratings and weights, as in our measure, occupation pressure is exposure times one minus exposure.

Greater AI exposure does not necessarily mean greater bottleneck pressure for the entire occupation. Consider accountants, for whom about 90 percent of the advertised work is AI-feasible. The remaining AI-infeasible tasks face high pressure. However, those tasks nevertheless account for a small share of the overall job. As a consequence, the overall pressure on accountants averages to about 8.7 on a scale of 100. Wholesale sales representatives, on the other hand, have much lower exposure, at about 72 percent. In contrast to accountants, however, a comparatively greater AI-infeasible share of work remains alongside AI-feasible work. The product of these shares is therefore around 20, more than twice the pressure on accountants despite exposure being only about 18 percentage points lower. Finally, consider chemical technicians, whose advertised work is about evenly split between AI-feasible and AI-infeasible tasks. As a consequence, their occupation pressure is near the maximum of 25, despite having lower exposure and lower pressure on each AI-infeasible task than either accountants or wholesale sales representatives. These differences across the three occupations therefore reflect not only how much surrounding work AI can speed up but also how much remaining work faces the resulting pressure.

Under our framework, higher occupation pressure means a larger first-order proportional bottleneck effect on the marginal value of AI-infeasible work, averaged over the occupation's advertised tasks. On the other hand, low occupation pressure arises in two ways: from little exposure or from little AI-infeasible work. Note that low bottleneck pressure does not imply protection from automation, including from technologies outside the scope of these ratings.

To build an empirical counterpart of this index, we measure both exposure and the

share of AI-infeasible work from the work employers advertise, rating tasks directly with the GPT-4 feasibility ratings of Eloundou et al. (2024). We use the broad measure, $E1 + E2$: tasks whose time can be at least halved at unchanged quality by a language model alone ($E1$) or only with complementary software ($E2$).[1] We ask which work remains a potential constraint even allowing complementary software, giving a conservative definition of infeasibility. The ratings describe what the technology is capable of doing, conditional on successful deployment and adoption, rather than whether firms have adeptly integrated it into their workflow. Our index therefore measures pressure from capability bottlenecks, tasks AI cannot speed up enough to meet the threshold, rather than integration bottlenecks, where AI could do the work but is not yet integrated into production. We use over 288 million U.S. job postings collected by the Burning Glass Institute (BGI), from January 2018 to June 2026. Job posting descriptions are first split into lines, and the lines tagged as job responsibilities, to reduce matching to boilerplate text, are then matched to their closest O*NET tasks. Each matched line inherits the feasibility rating of the associated task from Eloundou et al. (2024).[2] For each occupation, exposure is constructed empirically using the share of labeled matched task mentions rated AI-feasible, and the AI-infeasible share is its complement.[3] Tasks mentioned more frequently receive greater weight in occupation pressure, although how often a task is advertised does not establish how essential it is to production. The weights reflect how often postings mention each task. Removing widely posted generic statements leaves occupation rankings highly correlated overall and preserves the broad task-level patterns, although the highest-pressure occupations change.

There are two reasons why we prefer job postings over the O*NET catalog to measure the task content of occupations and bottleneck pressure through it. First, about 90 percent of the labeled task mentions we match via job posting lines fall outside the occupation's own O*NET task list, despite the matched statements themselves coming from O*NET. If an occupation's catalog comprises only AI-feasible tasks, bottleneck pressure scores constructed using only the catalog would imply zero pressure. However, employers in that occupation could also advertise AI-infeasible tasks, precisely those whose marginal value may rise as AI is able to perform the remainder of the job. In our data, despite about 16

[1]The categories are mutually exclusive: $\alpha = E1$ and $\beta = E1 + \frac{1}{2}E2$. β discounts $E2$ tasks for the complementary investment they require. The broad measure counts both fully because both meet the same threshold, and our question is which work stays below it.

[2]Lines partially advertising feasible parts of an AI-infeasible composite statement could still inherit an overall infeasible label. BGI's classifier guards against poor matches by comparing each line with the entire list of O*NET task statements and keeping only close matches based on a high-confidence threshold, allowing statements describing only the duty in the line to compete with composite statements when both exist.

[3]Exposure measures built from O*NET tasks and work activities include Brynjolfsson, Mitchell and Rock (2018), Webb (2020) and Eloundou et al. (2024).

percent of the occupations having entirely AI-feasible core tasks in the catalog, each of them advertises AI-infeasible work in the job postings.

Second, postings let us follow the *same* AI-infeasible task across occupations, holding its feasibility rating fixed while observing how pressure differs with the surrounding work. BGI's granular mapping of job posting lines to tasks makes such comparisons feasible. With only the O*NET catalog, task statements typically belong to a single occupation's list, and so the catalog's exact task statements rarely show the same task across jobs. Tracking the same task across jobs is critical for bottleneck pressure because a core insight of our framework is that pressure is a property not only of the task itself but also of the exposure of the job in which it sits. Indeed, 53 percent of the mention-weighted variation in pressure on AI-infeasible work lies within tasks, across the occupations that post them. Moreover, when we restrict to each occupation's own listed tasks while keeping posting exposure fixed, the share of variation in pressure that lies within tasks falls from 53 percent to an effectively negligible 0.3 percent, reflecting the limited scope the catalog offers for comparing pressure on the same tasks across occupations. While the catalog can link related tasks across occupations through shared work activities, those are much coarser and mix tasks AI can and cannot do. The key empirical finding that pressure varies for the same task across jobs crucially rests on our granular mapping of posting lines to tasks (and, of course, on how accurate its matches are). This map also shows that AI-infeasible tasks are commonly advertised alongside feasible ones: 82 percent of AI-infeasible task mentions appear in postings that also list a feasible task.

The composition of AI-infeasible work carrying pressure differs across task-pressure quintiles. Whereas physical and mechanical work accounts for 75 percent of pressure in the lowest quintile and 27 percent in the highest, interpersonal and supervisory work accounts for 17 percent in the lowest and 54 percent in the highest. Overall, relative to its share of posted work, pressure concentrates on relationship, care, coaching, training and selling work and on physical work (relationship work carries 4.0 percent of pressure against 1.5 percent of posted work), and falls well short for data analysis, documentation and strategy (documentation carries 0.5 percent of pressure against 7.8 percent of posted work).

The pressure rankings of occupations remain highly positively correlated across a host of robustness checks that vary how task matches are filtered, which years are used, and whether near-universal statements are excluded from the posting-to-task map. They also remain highly correlated when we vary how job postings are filtered, specifically adding back staffing-agency postings that are excluded from the baseline measure, although the specific set of highest-pressure occupations changes across these checks. Of course, these rankings depend on the feasibility assessment: the index measures pressure conditional

on what AI is rated as capable of doing, and it can be recomputed with ratings of newer models.

We show some key empirical patterns with our measure of bottleneck pressure taken to the postings data. First, in the first half of 2026, AI-infeasible tasks face about 4 points or about 6.5 percent more pressure in senior postings than in junior ones, mostly because junior postings carry more hands-on physical work that AI cannot do. Second, pressure also rises over time, with mean occupation pressure rising from 17.6 in 2018 to 18.7 in 2026H1. Moreover, after 2022, postings grew faster in higher-pressure occupations, which typically sit in the middle of the exposure range, although these occupations were already somewhat differentially trending before 2022 with the shifts beginning in late 2022, which aligns with our view that a single release date in November 2022 is often asked to carry more causal weight than it can bear. Third, occupation-level pressure also predicts this posting growth beyond what a linear exposure term captures, at about 5 log points per standard deviation, a predictive pattern rather than a test derived from the model. Finally, our model also predicts that under gross complementarity and if advertised task shares track work allocation, the same AI-infeasible task gains share where its occupation is more exposed. While our test gives imprecise nulls, more work is needed to confirm or reject this prediction. Overall, we believe these results are encouraging in that they show the same task facing different pressure in different jobs, as the framework implies, and point toward sharper tests that compare employers that adopt AI with those that do not.

We close by discussing some current limitations and guidance for future research. Pressure, as conceptualized in this paper, is potential pressure. Moreover, it assumes the feasible tasks are actually sped up. Of course, in practice, whether this happens depends on the integration of AI within the organization and incentives therein (Brynjolfsson, Rock and Syverson, 2021). As defined above, we are thinking of bottlenecks as *capability bottlenecks* rather than integration bottlenecks. This is because the ratings describe what AI can do, and that too a specific version of it, not whether firms have built it into how work gets done. We are aware that updating capability ratings alone would not tell us how well AI is integrated. But one can update feasibility and therefore pressure as capabilities evolve, redefine it to require integration where integration can be measured, and extend the task list as new tasks emerge in the age of AI, provided the relevant tasks, their feasibility and their shares can be measured. We discuss these limitations and possibilities for future research in more detail toward the end of the paper.

Our results suggest that reporting bottleneck pressure alongside AI exposure helps identify both the work AI can perform and the remaining work whose improvement may become more valuable as AI capabilities expand.

Related literature. This paper contributes to several literatures. First, it complements measures of automation and AI exposure (Brynjolfsson, Mitchell and Rock, 2018; Eloundou et al., 2024; Felten, Raj and Seamans, 2021, 2023; Frey and Osborne, 2017; Lassébie and Quintini, 2022; Tomlinson et al., 2025; Webb, 2020), including measures that distinguish exposure profiles using the level and dispersion of task exposure within occupations (Gmyrek et al., 2025) or that adjust exposure for complementarity at the occupation level (Pizzinelli et al., 2023). Existing measures describe occupational exposure and, in some cases, potential complementarity with AI. Our index instead measures pressure on particular AI-infeasible tasks arising from exposure elsewhere in their occupation.

Second, our paper builds on task-based models of technological change (Acemoglu, 2025; Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2019, 2022; Althoff and Reichardt, 2026; Autor, Levy and Murnane, 2003; Zeira, 1998), using the within-occupation complementarity assumption to derive an index whose first-order ranking requires no estimated parameters when the elasticities and the size of the AI gain are common across occupations. Recent work studies how AI reshapes the tasks inside jobs: reallocation toward the remaining human tasks and its implications for earnings and labor demand (Freund and Mann, 2025; Hampole et al., 2025), how the cost of separating tasks shapes job boundaries (Garicano, Li and Wu, 2026*a*,*b*), and how the sequence of tasks shapes which can be automated (Demirer et al., 2026).

Our work is closely related to Hampole et al. (2025), who study how the mean and concentration of task exposure shape reallocation and labor demand. We differ from them in measuring where pressure on AI-infeasible work lands within occupations, which can be thought of as measuring pressure on the remaining human tasks toward which labor may be reallocated as AI capabilities expand. Such reallocation could concentrate human work in fewer tasks, with a possible countereffect coming from the emergence of new tasks. Autor and Thompson (2025) is another related counterpart, emphasizing that a task's role depends on its occupational bundle and studying how changing task requirements affect expertise, worker entry, and wages. While we hold the task bundle in our setting fixed, we believe our results relate to their emphasis on the surrounding bundle and help clarify how AI gains elsewhere in that bundle may raise the marginal value of the remaining human work.

Third, it relates to work on complementarity and weak links in production (Aghion, Jones and Jones, 2019; Autor, 2015; Baumol, 1967; Becker and Murphy, 1992; Gans and Goldfarb, 2026; Jones, 2011; Jones and Tonetti, 2026; Kremer, 1993), which establishes that bottlenecks constrain the gains from automation in principle. Frey and Osborne (2017) use the term for the abilities that limit computerisation, and Gans and Goldfarb (2026)

show that automating some tasks raises the value of those that remain when tasks are quality complements. We measure where these bottlenecks arise within jobs, identifying and ranking AI-infeasible tasks whose improvement may become more valuable as other tasks in the same job become feasible.

Fourth, we use job postings to measure the task content of work (Acemoglu et al., 2022; Atalay et al., 2020; Das et al., 2020; Hershbein and Kahn, 2018; Wang, Wei and Wang, 2026). As in Meisenbacher, Nestorov and Norlander (2025), we work at the level of individual O*NET task statements. Our paper also complements survey evidence that tasks vary within occupations (Arntz, Gregory and Zierahn, 2016; Autor and Handel, 2013; Nedelkoska and Quintini, 2018). Mapping individual responsibility lines to task statements lets us compare the same task across the occupations that post it and measure how its bottleneck pressure differs with the surrounding job.

Finally, our paper relates to research in management and economics on automation and augmentation (Brynjolfsson, Li and Raymond, 2025; Choudhury, Starr and Agarwal, 2020; Fügener, Walzner and Gupta, 2026; Imas and Shukla, 2026*b*; Noy and Zhang, 2023; Raisch and Krakowski, 2021) and on how unevenly AI performs across the tasks of a single job (Dell'Acqua et al., 2026). Our measure describes where AI-infeasible work faces pressure inside jobs, without estimating how organizations subsequently redesign that work or invest in improving it. Both are promising avenues for future research.

The rest of the paper proceeds as follows. Section 2 presents the model and derives the index. Section 3 describes the data and measurement. Sections 4 and 5 document pressure across occupations and across tasks. Section 6 examines robustness, Section 7 discusses the inputs, scope and limitations of the measure, and Section 8 concludes.

2 A model of bottleneck pressure

The goal of this section is to show how the work AI cannot do faces different pressures in different jobs. While whether a task can face pressure depends on the task itself, how much pressure it faces depends on how much of the *rest* of the job AI can do. Empirically measuring this pressure on tasks inside a job will be the core goal of this paper.

We use a standard task-based production model drawing on Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018). The model is used as a building block to define a *technology bottleneck* and derive a measure of the pressure on it. The final output in the model combines occupations, indexed by o, through a CES aggregator with elasticity $\rho > 0$. Each occupation is composed of many tasks t that are aggregated using another

CES aggregator with elasticity $\sigma > 0$:

$$Y = \left[\sum_o \alpha_o Y_o^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \qquad Y_o = \left[\sum_t \alpha_{ot} Y_{ot}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where α_o and α_{ot} are positive CES weights. In the absence of technology, labor alone can perform the task. The output of task t in occupation o then is $Y_{ot} = L_{ot}$. We define a task as *AI-feasible* ($F_t = 1$) if, holding labor fixed, the technology raises its output by a factor $\delta > 1$. Otherwise, we call the task *AI-infeasible* ($F_t = 0$).[4] With the technology, $Y_{ot} = \delta^{F_t} L_{ot}$. The exposure of occupation o is then the weighted feasible share of its total work, $E_o \equiv \sum_t \pi_{ot} F_t$, where π_{ot} is the baseline cost share of task t in occupation o. Under standard assumptions,[5] such as competitive pricing and a common wage across the tasks of an occupation, this cost share is equivalent to the share of the occupation's labor spent on that task, $\pi_{ot} = L_{ot} / \sum_s L_{os}$. Aggregate exposure sums over all occupations in the economy and is defined as $\bar{E} \equiv \sum_o \pi_o E_o$, where π_o is the baseline cost share of the occupation in the economy.

Assumption 1. Tasks are stronger complements within occupations than occupations are across the economy: $\sigma < \rho$.

Becker and Murphy (1992) emphasize specialization and the costs of coordinating work across specialists. We assume that tasks within an occupation are more complementary than occupation outputs are across the economy (Assumption 1). This is a relative condition and does not require $\sigma < 1$.

Definition 1 (Technology bottleneck)**.** A *technology bottleneck* is a task that (*i*) the technology cannot perform, but (*ii*) shares an occupation with tasks that it can perform, under Assumption 1. The *bottleneck pressure* on a task is the within-occupation component of the resulting increase in the marginal value product of labor (MVPL) in that task.

Bottleneck effect. Holding labor fixed at its baseline allocation, we compare a scenario in which no task is AI-feasible with one in which the tasks with $F_t = 1$ become AI-feasible. To

[4] Eloundou et al. (2024) ask whether a large language model can at least halve the time needed to perform a task at equal quality, which corresponds to $\delta \geq 2$. In our framework, AI is modeled as a productivity multiplier on labor in feasible tasks. We do not model the replacement of labor by capital, as Acemoglu and Restrepo (2018) do. Constructing the index requires knowing which tasks are AI-feasible and the share of each job they account for, rather than whether AI augments or replaces labor. What ultimately matters for an infeasible task is the rise in output of the feasible tasks *around it* (roughly speaking, its occupation's exposure), whatever its sources. The magnitude of this resulting change in marginal value, however, is derived under assumptions about the productivity multiplier.

[5] See, for example, Acemoglu and Autor (2011) and Acemoglu and Restrepo (2018, 2022).

first order, the marginal value of labor in an AI-infeasible task changes by

$$\Delta \ln \text{MVPL}_{ot} \approx \underbrace{\ln \delta \times \frac{1}{\rho} \times \bar{E}}_{\text{scale effect}} + \underbrace{\ln \delta \times \left(\frac{1}{\sigma} - \frac{1}{\rho}\right) \times E_o}_{\text{bottleneck effect}}, \qquad F_t = 0. \tag{2}$$

Equation (2) is derived in Appendix A, which also separates capability from integration. The equation has two pieces. The first is the *scale effect* that is common to all tasks: as feasible tasks become more productive, total output expands and raises the demand for all labor. The second piece is the *bottleneck effect* that operates within occupations. Under Assumption 1, this bottleneck effect is nonnegative and proportional to the exposure of the task's own occupation. When $\sigma < 1$, the remaining AI-infeasible tasks also cap occupation output as feasible-task productivity grows, holding labor fixed: the more of a job the technology speeds up, the more the job's output is *constrained* by the tasks it cannot do. When $1 \leq \sigma < \rho$, the positive within-occupation spillover remains, but this output-cap interpretation does not. With $\sigma > 1$, tasks are gross substitutes within occupations. The AI-feasible tasks in a job then gain more in marginal value, in proportional terms, than its infeasible tasks, and when labor can move across the tasks of a job, it shifts toward the feasible tasks (Appendix A). Bottleneck pressure is then a relative spillover, raising the value of AI-infeasible work more in exposed occupations than in less exposed ones, rather than a constraint on output. The ratio of the two effects is $(\rho/\sigma - 1)\, E_o/\bar{E}$. Therefore, bottlenecks matter more relative to the scale effect when either of two things is true. First, complementarity within jobs is strong relative to complementarity across jobs (a larger ρ/σ) and second, the infeasible task sits in a job *more exposed* than the economy as a whole. Note that if feasible and infeasible tasks were perfectly segregated across occupations in the economy, every infeasible task would necessarily sit inside a job with $E_o = 0$, and there would be no bottleneck pressure.

If instead $\sigma > \rho$, the coefficient on E_o in Equation (2) turns negative. AI-infeasible work would then gain less in more exposed occupations and could lose value outright. With tasks perfect substitutes within jobs and $\rho = 1$, the first-order change is $\ln \delta\, (\bar{E} - E_o)$, which is negative for any AI-infeasible task in an occupation more exposed than average. Greeting customers would lose value in customer service precisely because AI sped up the rest of that job. This runs against the idea that the tasks bundled into a job complement one another (Garicano, Li and Wu, 2026*a*), and against evidence that automating a job's less expert tasks raises the wages of those who do the remaining work (Autor and Thompson, 2025).

Bottleneck pressure index. Because the scale effect in Equation (2) is the same for every task, it does not alter how AI-infeasible tasks are ranked across occupations. The coefficient on E_o, $\ln \delta \, (1/\sigma - 1/\rho)$, is positive under Assumption 1 and, with common elasticities and a common AI gain, the same for every task. To first order, a higher E_o therefore implies a larger proportional increase in the marginal value of labor in an AI-infeasible task, and the bottleneck effect ranks AI-infeasible tasks by

$$B_{ot} \equiv (1 - F_t) \times E_o. \tag{3}$$

We call B_{ot} the *bottleneck pressure index* on task t in occupation o. The ranking does not depend on the first-order approximation. At any finite gain, the exact bottleneck term with labor fixed is $(1/\sigma - 1/\rho) \, \Delta \ln Y_o$, and the change in occupation output $\Delta \ln Y_o$ rises with E_o for every σ and every $\delta > 1$. Under Assumption 1, the index therefore orders AI-infeasible tasks the same way whatever the size of the AI gain (Appendix A). When the task is AI-feasible, there is an extra term: the own-gain term, $-(1/\sigma - 1) \ln \delta$, which enters the formula for the change in marginal value in Appendix A. When $\sigma < 1$, this extra term is negative. The basic intuition is that even though each extra hour of labor produces more of the task, because of complementarity ($\sigma < 1$), the own-productivity effect lowers its value per unit proportionally more than output per hour rises, holding occupation and aggregate output fixed. This negative effect weakens as σ becomes closer to one; the term reaches zero at $\sigma = 1$ and becomes positive for $\sigma > 1$. When $\sigma < 1$, we cannot sign the net change in marginal value. From Equation (3), the bottleneck pressure index on the task is zero. By construction, $B_{ot} = 0$ whenever the task is feasible or its occupation has no exposure, so only infeasible tasks in exposed occupations are technology bottlenecks. The index therefore identifies *which* tasks are bottlenecks and ranks them. Their magnitude, as a proportional change in MVPL, depends on both the AI gain $\ln \delta$ and the complementarity gap $1/\sigma - 1/\rho$, which are not part of the index.

Gains below the threshold. In our empirical application, we will follow Eloundou et al. (2024) and count a task as AI-infeasible when a language model is rated as unable to halve the time it takes to perform the task at the same quality, even with complementary software, and so an infeasible task may still lead to gains in productivity. If each infeasible task gains a common factor δ_0, with $1 \leq \delta_0 < \delta$, there is no change in the task ranking: the bottleneck effect becomes $\ln(\delta/\delta_0) \, (1/\sigma - 1/\rho) \, E_o$, and the remaining terms are common to *all* infeasible tasks (Appendix A).

What suffices for the index, therefore, is that the gain is common within each *class of*

Table 1: Which tasks are technology bottlenecks

Task statement	Occupation	F_t	E_o	B_{ot}
Develop pricing strategies, balancing firm objectives and customer satisfaction.	Marketing Managers	1	90.4	0.0
Analyze financial information obtained from clients to determine strategies for meeting clients' financial objectives.	Personal Financial Advisors	1	78.4	0.0
Wash dishes, glassware, flatware, pots, or pans, using dishwashers or by hand.	Dishwashers	0	4.9	4.9
Clean building floors by sweeping, mopping, scrubbing, or vacuuming.	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	0	8.3	8.3
Direct the hiring, training, or performance evaluations of marketing or sales staff and oversee their daily activities.	Marketing Managers	0	90.4	90.4
Meet with clients' other advisors, such as attorneys, accountants, trust officers, or investment bankers, to fully understand clients' financial goals and circumstances.	Personal Financial Advisors	0	78.4	78.4

Notes: Each row shows an example O*NET task statement matched in the corresponding occupation's postings. AI feasibility F_t is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. E_o is posting exposure, the AI-feasible share of labeled matched task mentions, and $B_{ot} = (1 - F_t)E_o$ is the bottleneck pressure index on the task in that occupation. Both are on a 0–100 scale. Examples are illustrative. Postings for dishwashers and janitors contain some AI-feasible work, so their AI-infeasible tasks have low positive pressure.

tasks. If the gain varies across infeasible tasks or across occupations, the variation enters the term that differs across tasks, and the index ranks two AI-infeasible tasks correctly whenever the absolute difference in that variation is small relative to the absolute difference in their occupations' exposure (Appendix A).

Table 1 illustrates our task classifications using O*NET task statements matched to postings, with feasibility ratings from Eloundou et al. (2024). Washing dishes and cleaning floors are rated AI-infeasible tasks. Because they sit inside occupations where a small share of advertised work is rated AI-feasible, such as dishwashers and janitors, they face low bottleneck pressure. On the other hand, while other tasks such as directing the hiring and evaluation of marketing staff, and meeting with a client's attorneys and accountants, are also rated AI-infeasible, they sit inside occupations, such as marketing managers and

personal financial advisors, where a much larger share of advertised work is rated AI-feasible. These tasks face much higher bottleneck pressure. Figure 1 shows this for a single task: greeting customers is rated AI-infeasible in both jobs, but faces pressure of 23 for fast food workers and 83 for customer service representatives.

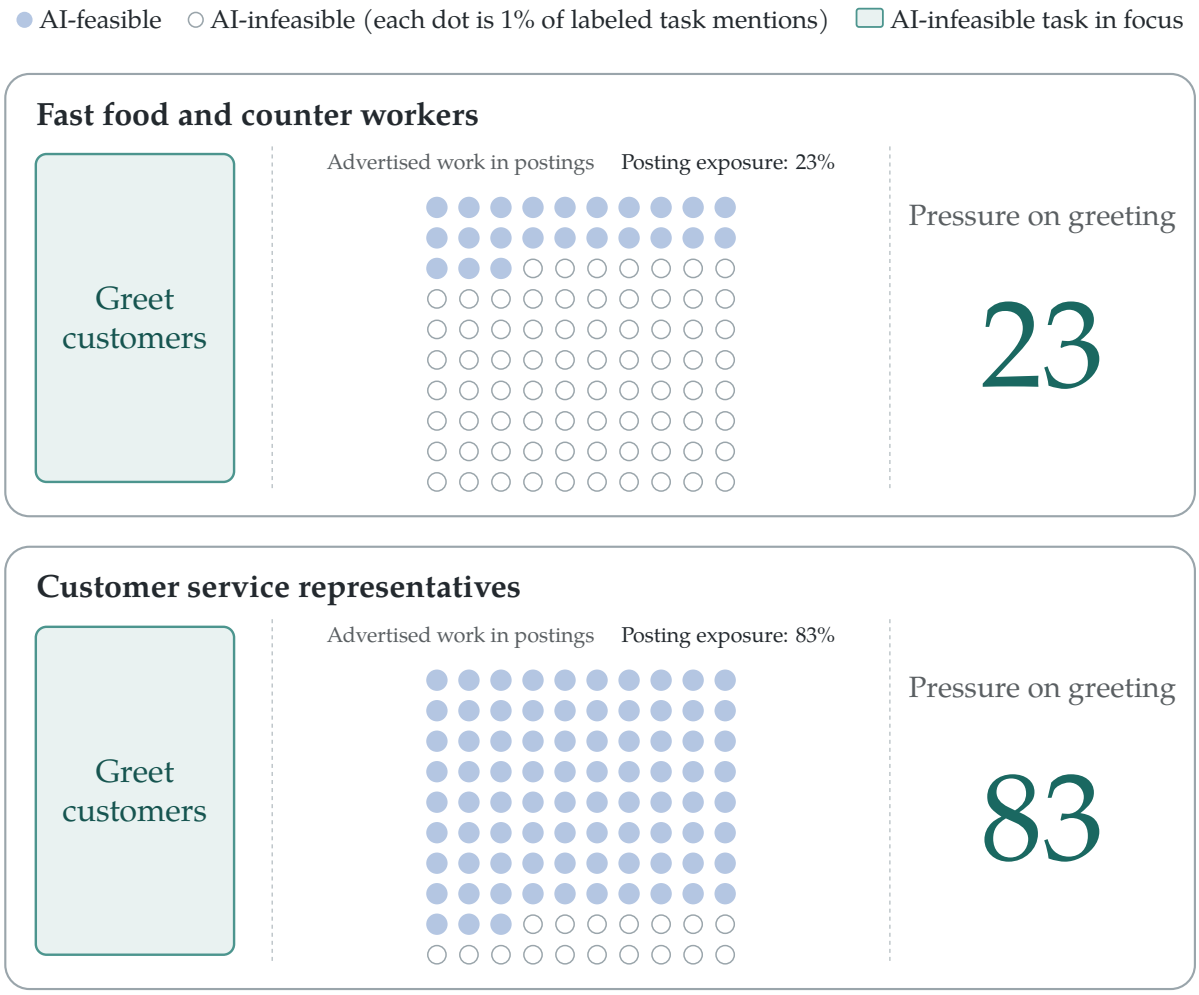


Figure 1: The same task faces different pressure in different jobs

Notes: Each rounded box represents an occupation. Dots show the occupation's labeled task mentions in postings, one dot per percent, rounded: filled dots are rated AI-feasible and hollow dots AI-infeasible, so the share of filled dots is posting exposure (23 percent for fast food and counter workers and 83 percent for customer service representatives). "Greet customers and make them feel welcome" is matched in both occupations' postings and rated AI-infeasible. Its bottleneck pressure index B_{ot} in each job equals the job's posting exposure. The greeting box highlights the task; its size does not represent its mention share. BGI harmonized U.S. job postings, January 2018 to June 2026, high-confidence line-to-task matches only. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. Pressure is on a 0–100 scale.

From tasks to occupations. Averaging the bottleneck pressure index over a job's work gives occupation-level pressure,

$$B_o \equiv \sum_t \pi_{ot} B_{ot} = E_o \times \underbrace{\sum_t \pi_{ot}(1 - F_t)}_{S_o}, \tag{4}$$

the product of the occupation's exposure and S_o, the AI-infeasible share of its work. With our posting data, occupation pressure is simply exposure times the share of AI-infeasible task mentions advertised in its postings. Given both shares use the same tasks, weights, and ratings, $S_o = 1 - E_o$ and $B_o = E_o(1 - E_o)$. This function of exposure is a fixed hump that is zero at the extremes, peaks at one-half, and can never exceed one-quarter. Two jobs with the same exposure always face the same occupation pressure, even though pressure ranks can vastly differ from exposure ranks, because occupation pressure rises with exposure below one-half and falls above it. The pressure on each AI-infeasible task keeps rising with exposure, but above one-half fewer such tasks remain to carry it.

We measure occupation pressure, constructing an empirical counterpart of Equation (4), by averaging the bottleneck pressure index B_{ot} over the work an occupation advertises, weighted by labeled matched task mentions rather than by the cost shares π_{ot}. These mention shares also define occupational exposure. As a benchmark against the measure constructed using only postings information, we report scores constructed only from the O*NET catalog as well as hybrid scores combining catalog exposure with advertised task composition from job postings data in Appendix B.

Scope and interpretation. The task ranking can extend beyond the fixed-labor setting we led with. Appendix A considers labor fixed by task, labor mobile across tasks within occupations, and labor fully mobile across tasks and occupations. With labor fixed, the pressure index ranks the bottleneck component of proportional changes in MVPL. This is the main case developed above. In all three regimes, the index also ranks, to first order, proportional changes in a task's share of aggregate income and in the return to developing technology that speeds it up. Across the three labor regimes, the index gives the same ordering of AI-infeasible tasks whenever the coefficient on exposure is positive in each regime: with labor fixed by task or fully mobile across tasks and occupations, Assumption 1 ensures a positive coefficient, whereas with labor mobile only within occupations, we also require $\sigma < 2 - 1/\rho$. This condition holds whenever $\sigma < 1 \leq \rho$, but can fail when $\rho < 1$. Absolute changes also depend on the task's initial income share or initial return, so they need not follow the same order.

These results, including those from our baseline model, allow us to interpret bottleneck pressure through the lens of innovation incentives. Specifically, to first order and whenever the coefficient on exposure is positive, AI raises the return to investments in speeding up AI-infeasible work proportionally more when that work sits inside a more exposed occupation. Appendix Figures A.1 and A.2 illustrate this mechanism, and what it implies for output, in simulations calibrated to the 708 occupations in our analysis sample, under specified productivity gains, elasticities, and development costs.

The size of the effect of AI on AI-infeasible work, and whether adjustment occurs through wages or employment, differ across the labor regimes. With labor fixed by task, differences across tasks appear in wages. With fully mobile labor across tasks and occupations, differences appear instead in the employment margin, while workers earn a common wage. The bottleneck pressure index does not estimate these wage or employment changes. It is necessarily conditional on the technology's assessed capabilities, and so its rankings can change when that assessment changes. The pressure index is also not a share of working time on a job's tasks or a forecast of wages, employment, or AI adoption (Section 7). What it does capture is how much pressure an AI-infeasible task faces, which depends on how much of the rest of the job AI can do. Section 3 explains how we empirically measure the inputs to this index using feasibility ratings, O*NET task statements, and job postings data.

3 Measuring bottleneck pressure

Section 2 points to three key objects we need for empirically measuring bottleneck pressure. They are which tasks AI can do, how exposed each occupation is, and how much AI-infeasible work it contains. To do so, we combine ratings of task feasibility from Eloundou et al. (2024) with information on job postings that supplies both occupation-level exposure and the share of AI-infeasible work. Since BGI's matching pipeline splits each job posting into lines, and the lines describing responsibilities are subsequently mapped onto O*NET task statements, we can follow the same task statement across occupations (Appendix Figure C.1). Table 2 summarizes the measured objects. Appendix Table C.1 documents the sample coverage.

3.1 Data

The sample. We use BGI's harmonized U.S. job postings data from January 2018 to June 2026. The data comprises multiple sources of postings information that are eventually cleaned and deduplicated before release. We filter the data using BGI's recommendations

Table 2: Measures and their relationships

Panel A. From inputs to pressure

Row	Measure	Mean or share	P10	P50	P90
Occupations (708)					
A1	Catalog exposure, E_o^{cat}	57.2	7.1	63.6	100.0
A2	Posting exposure, E_o^{post}	57.5	21.5	61.2	89.6
A3	AI-infeasible share of advertised work, S_o	42.5	10.4	38.8	78.5
A4	**Bottleneck pressure**, B_o	17.8	9.1	18.8	24.6
A5	Catalog-only benchmark	12.1	0.0	12.2	24.3
A6	Hybrid benchmark	15.9	5.0	15.5	27.5
AI-infeasible tasks with 1,000+ mentions (6,309)					
A7	**Task pressure**, P_t	40.3	22.2	37.5	62.2
All AI-infeasible tasks (7,485)					
A8	Share of pressure variance within tasks, across occupations	53.2%			

Panel B. Correlations across the 708 occupations

Row	Pair of measures	Pearson	Spearman
B1	Catalog exposure and posting exposure	0.93	0.92
B2	Bottleneck pressure and catalog exposure	−0.35	−0.37
B3	Bottleneck pressure and posting exposure	−0.40	−0.43
B4	Bottleneck pressure and catalog-only benchmark	0.70	0.72
B5	Bottleneck pressure and hybrid benchmark	0.59	0.62

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. Feasibility is the broad GPT-4 rating of Eloundou et al. (2024). Indices use the 0–100 scale; formulas below use shares. Catalog exposure weights core tasks equally. Posting exposure weights tasks by posting incidence; $S_o = 1 - E_o^{\text{post}}$. Mean posting exposure weights occupations equally; pooled over all labeled mentions, the AI-feasible share is 57.1 percent (Appendix Table C.1). Pressure is $B_o = E_o^{\text{post}} S_o = E_o^{\text{post}}(1 - E_o^{\text{post}})$. The catalog-only benchmark is $E_o^{\text{cat}}(1 - E_o^{\text{cat}})$; the hybrid benchmark is $E_o^{\text{cat}} S_o$. Task pressure averages $(1 - F_t)E_o^{\text{post}}$ over occupations, weighted by postings. A8 is a share, not a mean. A8 covers all 7,485 AI-infeasible tasks, without the 1,000-mention restriction, since the variance is mention-weighted rather than equally weighted across tasks. It is the within-task share of mention-weighted pressure variance across AI-infeasible occupation–task cells. Occupation statistics and correlations are unweighted.

for analysis spanning our time period. These filters exclude staffing-agency postings and one large job board with inconsistent coverage. We retain postings whose detailed O*NET occupation code is assigned with high confidence. We also restrict the sample to occupations with at least 10,000 eligible postings over the full sample period. The resulting data has 321.2 million postings spanning 784 occupations. Catalog exposure is available for 708 of these occupations, which contain 288.3 million postings. The remaining 76 occupations lack an exposure score from the O*NET catalog in the matched data. We exclude those from the common sample. Overall, 708 occupations form our main analysis sample, and we compare our baseline bottleneck measure from this sample to the catalog-only and hybrid benchmarks (Appendix Table C.1).

From posting lines to tasks. BGI's matching pipeline begins by splitting the full text of the posting into lines using a parser and tagging whether each line describes a responsibility. Only lines tagged as responsibilities are then matched to O*NET task statements. The step to match responsibility lines is designed to reduce the undesirable behavior wherein boilerplate content in postings is mapped to O*NET tasks. While we cannot reveal the algorithm, at a high level, the responsibility lines and O*NET task statements are matched using an embedding-based classifier. For each responsibility line, it identifies the top two most similar O*NET task statements, and we further limit our main sample to rank-1 matches tagged as "use," meaning they cross the highest quality threshold determined by our data team. In principle, a posting can map to any number of tasks. Additionally, if several responsibility lines match to the same task, we only include the matched task once in the list of tasks associated with that posting. So a posting–task mention records the presence of a matched task statement rather than the number of times a task is repeated in a posting or the time spent on it.

Across all 321.2 million postings in 784 occupations, the mapping provides an average of 4.7 tasks per job posting, with a median of 3; 19.9 percent of job postings have no high-confidence task match and contribute no task mentions to the measure of bottleneck pressure. When we pool job postings across employers and years, the average occupation in the analysis sample advertises 4,724 distinct task statements.

Feasibility and the unit of observation. As discussed in the introduction, we use the broad GPT-4 rating of Eloundou et al. (2024): $F_t = 1$ for either $E1$ or $E2$, and $F_t = 0$ otherwise. The label is binary and is attached to each O*NET task statement. Thus a task is AI-infeasible only if it is rated unable to have its completion time at least halved at the same quality, even with complementary software.

We rate task statements rather than O*NET detailed work activities, a coarser unit that links related tasks across occupations, because a detailed work activity can mix AI-feasible and -infeasible tasks, and a binary activity-level label must then classify the whole activity one way. Classifying mixed activities as feasible, by counting a task as infeasible only if every task linked to each of its detailed work activities is infeasible, would discard 61 percent of AI-infeasible mentions, including common tasks such as developing client relationships, greeting customers and supervision (Appendix Table D.1). This is precisely the kind of work that can become a bottleneck. Classifying mixed activities as infeasible would instead overstate infeasibility. Task-level ratings avoid imposing one label on different task statements, although a posting line describing only a feasible part of an AI-infeasible composite statement can still inherit its infeasible label.

Our analysis sample includes 7,485 AI-infeasible tasks. These counts retain the duplicate statements discussed in Appendix E. Among labeled tasks with at least 1,000 mentions across postings, a task appears in 211 occupations on average. Therefore, the same task statement can typically be compared across occupations. The analysis sample contains a total of 1.30 billion labeled posting–task mentions, of which 57.1 percent are AI-feasible (Appendix Table C.1).

Work outside the occupation's task list. BGI's matching algorithm searches and matches against all O*NET task statements, rather than just those on the posting occupation's O*NET catalog. Only 8.6 percent of labeled task mentions map to core tasks in that occupation's catalog and 1.2 percent to its supplemental tasks, while 90.1 percent map to statements outside its list. Another 0.1 percent are on-list mentions whose core or supplemental status is unverified. For AI-infeasible mentions specifically, the off-list share is 89.4 percent. Occupation-specific lists therefore cannot produce the rich posting-to-task maps we leverage to compare the same task statement across occupations.

Off-list mentions do not mean new work, and the off-list share also partly reflects the matcher's scope. Among all off-list mentions, including unlabeled ones, 18 percent share a detailed work activity with one of the occupation's own core tasks, 51 percent share only a generalized work activity, and 31 percent share neither. While these links help distinguish related catalog descriptions from potentially omitted work duties, they should not be taken as evidence of either equivalence or novelty.

Matching accuracy matters for our pressure score construction for two reasons. First, if the match is wrong, that could potentially alter the AI-feasibility label and therefore the AI-infeasible share of tasks and occupational exposure. Second, even if the match gets the label correct, it can group different duties under one statement (e.g., generic physical-

ability lines matched to "perform physically demanding tasks"), thereby making work across occupations look more alike even when it is not. If such errors are unrelated to an occupation's exposure, they can raise the within-task share of the variation in bottleneck pressure. We exclude two statements from our main ranked task tables after a posting-line audit because the lines matched to them were mostly generic physical-ability or working-condition statements rather than work duties (Appendix C). While these mentions remain in the baseline pressure score, they account for only 1.1 percent of the total posting-weighted pressure. To check sensitivity, we drop these statements and report our task-level results without them in Section 5 and, in addition, examine assumed contamination rates in our matching procedure and occupation-rank sensitivity in Section 6, and discuss in Section 7 what remains unverified about the matches and its implications for our core results.

3.2 Empirical counterparts

To construct the index, we use the relevant shares between zero and one and then report final values after multiplying by 100. Let c_{ot} denote the number of job postings in occupation o that include labeled task t. To calculate the AI-infeasible share of advertised work in occupation o, denoted by S_o, we use posting weights, which gives us $S_o = \sum_t c_{ot}(1 - F_t)/\sum_t c_{ot}$. Note that the exposure measure constructed from the job postings data, $E_o = E_o^{\text{post}}$, is the complement of S_o, i.e., $E_o = 1 - S_o$. Finally, occupation pressure is $B_o = E_o S_o = E_o(1 - E_o)$ (Appendix Figure B.1), the empirical analog of Equation (4), whereas the pressure on a given task within a job is calculated by $B_{ot} = (1 - F_t)E_o$, which is the empirical analog of Equation (3). For comparison, following Eloundou et al. (2024), catalog exposure E_o^{cat} is the equally weighted feasible share of the occupation's core O*NET tasks.

We do not have cost shares or the time spent on each task. Mapping these objects to our model developed in Section 2 requires posting incidence shares to stand in for these, and we recognize this is an imperfect proxy.

To compare pressure across tasks, we use the average within-job task pressure over the occupations that post the labeled task t: $P_t = \sum_o c_{ot} B_{ot}/N_t$, where $N_t = \sum_o c_{ot}$ is the number of postings that mention task t. Task t's contribution to total bottleneck pressure is instead

$$\frac{\sum_o c_{ot} B_{ot}}{\sum_s \sum_o c_{os} B_{os}} = \frac{N_t P_t}{\sum_s N_s P_s},$$

a share of the sum over all tasks. The first measures pressure intensity because it takes into account which occupations advertise the task, whereas the second additionally reflects how often it is advertised. Section 5 uses these two concepts to distinguish tasks facing high average pressure from those contributing to a large share of total pressure.

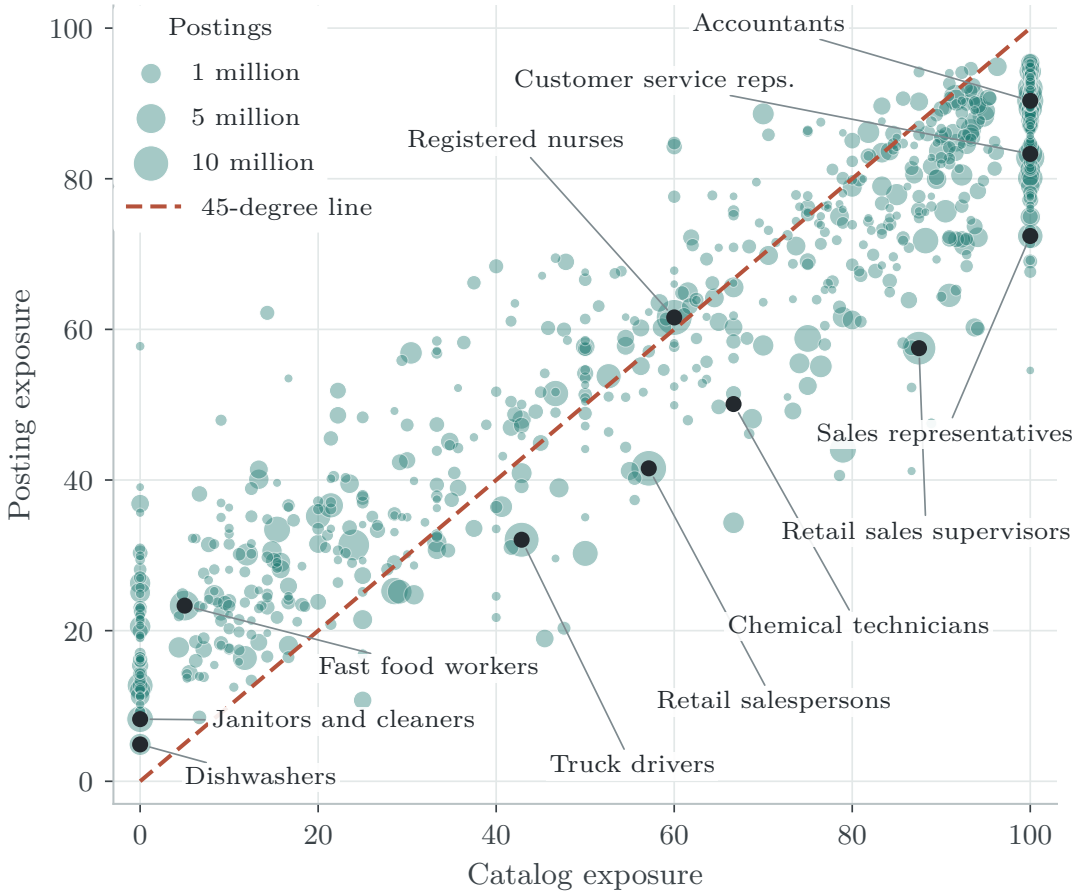


Figure 2: Posting exposure and catalog exposure

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026. Each circle is one of the 708 occupations with a catalog exposure score, sized by its number of postings. Catalog exposure is the share of the occupation's core O*NET tasks rated AI-feasible, weighting tasks equally. Posting exposure is the AI-feasible share of the task mentions in the occupation's postings. Both are on a 0–100 scale. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. Feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. The dashed line is the 45-degree line. Labels identify selected occupations discussed in the paper. "Sales representatives" refers to O*NET-SOC 41-4012.00 and "Retail sales supervisors" to 41-1011.00. The rank correlation between the two measures is 0.92.

3.3 Comparing the two exposure measures

Figure 2 shows the catalog exposure on the x-axis and the posting exposure on the y-axis. Each circle represents an occupation and is sized by postings. Along the dashed 45-degree line, the two sources assign the same AI-feasible share. Below it, postings advertise a lower share of AI-feasible work than the catalog. Above the line, this relationship reverses.

Catalog and posting exposure have occupation means of 57.2 and 57.5, respectively, and a rank correlation of 0.92. Despite the broad agreement, the two sources differ at the extremes. Whereas the 10th and 90th percentiles of catalog exposure are 7.1 and 100, they are 21.5 and 89.6 for posting exposure (Table 2, Panel A). The differences at the extremes could be attributable to two factors. First, postings may describe work more broadly than the catalog: core task lists from the catalog can be entirely AI-feasible or entirely AI-infeasible, while almost every occupation advertises some tasks of both types. Second, errors in the matching algorithm could pull occupations toward more commonly matched tasks, thereby compressing the distribution of exposure scores calculated from the postings; the figure alone cannot distinguish the two. Section 6 examines robustness of bottleneck pressure to potential contamination from assumed rates of such error.

We compare our posting exposure measure against published measures of Eloundou et al. (2024) and Felten, Raj and Seamans (2021, 2023), finding rank correlations of 0.84 to 0.91, and 0.65 with the AI-applicability score of Tomlinson et al. (2025) (Appendix Table D.2). The 0.91 correlation with the GPT-4 β measure of Eloundou et al. partly reflects shared task ratings; their human-rated measure gives 0.87.

As a check on whether posting incidence, or how often a task appears in an occupation's postings, which we use to weight tasks in both E_o and S_o, reflects how central a task is to the job, we examine whether it aligns with O*NET task importance. Across 692 of the 708 occupations in our main sample, the median within-occupation rank correlation between a task's posting incidence and its O*NET importance rating is 0.38, and 90 percent are positive (Appendix Figure C.2).[6] This comparison can only be done for tasks that are both on the occupation's own O*NET list, as only those carry importance ratings, and in its postings. Note that while these correlations show alignment between posting incidence and rated task importance on this overlap, the overlap nonetheless covers only the roughly 10 percent of mentions that fall on occupations' own catalog lists. As such, these correlations do not establish whether matches of posting responsibility lines to O*NET task statements outside the occupation's catalog list are accurate.

4 Bottleneck pressure across occupations

This section describes the distribution of bottleneck pressure across occupations, which aggregates the pressure on each occupation's AI-infeasible tasks, and how it relates to exposure.

[6]These are the occupations with at least ten rated tasks from their own O*NET list that appear in postings.

Pressure is not exposure. Bottleneck pressure is different from occupational exposure. Table 2, Panel B, shows that bottleneck pressure has a rank correlation of −0.37 with catalog exposure and −0.43 with posting exposure. Occupations with higher posting exposure need not have higher bottleneck pressure. Table 3 shows four large occupations—wholesale and manufacturing sales representatives, medical secretaries, accountants and auditors, and computer systems engineers—whose posting exposure rises from 72.4 to 82.8, 90.4 and 92.1, respectively, while their bottleneck pressure falls from 20.0 to 14.2, 8.7 and 7.3. In these occupations, the shrinking share of AI-infeasible work outweighs the rising pressure on each remaining AI-infeasible task. For example, greeting customers faces pressure of 83 in customer service, yet customer service representatives score only 13.9 as an occupation, because little of their advertised work is AI-infeasible.

Where pressure is highest. Bottleneck pressure ranges from 4.2 to 25 (Appendix Figure B.2 shows the full distribution). Pressure is highest where advertised work is evenly split between AI-feasible and AI-infeasible tasks (Appendix Figure B.1).

Table 3 shows the two largest occupations by postings, among those with at least 100,000 postings, within each five-point band of bottleneck pressure. The large occupations under the most pressure are substantially exposed and *still* advertise much work that is AI-infeasible. For example, chemical technicians, retail loss prevention specialists and food science technicians each score approximately 25, near the peak. Score differences near the peak are small, and finite productivity gains can change the ordering of the highest-pressure occupations (Appendix A). High bottleneck pressure is not limited to just a handful of small occupations. Retail salespersons (24.3) and supervisors of retail sales workers (24.4) are the 2nd- and 4th-largest occupations by postings, and have bottleneck pressures in the 87th and 89th percentiles, respectively. Low bottleneck pressure typically arises in two ways. Consider, for example, dishwashers and janitors and cleaners. Their occupation bottleneck pressures are 4.7 and 7.6 respectively because only a small share of their advertised work is rated AI-feasible. On the other hand, accountants and auditors (8.7) and computer systems engineers (7.3) are highly exposed, so they advertise little AI-infeasible work. Relatively high bottleneck pressure occupations, such as registered nurses (23.7) and heavy and tractor-trailer truck drivers (21.8), fall in between these two cases because they are moderately exposed *and* advertise a decently large share of AI-infeasible work in their job postings. Appendix Table E.1 reports pressure and its components for all 708 occupations. Appendix E collects the full tables and figures.

Table 3: Bottleneck pressure across occupations

Band	Occupation	Postings (m)	Posting exposure	AI-infeasible share	Pressure	Rank (of 708)
Panel A. The two largest occupations in each five-point band						
20–25	Registered Nurses	10.65	61.6	38.4	23.7	138
	Retail Salespersons	10.29	41.6	58.4	24.3	95
15–20	Fast Food and Counter Workers	5.55	23.3	76.7	17.9	399
	Maintenance and Repair Workers, General	3.48	25.3	74.7	18.9	348
10–15	Medical Secretaries and Administrative Assistants	4.54	82.8	17.2	14.2	502
	Maids and Housekeeping Cleaners	2.75	12.7	87.3	11.1	594
5–10	Accountants and Auditors	3.37	90.4	9.6	8.7	644
	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	3.12	8.3	91.7	7.6	665
0–5	Dishwashers	1.40	4.9	95.1	4.7	704
	Software Quality Assurance Analysts and Testers	0.86	94.9	5.1	4.9	702
Panel B. Higher exposure, lower pressure: four examples						
	Wholesale and Manufacturing Sales Representatives	2.58	72.4	27.6	20.0	319
	Medical Secretaries and Administrative Assistants	4.54	82.8	17.2	14.2	502
	Accountants and Auditors	3.37	90.4	9.6	8.7	644
	Computer Systems Engineers and Architects	2.70	92.1	7.9	7.3	670

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. Panel A lists the two occupations with the most postings within each five-point band, among occupations with at least 100,000 postings (366 of 708). Bands are assigned before rounding. Panel B reports the four examples discussed in the text. Posting exposure is the AI-feasible share of labeled matched task mentions, and the AI-infeasible share is its complement. Pressure is their product, on a 0–100 scale. Rank is among all 708 occupations, with rank 1 highest and exact ties sharing the minimum rank. Across them, 9 score 0–5, 82 score 5–10, 133 score 10–15, 167 score 15–20, 317 score 20–25. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold, binary at the task level. The full ranking is in Appendix Table E.1.

Occupation groups. Figure 3 compares each major occupation group's share of advertised work with its share of total pressure. For example, sales and related occupations account for 11.2 percent of advertised work and 13.9 percent of pressure, and management occupations for 11.0 percent of advertised work and 10.4 percent of pressure. Groups that carry less pressure than their share of advertised work include food preparation and serving (7.0 percent of advertised work, 6.6 percent of pressure), computer and mathematical occupations (5.4 and 2.3), business and financial (5.1 and 3.0), office and administrative (11.3 and 9.7), and building and grounds cleaning (3.4 and 2.2).

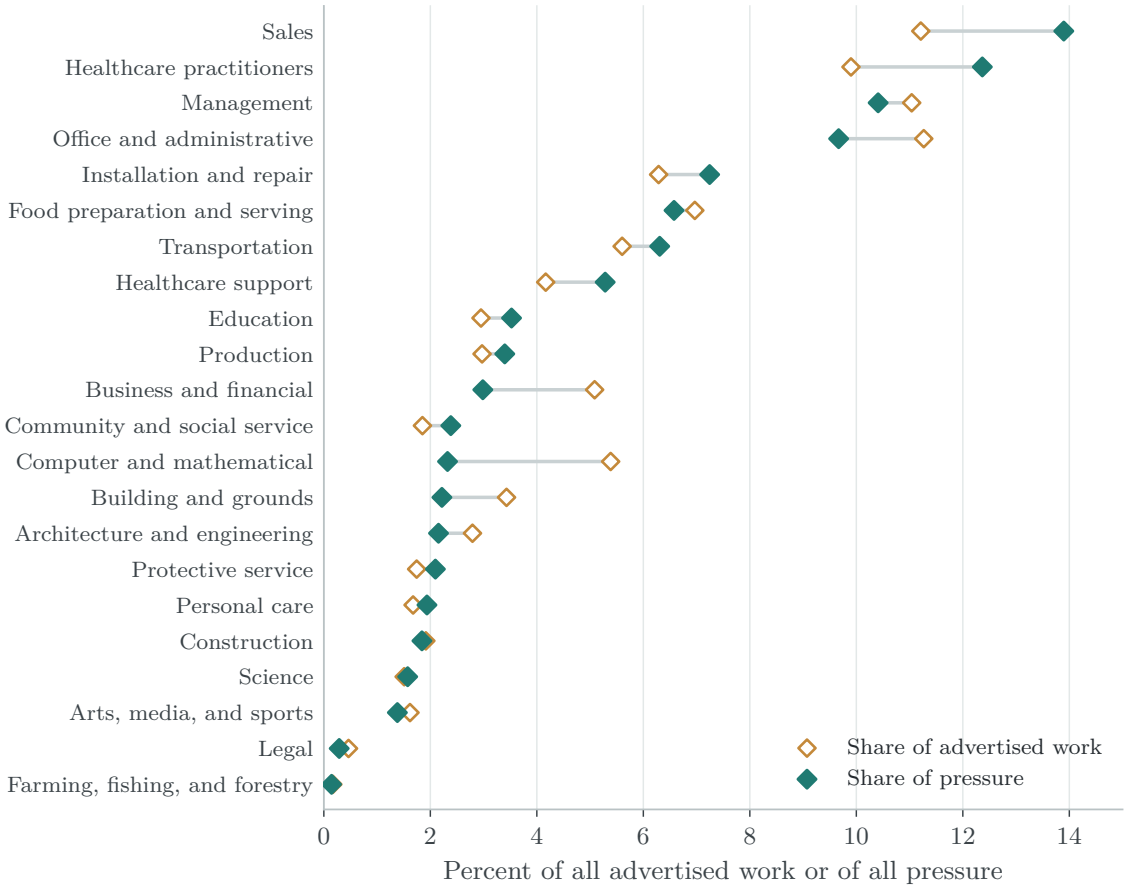


Figure 3: Shares of advertised work and of bottleneck pressure by occupation group

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, for the 708 occupations with a catalog exposure score, grouped into Standard Occupational Classification major groups. Hollow diamonds show each group's share of advertised work (all labeled task mentions). Filled diamonds show its share of total bottleneck pressure, where each occupation's pressure is weighted by its labeled posted task mentions (high-confidence line-to-task matches only). AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. Groups are ordered by their share of pressure. Groups with no occupation in the sample are omitted.

5 Bottleneck pressure across tasks

Figure 4 shows selected AI-infeasible tasks across nine occupations, with bubble positions indicating pressure and bubble areas proportional to posting counts. To help show that the same AI-infeasible task faces different pressure depending on the occupation that posts it, Figure 5 follows a single AI-infeasible task, "greet customers and make them feel welcome", across the occupations that post it. Panel A shows 24 occupations whose postings include this task most often, ranked by the bottleneck pressure the task faces there, which equals that occupation's posting exposure (Equation (3)). Panel B shows where all of the task's postings fall. About 4 percent are in occupations with pressure below 20, and about 4 percent are in those with pressure above 80. Appendix Figure E.1 plots each of the 143 occupations whose postings include the task, "greet customers and make them feel welcome", at least 1,000 times. There is large variation in the task's bottleneck pressure across occupations. While the average pressure is around 41, situating it at approximately the 58th percentile among AI-infeasible tasks with at least 1,000 mentions, pressure is 13 for housekeeping cleaners, 23 for fast food workers, 37 for cashiers, and 42 for retail salespersons, compared with 65 for receptionists and 83 for customer service representatives.

The pattern generalizes to other tasks. Across AI-infeasible task–occupation pairs, 53 percent of the variation in pressure lies within tasks, across the occupations that post them (Table 2, Panel A). When dropping near-universal statements or the two audited statements, whose matched posting lines were mostly generic physical-ability or working-condition statements (Section 3.1 and Appendix C), while keeping posting exposure fixed, the share stays between 49 and 53 percent. We achieve similar shares (58 and 56 percent) under other sensitivity checks, including when medium-confidence matches are kept, or when the sample is limited to tasks posted at least 1,000 times in each of ten or more occupations (Appendix D). Appendix Figure E.2 follows twenty AI-infeasible tasks across the occupations that post them most.

By contrast, restricted to tasks on each occupation's own O*NET catalog list while keeping posting exposure fixed, the within-task share is only 0.3 percent, as most catalog statements belong to only one occupation. In other words, a measure built solely from the catalog's task statements has limited scope to compare the pressure on the same work across different jobs. The 0.3 percent therefore shows a core limitation of comparing exact catalog statements. While related work can be linked in the catalog and compared across occupations through shared detailed work activities, these activities are coarser than task statements and often mix tasks AI can and cannot do. Therefore, they would not reproduce

this comparison (Appendix Table D.1). How accurate our map between job-posting lines and O*NET task statements is also matters for the within-task share. If our matching pipeline assigns different work duties to the same O*NET task statement, this can raise the within-task share. The checks above don't necessarily test for such errors. Moreover, the within-task pattern is not confined to a handful of tasks. The same O*NET task statements appear in postings at both ends of the exposure distribution: among AI-infeasible tasks posted by at least ten occupations, 12 percent are posted at least 1,000 times both in an occupation in the bottom quartile of posting exposure and in one in the top quartile, and these tasks hold 58 percent of the mentions. For an AI-infeasible task, where it is posted determines how much pressure it faces.

The kind of work under pressure. Figure 6 groups AI-infeasible task–occupation pairs into pressure quintiles, each holding about a fifth of AI-infeasible posting mentions, and shows the type of work that carries the pressure within each. Physical and mechanical work accounts for 75 percent of pressure in the lowest-pressure fifth and 27 percent in the highest. By contrast, interpersonal and supervisory work accounts for 17 percent in the lowest fifth and 54 percent in the highest, while information and cognitive work makes up the rest. Appendix Figure E.3 compares the share of pressure belonging to each finer O*NET work-activity family with its share of posted work. Given that the bottleneck pressure on an AI-infeasible task is its occupation's posting exposure (Equation (3)), the pressure quintiles sort occupations and the advertised work they post. Higher pressure on supervisory work need not mean rising demand for it: evidence from postings suggests that generative AI has lowered demand for some organizing skills, such as coordination and monitoring (Devigili et al., 2026). Dropping the 59 near-universal statements while keeping posting exposure fixed and recomputing the quintiles moves these shares by at most 2.9 points, suggesting that the shift from physical to interpersonal work across the quintiles is not driven by the near-universal generic statements. Furthermore, dropping the two audited statements that absorb generic physical requirements (see Section 3.1 and Appendix C) moves them by at most 1.1 points: whereas physical work falls from 74.5 percent in the lowest fifth to 26.3 percent in the highest, against 74.7 to 26.8 at baseline, interpersonal and supervisory work rises from 17.5 percent in the lowest fifth to 54.5 percent in the highest, against 17.4 to 54.1.

Seniority within occupations. Pressure in a task differs by seniority within the occupation. We proxy seniority by using advertised job experience as a proxy, defining juniors as 0–3 years and seniors as 7 or more years. Each group is its own job, so a junior software developer is a different job than a senior one. A task's share in the job is its fraction of

the labeled task mentions listed in the job ads, and exposure, as always, is the overall share of the advertised AI-feasible tasks. Recall that for an AI-infeasible task, pressure $B_{ot} = (1 - F_t)E_o$ from Equation (3) is just the exposure E_o, since $F_t = 0$.

Since required experience mentions in postings are often sparse, complete in 50 to 57 percent of cases for the US, we restrict to occupations with sufficient junior and senior postings, i.e. at least 100 labeled task mentions in each group in every year from 2018 to 2026. We subtract junior exposure from senior exposure within each occupation and average these differences using each occupation's share of 2021 labeled task mentions as its weight. In senior postings, the *same* AI-infeasible task faces about 4 points or 6.5 percent more pressure than in junior ones, in the first half of 2026 (95 percent interval 2.5 to 5.6).

Figure 7 shows where this gap comes from. As the shares within each group must sum to one, the gap can be read as either AI-feasible work that is more common in senior postings or AI-infeasible work that is more common in junior ones. We find that junior postings carry, on average, more hands-on physical work that is AI-infeasible and accounts for 2.5 out of 4 points or 62%. On the other hand, AI-infeasible work in senior postings is more often of the interpersonal kind, including mentoring junior staff and managing client relationships. The gap in pressure between senior and junior postings for the same AI-infeasible task is robust to different weights, keeping the occupation's industry mix fixed, dropping the largest employers, or following only continuing employers.[7]

The gap in pressure is typically the largest when junior work is more hands-on, as in general maintenance and repair. Whereas junior postings include tasks such as sweeping, painting and inspecting premises, senior postings additionally include planning, scheduling, and cost estimates, and therefore the work that is AI-infeasible sits typically among more feasible work, thereby increasing the pressure relatively more on the same task in senior postings. However, this gap is reversed in several information-intensive professions, including credit analysis, accounting and financial advising. Among those, junior postings already have mostly AI-feasible work such as processing loan applications, reconciling accounts and drafting financial plans, whereas senior postings typically add more AI-infeasible work that is more interpersonal, such as managing client relationships and mentoring. Therefore, the comparatively fewer AI-infeasible tasks in junior postings among information-intensive professions face more pressure on average than comparable senior ones.

[7] Indeed, among the 79 occupations with at least 1,000 labeled postings in both groups, it has been about 3 points or 4 percent in every year since 2018.

Seniority over time and by occupation. Appendix Figure F.1 shows the junior–senior gap from above over time. Among the occupations with sufficient number of seniority postings, the gap rises from 1.6 points in 2022 to 4.0 in the first half of 2026. This rise survives if we only use January–June data or weight postings equally, although it is about half as large when largest employers are dropped and only about 0.2 points for continuing employers versus 0.4 for all employers in the same 258 occupations. While the level of the gap is positive in every year under these alternative specifications, its recent rise depends on which occupations and employers are counted. Appendix Figure F.2 shows the gap by occupations, displaying it falls with exposure in the first half of 2026.

Among the occupations with at least 1,000 labeled postings in both groups, with fixed 2021 weights, the gap averages 7.9 points in the 6 occupations with exposure below 0.6, 5.6 between 0.6 and 0.8, 1.0 between 0.8 and 0.9, and only 0.1 above 0.9. The gap is negative in about 1/3 of these occupations, which hold nearly 29 percent of their weights, and 12 or 46 percent of them are negative in at least 7 of the nine years in our sample. Among these are professions such as credit analysts, accountants and auditors, architects, loan officers, personal financial advisors and management analysts. Of course, part of this decline is mechanical because junior postings in the most exposed occupations are already highly exposed, with about 90 percent of their labeled task mentions AI-feasible, leaving little room for senior exposure, and therefore the pressure on AI-infeasible tasks, to be higher. Also, the two largest contributions come from occupations with few senior postings, and so requiring our sample to restrict to occupations with at least 1,000 labeled postings in both groups lowers the average gap from 4.0 to 3.0 points.

Which tasks face the most pressure. Table 4 ranks AI-infeasible tasks in two ways that answer different questions. First, Panel A ranks tasks by their contribution to total pressure, which combines how often a task is posted with the pressure it faces where it is posted. Second, Panel B ranks tasks by their average pressure in the jobs that post them, restricting to tasks with at least 50,000 postings. The two lists do not overlap, as high-pressure tasks are posted far less often, typically in highly exposed jobs, thereby contributing little in total, whereas the largest contributors to pressure are posted widely but at moderate pressure.

Health-care teamwork, customer and store-floor work, and community relationships are the largest contributors in Panel A, with tasks such as collaborating with other health-care professionals (0.68 percent of all pressure), keeping storage areas stocked and clean (0.56 percent), sales-floor work, receiving and stocking merchandise, conferring with customers, and maintaining relationships with community referral sources. These tasks are posted millions of times, in hundreds of occupations, at average pressures of 39 to 61.

The AI-infeasible tasks in Panel B face average pressures of about 83 to 90 but are each posted far less often, so none accounts for more than about 0.18 percent of the total. They are mostly supervision, coordination and client work inside highly exposed professional jobs, including supervising legal assistants, discussing data presentation requirements with clients, conferring with realtors and lenders, and discussing project goals with colleagues. Appendix Figure E.4 places AI-infeasible tasks posted at least 1,000 times, excluding the two audited statements, by their average bottleneck pressure and posting volume, and shows the two rankings drawing on different parts of the distribution. Appendix Tables E.2 and E.3 extend both of Table 4's rankings to the top 100 tasks, including the near-universal statements. Task names are O*NET's standardized wording for the matched posting lines: 163 of the 192 distinct (85 percent) ranked tasks are *not* on the task list of the occupation that posts them most, and so a narrowly worded statement can stand for broader work.

Generic statements. Of course, job posting text also contains boilerplate, and some AI-infeasible statements appear in almost every occupation's postings. The 59 near-universal statements, excluding the two audited statements, posted in at least 650 of the 708 occupations, including developing client relationships, greeting customers, keeping work areas clean, following safety and compliance rules, and attending meetings, carry about 18 percent of AI-infeasible pressure. To be clear, these statements, despite their genericness, can be *central work* in some jobs (such as greeting customers for cashiers and retail salespersons) and boilerplate in others, and so we keep them in the measure rather than discarding them wholesale. Panel A of Table 4 ranks tasks posted in fewer than 650 occupations. The near-universal statements remain in the full ranking (Appendix Table E.3, where they are marked). Dropping these statements from the measure altogether leaves occupation rankings highly correlated with the baseline, although the highest-pressure occupations change (Section 6).[8]

[8]We leave a task out of the ranked tables on match-quality grounds only when a posting-line audit shows that its matches are generic statements rather than duties, as for the two tasks discussed in Section 3.1 (Appendix C).

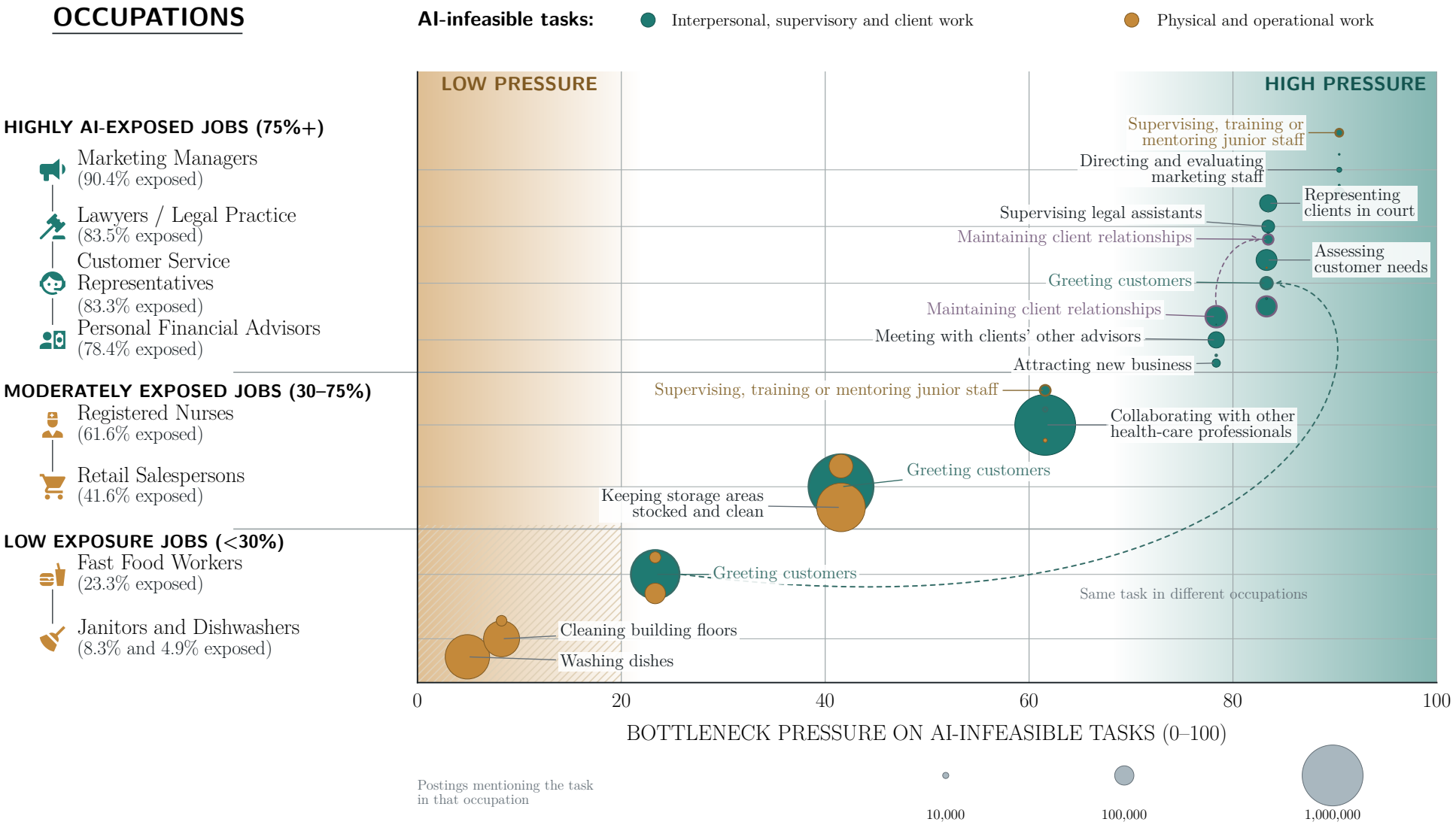


Figure 4: Selected AI-infeasible tasks and the pressure they face inside nine occupations

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, baseline sample, rank-1 high-confidence responsibility-line matches. Each bubble is a task–occupation pair, with area proportional to the number of distinct postings mentioning the task in that occupation. All displayed tasks are considered AI-infeasible under the GPT-4 rating of Eloundou et al. (2024), so each faces pressure equal to its occupation's posting exposure (Equation (3)), on a 0–100 scale. Rows are ordered by exposure, and the last row combines janitors and dishwashers. These examples are illustrative rather than a ranking. Dashed connectors link the same tasks across occupations.

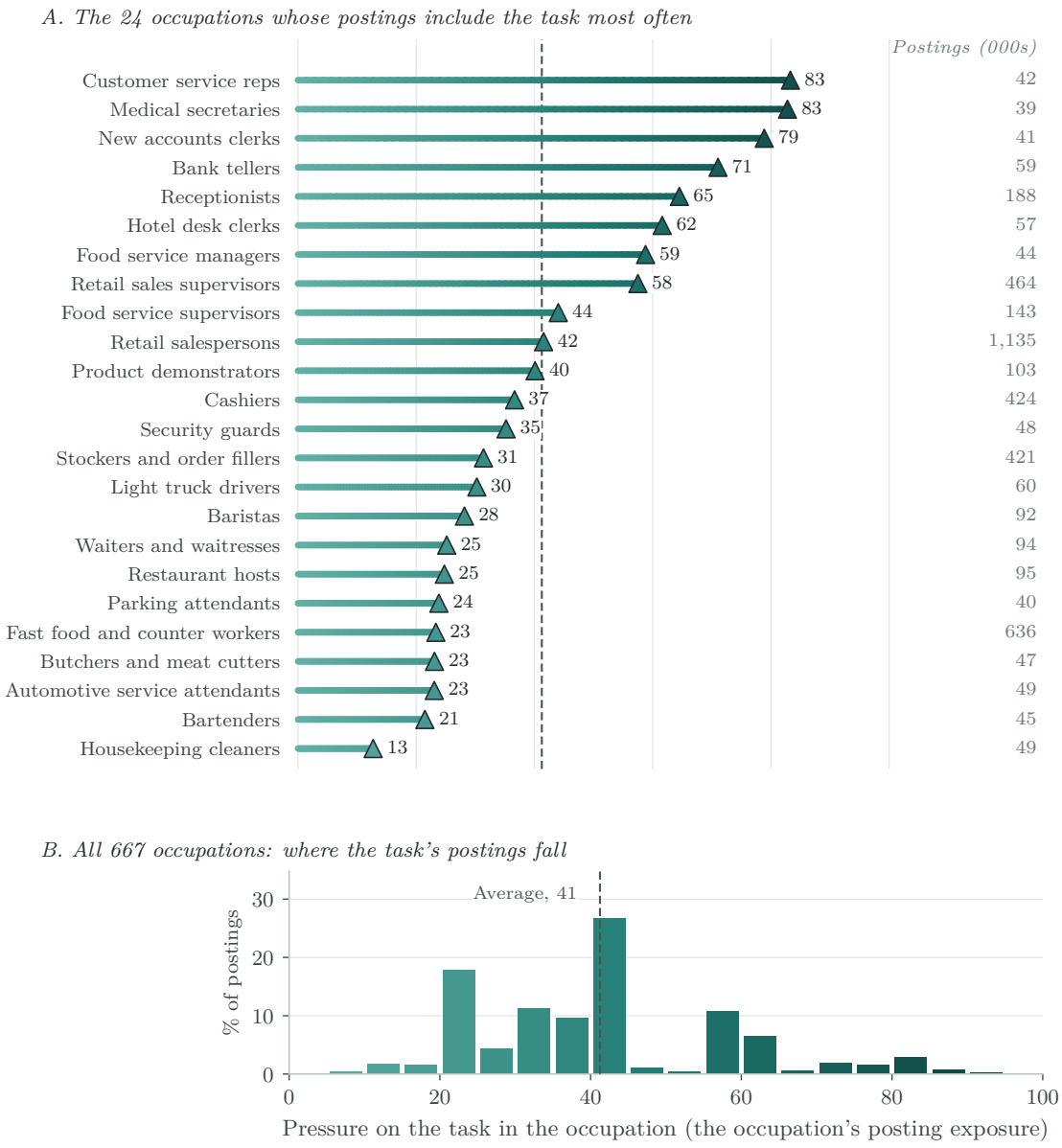


Figure 5: One task across occupations: "Greet customers and make them feel welcome"

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, keeping high-confidence line-to-task matches only. The task is an illustrative example: it is AI-infeasible and among the most widely posted tasks, appearing in the postings of 667 of the 708 occupations with a catalog exposure score. The pressure on the task in an occupation equals that occupation's posting exposure, on a 0–100 scale. Panel A shows the 24 occupations whose postings include the task most often, which together hold 84 percent of its postings; each triangle is an occupation, shaded darker as pressure rises, the number next to it is the pressure on the task there, and the right-hand column gives the number of postings that include it. Panel B shows the share of all postings that include the task falling in each five-point band of pressure. The darker shaded bars denote rising pressure. The dashed line is the average pressure across all 667 occupations, weighted by postings. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold.

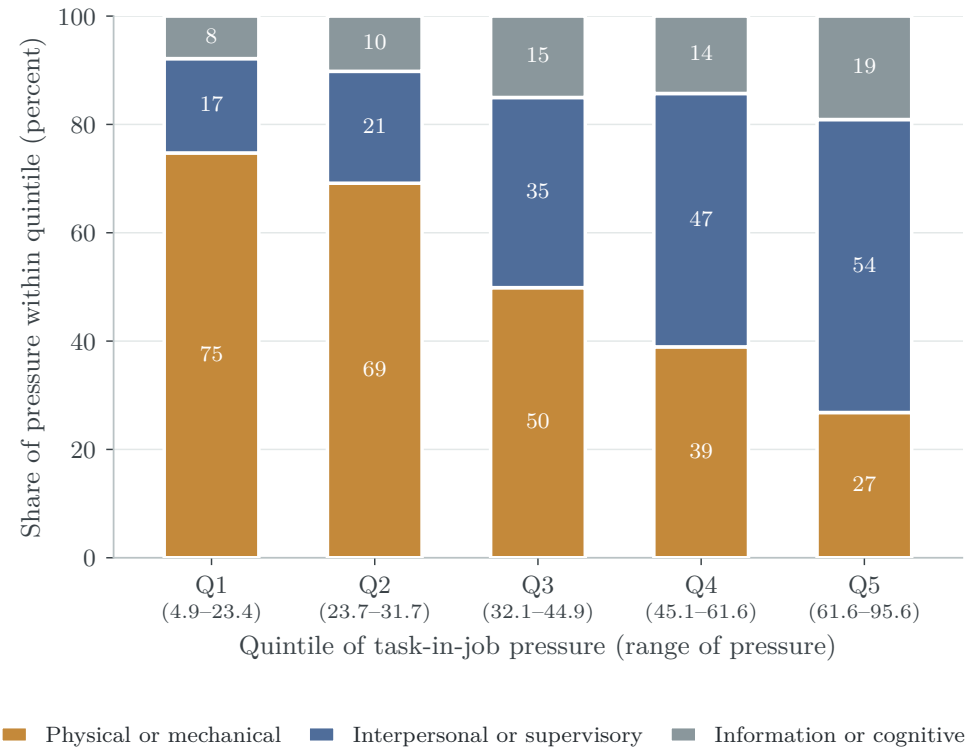


Figure 6: The kind of AI-infeasible work under pressure, by pressure quintile

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, keeping high-confidence line-to-task matches only. AI-infeasible task–occupation pairs in the 708 occupations with a catalog exposure score are grouped into five quintiles of task-in-job pressure B_{ot}, each holding about 20 percent of AI-infeasible posting mentions; ranges in parentheses. Bar segments show each broad type of work's share of pressure within the quintile, $\sum c_{ot} B_{ot}$, in percent; shares may not sum to 100 because of rounding. We classify tasks through O*NET's links from tasks to detailed work activities and then to generalized work activities. When matched task statements link to more than one detailed work activity, we split a task equally across its activities. The three types group generalized work activities by the kind of work they describe. Physical and mechanical: performing general physical activities; handling and moving objects; controlling machines and processes; operating vehicles and equipment; monitoring processes and surroundings; inspecting equipment and structures; repairing and maintaining equipment; and drafting technical devices. Interpersonal and supervisory: communicating inside and outside the organization; relationships; assisting and caring for others; selling; resolving conflicts; working with the public; training, coaching, guiding and coordinating others; building teams; staffing; and monitoring resources. Information and cognitive: all other generalized work activities. Pressure on an AI-infeasible task equals its occupation's posting exposure, so the quintiles sort occupations and the work they post. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold.

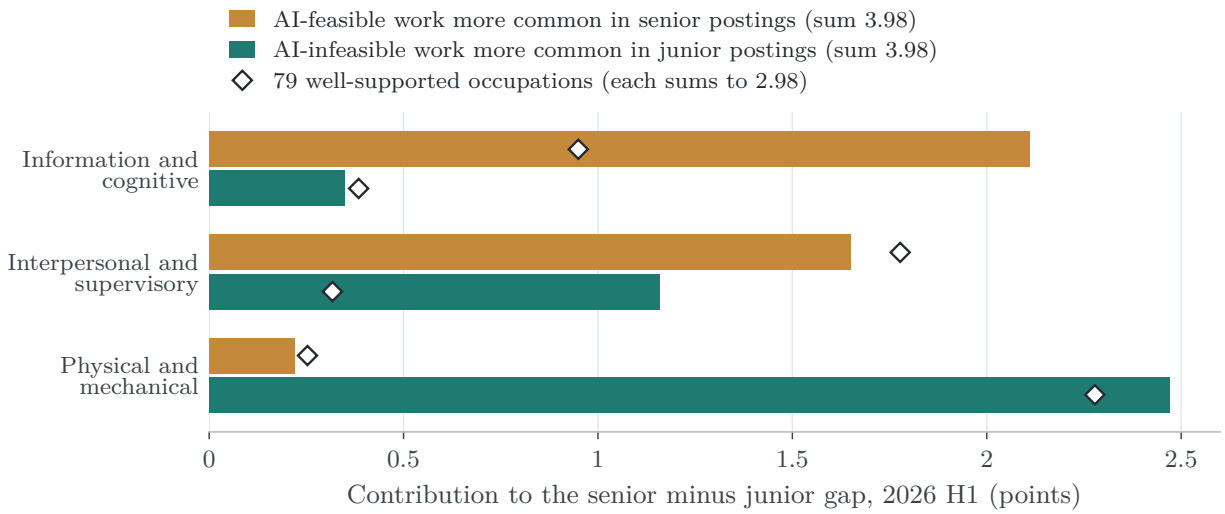


Figure 7: Where the junior–senior gap comes from, by type of work

Notes: BGI harmonized U.S. job postings, high-confidence matches only. For the seniority filter, we keep only 358 occupations as the experience filter is somewhat sparse (50–57% filled). Junior means 0–3 years of required experience and senior means 7 or more. Bars show the gap between seniority groups by broad O*NET matched activity. Diamonds show the same split but for occupations with at least 1,000 labeled postings in both groups, with the same 2021 weights rescaled. The values of the gold bars for information, interpersonal and physical work are 2.11, 1.65 and 0.22. For the teal bars, the same groups are 0.35, 1.16 and 2.47. For diamonds the values are 0.95, 1.78 and 0.25 (gold) and 0.38, 0.32 and 2.28 (teal).

Table 4: AI-infeasible tasks ranked by bottleneck pressure

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)
Panel A. Largest share of total pressure (tasks posted in fewer than 650 occupations)					
1	Collaborate with other health care professionals and service providers to ensure…	372	2,698	60.1	0.682
2	Keep storage areas and carts well-stocked, clean, and tidy	559	3,333	40.2	0.565
3	Perform sales floor work, such as greeting or assisting customers, stocking shelves,…	437	2,386	42.3	0.425
4	Confer with customers to assess customer needs or obtain feedback	644	1,567	58.3	0.385
5	Stock shelves, racks, cases, bins, and tables with new or transferred merchandise	380	2,117	41.7	0.372
6	Receive, unload, open, unpack, or issue sales floor merchandise	382	2,089	40.9	0.360
7	Perform general cleaning duties in the store to ensure the shop is clean and tidy	369	2,170	38.9	0.356
8	Establish and maintain standards of behavior to create safe, orderly, and effective…	611	1,463	54.0	0.333
9	Refer guest problems or complaints to supervisors	503	1,757	44.7	0.331
10	Develop and maintain relationships with community referral sources, such as schools…	561	1,278	60.6	0.327
Panel B. Highest average pressure (tasks with 50,000 or more postings)					
1	Discuss data presentation requirements with clients	373	102	89.9	0.039
2	Implement or test design solutions	303	64	87.9	0.024
3	Discuss project goals, equipment requirements, or methodologies with colleagues or…	379	103	86.8	0.038
4	Confer with realtors, lending institution personnel, buyers, sellers, contractors,…	191	58	85.2	0.021
5	Direct and participate in formal and informal meetings with bank directors,…	233	64	84.3	0.023
6	Supervise legal assistants	126	63	84.3	0.022
7	Present project plans or designs to public stakeholders, such as government agencies…	382	68	84.0	0.024
8	Consult with, or serve as, technical liaison between business, industry, government,…	585	497	83.7	0.175
9	Supervise technical personnel and postdoctoral research fellows	411	99	83.5	0.035
10	Meet with job search committees or coordinators…	391	59	83.4	0.021

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold, binary at the task level. A task's pressure in an occupation equals that occupation's posting exposure. Average pressure P_t averages it over the occupations that post the task, weighted by postings; share of all pressure is the task's posting-weighted pressure as a share of the total across all tasks; occupations counts those whose postings include the task at least once. Panel A ranks tasks by their contribution to total pressure, among tasks posted in fewer than 650 of the 708 occupations; the 59 near-universal statements this leaves out (client relationships, greeting customers, cleanliness, safety and compliance, meetings; 18 percent of AI-infeasible pressure) remain in the full ranking: the largest appear in Appendix Table E.3. The 650 cutoff is a simple rule; tasks just below it remain. Panel B ranks tasks by average pressure in the jobs that post them. Between 30 and over 99 percent of its tasks' mentions are matches outside the posting occupation's O*NET list, so their reading depends on those matches. Two widely posted statements are excluded from the rankings, though their mentions remain in occupation pressure, because posting-line checks found that they absorb generic physical-ability and working-condition statements rather than actual work duties: "Climb trees, using climbing hooks and belts, or climb ladders…" and "Perform physically demanding tasks, such as digging trenches…"; see Appendix C. Long statements are shortened, marked by an ellipsis. Full statements and rankings are in Appendix Tables E.2 and E.3.

6 Robustness

In this section, we check the robustness of our pressure score construction to various choices and sample restrictions, including match confidence, sample composition, time period and feasibility labels.

To start, Table 5 shows the rank correlation between the baseline pressure rankings and rankings built under alternative choices, for occupation pressure across the 708 occupations and for average pressure P_t across AI-infeasible tasks with at least 1,000 mentions. The rankings remain highly correlated across differences in how task matches are filtered, the time period used, and whether staffing-agency postings are included in the analysis sample. Keeping medium-confidence matches, in addition to our preferred high-confidence ones, gives occupation and task correlations of 0.987 and 0.973, and 9 of the 20 highest-pressure occupations are the same (Appendix Table D.3 and Figure D.1).

We recommend caution when reading or interpreting fine rankings near the peak. In the baseline, 31 occupations have pressure scores that round to 25.0. This means that small changes in the pressure score can reorder the rankings, especially at the top of the distribution, without meaningful changes in pressure. When we include medium-confidence matches in our sample as well, 64 of the baseline's top 71 occupations remain in that group, and all of its top 20 still have pressure above 24.

Building the measure separately from 2018–2021 and 2022–2026 postings gives 0.984 and 0.978, whereas including staffing-agency postings gives 1.000 and 0.999. To check sensitivity to sampling noise in the postings, we split an occupation's postings by a fixed hash to show correlations of 1.000 for both occupations and tasks, showing that the rankings are stable across these posting-level halves. To be clear, this check does not establish robustness to changes in employer or template composition, since postings from the same employer or template can appear in both halves. Dropping our two audited task statements retained in occupation pressure (see Section 3.1 and Appendix C) gives a rank correlation of 0.9996 and leaves 17 of the top 20 occupations unchanged. Appendix Figure D.2 plots occupation pressure under five alternatives against the baseline, and compares the two time periods with each other.

Recomputing exposure after dropping the two audited statements changes the share of pressure variation within tasks, across occupations, from 53.2 to 52.8 percent. When we drop the near-universal statements (59 of them), this falls to 49.9 percent. Merging the 24 pairs of task statements that differ only by minor punctuation (e.g., "Maintain customer records, using automated systems" versus "Maintain customer records using automated

Table 5: Stability of the rankings

	Rank correlation with the baseline	
Alternative	Occupations	Tasks
Medium-confidence matches also kept	0.987	0.973
2018–2021 versus 2022–June 2026	0.984	0.978
Staffing-agency postings included	1.000	0.999
Split halves of postings	1.000	1.000
Strictly infeasible: GPT-4 and human raters agree	0.905	0.994
Strictly infeasible: every task in its work activities infeasible	0.423	0.943
Near-universal statements dropped (59 tasks)	0.971	0.999
Feasibility labels		
GPT-4, α (direct exposure only)	−0.146	0.806
GPT-4, β	−0.220	0.993
Human raters	−0.335	0.790

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. Each cell is the Spearman rank correlation between the baseline ranking and the ranking under the listed alternative, except the window and split-half rows, which compare the two rankings with each other: occupation pressure, recomputing both posting exposure and its complementary infeasible share, across the 708 occupations (707 in the alternative-label rows, which exclude Models, O*NET-SOC 41-9012.00), and average pressure P_t across AI-infeasible tasks with at least 1,000 mentions in both rankings (at least 500 in each half for the split-half row). The first row also keeps matches in BGI's medium-confidence tier. Split halves divide postings within each occupation and year by a fixed hash. The strict-infeasibility rows count a task as AI-infeasible only if human raters also rate it fully infeasible, or only if every O*NET task linked to each of its detailed work activities is infeasible; tasks that fail the rule count as feasible. The near-universal row drops the 59 AI-infeasible statements posted in at least 650 of the 708 occupations, excluding the two audited statements, from both the infeasible mentions and all mentions of each occupation. For the strict-infeasibility rows, task correlations cover only tasks that remain AI-infeasible under the alternative. Their pressure can change because posting exposure is recomputed. Including baseline-infeasible tasks reclassified as feasible gives task correlations of 0.673 for human agreement and −0.345 for the activity rule. Appendix Table D.1 reports how much AI-infeasible work each rule keeps and how the top 20 change. Label rows replace the GPT-4 broad rating with the listed rating of Eloundou et al. (2024) on the tasks and catalog entries both rate; task correlations cover tasks infeasible under the baseline. β and the human ratings give partly feasible tasks a value of 0.5, an alternative score that need not equal the feasible share of the task.

systems") with consistent feasibility ratings leaves this share virtually unchanged, at 53.2 percent.

Strictly infeasible tasks. To further check the robustness of our rankings, we employ two stricter definitions of AI-infeasible work to test how much the results depend on which

tasks count as infeasible. A requirement that human raters, as in Eloundou et al. (2024), agree with the GPT-4 rating for advertised tasks, recomputing posting exposure under this rule, keeps 87 percent of AI-infeasible mentions. Under this restriction, occupation pressure correlates 0.905 with the baseline, and only one of the 20 highest-pressure occupations remains. The tasks it drops include compliance and confidentiality statements that human raters judged at least partly feasible. Furthermore, employing the strictest rule an activity-level measure could use, i.e., counting a task as infeasible only if every O*NET task linked to each of its detailed work activities is infeasible, keeps only 39 percent of AI-infeasible mentions, because most AI-infeasible tasks share a work activity with some task AI can do. This restriction drops developing client relationships and greeting customers, and the occupation ranking correlates 0.423 with the baseline (Appendix Table D.1). Direct matches to activities whose linked tasks are all AI-infeasible cover only 16 percent of posting–activity mentions, although 69 percent of the variation in pressure among them lies within activities (Appendix Table D.4). Note that both rules change which tasks count as AI-infeasible and the pressure on the tasks that remain, because posting exposure is recomputed. Among retained AI-infeasible tasks, the average-pressure rankings correlate 0.994 and 0.943 with the baseline under the human-agreement and activity rules, respectively. The activity rule is therefore a test of how narrow the set of infeasible tasks can be made rather than evidence against the task ratings. Moreover, it helps emphasize why we rate tasks directly because grouping tasks by detailed work activity would mix interpersonal work with feasible neighbors and remove most of it.

Near-universal statements. Dropping the 59 AI-infeasible and near-universal statements posted in at least 650 occupations, excluding the two audited statements, from each occupation's mentions leaves occupation rankings highly correlated with the baseline, although the highest-pressure occupations change. The rank correlation with the baseline is 0.971, and only one of the 20 highest-pressure occupations remains (0.975 and 4 of 20 when medium-confidence matches are also kept).

Here as well, the broader group is more stable. Out of the baseline's 71 top occupations, 55 still remain in the group under the new scheme, and all of its top 20 still have pressure above 24.

Counting the near-universal statements as feasible instead gives a rank correlation of 0.853, with one of the top 20 remaining. The occupations that fall furthest include production supervisors, occupational health and safety specialists, transportation managers, general and operations managers (from rank 356 to 473), and personal financial advisors. About a third to a half of their AI-infeasible mentions fall on near-universal statements (47

percent for personal financial advisors), near or above the 90th percentile across occupations (34 percent) and far above the median (16 percent). Because dropping these statements raises posting exposure, pressure can rise or fall depending on where an occupation sits on the hump. Mean pressure declines from 17.8 to 17.2, but pressure rises in 267 of the 708 occupations.

Matching contamination. We now test the sensitivity of our measure to errors in matching posting lines to tasks. BGI validates the matcher on samples of matches, but no estimate yet measures how often an error changes a mention's assigned feasibility label, thereby changing the measured AI-infeasible share. As a conditional check, however, suppose a share m of each occupation's mentions are not its own work but draws from the pool of all labeled matched mentions, of which 42.9 percent are AI-infeasible, and recover each occupation's AI-infeasible share by inverting that mixture. We then recompute pressure using this recovered share and its complement.

When matching errors are random, contamination barely moves the occupation ranking. Even when the target contamination rate is over three times the baseline bad-match rate, the rank correlation with the baseline is 0.99. Of course, because in this scenario a common rate rescales every occupation's share in the same way, much of this stability is built in. Nonetheless, this check is reassuring.

To perform an even more stringent, and, to be fair, counterfactual test, we check what happens when all wrong matches are solely concentrated on AI-infeasible statements. In this scenario, as one would expect, the ranking does change more, but the pressure rankings remain strongly correlated with the baseline. When we use a target contamination rate of 20 percent, over three times the baseline bad-match rate, *and* restrict every wrong match strictly to an AI-infeasible task, the rank correlation is still quite high, at 0.80. The effective contamination rate is lower for 189 occupations, where 20 percent would be inconsistent with their observed shares. Levels are less robust than rankings: mean pressure falls from 17.8 to 14.3 at a target random contamination rate of 20 percent, capped where necessary (Appendix Table D.5).

Feasibility labels. We change the AI-feasibility labels and examine how much our rankings move. Replacing the GPT-4 broad rating with the narrower α rating of Eloundou et al. (2024), which counts only direct exposure to the language model in its feasibility assessment, reduces the occupation correlation to −0.15. The β rating, which gives half credit for exposure that requires complementary software, gives −0.22, and the human ratings give −0.34. Task rankings are comparatively more stable across the range of feasibility

assessments employed, at 0.81 (α), 0.99 (β), and 0.79 (human). Note that the occupation correlations under α and β turn negative. This is largely because these narrower labels lower or leave unaltered each occupation's exposure, and pull occupations toward or away from an even split, where pressure peaks due to the functional form (see Appendix Figure B.1). Occupations initially at an even split lose pressure if their exposure falls. On the other hand, highly exposed occupations further to the right can gain even more pressure as exposure falls toward the center, although moving further down the left can leave them with lower pressure because of the hump-shaped curve. Of course, differences between human and GPT-4 ratings also reflect disagreement about what the same technology can do, and therefore these results need to be interpreted with that context in mind.[9]

On the labels' common support, task rankings remain similar because a task the broad rating counts as infeasible stays infeasible under α and β, and only the exposure of the job around it changes. Our baseline uses the conservative feasibility assessment of Eloundou et al. (2024), wherein a task counts as AI-infeasible only if a language model cannot halve its time even with complementary software (Section 3.1). Bottleneck pressure is defined *relative* to a technology, and should be regularly updated as technological advancements change the frontier of what is AI-feasible. Section 7 returns to the choice of feasibility labels. A user with a different view of what AI can do can recompute the measure with other labels.

7 Discussion

Our bottleneck measure is descriptive and conditional on a technology assessment borrowed from Eloundou et al. (2024). This section discusses what the posting weights measure, the feasibility labels, matching, and the scope of our measure, as well as the limitations of these inputs.

Posting weights. A job posting is a signal from an employer to applicants. While job postings data have been widely employed in economics to study novel questions (e.g., Acemoglu et al., 2022; Atalay et al., 2020; Hershbein and Kahn, 2018), they nonetheless have key limitations. They are not a record of how workers spend their time, which tasks they do the most, or what technologies they employ. Employers may omit duties that are too standard to mention and highlight ones that are unusual or attractive. Posting incidence stands in for the weights on a job's work, and the AI-infeasible share of posted work should

[9]The human ratings describe the same technology as the baseline, judged by different raters, but they also score partial feasibility as 0.5, which enters as a fraction, while the baseline is binary.

be read as the share of advertised work, not of working hours.

While the bottleneck pressure index pools an occupation's postings, most of the mixing of advertised AI-feasible and AI-infeasible work occurs *inside* individual postings. Of all AI-infeasible mentions, 82 percent appear in postings that also list a feasible task. Nonetheless, a job posting that advertises two duties does not establish that one worker performs both, how time is split between them, or that they are complements in production.

Feasibility labels. The AI-feasibility labels we employ to construct bottleneck pressure are a single assessment of one technology at one point in time. They are also binary: a task is rated AI-feasible if a language model, with complementary software where needed, can halve its completion time at the same quality. Falling below this threshold does not mean AI can offer no assistance. The ratings do not cover other technologies, such as robotics, which may automate work rated AI-infeasible here. Graded ratings would not simply give a graded index such as $(1 - \beta_t)E_o$. If a partial rating $\beta_t \in [0, 1]$ means a smaller gain on the whole task, $\beta_t \ln \delta$, with labor fixed, the model would rank proportional changes in tasks' MVPL, to first order, by $\ln \delta \left[(1/\sigma - 1/\rho)E_o - (1/\sigma - 1)\beta_t\right]$ (with E_o computed from the graded ratings), which depends on the elasticities of substitution between tasks (σ) and between occupations (ρ). Effectively, the graded version of the product in Equation (3) measures pressure on the part of a task AI cannot do only if a rating is read as the feasible fraction of its subtasks (Appendix A). Of course, even assessments of the same technology disagree (Section 6), so the leading occupations should be read as conditional on the GPT-4 assessment of Eloundou et al. (2024), whose GPT-based ratings have also informed the literature (e.g., Acemoglu, 2025).

Matching. Matching posting lines to O*NET tasks is imperfect. For occupations whose core tasks are all rated feasible, pressure comes entirely from AI-infeasible matches outside the core catalog. To assess such concerns, Section 6 shows two results. First, when wrong matches are random, even at a target contamination rate just over three times the bad-match rate, occupation rankings are highly correlated with the baseline. Second, if we restrict every bad match to an AI-infeasible task, then, although the ranking changes more, the correlation is still strong, at about 0.80 at a target rate of 20 percent, lowered where inconsistent with observed shares in our data.

Widely posted generic statements are a particular concern, and we show robustness to their exclusion in Section 6. Furthermore, we read the matched posting lines for two statements that ranked among the 20 largest contributors to pressure although their wording names a narrow physical activity, and excluded both from the ranked task tables because

their matches were mostly generic statements (Appendix C). Our audit covers two selected statements, not a random sample of matched posting lines. It therefore cannot establish the overall matching-error rate, and similar errors may remain elsewhere in the data. These are comparisons of matched task statements, and therefore the mapping does not establish that the underlying duties are equivalent across occupations.

Finally, errors in assigning postings to occupations are a separate channel, since a misassigned posting's tasks inherit the wrong occupation's posting exposure, and the misassignment can also change the measured task mix and exposure of the affected occupations. To mitigate errors stemming from this source, we retain only postings whose O*NET occupation code is assigned with a confidence at or above BGI's recommended threshold.

Scope. Our measure captures bottlenecks that arise from complementarity among tasks within an occupation. By construction, we miss bottlenecks across occupations, whether along supply chains (Acemoglu, Autor and Patterson, 2024) or between complementary roles whose tasks sit in different occupations (Becker and Murphy, 1992; Kremer, 1993). If firms reorganize tasks across workers or redraw jobs, pressure may instead show up in team composition and specialization (Garicano, Li and Wu, 2026*a*). The index ranks the bottleneck component of a proportional change in the marginal value of labor and is not a forecast of wages, employment or adoption. Pressure here is potential pressure. And it assumes the feasible tasks are actually sped up. Of course, in practice, whether this happens depends on the integration of AI within the organization and incentives there. In the model, integration would enter through the *size* of the AI gain, so differences in integration across occupations can change the effective gains and the ranking, subject to the condition discussed in Section 2. Integration could also change which tasks are effectively "feasible". Such integration raises pressure on the remaining work. Rising pressure can therefore reflect successful integration, rather than its failure (Appendix A). We are thinking of bottlenecks as capability bottlenecks because the ratings in Eloundou et al. (2024) describe capabilities. But one can also think about integration and use a different criterion for $F = 1$: feasible and actually integrated enough to meet the time-saving threshold. We would then recompute exposure using that criterion. Since integration can differ across occupations or firms, feasibility under this definition would also depend on where the task is done. A zero would then include both tasks AI cannot speed up enough and tasks it could speed up but has not been integrated to do. To distinguish the two, we would need separate information on capabilities and integration (Appendix A). The bottleneck pressure index can accommodate such changes, however: we would need an updated list

of feasible tasks in each occupation, or each occupation within a firm, and their shares in the work advertised, reflecting the decisions being made in the production process. The weights on tasks from our baseline can also be complemented with evidence on AI use and realized gains, rather than inferring whether the technology was successfully deployed or integrated from the job-posting data itself. This is not to say understanding what is and is not "feasible" from a capabilities point of view is simple and, indeed, this is conceptually distinct from an integration bottleneck. Our framework holds the task bundle fixed. Firms may reorganize the production process so that some tasks become obsolete, a margin the present index does not capture because it holds the task bundle fixed. It matches posting text to task statements in the existing O*NET catalog. The emergence of new tasks arising as AI is adopted would be a fruitful avenue for further research. The index also speaks only to tasks that already exist and can be posted and matched to O*NET task statements, not to new tasks a technology creates (Acemoglu and Restrepo, 2019; Autor et al., 2024). But one can update feasibility and therefore pressure as capabilities and incentives to integrate evolve. These and many other possibilities are left for future research, but we note that they can be studied through this simple index, provided the relevant tasks, their feasibility and their shares can be measured.

What the framework predicts. We examine two empirical questions with our postings data. First, recall that pressure on an AI-infeasible task is proportional to exposure. Under gross complementarity, and assuming that advertised task shares are a good proxy for work allocation, we should find the *same task* gain ground in postings where the occupation is more exposed, once AI speeds up the rest of the job (tested in Appendix Table F.1). Second, we ask whether task pressure, aggregated to occupations, given by $E(1-E)$ predicts *changes* in postings that would be missed by a linear exposure term or E (tested in Appendix Table F.2).

Changes over time. Average pressure across occupations rose from 17.6 in 2018 to 18.7 in 2026H1, with nearly all of the uptick coming by 2023, and about three-quarters of the rise reflecting labeled task mentions shifting *away* from low-pressure occupations rather than more pressure within them (Appendix Figure F.3). Holding occupation weights at their 2021 level to remove shifts in the occupation mix, average pressure barely moves, from 17.9 to 18.1. The seniority comparison in Section 5 is the counterpart within occupations. After 2022, occupations with higher pressure grew about 11 log points faster in postings than the lowest-pressure quartile, a shift that has lasted through June 2026 (Appendix Table F.3 and Figure F.4). Note that these occupations were already moving differentially before 2022,

and the shift began in 2022. We do not claim a sharp causal effect of generative AI tied to the rollout of ChatGPT and generally believe that it is important to report transparently on a question where a single release date in November 2022 is often asked to carry more causal weight than it can bear. We also performed a much sharper test of the model, following the same AI-infeasible tasks across occupations and relying on gross complementarity. This test, described in Appendix Table F.1, gives imprecise nulls and more work needs to be done to confirm or reject the mechanism.

Task pressure, aggregated, predicts posting growth. While the main thrust of the paper is to show pressure at the task level, we show that occupation-level bottleneck pressure, which adds up the pressure on the tasks in an occupation's postings, $\sum_t \pi_{ot}(1-F_t)E_o = E_o(1-E_o)$ by Equation (4), predicts posting growth that linear exposure measures do not. We fix the industry and broad occupation group, and control linearly for 2021 exposure. The coefficient on 2021 pressure is 5.11 log points per standard deviation (standard error 1.25), while exposure alone does not predict any significant change in the baseline log-postings specification (Appendix Table F.2). Because occupation-level pressure is exposure minus its square, it captures a nonlinear pattern in exposure, allowing for faster posting growth in the middle of the exposure range. The pattern we document is robust to many robustness checks, including dropping the largest employers, computer and mathematical occupations, and alternative specifications. A placebo start date in 2019 or 2020 rather than 2022 finds nothing. The coefficient on pressure rises from late 2022, whereas its movements before 2022 are generally smaller but nevertheless jointly different from zero (Appendix Figure F.5). An occupation-level test on the share of AI-infeasible task mentions favors exposure instead. We therefore present it as prediction, not as an effect of AI.

8 Conclusion

Measures of AI exposure describe the work AI can do. This paper measures where the work AI cannot do comes under pressure. We show that the pressure on a task is a property not only of the task but also of the entire job surrounding it: "greet customers" faces pressure of 23 in fast food work and more than three and a half times that, at 83, in customer service (Figure 5).

With 288 million U.S. job postings mapped line by line to their closest O*NET tasks and published GPT-4 feasibility ratings, we construct a novel measure of bottleneck pressure that builds on and complements previous occupational AI measures, such as exposure. At the occupation level, bottleneck pressure is simply the product of occupational exposure

and the share of advertised work that is AI-infeasible. Because occupation pressure peaks where advertised work is evenly split between AI-feasible and AI-infeasible tasks, it ranks occupations differently than exposure. At higher levels of task pressure, interpersonal and supervisory work accounts for a larger share of the AI-infeasible work carrying that pressure, and physical work for a smaller share.

AI capabilities are rapidly expanding (Kwa et al., 2025; Patwardhan et al., 2025). If tasks within jobs are gross complements, then as AI speeds up the tasks it can do, the tasks it cannot do may absorb a growing share of labor within jobs, a "mini Baumol" effect (Aghion, Jones and Jones, 2019; Baumol, 1967), while jobs may also expand to take on new tasks (Acemoglu and Restrepo, 2019; Autor et al., 2024; Humlum and Vestergaard, 2025). Both are open empirical questions. Repeating our measurement as the technology changes can help track pressure alongside the emergence of new work. Exposure measures are now widely reported and used in research (e.g., Acemoglu et al., 2022; Brynjolfsson, Chandar and Chen, 2025). Bottleneck pressure should be reported with them, so that the work AI cannot do is measured alongside the work it can.

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A Model derivation

Recall the notation of Section 2. Final output Y combines occupations o with weights α_o and elasticity ρ, and each occupation's output Y_o combines its tasks t with weights α_{ot} and elasticity σ; L_{ot} is labor in task t of occupation o. A task is AI-feasible ($F_t = 1$) if the technology raises its output by a factor $\delta > 1$, and AI-infeasible ($F_t = 0$) otherwise. With π_{ot} the baseline cost share of task t in occupation o and π_o that of occupation o in the economy, exposure is $E_o = \sum_t \pi_{ot} F_t$, aggregate exposure is $\bar{E} = \sum_o \pi_o E_o$, and the AI-infeasible share is $S_o = \sum_t \pi_{ot}(1 - F_t)$. Bottleneck pressure is $B_{ot} = (1 - F_t)E_o$ on a task and $B_o = E_o S_o$ on an occupation, and $\kappa \equiv \ln \delta \, (1/\sigma - 1/\rho)$.

Marginal value of labor. Normalize $\sum_o \alpha_o = 1$ and $\sum_t \alpha_{ot} = 1$ and take final output as the numeraire. By the chain rule through both aggregators in Equation (1),

$$\ln \text{MVPL}_{ot} = \ln \alpha_o \alpha_{ot} + \frac{1}{\rho} \ln Y + \left(\frac{1}{\sigma} - \frac{1}{\rho}\right) \ln Y_o - \frac{1}{\sigma} \ln Y_{ot} + \ln \frac{\partial Y_{ot}}{\partial L_{ot}}.$$

Compare a baseline with no feasible task to a scenario in which the tasks with $F_t = 1$ become feasible, holding labor fixed. Because the output elasticity of each CES input equals its cost share, to first order $\Delta \ln Y_o \approx \ln \delta \, E_o$ and $\Delta \ln Y \approx \ln \delta \, \bar{E}$. For task t, $\Delta \ln Y_{ot} = \Delta \ln(\partial Y_{ot}/\partial L_{ot}) = F_t \ln \delta$. Hence

$$\Delta \ln \text{MVPL}_{ot} \approx \ln \delta \Big[\underbrace{\frac{1}{\rho} \bar{E}}_{\text{scale}} + \underbrace{\left(\frac{1}{\sigma} - \frac{1}{\rho}\right) E_o}_{\text{spillover from the job}} - \underbrace{\left(\frac{1}{\sigma} - 1\right) F_t}_{\text{own productivity}} \Big].$$

Infeasible and feasible tasks. With $F_t = 0$ the last term vanishes, which gives Equation (2); the ratio of the bottleneck effect to the scale effect is $(\rho/\sigma - 1)E_o/\bar{E}$. With $F_t = 1$ and $\sigma < 1$, the own-productivity term works against the spillover, and the net sign depends on σ, ρ, E_o and $\bar{E}$, so the index sets the pressure on feasible tasks to zero. Dividing the term that varies across infeasible tasks by $\kappa \equiv \ln \delta \, (1/\sigma - 1/\rho)$ gives $B_{ot} = (1 - F_t)E_o$. With σ, ρ and δ common across occupations, it ranks infeasible tasks by their bottleneck effect.

Gains below the threshold and graded ratings. Write task output as $Y_{ot} = A_{ot} L_{ot}$ and let $g_{ot} = \Delta \ln A_{ot}$ be task t's productivity gain, $g_o = \sum_t \pi_{ot} g_{ot}$ and $\bar{g} = \sum_o \pi_o g_o$. The same steps give $\Delta \ln \text{MVPL}_{ot} \approx \bar{g}/\rho + (1/\sigma - 1/\rho) \, g_o - (1/\sigma - 1) \, g_{ot}$. If infeasible tasks gain $\ln \delta_0$ and feasible tasks $\ln \delta$, with $1 \le \delta_0 < \delta$, then $g_o = \ln \delta_0 + E_o \ln(\delta/\delta_0)$, and for an infeasible

task

$$\Delta \ln \text{MVPL}_{ot} \approx \underbrace{\frac{\bar{g}}{\rho} + \left(\frac{1}{\sigma} - \frac{1}{\rho}\right) \ln \delta_0 - \left(\frac{1}{\sigma} - 1\right) \ln \delta_0}_{\text{common to infeasible tasks}} + \ln \frac{\delta}{\delta_0} \left(\frac{1}{\sigma} - \frac{1}{\rho}\right) E_o,$$

so B_{ot} ranks infeasible tasks as before, with $\ln(\delta/\delta_0)$ in place of $\ln \delta$. If the gains also deviate by ε_{ot}, with occupation average $\bar{\varepsilon}_o = \sum_t \pi_{ot} \varepsilon_{ot}$, the term that differs across infeasible tasks becomes $(1/\sigma - 1/\rho)\left[\ln(\delta/\delta_0) E_o + \bar{\varepsilon}_o\right] - (1/\sigma - 1)\varepsilon_{ot}$. Two infeasible tasks retain their ordering by E_o if the following sufficient condition holds: the absolute difference in $(1/\sigma - 1/\rho)\bar{\varepsilon}_o - (1/\sigma - 1)\varepsilon_{ot}$ between them is smaller than $(1/\sigma - 1/\rho)\ln(\delta/\delta_0)$ times the absolute difference in their occupations' exposure.

If a rating $\beta_t \in [0, 1]$ means that the whole task gains $\beta_t \ln \delta$, the term that differs across tasks is $\ln \delta \left[(1/\sigma - 1/\rho) E_o^\beta - (1/\sigma - 1)\beta_t\right]$, with $E_o^\beta = \sum_t \pi_{ot} \beta_t$, which depends on the elasticities and is not proportional to $(1 - \beta_t) E_o$. The product $(1 - \beta_t) E_o^\beta$ instead measures the pressure on the part of a task AI cannot do if β_t is read as the baseline cost-share-weighted feasible fraction of the task's subtasks, each of which is either feasible or not.

Capability and integration. Recall, in our setting F_t describes *capability*, i.e. whether the technology could meet the time-saving threshold under the broad definition of Eloundou et al. (2024). Whether this time-saving extends to production also depends on *integration*. We show how the basic model can be extended to incorporate this channel and leave its empirical implementation to future work.

Specifically, let $I_{ot} = 1$ if AI is integrated, and permitted, well enough to deliver that gain in task t of occupation o, which can also be an occupation within a firm. Likewise, let deployment be $D_{ot} = F_t I_{ot}$. Replacing F_t with D_{ot} in the derivation above of Equation (2), the bottleneck effect on a task that is not deployed is proportional to $E_o^D = \sum_t \pi_{ot} D_{ot}$, so, to first order, $(1 - D_{ot}) E_o^D$ ranks these tasks as B_{ot} ranks AI-infeasible ones. Since $1 - F_t I_{ot} = (1 - F_t) + F_t (1 - I_{ot})$,

$$(1 - D_{ot}) E_o^D = \underbrace{(1 - F_t) E_o^D}_{\text{capability}} + \underbrace{F_t (1 - I_{ot}) E_o^D}_{\text{integration}}.$$

Our key index from Equation (3) is therefore a special case when $I_{ot} = 1$ for every capable task: the pressure on the work AI cannot do if everything it can do were integrated.

Two implications follow from this extension. First, integration raises pressure on the remaining work. Say a job has five equally weighted tasks, with three of them being "AI-capable." In that instance, integrating one raises the pressure on each of the other four

from 0 to 20, whereas integrating all three raises it to 60 on the two that the technology cannot do. Rising pressure can therefore reflect successful integration, rather than its failure, but it comes with higher pressure on the "infeasible" tasks. Second, the own-gain term captures what happens when AI speeds up the task *itself*, rather than other tasks around it. On the one hand, AI speeding up tasks around a specific one can make that task more constraining (this is the standard pressure argument). However, when AI speeds up the task itself, it can also relieve that constraint. This is what the own-gain term captures. Whether the gain should be pursued is outside the scope of the model, but we note it would depend on integration costs and adoption frictions within the organization. Note also that with partial integration, the own-gain term $-(1/\sigma - 1)g_{ot}$ no longer vanishes, and so a graded integration share cannot simply replace F_t in B_{ot}. Of course, separating the terms in the decomposition above therefore would require, for the same tasks, both a capability assessment and evidence of realized gains on the job.

The single-source identity. If exposure and the AI-infeasible share use the same weights, then $S_o = 1 - E_o$ for any weights, so $B_o = E_o(1 - E_o)$: zero at $E_o = 0$ and $E_o = 1$ and maximal at one-half. With binary feasibility, this also equals the weighted within-occupation variance of feasibility. Equivalently, $E_o(1 - E_o)$ is the probability that, of two tasks drawn from the job with replacement, the first is feasible and the second infeasible.

General equilibrium. A representative household supplies labor inelastically, tasks are produced as $Y_{ot} = A_{ot}L_{ot}$ with $A_{ot} = \delta^{F_t}$ after the technology arrives, and markets are competitive. We consider three regimes: (S) labor fixed by task; (M) labor mobile across tasks within an occupation; and (L) labor fully mobile. Let λ_{ot} be the share of aggregate income earned in task t of occupation o. By Hulten's theorem (Hulten, 1978), $\partial \ln Y / \partial \ln A_{ot} = \lambda_{ot}$, so a small improvement of size η in task t, of which its developer captures a fraction θ, returns $R_{ot} = \theta\eta\lambda_{ot}Y$.

Proposition A.1. *To first order, for a task the technology cannot yet perform,*

$$\Delta \ln \lambda_{ot} \approx \ln \delta \left(\gamma_r E_o - \mu_r \bar{E}\right), \qquad \Delta \ln R_{ot} \approx \ln \delta \left(\gamma_r E_o + (1 - \mu_r)\bar{E}\right),$$

with, for regime $r \in \{\mathrm{S}, \mathrm{M}, \mathrm{L}\}$, (γ_r, μ_r) equal to $(1/\sigma - 1/\rho,\ 1 - 1/\rho)$ in regime (S), $\left(2 - \sigma - 1/\rho,\ 1 - 1/\rho\right)$ in regime (M), and $(\rho - \sigma,\ \rho - 1)$ in regime (L). The coefficient γ_r is positive if and only if $\sigma < \rho$ in regimes (S) and (L), and if and only if $\sigma < 2 - 1/\rho$ in regime (M).

Proof sketch. Use a common pre-AI competitive allocation compatible with full labor mobility, so all three regimes start from the same shares, and evaluate all shares at that baseline. Write $\lambda_o = \sum_t \lambda_{ot}$, $s_{ot} = \lambda_{ot}/\lambda_o$, and $h = \ln \delta$, so initially $\lambda_o = \pi_o$, $s_{ot} = \pi_{ot}$, and $\bar{E} = \sum_o \pi_o E_o$. For an infeasible task, CES income shares give

$$\begin{aligned}
\Delta \ln s_{ot} &\approx a_r E_o h, \\
\Delta \ln \lambda_o &\approx b_r (E_o - \bar{E}) h, \\
\Delta \ln \lambda_{ot} &\approx \left[(a_r + b_r) E_o - b_r \bar{E} \right] h, \\
\Delta \ln Y &\approx \bar{E} h, \\
\Delta \ln R_{ot} &\approx \Delta \ln \lambda_{ot} + \Delta \ln Y,
\end{aligned}$$

where (a_r, b_r) equals $(1/\sigma - 1,\ 1 - 1/\rho)$ in (S), $(1 - \sigma,\ 1 - 1/\rho)$ in (M), and $(1 - \sigma,\ \rho - 1)$ in (L), holding θ and η fixed. Thus $\gamma_r = a_r + b_r$ and $\mu_r = b_r$. The income share is the relevant object because it is both the elasticity of aggregate output to the task's productivity and the developer's gross return divided by $\theta \eta Y$.

Whenever $\gamma_r > 0$, both the proportional change in a task's income share and the proportional change in the return to speeding it up vary across infeasible tasks only through E_o, so B_{ot} ranks these proportional changes the same way in every regime. Absolute changes are these times the task's initial share or return, so they need not follow the same order. Assumption 1 guarantees $\gamma_r > 0$ in regimes (S) and (L); in regime (M) it also requires $\sigma < 2 - 1/\rho$, which holds whenever $\sigma < 1 \leq \rho$ but can fail when $\rho < 1$ (for example, $\sigma = 0.5$ and $\rho = 0.6$). The constant and the size of γ_r differ across labor regimes, as does the margin through which the rise occurs. Under the assumption of fixed labor by task, wages are the margin of adjustment. By contrast, when labor is fully mobile across tasks and occupations, adjustment occurs through employment.

The return for a whole occupation. For a common speedup η and capture fraction θ, summing over an occupation's remaining infeasible tasks gives

$$\sum_{t:F_t=0} \pi_{ot} \Delta \ln R_{ot} \approx \ln \delta \left[\gamma_r E_o S_o + (1 - \mu_r) \bar{E} S_o \right].$$

The scale component also varies across occupations through S_o. The bottleneck component of the rise in the return to speeding up all of them, per unit of the occupation's income before AI, is proportional to $E_o S_o$, the occupation index in Equation (4). With the same weights for both factors, as in our postings-only measure, this is $E_o(1 - E_o)$, a function of exposure alone.

A calibrated simulation. Proposition A.1 says that pressure ranks the proportional change in the return to developing technology that speeds up a task AI cannot yet perform, which is also the change in that return per unit of the task's size before AI. Figures A.1 and A.2 put that result in the exact general-equilibrium model, rather than its first-order approximation, calibrated to the 708 occupations. The simulation uses a baseline-share representation of the CES model, setting each occupation's baseline income share π_o equal to its share of eligible postings. Within each occupation, the AI-feasible tasks hold a share E_o of its income before AI and the AI-infeasible tasks a share $1 - E_o$, so each occupation's AI-infeasible work forms one bundle whose pressure is E_o. The simulation uses posting exposure for E_o and its complement for the AI-infeasible share. AI doubles the productivity of feasible tasks ($\delta = 2$), and the baseline elasticities are $\sigma = 0.5$ and $\rho = 1$. We take the cost of speeding up a bundle to be proportional to its income share before AI.

The return to a speedup. A developer who captures a share θ of a small speedup of size η earns $R_{ot} = \theta\eta\lambda_{ot}Y$. Panel A of Figure A.1 plots this return per unit of work, relative to its value before AI, against pressure. AI raises the return on every bundle, because it raises output; this is the scale effect. The return rises further with pressure, which is the bottleneck effect. With labor fixed by task, the return averages 1.54 times its value before AI for bundles with pressure below 25 and 2.44 times for bundles at or above 75, weighting by size. When labor is mobile, the gradient is flatter: 1.52 and 1.92 times. With $\rho = 1$, mobility within occupations and full mobility give the same result. Stronger complementarity within occupations steepens the gradient ($\sigma = 0.3$: 1.55 and 4.17 times, with labor fixed), and weaker complementarity flattens it ($\sigma = 0.8$, $\rho = 1.2$: 1.44 and 1.75 times). In every regime and for every pair of elasticities considered, the return depends on pressure alone and rises with it, as Proposition A.1 implies; for a small gain ($\ln \delta = 0.001$), the maximum absolute error in the proposition's predicted log returns is below 0.04 percent of the largest first-order predicted log change.

Which work to speed up first. The incentive and the gain to output point the same way here: the developer's return is proportional to the bundle's income share, which by Hulten's theorem is also the rise in aggregate output. Panel B speeds up bundles by 10 percent each, one after another, in three orders: highest pressure first, the largest bundles first, and random. With labor fixed, speeding up a tenth of AI-infeasible work, measured by income before AI, delivers 13.1 percent of the gain in log output from speeding up all of it when the highest-pressure bundles go first. When the largest bundles go first, we get 9.5 percent compared to 10.1 percent when all bundles go in a random order. At a quarter of the work, the figures are 30.2, 25.0 and 24.1 percent for highest pressure first, random order and largest bundles first, respectively. With labor fully mobile, they are 11.5, 10.1 and 9.8

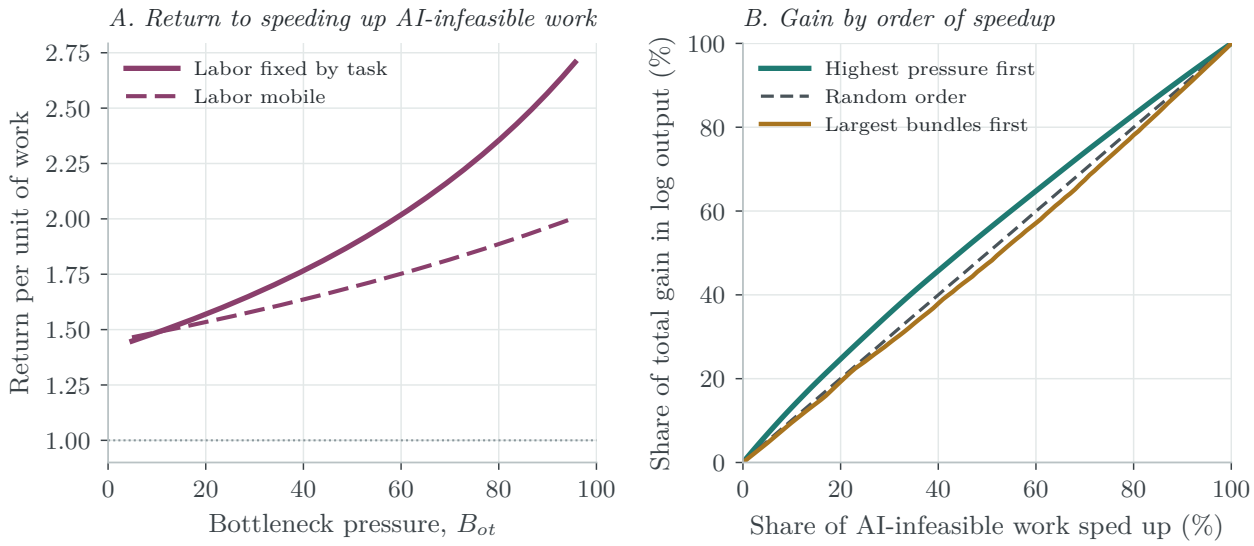


Figure A.1: The return to speeding up AI-infeasible work, in the model

Notes: Simulation of the general-equilibrium model in Section 2 and Appendix A, calibrated to the 708 occupations in our main sample. Occupation weights are shares of eligible BGI harmonized U.S. job postings, January 2018 to June 2026. Within each occupation, AI-feasible tasks hold a share of its work equal to its posting exposure E_o and AI-infeasible tasks the rest, so each occupation's AI-infeasible work is one bundle with pressure E_o. AI multiplies the productivity of feasible tasks by 2. $\sigma = 0.5$ and $\rho = 1$. Panel A: the return to a small speedup of each bundle, $\theta\eta\lambda_{ot}Y$, per unit of the bundle's income share before AI and relative to its value before AI; a value of one is the return before AI. The solid line holds labor fixed by task; the dashed line lets labor move, within occupations or fully, which give the same result when $\rho = 1$. Panel B, with labor fixed by task: the cumulative gain in log aggregate output from speeding up bundles by 10 percent each, as a share of the gain from speeding up all of them, against the share of AI-infeasible work sped up, measured by income before AI; values at a tenth and a quarter of the work interpolate between whole bundles. The random order averages 60 draws. Pressure is on a 0–100 scale. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold.

percent at a tenth. The largest bundles sit in less exposed occupations: across occupations, the rank correlation between a bundle's size and its pressure is −0.38.

Growth. Figure A.2 lets AI productivity in feasible tasks keep rising, by 10 percent per period, with labor fixed. If no AI-infeasible work is sped up, growth of aggregate output falls from 4.1 percent in the first period to 0.7 percent by period 30, as the work AI cannot do takes up a growing share of income (Baumol, 1967; Jones and Tonetti, 2026). A program that raises the productivity of a fixed set of bundles by 3 percent per period slows that decline. We assume that every program has the same cost as applying the full rate to a tenth of AI-infeasible work, measured by income before AI. Under this assumption, bundles are taken whole until the last one reached, which is sped up at the fraction of the log growth rate that keeps the program within that cost. When the program targets the highest-pressure bundles, growth is still 1.8 percent in period 30, against 1.0 percent for a

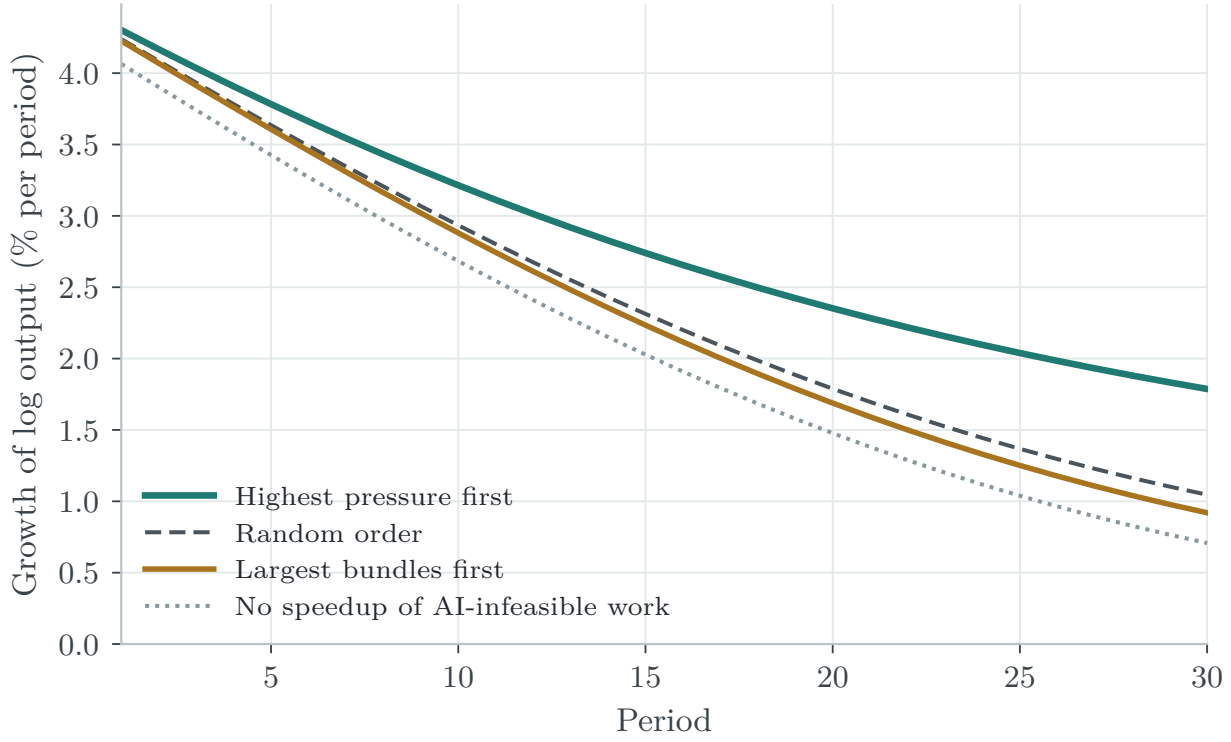


Figure A.2: Growth when AI keeps improving, in the model

Notes: Simulation of the model in Section 2 with labor fixed by task, $\sigma = 0.5$ and $\rho = 1$, calibrated as in Figure A.1. The productivity of AI-feasible tasks starts at twice its level before AI and rises by 10 percent per period. Each program raises the productivity of a fixed set of AI-infeasible bundles by 3 percent per period. With the cost of a speedup proportional to the size of the work, measured by income before AI, times its log growth rate, each program costs the same as applying the full rate to 10 percent of AI-infeasible work: bundles are taken whole until the last one reached, which is sped up at a fraction of the log growth rate. Highest pressure first selects the bundles in the most exposed occupations; largest bundles first selects the bundles with the largest income share before AI; the random set averages 60 draws. Growth is the change in log aggregate output per period, in percent.

random set of bundles and 0.9 percent for the largest bundles. After 30 periods, the targeted program raises the level of output by 21.1 log points relative to no program, against 8.3 and 6.0. When we relax the restriction of keeping labor fixed and allow it to be fully mobile across tasks and occupations, the growth decline is somewhat milder. It falls from 4.7 to 2.5 percent, and the program adds 11.7 log points when it targets the highest-pressure bundles, against 6.5 for a random set and 5.5 for the largest bundles. Under our assumed cost structure, a given outlay buys more growth in high-pressure work. This is because that work is a small part of jobs whose AI-feasible remainder has become more productive. So, it holds back a large share of total output.

Beyond first order. For large gains the first-order terms overstate the rise in marginal value in the baseline calibration, though with $\rho > 1$ they can understate it; with $\sigma < 1$, as $\delta \to \infty$ in regime (S), an occupation with $E_o < 1$ has its output capped by its remaining tasks, the weak-link logic of Kremer (1993). The model holds the elasticities and the size of the gain common across occupations, treats the technology as costless, and has one type of labor. At a finite gain, the exact bottleneck term with labor fixed is $(1/\sigma - 1/\rho)\,\Delta \ln Y_o$, with $\Delta \ln Y_o = \frac{\sigma}{\sigma-1} \ln \left[E_o \delta^{(\sigma-1)/\sigma} + 1 - E_o\right]$; for $\sigma = 0.5$, $\rho = 1$ and $\delta = 2$ it is $-\ln(1 - E_o/2)$, which is increasing in E_o, so the ordering of AI-infeasible task–occupation pairs is unchanged. The same holds for every $\sigma < \rho$ and $\delta > 1$, since $\exp(\Delta \ln Y_o)$ is a power mean of δ and 1 with weight E_o on δ (geometric at $\sigma = 1$). The ordering of task–occupation pairs comprising only AI-infeasible tasks remains unchanged at finite productivity gains. This invariance does not generally extend to posting-weighted task averages P_t. Neither does it generally extend to contribution shares of tasks, the within-task variance share or the pressure-weighted composition of the quintiles. When we average over advertised work in the job postings, the exact occupation bottleneck effect is proportional to $S_o \Delta \ln Y_o$, rather than to $E_o S_o$. Across the 708 occupations, its rank correlation with the baseline index is 0.973, with none of the 20 highest-pressure occupations in common, at $\sigma = 0.5$ and $\rho = 1$; 0.998 and 12 of 20 at $\sigma = 0.8$ and $\rho = 1.2$; and 0.888 and none of 20 at $\sigma = 0.3$ and $\rho = 1$. The occupation ranking is close to the first-order one at moderate complementarity, although the highest-pressure occupations change. Both occupation indices remain functions of posting exposure alone, but the finite-gain index peaks at a different exposure level (54.0 rather than 50.0 when $\sigma = 0.5$, $\rho = 1$ and $\delta = 2$). In the simulation, the analytic income shares match finite differences of the exact model to within 0.01 percent in every regime and for every pair of elasticities considered, and, for a small gain, the maximum absolute error of the first-order formulas of Proposition A.1 is below 0.04 percent of the largest first-order predicted log change.

B Alternative source constructions

Let E_o^{post} denote exposure measured from postings and E_o^{cat} exposure measured from the occupation's core O*NET tasks. The three constructions are

$$
\begin{aligned}
B_o^{\text{post}} &= E_o^{\text{post}}(1 - E_o^{\text{post}}), \\
B_o^{\text{cat}} &= E_o^{\text{cat}}(1 - E_o^{\text{cat}}), \\
B_o^{\text{hybrid}} &= E_o^{\text{cat}}(1 - E_o^{\text{post}}).
\end{aligned}
$$

Figure B.1 plots the postings-only score against posting exposure. By construction, every occupation lies on the curve.

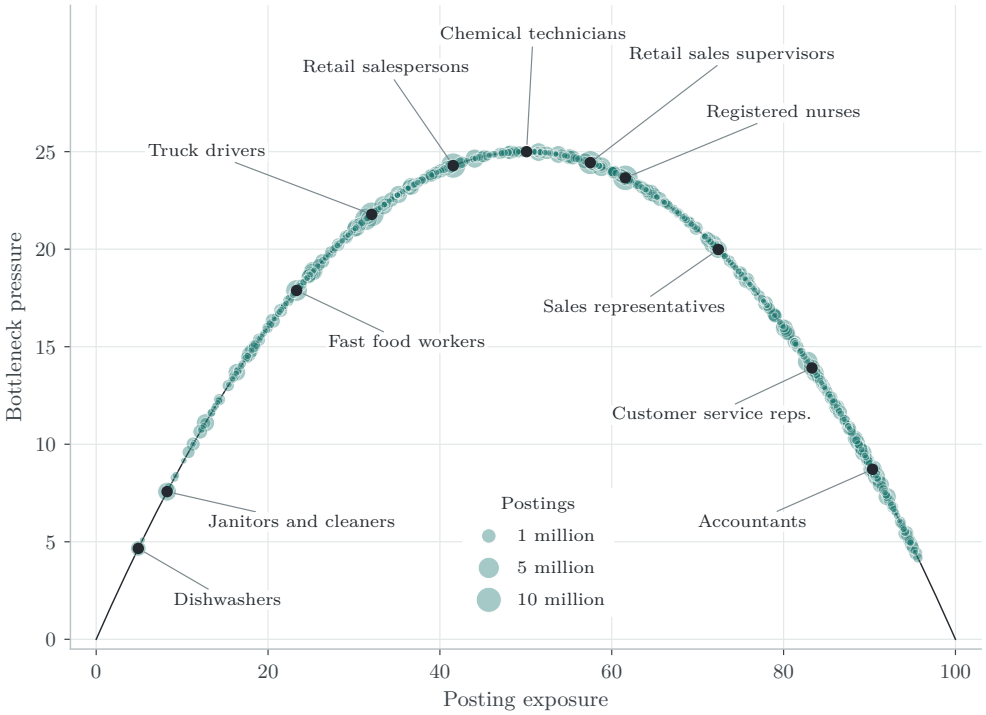


Figure B.1: Bottleneck pressure and posting exposure

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. Each circle is one of the 708 occupations, with its area proportional to the number of eligible postings. Labels identify selected occupations discussed in the paper. Posting exposure is the AI-feasible share of labeled matched task mentions. Occupation pressure is posting exposure times its complement, and each AI-infeasible task in an occupation faces pressure equal to its posting exposure. Both are on a 0–100 scale. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. Writing exposure as a share e, the curve is the exact identity $100e(1 - e)$, not an estimated relationship.

The hybrid combines catalog exposure with the posted AI-infeasible share. Because these use different weights and need not sum to one, their product can exceed the single-source maximum of 25 on the 0–100 scale. Figure B.2 compares the three distributions across the same 708 occupations.

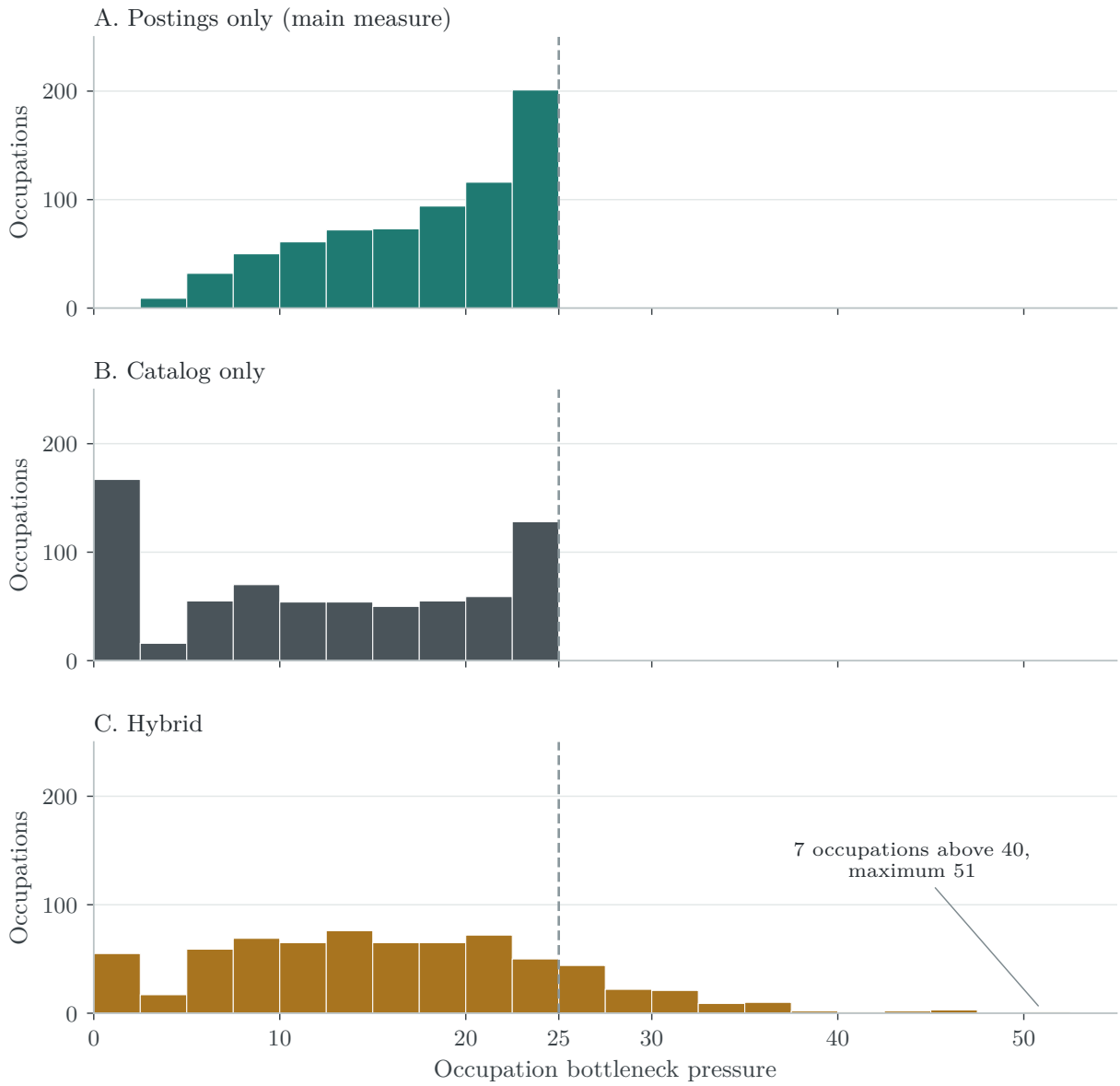


Figure B.2: Distribution of occupation pressure under three source constructions

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, keeping high-confidence line-to-task matches only. Each panel counts the same 708 occupations in bins of 2.5 points, each including its upper edge, with identical axes. The dashed line shows the maximum value (25) of the bottleneck pressure constructed from a single source (postings or catalog). Pressure is on a 0–100 scale.

C Measurement pipeline and mapping audit

This appendix documents the key steps in the pipeline that translates job postings data into bottleneck pressure scores, along with information about the quality of the matches between job posting descriptions and O*NET tasks. Figure C.1 summarizes the key steps in the matching and scoring pipeline. Job postings, matched line by line to O*NET tasks (only lines that BGI's parser tags as "responsibilities"), give both occupational exposure and the AI-infeasible share of each occupation's posted work. The GPT-4 feasibility labels of Eloundou et al. (2024) enter both factors. We next describe the main analysis sample (Table C.1), match confidence and posting sections, the two widely matched tasks we audited and excluded from the ranked task tables, and the treatment of generic statements. Finally, we show how posting incidence, the share of an occupation's postings that include a task, compares with O*NET's own task information (Figure C.2).

Match confidence and posting sections. BGI's task pipeline assigns each job posting line-to-task match a confidence tier based on its similarity score. The threshold is internal to BGI. The pipeline labels each match "use" (high confidence), "review" (medium) or "exclude" (low), and BGI checks the quality of these tiers by reviewing samples of matches (Section 6). Our main sample uses the top-ranked matches tagged with a "use" label. Our baseline already retains only lines assigned to job responsibilities, so applying that section filter again would leave the sample unchanged. Indeed, considering only responsibility lines tagged by BGI's parser in the downstream task matching algorithm is part of the design to avoid matching and assigning task labels to boilerplate text in job postings. Of course, this does not rule out requirement-style statements within the section, such as those absorbed by the two audited tasks below.

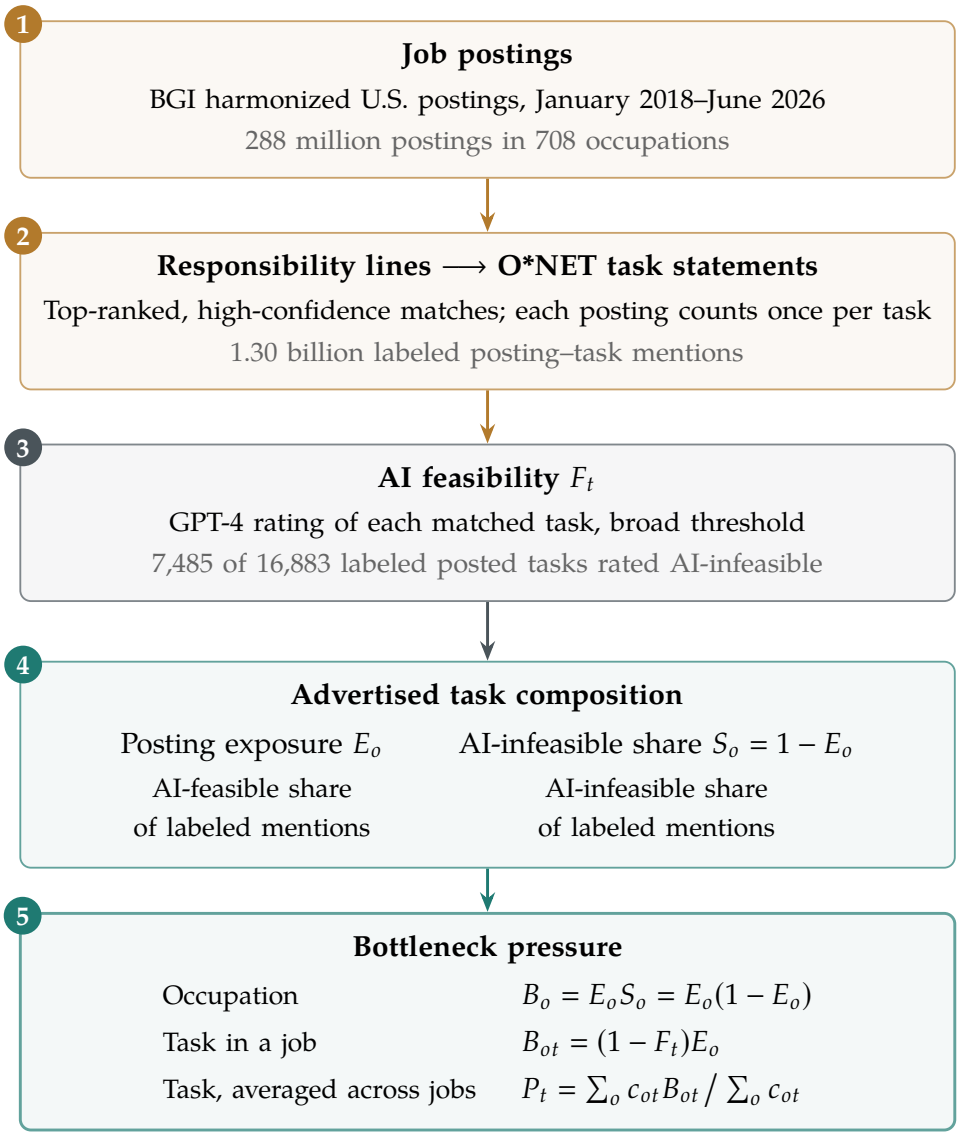


Figure C.1: From job postings to bottleneck pressure

Notes: (1) BGI's harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time. (2) Each posting is split into lines, and lines that BGI's parser tags as responsibilities are matched to task statements anywhere in O*NET. Next, a line's top match is kept only if it meets BGI's internal high-confidence threshold. We de-duplicate all matches between posting lines and tasks within a job posting, ensuring that a posting counts only once per task. (3) Each task carries the binary GPT-4 feasibility rating of Eloundou et al. (2024) at the broad threshold, which enters both factors. (4) Posting exposure E_o is the AI-feasible share of labeled matched task mentions, and $S_o = 1 - E_o$. (5) Occupation pressure is $B_o = E_o S_o = E_o(1 - E_o)$; task-in-job pressure is $B_{ot} = (1 - F_t)E_o$; task pressure P_t is the posting-weighted average of B_{ot} across the occupations that post the task, where c_{ot} counts postings in occupation o that include task t.

Table C.1: Sample coverage and observation units

From postings to task mentions						
Row	Observation	Total or share	Mean	P10	P50	P90
Posting coverage						
C1	Postings, January 2018–June 2026	321.2m				
C2	Postings in the analysis sample	288.3m				
C3	Matched tasks per posting (all occupations)		4.7	0	3	11
C4	Postings with no matched task (all occupations)	19.9%				
Occupation coverage						
C5	Detailed O*NET occupations	784				
C6	Occupations in the analysis sample	708				
C7	Postings per occupation (thousands) (analysis sample)		407	18	105	964
C8	Distinct tasks posted per occupation (analysis sample)		4,724	1,823	4,227	8,440
C9	Mentions in the 20 most-posted tasks (%) (all 784 occupations)		31.0	18.7	28.7	45.5
Task coverage (*sample specified below*)						
C10	Distinct tasks posted, all 784 occupations	17,526				
C11	Labeled posted tasks, 708-occupation sample	16,883				
C12	AI-infeasible tasks, 708-occupation sample	7,485				
C13	Occupations posting each labeled task (708-occupation sample; 1,000+ mentions)		211	56	169	440
The observations used to construct the index						
C14	Occupation–task cells, analysis sample	3,206,572				
C15	Labeled posting–task mentions	1.30bn				
C16	AI-feasible share of labeled mentions	57.1%				
C17	Mentions on the occupation's core task list	8.6%				
C18	Mentions on its supplemental task list	1.2%				
C19	Mentions outside its own task list	90.1%				

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time and high-confidence detailed O*NET occupation codes. Our main analysis sample contains the 708 occupations with catalog exposure scores. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. Rows C3–C4, C9 and C10 cover all 784 occupations, whereas C11–C13 use labeled tasks in the 708-occupation analysis sample. Row C8 counts any task posted at least once. C9 summarizes each occupation's share of mentions in its own 20 most-posted tasks. The pooled AI-infeasible share complementary to C16 is 42.9 percent. In C17–C19, task-list membership is relative to the posting's occupation; these are shares of all labeled matched mentions, without renormalization, and omit the 0.1 percent whose on-list core or supplemental status is unverified. Occupation distributions are unweighted. The 10th, 50th and 90th percentiles are denoted by P10, P50 and P90, respectively; m and bn denote millions and billions.

Two audited tasks. Systematic matching errors in widely matched task statements can distort task rankings and measured contributions to total pressure. As an additional robustness check on our posting-to-task matching, two widely matched AI-infeasible tasks were checked at the level of the posting lines matched to them. Both these tasks rank among the 20 largest AI-infeasible contributors to pressure (10th and 14th) and are posted in 700 or more occupations, although their wording names a narrow physical activity:

- "Climb trees, using climbing hooks and belts, or climb ladders to gain access to work areas." The check uses 93 distinct texts obtained from 100 deterministically hash-selected matched rows, including high- and medium-confidence matches, without restricting to the eligible-posting sample. Of 93 distinct matched lines, 67 contain a climbing-related word and none mentions trees; most are generic statements of physical ability or working conditions.
- "Perform physically demanding tasks, such as digging trenches to lay conduit or moving or lifting heavy objects." Of 150 hash-selected description–line–occupation matches from eligible postings, 50 from each equal-sized third of occupations ranked by catalog exposure, 140 are generic physical requirements or working conditions (for example, "must be able to lift 25 pounds"), 6 describe physical work the job involves, and 4 are unrelated. The pattern holds in every third of exposure and when medium-confidence matches are kept. A lexical check would have missed it: 148 of the 150 lines contain a physical term.

Both checks are unweighted and do not estimate the prevalence of mismatches among posting–task mentions. Because generic statements like these can be matched to AI-infeasible tasks and alter measured pressure, we check whether our occupation rankings are robust to their exclusion: as shown in Section 6, the rankings remain highly correlated with the baseline when we exclude the 59 near-universal task statements or drop the audited tasks that commonly show up in the postings of hundreds of occupations, although the highest-pressure occupations change. Both these tasks are excluded from the ranked task tables under either matching rule. Their mentions remain in the occupation measure, where together they carry only 1.2 percent of AI-infeasible mentions and 1.1 percent of total pressure. Dropping them from every count and recomputing posting exposure gives an occupation rank correlation of 0.9996, with 17 of the 20 highest-pressure occupations unchanged. Excluding these tasks while keeping posting exposure fixed gives a within-task share of 52.8 percent (53.2 percent at baseline). The shares of physical and interpersonal work in Figure 6 remain within about 1.1 percentage points of the baseline under this fixed-exposure check.

Generic statements. Our baseline measure does not exclude widely posted generic statements, as their commonality does not necessarily imply irrelevance to that job, although our occupation rankings remain highly correlated with the baseline when we exclude the 59 near-universal statements. Panel A of Table 4 ranks tasks posted in fewer than 650 of the 708 occupations. The 59 near-universal statements stay in the measure and are marked in Appendix Table E.3, but are dropped as a sensitivity check in Section 6. We leave a task out of the ranked tables on poor-match-quality grounds if a posting-line check shows that matched lines are generic statements rather than the work duty the task describes. For example, the task "Perform physically demanding tasks, such as digging trenches…" was matched mostly to lines such as "must be able to lift 25 pounds" rather than to lines describing actual physical work duties. Thus far, we have checked two widely matched tasks in this way, whose sampled posting lines were mostly generic statements. We are in the process of checking more such widely matched task statements. Comparable mismatches may still remain among the ranked tasks.

Postings and O*NET ratings. Are the tasks an occupation posts most often also the ones O*NET considers central to it? Figure C.2 shows that indeed the two are positively related: the share of tasks on the occupation's core O*NET list, and their average O*NET importance and relevance ratings, all rise with how often a task is posted. Restricting to the 692 occupations with at least ten rated listed tasks, the median rank correlation between a task's posting incidence and its importance rating is 0.38. Moreover, 90 percent of occupations show a positive correlation between the two. This check covers only the roughly 10 percent of labeled matched mentions that fall on the occupation's own task list.

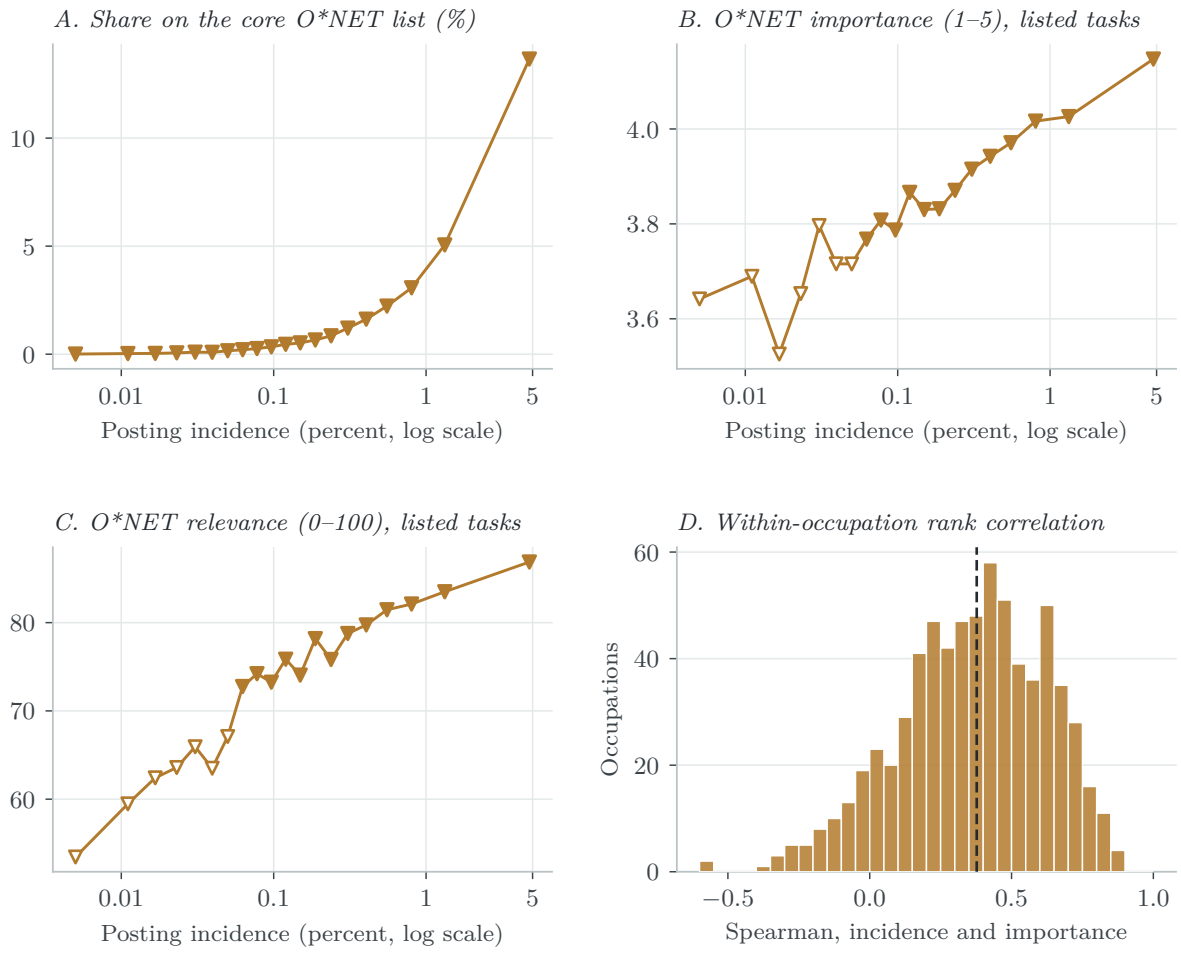


Figure C.2: Posting incidence and O*NET task ratings

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026. We keep only high-confidence line-to-task matches. In panels A to C, we use occupation–task cells with at least 100 mentions. Posting incidence is defined as the share of the occupation's eligible postings that include the task. Panels A to C group about 624,000 occupation–task cells into 20 equal-count bins ordered by posting incidence. Panel A shows the share of cells whose task is on the occupation's core O*NET task list. Panels B and C show mean O*NET importance and relevance ratings among listed cells with ratings, with hollow markers flagging bins with fewer than 100 rated cells. Finally, Panel D shows the Spearman correlation between a task's incidence and its O*NET importance, restricting the sample to the 692 occupations with at least ten rated listed tasks.

D Robustness

Strictly infeasible tasks. Table D.1 shows the two stricter definitions of AI-infeasible work discussed in Section 6, under both our matching rules. Under high-confidence matching, requiring human raters to agree with GPT-4 keeps 87 percent of AI-infeasible mentions. Among the 30 largest contributors to bottleneck pressure, excluding the two audited statements, it drops five, with the exclusions covering confidentiality, compliance, health-care collaboration, facility safety and hazard reporting. If, instead, we require every task in a task's work activities to be infeasible, then we keep only 39 percent and drop 21 of the 30 largest contributors to bottleneck pressure, including client relationships, greeting customers and supervision.

Table D.1: Stricter definitions of AI-infeasible work

	Mentions	Removed per	Rank	Top 20 in common		
Definition	kept (%)	occ. (%)	corr.	Occ.	Tasks (A)	Tasks (B)
High-confidence matches (main specification)						
GPT-4 and human raters agree	86.6	15 (6–28)	0.905	1	16	17
Every task in its work activities infeasible	38.9	78 (37–94)	0.423	0	4	1
High- and medium-confidence matches						
GPT-4 and human raters agree	85.6	16 (6–27)	0.901	0	17	14
Every task in its work activities infeasible	36.6	76 (39–92)	0.452	0	4	2

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Both panels retain rank-1 matches; the second also includes medium-confidence matches. The baseline counts a task as AI-infeasible if the GPT-4 broad rating of Eloundou et al. (2024) is zero. "GPT-4 and human raters agree" also requires the human rating to be zero; tasks with a human rating of 0.5 or 1 count as feasible, and the few infeasible tasks without a human rating (0.2 percent of infeasible mentions) do not pass. "Every task in its work activities infeasible" requires every O*NET task linked to each of the task's detailed work activities to be rated infeasible. Tasks that fail a rule count as feasible; posting exposure and its complementary AI-infeasible share are recomputed. Mentions kept is the share of baseline AI-infeasible posting mentions that still count as infeasible; removed per occupation gives the median and, in parentheses, the 10th and 90th percentiles across the 708 occupations. Rank corr. is the Spearman correlation of occupation pressure with the baseline. Top-20 columns count overlaps for occupation pressure and for two task rankings. Task overlaps exclude the two audited statements and compare rankings by contribution to total pressure, including near-universal statements (A), and by average pressure among tasks with at least 50,000 mentions (B). A retained task's average pressure can change because posting exposure changes; the rules change both which tasks count and the pressure on those that remain.

Posting exposure and existing exposure measures. Table D.2 shows the correlations of our posting exposure with catalog exposure as well as with published measures of AI

exposure. Rank correlations are 0.84 to 0.91 with the measures of Felten, Raj and Seamans (2021), Felten, Raj and Seamans (2023) and Eloundou et al. (2024), and 0.65 with the AI-applicability score of Tomlinson et al. (2025).

Table D.2: Posting exposure and existing measures of AI exposure

Measure	Occupations	Spearman	Pearson
This paper			
Core-task catalog exposure	708	0.92	0.93
Published exposure measures			
Eloundou et al. (2024), GPT-4 β	679	0.91	0.90
Eloundou et al. (2024), human rating	679	0.87	0.87
Felten, Raj and Seamans (2021), AI occupational exposure	639	0.88	0.90
Felten, Raj and Seamans (2023), language-model exposure	639	0.84	0.86
Tomlinson et al. (2025), AI applicability	708	0.65	0.64
Other BGI scores			
BGI automation score	679	0.88	0.87
BGI augmentation score	679	0.91	0.93

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. Each row correlates the occupation's posting exposure (the AI-feasible share of its posted task mentions) with the listed occupation-level measure, on the occupations where both are available; the number of occupations varies for that reason. Catalog exposure is obtained from each occupation's core O*NET tasks. The BGI automation and augmentation scores are internal scores, not externally available yet.

Task-match confidence. Our main specification keeps only matches between posting lines and O*NET tasks that meet BGI's internal high-confidence threshold (labeled "use"). When we expand our criteria to also keep matches in BGI's medium-confidence tier, our labeled mentions rise from 1.30 to 2.31 billion, and the occupation rankings remain highly correlated with the baseline (Table D.3). The highest-pressure occupations change, however. Occupation pressure has a rank correlation of 0.987 across the two rules, 9 of the 20 highest-pressure occupations are the same, and mean pressure is 17.8 under one and 18.2 under the other. Task rankings agree closely as well under both rules. Average task pressure has a rank correlation of 0.973, and 16 of the 20 largest contributors are the same. Figure D.1 plots the two versions against each other.

Table D.3: High-confidence matches only versus including medium-confidence matches

	High-confidence matches (main)	Including medium confidence
Panel A. Coverage and headline numbers		
Labeled posting–task mentions (bn)	1.30	2.31
Share of each occupation's mentions kept, P10, P50, P90 (%)	47, 59, 67	100
Mean occupation pressure	17.8	18.2
P90 occupation pressure	24.6	24.6
AI-infeasible tasks with 1,000+ mentions	6,309	7,025
Share of pressure in the 20 largest tasks (%)	12.7	11.6
Panel B. Agreement between the two		
Rank correlation, occupation pressure		0.987
Rank correlation, posting exposure		0.997
Top 20 occupations in common		9 of 20
Rank correlation, average task pressure (6,309 tasks)		0.973
Top 20 tasks by contribution in common		16 of 20
Top 20 tasks by average pressure in common, same task set		18 of 20

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Both specifications match each posting line describing a responsibility to its rank-1 O*NET task. The main specification keeps matches in BGI's high-confidence tier; the alternative also keeps matches in its medium-confidence tier. Posting exposure and its complementary AI-infeasible share are computed from the mentions kept under each rule. Pressure is on a 0–100 scale. Task comparisons cover AI-infeasible tasks with at least 1,000 mentions under both rules; top-20 task comparisons exclude the two audited statements (Appendix C). For the last row, both rankings use the same candidate tasks: AI-infeasible tasks with at least 100,000 mentions when medium-confidence matches are included, excluding the two audited statements. This differs from the baseline display floor in Appendix Table E.2. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold, binary at the task level.

Figure D.2 plots occupation pressure under five of the alternatives discussed in Section 6 against the baseline, and compares the 2018–2021 and 2022–2026 rankings with each other. Under every alternative except the activity rule, which counts a task as AI-infeasible only if every task in its work activities is infeasible, occupation rankings remain highly correlated with the baseline, although the highest-pressure occupations change. By contrast, under the activity rule, pressure falls for most occupations and the ordering changes. Recall that the activity rule is the strictest of the five because it keeps only 39 percent of AI-infeasible mentions, and removes most client, customer and supervisory work. So in some sense the change in our rankings under this strict rule is a reflection of the fact that when the AI-infeasible set is dramatically shrunk to remove common tasks that many jobs require, then pressure is computed on a much narrower set of tasks, and the ordering of occupations changes with it (Section 6).

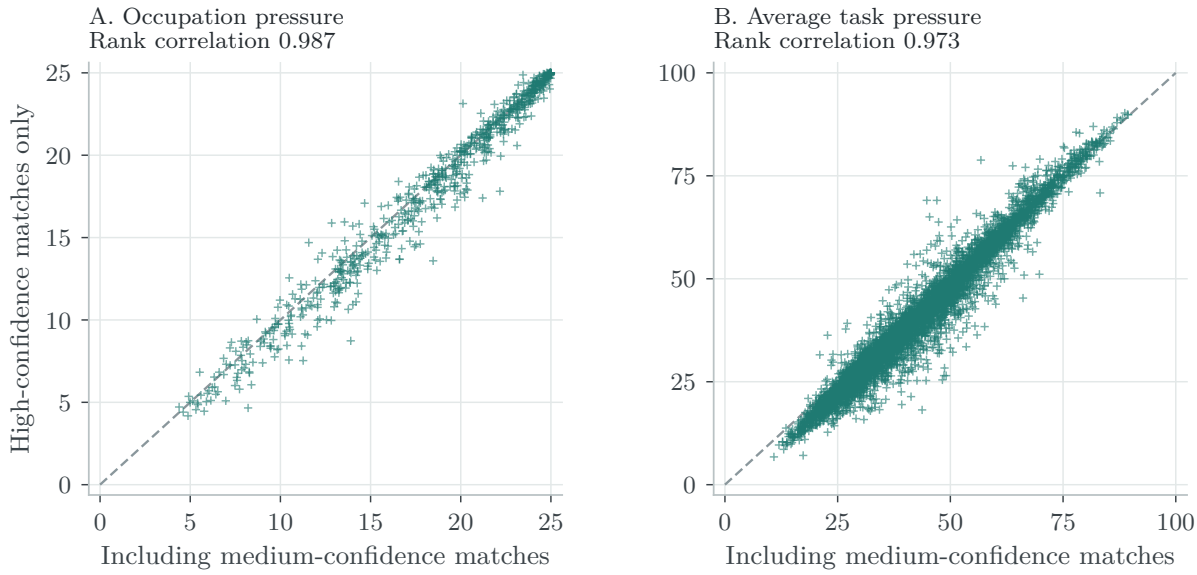


Figure D.1: Pressure with high-confidence matches only and including medium-confidence matches

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, in the 708 occupations with a catalog exposure score. Panel A plots occupation pressure; Panel B plots the average pressure P_t of AI-infeasible tasks with at least 1,000 mentions under both rules. Posting exposure is recomputed under each matching rule. The horizontal axis keeps every rank-1 line-to-task match in BGI's high- or medium-confidence tiers; the vertical axis keeps only high-confidence matches, the main specification. The dashed line is the 45-degree line. Pressure is on a 0–100 scale.

Within-task share of the variation in pressure. At the baseline, 53.2 percent of the variance of pressure, weighted by posting mentions, across AI-infeasible occupation–task cells lies *within* tasks. Holding posting exposure fixed, the same share is 49.2 percent when we drop the 59 near-universal statements (Appendix C) and 52.8 percent when the two audited matches are dropped (Appendix C). It is 57.7 percent when we expand our matching criterion to additionally keep medium-confidence matches and recompute posting exposure (Table D.3), and 55.6 percent when the sample is limited to tasks posted at least 1,000 times in each of ten or more occupations while keeping posting exposure fixed. Keeping only matches to tasks on the occupation's own O*NET list, core or supplemental, while keeping posting exposure fixed, leaves almost none (0.3 percent). This reflects the fact that most O*NET task statements belong to a single occupation's list, so this restriction largely removes comparisons across occupations using the same task statement, and strongly highlights the additional value of job postings, which map the same task statement to many occupations and so allow the comparison across occupations that the

catalog alone rarely permits at the level of exact task statements.

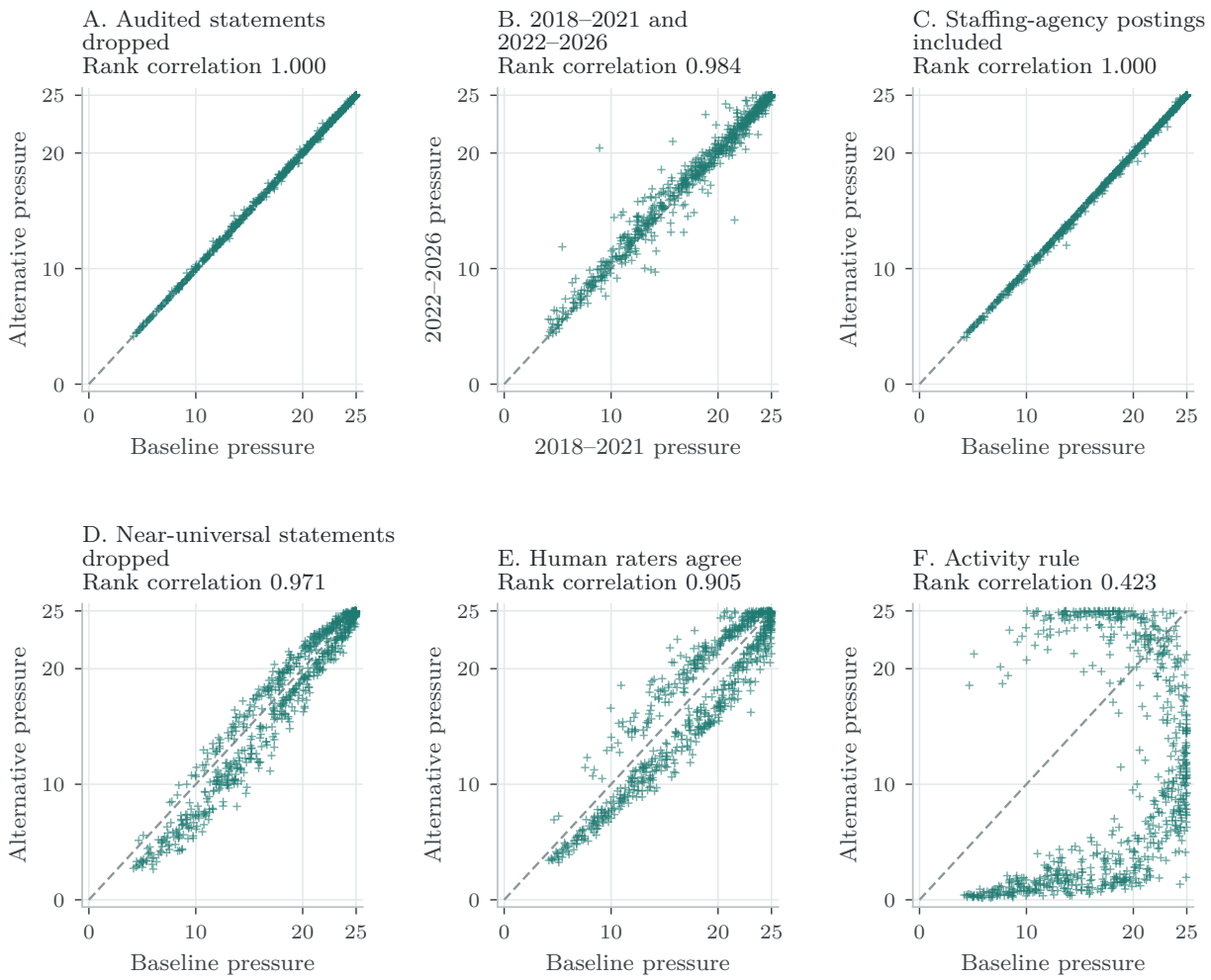


Figure D.2: Occupation pressure under alternative choices

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, in the 708 occupations with a catalog exposure score, keeping high-confidence line-to-task matches only. Each point is an occupation. The horizontal axis is baseline pressure, except in the second panel, which compares pressure built from 2018–2021 postings (horizontal) with pressure built from 2022–2026 postings (vertical). The vertical axis is pressure under the listed alternative: the two audited statements dropped from each occupation's mentions; staffing-agency postings included; the 59 near-universal statements dropped from each occupation's mentions; a task counted as AI-infeasible only if human raters agree; and a task counted as AI-infeasible only if every task in its work activities is infeasible. Both posting exposure and its complementary AI-infeasible share are recomputed under each alternative. Rank correlations are Spearman, across occupations. The dashed line is the 45-degree line. Pressure is on a 0–100 scale.

Detailed work activities. BGI also matches posting lines directly to O*NET detailed work activities. Using the same sample, filters and high-confidence rule as for tasks, we count an activity as AI-infeasible only if every task linked to it is rated AI-infeasible, and we leave out activities with any feasible or unrated linked task. As for a task, the pressure on such an activity in an occupation equals the occupation's posting exposure, and its average pressure weights occupations by the postings matched to the activity. The 425 qualifying activities account for 15.6 percent of posting–activity mentions under this restriction. Across them, 68.6 percent of the posting-weighted variation in pressure lies within activities, across the occupations that post them. The two are not directly comparable because this share describes a different population from the 53.2 percent within tasks. Table D.4 lists the 30 activities with the highest average pressure among those posted at least 50,000 times.

Table D.4: AI-infeasible detailed work activities ranked by average pressure

	Activity	Occupations	Postings (thousands)	Average pressure
1	Supervise activities of other legal personnel.	215	109.1	84.1
2	Schedule medical facility use.	265	99.2	70.3
3	Test performance of aircraft equipment.	242	68.5	64.7
4	Signal others to coordinate work activities.	592	75.1	63.4
5	Interact with patients to build rapport or provide emotional support.	419	1,159.5	62.3
6	Supervise production or support personnel.	578	528.7	60.2
7	Operate laboratory or field equipment.	425	77.8	59.2
8	Apply solutions to production equipment.	344	63.9	58.4
9	Test communications equipment to ensure proper functioning.	337	75.6	56.4
10	Encourage patients or clients to develop life skills.	255	349.3	55.6
11	Visit individuals in their homes to provide support or information.	462	824.1	55.6
12	Monitor work areas or procedures to ensure compliance with safety procedures.	664	774.4	55.3
13	Maintain test equipment.	537	373.2	54.4
14	Train employees in proper work procedures.	669	1,001.1	54.2
15	Treat patients using physical therapy techniques.	144	357.4	53.9
16	Communicate with coworkers to coordinate installations or repairs.	629	703.7	53.8
17	Instruct staff in work policies or procedures.	690	1,980.8	53.0
18	Assist practitioners to perform medical procedures.	371	1,014.4	53.0
19	Monitor instruments to ensure proper production conditions.	605	460.6	52.4
20	Prepare products for testing.	434	76.0	52.1
21	Administer blood or other fluids intravenously.	178	94.6	52.1
22	Transport clients to appointments.	471	426.4	52.0
23	Participate in athletic events.	517	153.9	51.7
24	Select medical equipment for addressing patient needs.	334	225.0	51.5
25	Administer anesthetics or sedatives to control pain.	134	186.1	51.3
26	Encourage patients during therapeutic activities.	305	291.9	50.9
27	Inspect buildings or grounds to determine condition.	378	285.0	50.8
28	Inspect completed work to ensure proper functioning.	627	305.4	50.1

Table D.4, continued

	Activity	Occupations	Postings (thousands)	Average pressure
29	Monitor work areas to provide security.	579	208.1	49.9
30	Move patients to or from treatment areas.	431	1,357.2	49.3

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time. Direct matches of posting lines to O*NET detailed work activities, rank 1 and high confidence ("use"). An activity is AI-infeasible only if every linked O*NET task is rated AI-infeasible by the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. These activities account for 15.6 percent of posting–activity mentions. Pressure on an activity in an occupation equals the occupation's posting exposure (Equation (3)), on a 0–100 scale. Average pressure weights occupations by postings matched to the activity. Occupations counts those with at least one matched posting. A posting can match several activities, so postings are posting–activity matches. The display floor of 50,000 postings follows Table 4. The full ranking of all 425 activities is in the supporting analysis files.

Mixing within and between postings. Most AI-infeasible work is advertised in the same postings as feasible work, suggesting that the pressure rankings are not driven solely by pooling an occupation's postings that each primarily advertise one "type" of work. Because our occupation pressure index pools an occupation's postings, feasible and infeasible work could, in principle, be advertised in *different postings* rather than together. To see how much of this mix occurs within postings rather than between them, for each posting p with at least one labeled matched task, let e_p be the feasible share of those tasks. With postings weighted equally within an occupation, $\bar{e}(1-\bar{e}) = \overline{e(1-e)} + \mathrm{Var}(e)$: the first term on the right is mixing within postings and the second is mixing between them. In our context, the within-posting term accounts for 65 percent of the total in the average occupation (median 66 percent), and for 64 to 66 percent in each tercile of posting exposure.

When we weight each posting instead by its number of labeled matched tasks, as both E_o and S_o do, so that the occupation's weighted mean feasible share equals its posting exposure, the within-posting term accounts for 79 percent of the total in the average occupation (median 80 percent; 10th and 90th percentiles 72 and 85 percent), and for 79 to 80 percent in each tercile of posting exposure. With these weights, the average within-posting term equals $E_o^{\mathrm{post}}(1-E_o^{\mathrm{post}}) - \mathrm{Var}_w(e_p)$, so it can differ across occupations with the same posting exposure. Overall, these decompositions show that most of the mixing of advertised feasible and infeasible work occurs within postings.

Counting by task mentions, 82 percent of AI-infeasible mentions appear in postings that also list a feasible task, rising from 72 percent in the least exposed tercile of occupations to 97 percent in the most exposed. Computing both exposure and S_o from these mixed postings alone gives occupation pressure with a rank correlation of 0.97 with the baseline and keeps 14 of its top 20 occupations. The composition gradient in Figure 6 survives, with physical work falling from 74 to 26 percent of pressure from the lowest pressure quintile to the highest, and interpersonal and supervisory work rising from 18 to 55 percent.

Matching contamination. Table D.5 reports the matching-contamination check discussed in Section 6. It removes an assumed share of contaminating mentions (proposed common rates of 10–30 percent, or exposure-dependent rates with $m = 10$ or 20 percent, capped where necessary) from each occupation's posted work and recomputes exposure and the AI-infeasible share. Occupation rankings remain strongly correlated with the baseline, though levels are less stable and the highest-pressure occupations change. The proposed common rates range from about one and a half to nearly five times the bad-match rate, under the conditions stated in Section 6. These checks are computed from occupation-level counts.

Table D.5: Conditional matching contamination

	Rank corr.	Mean pressure	Number capped
Baseline	1.000	17.8	–
Random matches: 42.9 percent AI-infeasible			
Common rate, $m = 10$ percent	0.998	16.3	2
Rising with exposure, $m = 10$ percent	0.996	15.9	34
Common rate, $m = 20$ percent	0.993	14.3	53
Rising with exposure, $m = 20$ percent	0.982	14.0	125
Common rate, $m = 30$ percent	0.982	12.1	142
Hypothetical errors: 80 percent AI-infeasible			
Common rate, $m = 10$ percent	0.977	15.6	37
Common rate, $m = 20$ percent	0.913	13.3	146
Common rate, $m = 30$ percent	0.811	11.4	231
Hypothetical errors: 100 percent AI-infeasible			
Common rate, $m = 10$ percent	0.941	15.2	63
Common rate, $m = 20$ percent	0.799	12.8	189
Common rate, $m = 30$ percent	0.604	10.9	287

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, in the 708 occupations with a catalog exposure score, keeping high-confidence line-to-task matches only. Rank correlations are Spearman, across occupations, with baseline occupation pressure. Let q be the AI-infeasible share of wrong matches. The check assumes that a share m_o of an occupation's mentions are wrong matches and recovers its AI-infeasible share as $S_o^* = (S_o - qm_o)/(1 - m_o)$. Pressure is then recomputed as $S_o^*(1 - S_o^*)$. Random matches use the pool of all labeled matched mentions, whose AI-infeasible share is 42.9 percent. Note that scenarios with 80 and 100 percent are hypothetical. This mixture is admissible only under the condition that $qm_o \leq S_o \leq 1 - (1 - q)m_o$. When an occupation's observed share in our data violates either condition at the proposed target rate, we revise the rate to the largest admissible value consistent with the observed share. Here, "number capped" still counts these occupations, whose effective contamination rates are lower than the proposed target rates. The target rate is denoted by m where the rate is common. Where it rises with exposure, it is denoted by $2mE_o$, where E_o is baseline exposure from the job-postings data. Actual matching errors need not follow these distributions, and how often they change a mention's feasibility label is not yet estimated. Pressure is on a 0–100 scale.

E Full tables and figures

This appendix collects the full tables and figures cited in the main text.

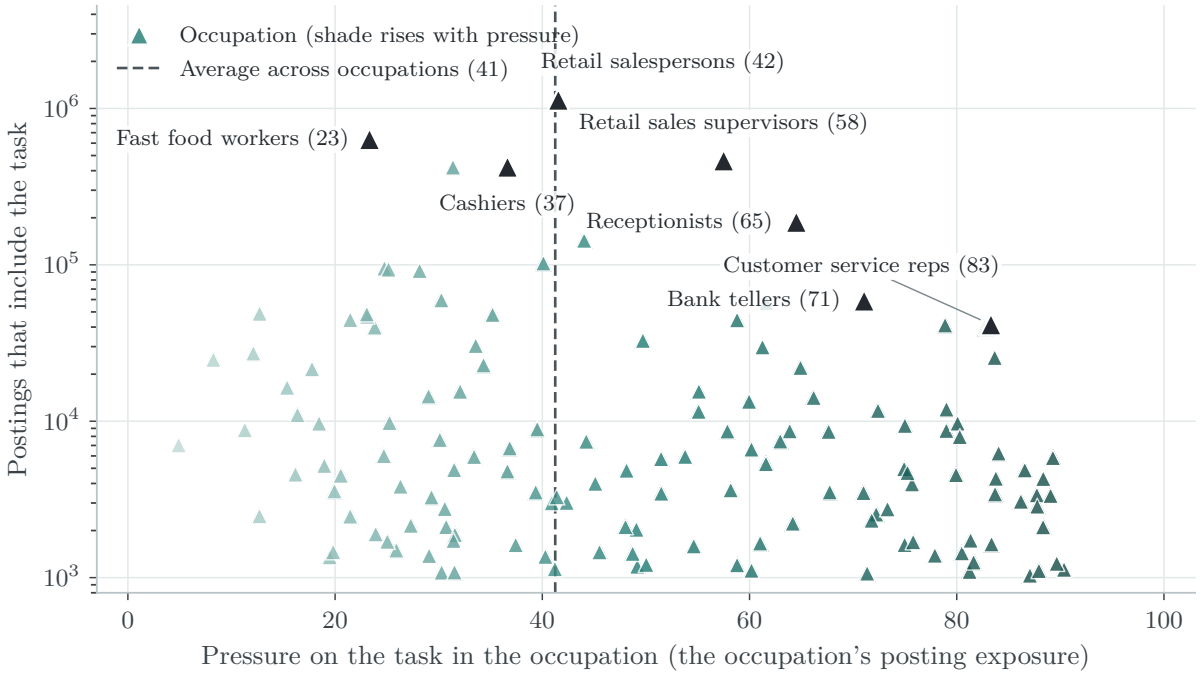


Figure E.1: "Greet customers" in every occupation that posts it often

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, keeping high-confidence line-to-task matches only. The task appears in the postings of 667 of the 708 occupations with a catalog exposure score; the figure shows the 143 whose postings include it at least 1,000 times. Each triangle is an occupation, shaded darker as pressure rises, as in Figure 5, Panel A; labeled occupations are drawn in black. The horizontal position is the pressure the task faces in the occupation, which equals the occupation's posting exposure; the vertical position is the number of postings that include the task (log scale). Values in parentheses are the pressure on the task in each labeled occupation. The dashed line is the average pressure across all 667 occupations, weighted by postings.

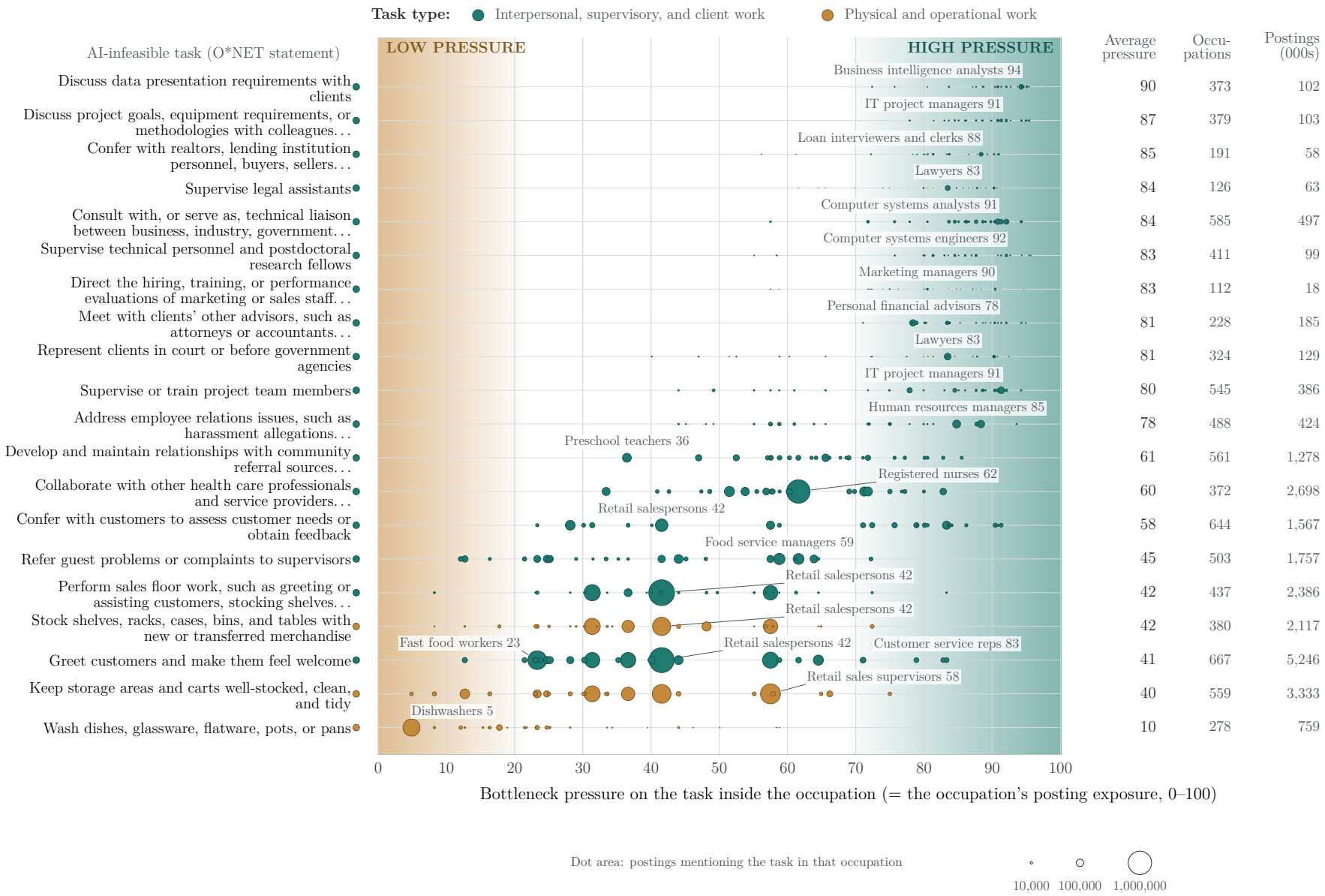


Figure E.2: Twenty AI-infeasible tasks across the occupations that post them

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, baseline sample, rank-1 high-confidence responsibility-line matches. Rows are AI-infeasible O*NET task statements, ordered by average pressure. Each dot is one of the 24 occupations whose postings mention the task most, placed at that occupation's posting exposure, which is the pressure on the task there (Equation (3)); dot area is proportional to the number of postings mentioning the task in that occupation. The right-hand columns give the posting-weighted average pressure across all occupations posting the task, as in Table 4, the number of such occupations, and total postings. Labels name the occupation with the most postings in each row, and three occupations in the greeting row. Fills are descriptive work groupings, and the shaded zones are visual guides rather than estimated cutoffs. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold. Task statements are catalog matches to posting lines, not individually verified duties.



Figure E.3: Shares of posted work and of bottleneck pressure by capability family

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, keeping high-confidence line-to-task matches only. Tasks are grouped into O*NET generalized work activities through O*NET's links from tasks to detailed work activities. A task that gets linked to several detailed work activities is split equally among those detailed activities. Hollow squares show each family's share of all labeled posted task mentions. Filled squares, on the other hand, show each family's share of total bottleneck pressure. Families are grouped by O*NET's four broad activity categories, which are ordered by their share of bottleneck pressure. Each category header gives the category's shares of pressure and of posted work. Within a category, families are ordered by their pressure share relative to their share of posted work, highest at the top. The figure shows the 37 families reached by posted tasks.

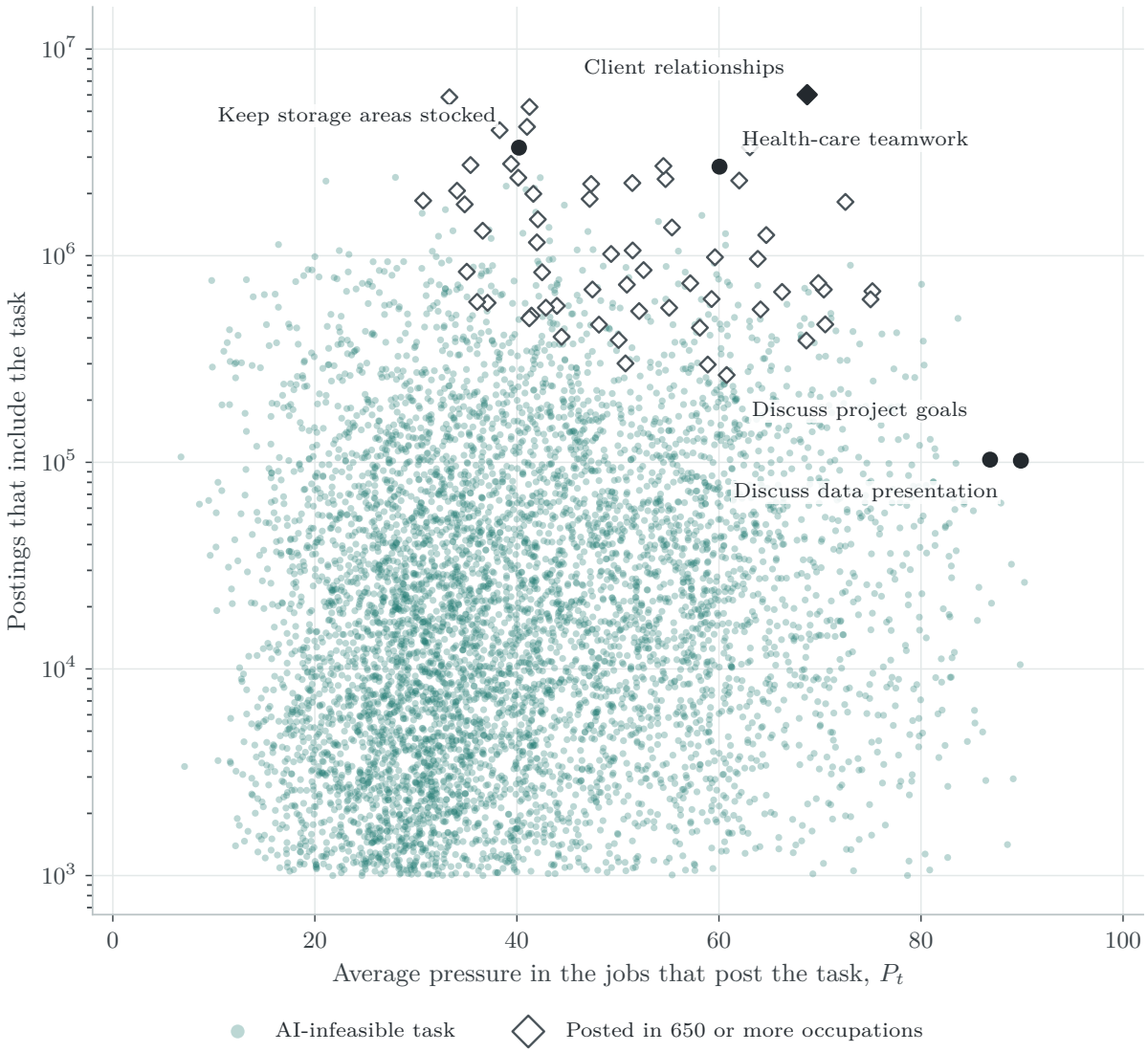


Figure E.4: Average pressure and posting volume across AI-infeasible tasks

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, keeping high-confidence line-to-task matches only. Each point is an AI-infeasible task posted at least 1,000 times, excluding the two audited statements (Appendix C). The horizontal position is the task's average pressure P_t across the occupations that post it, weighted by postings; the vertical position is the number of postings that include it (log scale). Hollow diamonds mark the near-universal statements, posted in at least 650 of the 708 occupations. Labeled tasks are drawn in black, as a diamond if near-universal (client relationships) and as a circle otherwise. Labeled tasks are among the largest contributors to total pressure (Table 4, Panel A, and Appendix Table E.3) or among the highest in average pressure (Table 4, Panel B). AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold.

Table E.1: Bottleneck pressure for all 708 occupations

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
1	43-3041.00	Gambling Cage Workers	45	25.0	42.9 (442)	50.0 (430)	50.0	24.5 (55)	21.4 (196)
2	29-1023.00	Orthodontists	21	25.0	60.0 (371)	49.9 (431)	50.1	24.0 (77)	30.0 (49)
3	19-4031.00	Chemical Technicians	132	25.0	66.7 (335)	50.1 (429)	49.9	22.2 (129)	33.3 (24)
4	33-9099.02	Retail Loss Prevention Specialists	311	25.0	65.0 (348)	49.7 (432)	50.3	22.7 (122)	32.7 (28)
5	19-4013.00	Food Science Technicians	108	25.0	41.7 (451)	50.4 (428)	49.6	24.3 (67)	20.7 (225)
6	17-3027.01	Automotive Engineering Technicians	19	25.0	50.0 (406)	50.4 (427)	49.6	25.0 (1)	24.8 (118)
7	19-4051.02	Nuclear Monitoring Technicians	15	25.0	28.6 (502)	49.2 (433)	50.8	20.4 (180)	14.5 (374)
8	47-1011.00	First-Line Supervisors of Construction Trades and Extraction Workers	560	25.0	73.3 (317)	49.2 (434)	50.8	19.6 (190)	37.3 (10)
9	19-4012.00	Agricultural Technicians	48	25.0	50.0 (406)	50.9 (426)	49.1	25.0 (1)	24.6 (122)
10	37-2021.00	Pest Control Workers	293	25.0	44.4 (441)	49.1 (435)	50.9	24.7 (48)	22.6 (158)
11	43-5041.00	Meter Readers, Utilities	39	25.0	54.5 (395)	51.0 (425)	49.0	24.8 (37)	26.7 (78)
12	19-4043.00	Geological Technicians, Except Hydrologic Technicians	12	25.0	72.7 (320)	51.0 (424)	49.0	19.8 (188)	35.6 (19)
13	17-3024.01	Robotics Technicians	65	25.0	46.7 (430)	49.0 (436)	51.0	24.9 (29)	23.8 (131)
14	29-1124.00	Radiation Therapists	56	25.0	52.6 (402)	51.1 (423)	48.9	24.9 (25)	25.8 (98)
15	49-9062.00	Medical Equipment Repairers	195	25.0	50.0 (406)	48.8 (437)	51.2	25.0 (1)	25.6 (101)
16	49-2094.00	Electrical and Electronics Repairers, Commercial and Industrial Equipment	386	25.0	42.1 (449)	48.7 (438)	51.3	24.4 (65)	21.6 (191)
17	17-3024.00	Electro-Mechanical and Mechatronics Technologists and Technicians	216	25.0	50.0 (406)	51.3 (422)	48.7	25.0 (1)	24.3 (125)
18	31-2021.00	Physical Therapist Assistants	514	25.0	22.2 (529)	48.6 (439)	51.4	17.3 (243)	11.4 (464)
19	39-1022.00	First-Line Supervisors of Personal Service Workers	354	25.0	66.7 (335)	51.5 (421)	48.5	22.2 (129)	32.4 (31)
20	29-2061.00	Licensed Practical and Licensed Vocational Nurses	2,934	25.0	46.7 (430)	51.5 (420)	48.5	24.9 (29)	22.6 (157)
21	33-1021.00	First-Line Supervisors of Firefighting and Prevention Workers	31	25.0	56.5 (388)	51.7 (419)	48.3	24.6 (54)	27.3 (74)
22	29-9091.00	Athletic Trainers	108	25.0	45.0 (439)	51.7 (418)	48.3	24.8 (45)	21.7 (190)
23	17-3029.08	Photonics Technicians	22	25.0	46.7 (430)	51.7 (417)	48.3	24.9 (29)	22.6 (162)
24	43-9051.00	Mail Clerks and Mail Machine Operators, Except Postal Service	120	25.0	25.0 (512)	48.3 (440)	51.7	18.8 (201)	12.9 (430)
25	19-4071.00	Forest and Conservation Technicians	64	25.0	40.0 (457)	51.7 (416)	48.3	24.0 (77)	19.3 (256)
26	29-2053.00	Psychiatric Technicians	427	25.0	22.2 (529)	51.9 (415)	48.1	17.3 (243)	10.7 (485)
27	27-1026.00	Merchandise Displayers and Window Trimmers	1,047	25.0	68.8 (331)	48.1 (441)	51.9	21.5 (159)	35.7 (17)
28	35-1011.00	Chefs and Head Cooks	763	25.0	42.9 (442)	48.0 (442)	52.0	24.5 (55)	22.3 (171)
29	21-1013.00	Marriage and Family Therapists	89	25.0	9.1 (618)	47.9 (443)	52.1	8.3 (441)	4.7 (641)
30	17-3029.01	Non-Destructive Testing Specialists	62	25.0	61.5 (366)	47.9 (444)	52.1	23.7 (97)	32.0 (36)
31	29-2091.00	Orthotists and Prosthetists	15	25.0	35.7 (468)	52.2 (414)	47.8	23.0 (115)	17.1 (311)
32	19-1031.03	Park Naturalists	45	24.9	86.7 (215)	52.3 (413)	47.7	11.6 (365)	41.4 (7)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
33	29-1161.00	Nurse Midwives	24	24.9	60.0 (371)	52.4 (412)	47.6	24.0 (77)	28.6 (60)
34	27-2041.00	Music Directors and Composers	52	24.9	88.9 (194)	47.5 (445)	52.5	9.9 (401)	46.7 (3)
35	21-1093.00	Social and Human Service Assistants	738	24.9	75.0 (302)	52.5 (411)	47.5	18.8 (201)	35.6 (18)
36	53-1041.00	Aircraft Cargo Handling Supervisors	17	24.9	50.0 (406)	52.6 (410)	47.4	25.0 (1)	23.7 (133)
37	31-2011.00	Occupational Therapy Assistants	311	24.9	33.3 (476)	47.4 (446)	52.6	22.2 (129)	17.5 (302)
38	53-2012.00	Commercial Pilots	66	24.9	38.9 (463)	47.3 (447)	52.7	23.8 (94)	20.5 (227)
39	49-2097.00	Audiovisual Equipment Installers and Repairers	174	24.9	30.0 (494)	47.3 (448)	52.7	21.0 (166)	15.8 (346)
40	29-1131.00	Veterinarians	373	24.9	42.9 (442)	47.2 (449)	52.8	24.5 (55)	22.6 (159)
41	33-3041.00	Parking Enforcement Workers	27	24.9	50.0 (406)	47.2 (450)	52.8	25.0 (1)	26.4 (86)
42	11-9013.00	Farmers, Ranchers, and Other Agricultural Managers	34	24.9	63.2 (358)	52.8 (409)	47.2	23.3 (109)	29.8 (50)
43	21-1021.00	Child, Family, and School Social Workers	532	24.9	41.7 (451)	47.0 (451)	53.0	24.3 (67)	22.1 (175)
44	19-5012.00	Occupational Health and Safety Technicians	35	24.9	63.6 (354)	53.4 (408)	46.6	23.1 (110)	29.7 (51)
45	29-1291.00	Acupuncturists	15	24.9	16.7 (555)	53.5 (407)	46.5	13.9 (305)	7.8 (573)
46	53-2011.00	Airline Pilots, Copilots, and Flight Engineers	11	24.9	61.1 (368)	53.5 (406)	46.5	23.8 (94)	28.4 (62)
47	29-1211.00	Anesthesiologists	84	24.9	50.0 (406)	53.5 (405)	46.5	25.0 (1)	23.2 (139)
48	27-2042.00	Musicians and Singers	43	24.9	52.6 (402)	46.4 (452)	53.6	24.9 (25)	28.2 (64)
49	31-9092.00	Medical Assistants	2,420	24.9	52.6 (402)	53.8 (404)	46.2	24.9 (25)	24.3 (126)
50	19-4042.00	Environmental Science and Protection Technicians, Including Health	70	24.9	68.4 (332)	46.1 (453)	53.9	21.6 (157)	36.8 (13)
51	29-2032.00	Diagnostic Medical Sonographers	466	24.8	50.0 (406)	54.2 (403)	45.8	25.0 (1)	22.9 (150)
52	33-2021.00	Fire Inspectors and Investigators	47	24.8	45.5 (436)	54.2 (402)	45.8	24.8 (37)	20.8 (221)
53	33-9011.00	Animal Control Workers	17	24.8	42.9 (442)	45.8 (454)	54.2	24.5 (55)	23.2 (140)
54	51-9141.00	Semiconductor Processing Technicians	21	24.8	37.5 (464)	45.7 (455)	54.3	23.4 (102)	20.4 (230)
55	49-2098.00	Security and Fire Alarm Systems Installers	286	24.8	21.4 (535)	45.5 (456)	54.5	16.8 (253)	11.7 (457)
56	27-1013.00	Fine Artists, Including Painters, Sculptors, and Illustrators	12	24.8	100.0 (1)	54.5 (401)	45.5	0.0 (542)	45.5 (4)
57	21-1092.00	Probation Officers and Correctional Treatment Specialists	118	24.8	58.8 (382)	54.6 (400)	45.4	24.2 (73)	26.7 (80)
58	39-1013.00	First-Line Supervisors of Gambling Services Workers	44	24.8	50.0 (406)	54.6 (399)	45.4	25.0 (1)	22.7 (156)
59	17-3021.00	Aerospace Engineering and Operations Technologists and Technicians	26	24.8	62.5 (359)	54.8 (398)	45.2	23.4 (102)	28.2 (65)
60	37-1011.00	First-Line Supervisors of Housekeeping and Janitorial Workers	658	24.8	34.8 (473)	45.1 (457)	54.9	22.7 (126)	19.1 (262)
61	29-1021.00	Dentists, General	418	24.7	45.0 (439)	44.9 (458)	55.1	24.8 (45)	24.8 (119)
62	49-1011.00	First-Line Supervisors of Mechanics, Installers, and Repairers	1,578	24.7	76.5 (295)	55.1 (397)	44.9	18.0 (226)	34.3 (22)
63	41-2022.00	Parts Salespersons	704	24.7	56.2 (389)	55.1 (396)	44.9	24.6 (52)	25.2 (109)
64	33-1011.00	First-Line Supervisors of Correctional Officers	63	24.7	34.8 (473)	44.6 (459)	55.4	22.7 (126)	19.3 (257)
65	29-2034.00	Radiologic Technologists and Technicians	1,115	24.7	74.1 (312)	55.5 (395)	44.5	19.2 (199)	33.0 (26)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
66	29-1125.00	Recreational Therapists	90	24.7	54.5 (395)	44.3 (460)	55.7	24.8 (37)	30.4 (46)
67	27-4011.00	Audio and Video Technicians	147	24.7	63.6 (354)	55.7 (394)	44.3	23.1 (110)	28.2 (66)
68	27-1023.00	Floral Designers	68	24.7	35.7 (468)	44.2 (461)	55.8	23.0 (115)	19.9 (241)
69	25-2051.00	Special Education Teachers, Preschool	87	24.7	29.4 (498)	55.9 (393)	44.1	20.8 (173)	13.0 (422)
70	39-3012.00	Gambling and Sports Book Writers and Runners	18	24.7	50.0 (406)	44.1 (462)	55.9	25.0 (1)	27.9 (68)
71	35-1012.00	First-Line Supervisors of Food Preparation and Serving Workers	3,299	24.6	78.9 (272)	44.0 (463)	56.0	16.6 (264)	44.2 (5)
72	49-2091.00	Avionics Technicians	57	24.6	33.3 (476)	43.9 (464)	56.1	22.2 (129)	18.7 (273)
73	53-6051.07	Transportation Vehicle, Equipment and Systems Inspectors, Except Aviation	72	24.6	66.7 (335)	56.2 (392)	43.8	22.2 (129)	29.2 (55)
74	43-5051.00	Postal Service Clerks	82	24.5	33.3 (476)	56.8 (391)	43.2	22.2 (129)	14.4 (377)
75	45-1011.00	First-Line Supervisors of Farming, Fishing, and Forestry Workers	27	24.5	40.7 (455)	43.2 (465)	56.8	24.1 (75)	23.2 (142)
76	29-1123.00	Physical Therapists	1,523	24.5	30.4 (493)	56.9 (390)	43.1	21.2 (164)	13.1 (419)
77	21-1094.00	Community Health Workers	147	24.5	57.1 (385)	57.1 (389)	42.9	24.5 (55)	24.5 (123)
78	25-4013.00	Museum Technicians and Conservators	21	24.5	33.3 (476)	57.1 (388)	42.9	22.2 (129)	14.3 (381)
79	29-1126.00	Respiratory Therapists	483	24.5	30.0 (494)	42.6 (466)	57.4	21.0 (166)	17.2 (307)
80	29-2031.00	Cardiovascular Technologists and Technicians	278	24.4	50.0 (406)	57.4 (387)	42.6	25.0 (1)	21.3 (203)
81	29-2033.00	Nuclear Medicine Technologists	97	24.4	50.0 (406)	57.5 (386)	42.5	25.0 (1)	21.2 (204)
82	41-1011.00	First-Line Supervisors of Retail Sales Workers	8,215	24.4	87.5 (203)	57.5 (385)	42.5	10.9 (377)	37.2 (12)
83	11-9031.00	Education and Childcare Administrators, Preschool and Daycare	315	24.4	86.7 (215)	57.6 (384)	42.4	11.6 (365)	36.8 (15)
84	49-2022.00	Telecommunications Equipment Installers and Repairers, Except Line Installers	430	24.4	29.2 (500)	42.4 (467)	57.6	20.7 (178)	16.8 (318)
85	33-3051.04	Customs and Border Protection Officers	68	24.4	60.0 (371)	57.7 (383)	42.3	24.0 (77)	25.4 (106)
86	29-1122.00	Occupational Therapists	850	24.4	50.0 (406)	57.7 (382)	42.3	25.0 (1)	21.1 (209)
87	41-9012.00	Models	24	24.4	0.0 (654)	57.8 (381)	42.2	0.0 (542)	0.0 (654)
88	29-1141.01	Acute Care Nurses	704	24.4	54.5 (395)	57.8 (380)	42.2	24.8 (37)	23.0 (147)
89	43-5071.00	Shipping, Receiving, and Inventory Clerks	1,195	24.4	70.0 (326)	57.9 (379)	42.1	21.0 (166)	29.5 (53)
90	29-1218.00	Obstetricians and Gynecologists	149	24.4	76.9 (290)	58.0 (378)	42.0	17.8 (233)	32.3 (33)
91	53-6051.01	Aviation Inspectors	26	24.3	60.0 (371)	58.1 (377)	41.9	24.0 (77)	25.1 (113)
92	39-6012.00	Concierges	105	24.3	85.7 (222)	58.2 (376)	41.8	12.2 (347)	35.8 (16)
93	41-9091.00	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	216	24.3	36.4 (467)	58.3 (375)	41.7	23.1 (110)	15.2 (366)
94	19-4021.00	Biological Technicians	288	24.3	66.7 (335)	58.4 (374)	41.6	22.2 (129)	27.7 (70)
95	41-2031.00	Retail Salespersons	10,286	24.3	57.1 (385)	41.6 (468)	58.4	24.5 (55)	33.4 (23)
96	29-2092.00	Hearing Aid Specialists	44	24.3	33.3 (476)	58.5 (373)	41.5	22.2 (129)	13.8 (397)
97	45-2011.00	Agricultural Inspectors	36	24.3	50.0 (406)	58.5 (372)	41.5	25.0 (1)	20.7 (223)
98	29-1128.00	Exercise Physiologists	31	24.3	48.0 (425)	58.5 (371)	41.5	25.0 (21)	19.9 (242)
99	39-5012.00	Hairdressers, Hairstylists, and Cosmetologists	723	24.3	13.3 (583)	41.4 (469)	58.6	11.6 (365)	7.8 (569)
100	25-3021.00	Self-Enrichment Teachers	711	24.2	55.0 (394)	41.2 (470)	58.8	24.8 (45)	32.3 (32)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
101	29-2099.01	Neurodiagnostic Technologists	99	24.2	62.5 (359)	58.8 (370)	41.2	23.4 (102)	25.8 (97)
102	11-9051.00	Food Service Managers	3,665	24.2	75.0 (302)	58.8 (369)	41.2	18.8 (201)	30.9 (43)
103	11-9179.01	Fitness and Wellness Coordinators	170	24.2	68.2 (334)	58.8 (368)	41.2	21.7 (156)	28.1 (67)
104	47-1011.03	Solar Energy Installation Managers	17	24.2	86.7 (215)	41.2 (471)	58.8	11.6 (365)	51.0 (1)
105	21-1023.00	Mental Health and Substance Abuse Social Workers	554	24.2	54.5 (395)	58.8 (367)	41.2	24.8 (37)	22.5 (166)
106	51-5112.00	Printing Press Operators	155	24.2	35.3 (471)	40.9 (472)	59.1	22.8 (121)	20.8 (218)
107	31-9091.00	Dental Assistants	1,116	24.2	42.9 (442)	40.9 (473)	59.1	24.5 (55)	25.3 (108)
108	21-2021.00	Directors, Religious Activities and Education	96	24.1	78.6 (279)	40.6 (474)	59.4	16.8 (253)	46.7 (2)
109	51-9011.00	Chemical Equipment Operators and Tenders	92	24.1	21.7 (534)	40.5 (475)	59.5	17.0 (251)	12.9 (427)
110	49-3091.00	Bicycle Repairers	45	24.1	23.1 (527)	40.3 (476)	59.7	17.8 (233)	13.8 (399)
111	37-1012.00	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	213	24.0	55.6 (391)	40.2 (477)	59.8	24.7 (48)	33.2 (25)
112	51-9083.00	Ophthalmic Laboratory Technicians	25	24.0	21.4 (535)	40.2 (478)	59.8	16.8 (253)	12.8 (432)
113	41-9011.00	Demonstrators and Product Promoters	989	24.0	13.3 (583)	40.1 (479)	59.9	11.6 (365)	8.0 (563)
114	29-2081.00	Opticians, Dispensing	275	24.0	47.6 (427)	60.0 (366)	40.0	24.9 (23)	19.1 (263)
115	17-3031.00	Surveying and Mapping Technicians	230	24.0	94.1 (124)	60.1 (365)	39.9	5.5 (518)	37.5 (9)
116	51-9071.00	Jewelers and Precious Stone and Metal Workers	21	24.0	30.8 (490)	39.9 (480)	60.1	21.3 (160)	18.5 (278)
117	49-2011.00	Computer, Automated Teller, and Office Machine Repairers	263	24.0	45.8 (435)	60.2 (364)	39.8	24.8 (36)	18.2 (284)
118	51-9061.00	Inspectors, Testers, Sorters, Samplers, and Weighers	570	24.0	56.2 (389)	60.2 (363)	39.8	24.6 (52)	22.4 (169)
119	29-1141.03	Critical Care Nurses	803	24.0	58.6 (383)	60.2 (362)	39.8	24.3 (72)	23.3 (137)
120	25-3041.00	Tutors	758	23.9	93.8 (129)	60.3 (361)	39.7	5.9 (509)	37.3 (11)
121	21-1022.00	Healthcare Social Workers	689	23.9	66.7 (335)	60.3 (360)	39.7	22.2 (129)	26.5 (85)
122	51-8092.00	Gas Plant Operators	15	23.9	15.4 (566)	39.6 (481)	60.4	13.0 (331)	9.3 (527)
123	31-9097.00	Phlebotomists	836	23.9	23.5 (525)	39.5 (482)	60.5	18.0 (226)	14.2 (386)
124	25-9044.00	Teaching Assistants, Postsecondary	46	23.9	76.9 (290)	60.5 (359)	39.5	17.8 (233)	30.4 (45)
125	39-5094.00	Skincare Specialists	281	23.9	33.3 (476)	39.4 (483)	60.6	22.2 (129)	20.2 (234)
126	33-3051.00	Police and Sheriff's Patrol Officers	249	23.8	42.9 (442)	39.2 (484)	60.8	24.5 (55)	26.1 (92)
127	51-9123.00	Painting, Coating, and Decorating Workers	13	23.8	0.0 (654)	39.1 (485)	60.9	0.0 (542)	0.0 (654)
128	51-1011.00	First-Line Supervisors of Production and Operating Workers	762	23.8	65.0 (348)	61.0 (358)	39.0	22.7 (122)	25.4 (107)
129	11-9179.02	Spa Managers	121	23.8	81.0 (261)	61.0 (357)	39.0	15.4 (288)	31.6 (38)
130	27-2022.00	Coaches and Scouts	924	23.8	47.1 (429)	39.0 (486)	61.0	24.9 (28)	28.7 (59)
131	29-1292.00	Dental Hygienists	515	23.8	35.7 (468)	38.9 (487)	61.1	23.0 (115)	21.8 (188)
132	25-2012.00	Kindergarten Teachers, Except Special Education	82	23.8	41.7 (451)	61.1 (356)	38.9	24.3 (67)	16.2 (338)
133	37-3012.00	Pesticide Handlers, Sprayers, and Applicators, Vegetation	177	23.8	12.5 (588)	38.9 (488)	61.1	10.9 (377)	7.6 (575)
134	33-1012.00	First-Line Supervisors of Police and Detectives	39	23.8	55.6 (391)	61.1 (355)	38.9	24.7 (48)	21.6 (192)
135	41-2021.00	Counter and Rental Clerks	882	23.7	80.0 (265)	61.2 (354)	38.8	16.0 (273)	31.0 (41)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
136	29-2035.00	Magnetic Resonance Imaging Technologists	178	23.7	59.1 (381)	61.4 (353)	38.6	24.2 (74)	22.8 (151)
137	43-9071.00	Office Machine Operators, Except Computer	72	23.7	50.0 (406)	61.4 (352)	38.6	25.0 (1)	19.3 (255)
138	29-1141.00	Registered Nurses	10,646	23.7	60.0 (371)	61.6 (351)	38.4	24.0 (77)	23.0 (146)
139	43-4081.00	Hotel, Motel, and Resort Desk Clerks	1,176	23.7	78.9 (272)	61.6 (350)	38.4	16.6 (264)	30.3 (47)
140	17-3026.01	Nanotechnology Engineering Technologists and Technicians	11	23.6	54.5 (395)	61.6 (349)	38.4	24.8 (37)	20.9 (215)
141	33-3021.02	Police Identification and Records Officers	18	23.6	63.6 (354)	61.7 (348)	38.3	23.1 (110)	24.4 (124)
142	19-1032.00	Foresters	29	23.6	66.7 (335)	61.8 (347)	38.2	22.2 (129)	25.5 (104)
143	31-1133.00	Psychiatric Aides	391	23.6	6.7 (639)	38.2 (489)	61.8	6.2 (497)	4.1 (648)
144	29-2057.00	Ophthalmic Medical Technicians	214	23.6	61.1 (368)	61.9 (346)	38.1	23.8 (94)	23.3 (138)
145	53-3052.00	Bus Drivers, Transit and Intercity	79	23.6	25.0 (512)	38.0 (490)	62.0	18.8 (201)	15.5 (353)
146	29-1151.00	Nurse Anesthetists	99	23.5	33.3 (476)	37.9 (491)	62.1	22.2 (129)	20.7 (224)
147	43-5111.00	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	258	23.5	14.3 (573)	62.2 (345)	37.8	12.2 (347)	5.4 (625)
148	53-2021.00	Air Traffic Controllers	13	23.5	57.1 (385)	62.3 (344)	37.7	24.5 (55)	21.5 (195)
149	49-9031.00	Home Appliance Repairers	207	23.5	25.0 (512)	37.6 (492)	62.4	18.8 (201)	15.6 (352)
150	41-2012.00	Gambling Change Persons and Booth Cashiers	15	23.4	33.3 (476)	37.4 (493)	62.6	22.2 (129)	20.9 (217)
151	51-4041.00	Machinists	282	23.4	35.0 (472)	37.4 (494)	62.6	22.7 (122)	21.9 (182)
152	49-2095.00	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	63	23.4	55.6 (391)	37.3 (495)	62.7	24.7 (48)	34.8 (21)
153	39-2011.00	Animal Trainers	58	23.4	20.0 (544)	37.2 (496)	62.8	16.0 (273)	12.6 (442)
154	51-9012.00	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	55	23.3	21.4 (535)	37.0 (497)	63.0	16.8 (253)	13.5 (411)
155	43-4181.00	Reservation and Transportation Ticket Agents and Travel Clerks	182	23.3	78.6 (279)	63.0 (343)	37.0	16.8 (253)	29.1 (57)
156	49-2021.00	Radio, Cellular, and Tower Equipment Installers and Repairers	119	23.3	25.0 (512)	37.0 (498)	63.0	18.8 (201)	15.7 (348)
157	29-1022.00	Oral and Maxillofacial Surgeons	26	23.3	9.1 (618)	37.0 (499)	63.0	8.3 (441)	5.7 (618)
158	25-2022.00	Middle School Teachers, Except Special and Career/Technical Education	420	23.3	61.8 (365)	63.1 (342)	36.9	23.6 (99)	22.8 (153)
159	25-2032.00	Career/Technical Education Teachers, Secondary School	115	23.3	51.5 (405)	63.1 (341)	36.9	25.0 (20)	19.0 (264)
160	39-9031.00	Exercise Trainers and Group Fitness Instructors	678	23.3	0.0 (654)	36.9 (500)	63.1	0.0 (542)	0.0 (654)
161	41-2011.00	Cashiers	2,438	23.2	21.4 (535)	36.6 (501)	63.4	16.8 (253)	13.6 (407)
162	39-3031.00	Ushers, Lobby Attendants, and Ticket Takers	149	23.2	16.7 (555)	36.6 (502)	63.4	13.9 (305)	10.6 (488)
163	29-1122.01	Low Vision Therapists, Orientation and Mobility Specialists, and Vision Rehabilitation Therapists	24	23.2	42.1 (449)	63.4 (340)	36.6	24.4 (65)	15.4 (357)
164	25-2021.00	Elementary School Teachers, Except Special Education	662	23.2	58.3 (384)	63.5 (339)	36.5	24.3 (67)	21.3 (202)
165	25-2011.00	Preschool Teachers, Except Special Education	1,281	23.2	40.6 (456)	36.5 (503)	63.5	24.1 (76)	25.8 (96)
166	39-9041.00	Residential Advisors	143	23.2	40.0 (457)	36.4 (504)	63.6	24.0 (77)	25.4 (105)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
167	19-1022.00	Microbiologists	26	23.2	70.0 (326)	63.6 (338)	36.4	21.0 (166)	25.5 (102)
168	49-2096.00	Electronic Equipment Installers and Repairers, Motor Vehicles	39	23.2	16.7 (555)	36.4 (505)	63.6	13.9 (305)	10.6 (487)
169	51-3091.00	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	16	23.1	10.0 (606)	36.3 (506)	63.7	9.0 (418)	6.4 (602)
170	35-2013.00	Cooks, Private Household	19	23.1	33.3 (476)	36.3 (507)	63.7	22.2 (129)	21.2 (205)
171	39-5011.00	Barbers	77	23.1	21.4 (535)	36.2 (508)	63.8	16.8 (253)	13.7 (403)
172	51-4034.00	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	55	23.1	20.0 (544)	36.1 (509)	63.9	16.0 (273)	12.8 (433)
173	11-9081.00	Lodging Managers	495	23.1	86.4 (219)	63.9 (337)	36.1	11.8 (362)	31.2 (40)
174	33-9031.00	Gambling Surveillance Officers and Gambling Investigators	21	23.1	62.5 (359)	63.9 (336)	36.1	23.4 (102)	22.6 (160)
175	19-3033.00	Clinical and Counseling Psychologists	258	23.1	62.5 (359)	63.9 (335)	36.1	23.4 (102)	22.5 (163)
176	43-4121.00	Library Assistants, Clerical	44	23.1	76.0 (301)	63.9 (334)	36.1	18.2 (222)	27.4 (73)
177	29-1129.02	Music Therapists	15	23.0	73.3 (317)	64.0 (333)	36.0	19.6 (190)	26.4 (87)
178	25-2031.00	Secondary School Teachers, Except Special and Career/Technical Education	871	23.0	64.5 (351)	64.2 (332)	35.8	22.9 (120)	23.1 (144)
179	29-2051.00	Dietetic Technicians	53	22.9	90.0 (181)	64.3 (331)	35.7	9.0 (418)	32.1 (35)
180	53-7073.00	Wellhead Pumpers	19	22.9	0.0 (654)	35.7 (510)	64.3	0.0 (542)	0.0 (654)
181	31-2022.00	Physical Therapist Aides	214	22.9	28.6 (502)	35.5 (511)	64.5	20.4 (180)	18.4 (281)
182	43-4171.00	Receptionists and Information Clerks	2,121	22.9	90.9 (169)	64.5 (330)	35.5	8.3 (441)	32.3 (34)
183	51-8091.00	Chemical Plant and System Operators	19	22.8	28.6 (502)	35.3 (512)	64.7	20.4 (180)	18.5 (279)
184	33-9032.00	Security Guards	2,588	22.8	20.0 (544)	35.2 (513)	64.8	16.0 (273)	13.0 (425)
185	17-3023.00	Electrical and Electronic Engineering Technologists and Technicians	221	22.8	60.9 (370)	64.8 (329)	35.2	23.8 (93)	21.4 (197)
186	51-8031.00	Water and Wastewater Treatment Plant and System Operators	128	22.8	12.5 (588)	35.2 (514)	64.8	10.9 (377)	8.1 (559)
187	51-9161.00	Computer Numerically Controlled Tool Operators	116	22.8	26.1 (511)	35.1 (515)	64.9	19.3 (198)	16.9 (314)
188	29-2052.00	Pharmacy Technicians	1,121	22.8	61.5 (366)	64.9 (328)	35.1	23.7 (97)	21.6 (193)
189	51-8093.00	Petroleum Pump System Operators, Refinery Operators, and Gaugers	16	22.8	29.4 (498)	35.1 (516)	64.9	20.8 (173)	19.1 (261)
190	49-2093.00	Electrical and Electronics Installers and Repairers, Transportation Equipment	25	22.8	30.0 (494)	35.1 (517)	64.9	21.0 (166)	19.5 (251)
191	17-3027.00	Mechanical Engineering Technologists and Technicians	73	22.8	84.2 (236)	64.9 (327)	35.1	13.3 (322)	29.5 (52)
192	33-9093.00	Transportation Security Screeners	19	22.8	50.0 (406)	35.1 (518)	64.9	25.0 (1)	32.5 (29)
193	49-9094.00	Locksmiths and Safe Repairers	37	22.8	9.1 (618)	35.0 (519)	65.0	8.3 (441)	5.9 (612)
194	51-9081.00	Dental Laboratory Technicians	57	22.7	14.3 (573)	34.8 (520)	65.2	12.2 (347)	9.3 (526)
195	51-9162.00	Computer Numerically Controlled Tool Programmers	78	22.7	91.7 (161)	65.2 (326)	34.8	7.6 (459)	31.9 (37)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
196	27-4014.00	Sound Engineering Technicians	21	22.7	76.9 (290)	65.2 (325)	34.8	17.8 (233)	26.7 (79)
197	51-8012.00	Power Distributors and Dispatchers	13	22.7	77.8 (284)	65.2 (324)	34.8	17.3 (243)	27.0 (75)
198	49-3011.00	Aircraft Mechanics and Service Technicians	157	22.6	17.2 (554)	34.6 (521)	65.4	14.3 (304)	11.3 (469)
199	11-9151.00	Social and Community Service Managers	1,099	22.6	66.7 (335)	65.6 (323)	34.4	22.2 (129)	22.9 (149)
200	53-5021.00	Captains, Mates, and Pilots of Water Vessels	26	22.6	32.0 (489)	34.4 (522)	65.6	21.8 (155)	21.0 (213)
201	53-3031.00	Driver/Sales Workers	1,267	22.5	66.7 (335)	34.3 (523)	65.7	22.2 (129)	43.8 (6)
202	53-6061.00	Passenger Attendants	11	22.5	25.0 (512)	34.1 (524)	65.9	18.8 (201)	16.5 (326)
203	19-4092.00	Forensic Science Technicians	11	22.4	60.0 (371)	66.0 (322)	34.0	24.0 (77)	20.4 (229)
204	51-4111.00	Tool and Die Makers	79	22.4	26.7 (509)	34.0 (525)	66.0	19.6 (190)	17.6 (300)
205	29-1181.00	Audiologists	47	22.4	77.3 (287)	66.1 (321)	33.9	17.6 (240)	26.2 (89)
206	17-3025.00	Environmental Engineering Technologists and Technicians	11	22.4	66.7 (335)	66.1 (320)	33.9	22.2 (129)	22.6 (161)
207	21-1015.00	Rehabilitation Counselors	235	22.4	64.3 (352)	66.1 (319)	33.9	23.0 (115)	21.8 (189)
208	31-9095.00	Pharmacy Aides	210	22.4	37.5 (464)	66.2 (318)	33.8	23.4 (102)	12.7 (436)
209	43-5052.00	Postal Service Mail Carriers	308	22.3	23.5 (525)	33.7 (526)	66.3	18.0 (226)	15.6 (351)
210	19-3034.00	School Psychologists	165	22.3	77.8 (284)	66.3 (317)	33.7	17.3 (243)	26.2 (90)
211	49-9081.00	Wind Turbine Service Technicians	33	22.3	10.0 (606)	33.6 (527)	66.4	9.0 (418)	6.6 (598)
212	51-3011.00	Bakers	577	22.3	37.5 (464)	33.6 (528)	66.4	23.4 (102)	24.9 (116)
213	25-1194.00	Career/Technical Education Teachers, Postsecondary	287	22.3	84.2 (236)	66.4 (316)	33.6	13.3 (322)	28.3 (63)
214	51-9082.00	Medical Appliance Technicians	20	22.3	21.4 (535)	33.5 (529)	66.5	16.8 (253)	14.2 (385)
215	51-4072.00	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	116	22.3	20.0 (544)	33.5 (530)	66.5	16.0 (273)	13.3 (415)
216	51-8013.00	Power Plant Operators	26	22.3	40.0 (457)	33.5 (531)	66.5	24.0 (77)	26.6 (83)
217	31-1131.00	Nursing Assistants	3,236	22.3	15.4 (566)	33.4 (532)	66.6	13.0 (331)	10.2 (502)
218	25-2058.00	Special Education Teachers, Secondary School	159	22.2	50.0 (406)	66.6 (315)	33.4	25.0 (1)	16.7 (321)
219	29-2056.00	Veterinary Technologists and Technicians	369	22.2	26.7 (509)	33.3 (533)	66.7	19.6 (190)	17.8 (297)
220	51-4035.00	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	22	22.1	28.6 (502)	33.1 (534)	66.9	20.4 (180)	19.1 (259)
221	25-2023.00	Career/Technical Education Teachers, Middle School	16	22.1	45.2 (438)	67.1 (314)	32.9	24.8 (44)	14.8 (369)
222	51-2011.00	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	35	22.1	10.0 (606)	32.8 (535)	67.2	9.0 (418)	6.7 (596)
223	19-4099.01	Quality Control Analysts	210	22.1	81.0 (261)	67.2 (313)	32.8	15.4 (288)	26.6 (84)
224	49-9091.00	Coin, Vending, and Amusement Machine Servicers and Repairers	108	22.0	33.3 (476)	32.7 (536)	67.3	22.2 (129)	22.4 (168)
225	49-9011.00	Mechanical Door Repairers	84	22.0	21.1 (542)	32.7 (537)	67.3	16.6 (264)	14.2 (388)
226	33-3021.00	Detectives and Criminal Investigators	76	22.0	53.3 (401)	67.4 (312)	32.6	24.9 (29)	17.4 (305)
227	49-9012.00	Control and Valve Installers and Repairers, Except Mechanical Door	70	21.9	33.3 (476)	32.5 (538)	67.5	22.2 (129)	22.5 (165)
228	53-2022.00	Airfield Operations Specialists	13	21.9	50.0 (406)	67.6 (311)	32.4	25.0 (1)	16.2 (339)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
229	13-1032.00	Insurance Appraisers, Auto Damage	127	21.9	100.0 (1)	67.6 (310)	32.4	0.0 (542)	32.4 (30)
230	25-2057.00	Special Education Teachers, Middle School	79	21.9	54.1 (400)	67.7 (309)	32.3	24.8 (35)	17.4 (304)
231	11-9199.08	Loss Prevention Managers	74	21.9	80.8 (263)	67.7 (308)	32.3	15.5 (286)	26.1 (93)
232	47-2142.00	Paperhangers	36	21.9	5.9 (646)	32.3 (539)	67.7	5.5 (518)	4.0 (649)
233	11-9032.00	Education Administrators, Kindergarten through Secondary	306	21.9	82.6 (251)	67.7 (307)	32.3	14.4 (303)	26.6 (81)
234	49-3092.00	Recreational Vehicle Service Technicians	46	21.8	6.2 (643)	32.2 (540)	67.8	5.9 (509)	4.2 (647)
235	29-1081.00	Podiatrists	21	21.8	60.0 (371)	67.8 (306)	32.2	24.0 (77)	19.3 (254)
236	53-3032.00	Heavy and Tractor-Trailer Truck Drivers	9,473	21.8	42.9 (442)	32.1 (541)	67.9	24.5 (55)	29.1 (56)
237	47-4011.01	Energy Auditors	18	21.7	85.0 (227)	68.3 (305)	31.7	12.8 (340)	27.0 (76)
238	49-9041.00	Industrial Machinery Mechanics	978	21.7	33.3 (476)	31.7 (542)	68.3	22.2 (129)	22.8 (155)
239	47-4011.00	Construction and Building Inspectors	262	21.6	40.0 (457)	68.4 (304)	31.6	24.0 (77)	12.7 (438)
240	43-5031.00	Public Safety Telecommunicators	147	21.6	92.9 (143)	68.4 (303)	31.6	6.6 (486)	29.3 (54)
241	39-3011.00	Gambling Dealers	28	21.6	12.5 (588)	31.6 (543)	68.4	10.9 (377)	8.6 (548)
242	47-2111.00	Electricians	735	21.6	20.0 (544)	31.5 (544)	68.5	16.0 (273)	13.7 (402)
243	25-4012.00	Curators	19	21.6	83.3 (243)	68.5 (302)	31.5	13.9 (305)	26.3 (88)
244	51-9041.00	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	50	21.6	8.3 (626)	31.5 (545)	68.5	7.6 (459)	5.7 (619)
245	39-6011.00	Baggage Porters and Bellhops	91	21.6	10.0 (606)	31.5 (546)	68.5	9.0 (418)	6.9 (594)
246	31-9011.00	Massage Therapists	373	21.6	7.7 (631)	31.4 (547)	68.6	7.1 (472)	5.3 (628)
247	21-1091.00	Health Education Specialists	152	21.5	80.0 (265)	68.6 (301)	31.4	16.0 (273)	25.1 (112)
248	53-7065.00	Stockers and Order Fillers	6,382	21.5	24.0 (523)	31.4 (548)	68.6	18.2 (222)	16.5 (327)
249	25-1121.00	Art, Drama, and Music Teachers, Postsecondary	105	21.5	75.0 (302)	68.6 (300)	31.4	18.8 (201)	23.5 (135)
250	13-1041.01	Environmental Compliance Inspectors	49	21.5	73.3 (317)	68.7 (299)	31.3	19.6 (190)	22.9 (148)
251	43-5021.00	Couriers and Messengers	317	21.4	41.7 (451)	31.0 (549)	69.0	24.3 (67)	28.7 (58)
252	21-1012.00	Educational, Guidance, and Career Counselors and Advisors	508	21.4	47.8 (426)	69.0 (298)	31.0	25.0 (22)	14.8 (370)
253	47-2231.00	Solar Photovoltaic Installers	82	21.4	20.8 (543)	31.0 (550)	69.0	16.5 (272)	14.4 (379)
254	17-3022.00	Civil Engineering Technologists and Technicians	241	21.4	100.0 (1)	69.0 (297)	31.0	0.0 (542)	31.0 (42)
255	29-1071.00	Physician Assistants	448	21.4	75.0 (302)	69.0 (296)	31.0	18.8 (201)	23.2 (141)
256	51-4021.00	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	61	21.3	0.0 (654)	30.9 (551)	69.1	0.0 (542)	0.0 (654)
257	13-1041.04	Government Property Inspectors and Investigators	38	21.3	100.0 (1)	69.2 (295)	30.8	0.0 (542)	30.8 (44)
258	39-9032.00	Recreation Workers	788	21.3	33.3 (476)	30.7 (552)	69.3	22.2 (129)	23.1 (145)
259	25-1193.00	Recreation and Fitness Studies Teachers, Postsecondary	21	21.3	89.5 (189)	69.3 (294)	30.7	9.4 (412)	27.5 (72)
260	25-1072.00	Nursing Instructors and Teachers, Postsecondary	174	21.3	63.6 (354)	69.3 (293)	30.7	23.1 (110)	19.5 (250)
261	31-9096.00	Veterinary Assistants and Laboratory Animal Caretakers	251	21.3	34.6 (475)	30.6 (553)	69.4	22.6 (128)	24.0 (128)
262	51-2031.00	Engine and Other Machine Assemblers	61	21.2	22.2 (529)	30.6 (554)	69.4	17.3 (243)	15.4 (356)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
263	49-9021.00	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	980	21.2	14.8 (572)	30.6 (555)	69.4	12.6 (346)	10.3 (499)
264	29-1229.04	Physical Medicine and Rehabilitation Physicians	44	21.2	46.7 (430)	69.5 (292)	30.5	24.9 (29)	14.3 (384)
265	27-4012.00	Broadcast Technicians	37	21.1	84.6 (232)	69.6 (291)	30.4	13.0 (331)	25.7 (100)
266	51-9111.00	Packaging and Filling Machine Operators and Tenders	322	21.1	0.0 (654)	30.3 (556)	69.7	0.0 (542)	0.0 (654)
267	27-2011.00	Actors	59	21.1	23.1 (527)	30.3 (557)	69.7	17.8 (233)	16.1 (343)
268	53-3033.00	Light Truck Drivers	2,774	21.1	50.0 (406)	30.3 (558)	69.7	25.0 (1)	34.9 (20)
269	51-9032.00	Cutting and Slicing Machine Setters, Operators, and Tenders	44	21.1	12.5 (588)	30.2 (559)	69.8	10.9 (377)	8.7 (544)
270	29-1127.00	Speech-Language Pathologists	918	21.1	70.6 (323)	69.8 (290)	30.2	20.8 (173)	21.3 (200)
271	51-4081.00	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	153	21.1	11.1 (600)	30.1 (560)	69.9	9.9 (401)	7.8 (572)
272	51-4193.00	Plating Machine Setters, Operators, and Tenders, Metal and Plastic	17	21.1	30.0 (494)	30.1 (561)	69.9	21.0 (166)	21.0 (214)
273	49-3023.00	Automotive Service Technicians and Mechanics	1,695	21.0	12.0 (596)	30.1 (562)	69.9	10.6 (394)	8.4 (552)
274	25-1071.00	Health Specialties Teachers, Postsecondary	140	21.0	82.4 (252)	69.9 (289)	30.1	14.5 (301)	24.8 (120)
275	29-1222.00	Physicians, Pathologists	41	21.0	92.9 (143)	69.9 (288)	30.1	6.6 (486)	27.9 (69)
276	49-3052.00	Motorcycle Mechanics	22	21.0	0.0 (654)	29.9 (563)	70.1	0.0 (542)	0.0 (654)
277	51-3092.00	Food Batchmakers	101	20.9	14.3 (573)	29.7 (564)	70.3	12.2 (347)	10.0 (507)
278	39-3092.00	Costume Attendants	14	20.8	46.7 (430)	29.6 (565)	70.4	24.9 (29)	32.9 (27)
279	51-9196.00	Paper Goods Machine Setters, Operators, and Tenders	41	20.7	0.0 (654)	29.4 (566)	70.6	0.0 (542)	0.0 (654)
280	47-4021.00	Elevator and Escalator Installers and Repairers	20	20.7	22.2 (529)	29.4 (567)	70.6	17.3 (243)	15.7 (350)
281	49-3042.00	Mobile Heavy Equipment Mechanics, Except Engines	387	20.7	15.0 (571)	29.3 (568)	70.7	12.8 (340)	10.6 (486)
282	51-4191.00	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	13	20.7	25.0 (512)	29.3 (569)	70.7	18.8 (201)	17.7 (299)
283	11-9161.00	Emergency Management Directors	67	20.7	86.4 (219)	70.8 (287)	29.2	11.8 (362)	25.2 (111)
284	25-1113.00	Social Work Teachers, Postsecondary	19	20.7	65.0 (348)	70.8 (286)	29.2	22.7 (122)	19.0 (267)
285	25-9021.00	Farm and Home Management Educators	45	20.6	66.7 (335)	70.9 (285)	29.1	22.2 (129)	19.4 (252)
286	39-9011.00	Childcare Workers	943	20.6	15.8 (564)	29.1 (570)	70.9	13.3 (322)	11.2 (471)
287	49-2092.00	Electric Motor, Power Tool, and Related Repairers	24	20.6	15.4 (566)	29.1 (571)	70.9	13.0 (331)	10.9 (479)
288	39-3091.00	Amusement and Recreation Attendants	337	20.6	28.6 (502)	29.0 (572)	71.0	20.4 (180)	20.3 (233)
289	27-4021.00	Photographers	242	20.6	68.4 (332)	71.0 (284)	29.0	21.6 (157)	19.8 (244)
290	39-4031.00	Morticians, Undertakers, and Funeral Arrangers	52	20.6	23.8 (524)	29.0 (573)	71.0	18.1 (224)	16.9 (316)
291	43-3071.00	Tellers	876	20.6	73.7 (314)	71.1 (283)	28.9	19.4 (195)	21.3 (199)
292	25-3011.00	Adult Basic Education, Adult Secondary Education, and English as a Second Language Instructors	142	20.5	62.1 (363)	71.2 (282)	28.8	23.5 (101)	17.9 (294)
293	29-1241.00	Ophthalmologists, Except Pediatric	29	20.5	81.2 (259)	71.2 (281)	28.8	15.2 (290)	23.4 (136)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
294	29-1171.00	Nurse Practitioners	1,329	20.5	92.6 (149)	71.2 (280)	28.8	6.9 (483)	26.6 (82)
295	53-7071.00	Gas Compressor and Gas Pumping Station Operators	19	20.4	30.8 (490)	28.7 (574)	71.3	21.3 (160)	22.0 (181)
296	25-4031.00	Library Technicians	124	20.4	76.5 (295)	71.4 (279)	28.6	18.0 (226)	21.9 (183)
297	49-3043.00	Rail Car Repairers	28	20.4	18.2 (551)	28.6 (575)	71.4	14.9 (293)	13.0 (420)
298	31-9099.01	Speech-Language Pathology Assistants	52	20.4	100.0 (1)	71.4 (278)	28.6	0.0 (542)	28.6 (61)
299	51-5111.00	Prepress Technicians and Workers	34	20.4	71.4 (322)	71.5 (277)	28.5	20.4 (180)	20.3 (232)
300	51-5113.00	Print Binding and Finishing Workers	45	20.3	15.4 (566)	28.3 (576)	71.7	13.0 (331)	11.0 (474)
301	25-1066.00	Psychology Teachers, Postsecondary	52	20.3	85.7 (222)	71.8 (276)	28.2	12.2 (347)	24.2 (127)
302	11-9111.00	Medical and Health Services Managers	3,049	20.3	88.2 (201)	71.8 (275)	28.2	10.4 (395)	24.9 (117)
303	25-1123.00	English Language and Literature Teachers, Postsecondary	49	20.2	78.3 (283)	71.8 (274)	28.2	17.0 (251)	22.0 (178)
304	35-3023.01	Baristas	752	20.2	15.8 (564)	28.2 (577)	71.8	13.3 (322)	11.3 (466)
305	33-3012.00	Correctional Officers and Jailers	143	20.2	27.8 (508)	28.1 (578)	71.9	20.1 (187)	20.0 (239)
306	49-3041.00	Farm Equipment Mechanics and Service Technicians	66	20.2	8.3 (626)	28.1 (579)	71.9	7.6 (459)	6.0 (611)
307	51-4031.00	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	161	20.2	0.0 (654)	28.1 (580)	71.9	0.0 (542)	0.0 (654)
308	51-7042.00	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	17	20.2	10.0 (606)	28.1 (581)	71.9	9.0 (418)	7.2 (587)
309	11-3071.00	Transportation, Storage, and Distribution Managers	495	20.2	92.3 (152)	72.0 (273)	28.0	7.1 (472)	25.9 (95)
310	11-3051.00	Industrial Production Managers	421	20.2	91.7 (161)	72.0 (272)	28.0	7.6 (459)	25.7 (99)
311	29-1215.00	Family Medicine Physicians	347	20.2	90.9 (169)	72.0 (271)	28.0	8.3 (441)	25.5 (103)
312	29-1229.02	Hospitalists	153	20.2	92.9 (143)	72.0 (270)	28.0	6.6 (486)	26.0 (94)
313	29-1141.02	Advanced Practice Psychiatric Nurses	193	20.1	85.7 (222)	72.2 (269)	27.8	12.2 (347)	23.9 (130)
314	51-9023.00	Mixing and Blending Machine Setters, Operators, and Tenders	79	20.1	11.8 (597)	27.8 (582)	72.2	10.4 (395)	8.5 (550)
315	19-5011.00	Occupational Health and Safety Specialists	456	20.1	61.9 (364)	72.2 (268)	27.8	23.6 (100)	17.2 (308)
316	11-9141.00	Property, Real Estate, and Community Association Managers	1,053	20.1	94.1 (124)	72.2 (267)	27.8	5.5 (518)	26.1 (91)
317	29-1223.00	Psychiatrists	241	20.0	90.9 (169)	72.3 (266)	27.7	8.3 (441)	25.2 (110)
318	51-7011.00	Cabinetmakers and Bench Carpenters	103	20.0	7.1 (634)	27.6 (583)	72.4	6.6 (486)	5.2 (632)
319	41-4012.00	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	2,577	20.0	100.0 (1)	72.4 (265)	27.6	0.0 (542)	27.6 (71)
320	29-1011.00	Chiropractors	64	19.9	72.7 (320)	72.5 (264)	27.5	19.8 (188)	20.0 (237)
321	25-1081.00	Education Teachers, Postsecondary	57	19.9	83.3 (243)	72.7 (263)	27.3	13.9 (305)	22.8 (154)
322	47-2031.00	Carpenters	548	19.9	25.0 (512)	27.3 (584)	72.7	18.8 (201)	18.2 (286)
323	25-1022.00	Mathematical Science Teachers, Postsecondary	51	19.8	76.9 (290)	72.9 (262)	27.1	17.8 (233)	20.8 (220)
324	49-9052.00	Telecommunications Line Installers and Repairers	139	19.7	0.0 (654)	27.1 (585)	72.9	0.0 (542)	0.0 (654)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
325	33-3011.00	Bailiffs	14	19.7	0.0 (654)	27.0 (586)	73.0	0.0 (542)	0.0 (654)
326	29-1221.00	Pediatricians, General	90	19.7	100.0 (1)	73.1 (261)	26.9	0.0 (542)	26.9 (77)
327	19-3091.00	Anthropologists and Archeologists	28	19.6	82.1 (253)	73.1 (260)	26.9	14.7 (300)	22.1 (177)
328	25-1122.00	Communications Teachers, Postsecondary	37	19.6	70.6 (323)	73.2 (259)	26.8	20.8 (173)	19.0 (266)
329	47-2121.00	Glaziers	86	19.6	14.3 (573)	26.7 (587)	73.3	12.2 (347)	10.5 (490)
330	51-4033.00	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	26	19.6	7.7 (631)	26.7 (588)	73.3	7.1 (472)	5.6 (621)
331	43-4111.00	Interviewers, Except Eligibility and Loan	110	19.6	83.3 (243)	73.3 (258)	26.7	13.9 (305)	22.2 (173)
332	27-1027.00	Set and Exhibit Designers	13	19.4	84.2 (236)	73.6 (257)	26.4	13.3 (322)	22.2 (172)
333	51-8021.00	Stationary Engineers and Boiler Operators	71	19.4	22.2 (529)	26.4 (589)	73.6	17.3 (243)	16.4 (328)
334	29-1216.00	General Internal Medicine Physicians	440	19.4	93.8 (129)	73.7 (256)	26.3	5.9 (509)	24.7 (121)
335	49-3031.00	Bus and Truck Mechanics and Diesel Engine Specialists	1,206	19.4	0.0 (654)	26.3 (590)	73.7	0.0 (542)	0.0 (654)
336	25-1111.00	Criminal Justice and Law Enforcement Teachers, Postsecondary	19	19.3	76.5 (295)	73.9 (255)	26.1	18.0 (226)	20.0 (238)
337	25-1124.00	Foreign Language and Literature Teachers, Postsecondary	42	19.3	80.0 (265)	73.9 (254)	26.1	16.0 (273)	20.9 (216)
338	11-1011.00	Chief Executives	205	19.2	84.2 (236)	74.0 (253)	26.0	13.3 (322)	21.9 (184)
339	47-2152.00	Plumbers, Pipefitters, and Steamfitters	588	19.2	16.7 (555)	25.9 (591)	74.1	13.9 (305)	12.3 (448)
340	25-1126.00	Philosophy and Religion Teachers, Postsecondary	24	19.2	76.2 (300)	74.1 (252)	25.9	18.1 (224)	19.7 (245)
341	25-1011.00	Business Teachers, Postsecondary	113	19.2	78.9 (272)	74.1 (251)	25.9	16.6 (264)	20.4 (228)
342	25-1052.00	Chemistry Teachers, Postsecondary	33	19.2	69.6 (329)	74.1 (250)	25.9	21.2 (164)	18.0 (290)
343	51-2051.00	Fiberglass Laminators and Fabricators	28	19.1	0.0 (654)	25.7 (592)	74.3	0.0 (542)	0.0 (654)
344	25-1042.00	Biological Science Teachers, Postsecondary	73	19.1	81.8 (254)	74.3 (249)	25.7	14.9 (293)	21.0 (211)
345	25-1054.00	Physics Teachers, Postsecondary	23	19.1	73.7 (314)	74.4 (248)	25.6	19.4 (195)	18.9 (268)
346	29-1229.05	Preventive Medicine Physicians	28	19.0	93.3 (136)	74.5 (247)	25.5	6.2 (497)	23.8 (132)
347	51-9021.00	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	16	18.9	13.3 (583)	25.3 (593)	74.7	11.6 (365)	10.0 (509)
348	49-9071.00	Maintenance and Repair Workers, General	3,480	18.9	28.6 (502)	25.3 (594)	74.7	20.4 (180)	21.4 (198)
349	47-5013.00	Service Unit Operators, Oil and Gas	20	18.9	8.3 (626)	25.2 (595)	74.8	7.6 (459)	6.2 (606)
350	27-2012.05	Media Technical Directors/Managers	18	18.9	81.8 (254)	74.8 (246)	25.2	14.9 (293)	20.6 (226)
351	25-1021.00	Computer Science Teachers, Postsecondary	67	18.9	87.5 (203)	74.8 (245)	25.2	10.9 (377)	22.1 (176)
352	17-1012.00	Landscape Architects	44	18.9	84.2 (236)	74.8 (244)	25.2	13.3 (322)	21.2 (206)
353	35-3031.00	Waiters and Waitresses	2,228	18.8	29.2 (500)	25.2 (596)	74.8	20.7 (178)	21.8 (186)
354	27-2023.00	Umpires, Referees, and Other Sports Officials	48	18.8	25.0 (512)	25.1 (597)	74.9	18.8 (201)	18.7 (272)
355	53-7064.00	Packers and Packagers, Hand	303	18.8	12.5 (588)	25.1 (598)	74.9	10.9 (377)	9.4 (524)
356	11-1021.00	General and Operations Managers	1,002	18.8	100.0 (1)	74.9 (243)	25.1	0.0 (542)	25.1 (114)
357	53-7051.00	Industrial Truck and Tractor Operators	1,071	18.8	0.0 (654)	25.0 (599)	75.0	0.0 (542)	0.0 (654)
358	41-1012.00	First-Line Supervisors of Non-Retail Sales Workers	333	18.8	100.0 (1)	75.0 (242)	25.0	0.0 (542)	25.0 (115)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
359	29-1051.00	Pharmacists	870	18.8	78.6 (279)	75.0 (241)	25.0	16.8 (253)	19.6 (247)
360	25-1112.00	Law Teachers, Postsecondary	20	18.7	76.5 (295)	75.0 (240)	25.0	18.0 (226)	19.1 (260)
361	25-1125.00	History Teachers, Postsecondary	20	18.7	85.0 (227)	75.1 (239)	24.9	12.8 (340)	21.2 (208)
362	51-9031.00	Cutters and Trimmers, Hand	19	18.7	0.0 (654)	24.9 (600)	75.1	0.0 (542)	0.0 (654)
363	51-2041.00	Structural Metal Fabricators and Fitters	114	18.7	4.8 (651)	24.9 (601)	75.1	4.5 (532)	3.6 (651)
364	17-3026.00	Industrial Engineering Technologists and Technicians	67	18.7	66.7 (335)	75.2 (238)	24.8	22.2 (129)	16.6 (325)
365	47-2211.00	Sheet Metal Workers	98	18.7	14.3 (573)	24.8 (602)	75.2	12.2 (347)	10.7 (483)
366	35-9031.00	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	985	18.6	30.8 (490)	24.8 (603)	75.2	21.3 (160)	23.2 (143)
367	43-2011.00	Switchboard Operators, Including Answering Service	228	18.6	75.0 (302)	75.2 (237)	24.8	18.8 (201)	18.6 (277)
368	35-2012.00	Cooks, Institution and Cafeteria	1,139	18.6	8.3 (626)	24.7 (604)	75.3	7.6 (459)	6.3 (605)
369	53-7072.00	Pump Operators, Except Wellhead Pumpers	28	18.5	40.0 (457)	24.6 (605)	75.4	24.0 (77)	30.2 (48)
370	51-6093.00	Upholsterers	24	18.5	16.7 (555)	24.6 (606)	75.4	13.9 (305)	12.6 (441)
371	25-1067.00	Sociology Teachers, Postsecondary	17	18.5	75.0 (302)	75.5 (236)	24.5	18.8 (201)	18.4 (282)
372	25-1192.00	Family and Consumer Sciences Teachers, Postsecondary	12	18.5	88.2 (201)	75.6 (235)	24.4	10.4 (395)	21.6 (194)
373	47-5023.00	Earth Drillers, Except Oil and Gas	52	18.5	14.3 (573)	24.4 (607)	75.6	12.2 (347)	10.8 (482)
374	27-3011.00	Broadcast Announcers and Radio Disc Jockeys	19	18.4	87.5 (203)	75.7 (234)	24.3	10.9 (377)	21.3 (201)
375	41-4011.00	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	1,827	18.4	90.5 (178)	75.7 (233)	24.3	8.6 (437)	22.0 (179)
376	19-2031.00	Chemists	107	18.4	66.7 (335)	75.7 (232)	24.3	22.2 (129)	16.2 (340)
377	13-1121.00	Meeting, Convention, and Event Planners	470	18.3	87.5 (203)	75.8 (231)	24.2	10.9 (377)	21.2 (207)
378	49-3051.00	Motorboat Mechanics and Service Technicians	39	18.3	7.7 (631)	24.1 (608)	75.9	7.1 (472)	5.8 (614)
379	31-9099.02	Endoscopy Technicians	56	18.3	16.7 (555)	24.1 (609)	75.9	13.9 (305)	12.6 (439)
380	25-1031.00	Architecture Teachers, Postsecondary	12	18.3	78.9 (272)	75.9 (230)	24.1	16.6 (264)	19.0 (265)
381	17-2171.00	Petroleum Engineers	16	18.2	100.0 (1)	76.0 (229)	24.0	0.0 (542)	24.0 (129)
382	33-9092.00	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers	260	18.2	10.0 (606)	23.9 (610)	76.1	9.0 (418)	7.6 (576)
383	25-1063.00	Economics Teachers, Postsecondary	20	18.2	84.2 (236)	76.1 (228)	23.9	13.3 (322)	20.1 (235)
384	25-1041.00	Agricultural Sciences Teachers, Postsecondary	12	18.2	77.3 (287)	76.1 (227)	23.9	17.6 (240)	18.5 (280)
385	53-6021.00	Parking Attendants	415	18.2	20.0 (544)	23.8 (611)	76.2	16.0 (273)	15.2 (365)
386	11-9033.00	Education Administrators, Postsecondary	350	18.1	75.0 (302)	76.2 (226)	23.8	18.8 (201)	17.9 (295)
387	53-7081.00	Refuse and Recyclable Material Collectors	273	18.1	16.7 (555)	23.8 (612)	76.2	13.9 (305)	12.7 (435)
388	29-9093.00	Surgical Assistants	53	18.1	8.7 (625)	23.7 (613)	76.3	7.9 (457)	6.6 (599)
389	51-6031.00	Sewing Machine Operators	61	18.1	11.8 (597)	23.7 (614)	76.3	10.4 (395)	9.0 (537)
390	17-2121.00	Marine Engineers and Naval Architects	25	18.1	74.1 (312)	76.3 (225)	23.7	19.2 (199)	17.6 (301)
391	25-1032.00	Engineering Teachers, Postsecondary	64	18.1	88.9 (194)	76.3 (224)	23.7	9.9 (401)	21.1 (210)
392	51-4121.00	Welders, Cutters, Solderers, and Brazers	255	18.1	9.5 (617)	23.7 (615)	76.3	8.6 (437)	7.3 (585)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
393	19-2042.00	Geoscientists, Except Hydrologists and Geographers	29	18.1	76.9 (290)	76.4 (223)	23.6	17.8 (233)	18.2 (285)
394	41-4011.07	Solar Sales Representatives and Assessors	207	18.1	92.3 (152)	76.4 (222)	23.6	7.1 (472)	21.8 (187)
395	19-1023.00	Zoologists and Wildlife Biologists	18	18.0	100.0 (1)	76.4 (221)	23.6	0.0 (542)	23.6 (134)
396	25-1062.00	Area, Ethnic, and Cultural Studies Teachers, Postsecondary	18	18.0	77.3 (287)	76.5 (220)	23.5	17.6 (240)	18.1 (288)
397	31-9093.00	Medical Equipment Preparers	225	17.9	18.2 (551)	23.4 (616)	76.6	14.9 (293)	13.9 (394)
398	25-1051.00	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary	14	17.9	78.6 (279)	76.7 (219)	23.3	16.8 (253)	18.3 (283)
399	35-3023.00	Fast Food and Counter Workers	5,548	17.9	5.0 (650)	23.3 (617)	76.7	4.8 (530)	3.8 (650)
400	51-6052.00	Tailors, Dressmakers, and Custom Sewers	54	17.9	13.6 (582)	23.3 (618)	76.7	11.8 (362)	10.5 (491)
401	29-1141.04	Clinical Nurse Specialists	262	17.9	83.3 (243)	76.7 (218)	23.3	13.9 (305)	19.4 (253)
402	47-4041.00	Hazardous Materials Removal Workers	155	17.8	10.0 (606)	23.2 (619)	76.8	9.0 (418)	7.7 (574)
403	33-2011.00	Firefighters	76	17.8	18.5 (550)	23.2 (620)	76.8	15.1 (292)	14.2 (387)
404	49-9063.00	Musical Instrument Repairers and Tuners	14	17.8	7.1 (634)	23.2 (621)	76.8	6.6 (486)	5.5 (622)
405	51-4122.00	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	89	17.8	6.7 (639)	23.2 (622)	76.8	6.2 (497)	5.1 (633)
406	51-3021.00	Butchers and Meat Cutters	294	17.8	14.3 (573)	23.1 (623)	76.9	12.2 (347)	11.0 (475)
407	53-6031.00	Automotive and Watercraft Service Attendants	208	17.7	0.0 (654)	23.1 (624)	76.9	0.0 (542)	0.0 (654)
408	45-4011.00	Forest and Conservation Workers	32	17.7	0.0 (654)	23.0 (625)	77.0	0.0 (542)	0.0 (654)
409	47-2044.00	Tile and Stone Setters	42	17.7	13.3 (583)	22.9 (626)	77.1	11.6 (365)	10.3 (500)
410	49-3022.00	Automotive Glass Installers and Repairers	60	17.7	0.0 (654)	22.9 (627)	77.1	0.0 (542)	0.0 (654)
411	29-2099.08	Patient Representatives	452	17.6	100.0 (1)	77.2 (217)	22.8	0.0 (542)	22.8 (152)
412	43-4061.00	Eligibility Interviewers, Government Programs	202	17.5	100.0 (1)	77.5 (216)	22.5	0.0 (542)	22.5 (164)
413	31-1132.00	Orderlies	163	17.4	0.0 (654)	22.5 (628)	77.5	0.0 (542)	0.0 (654)
414	25-4022.00	Librarians and Media Collections Specialists	118	17.4	92.6 (149)	77.5 (215)	22.5	6.9 (483)	20.8 (219)
415	11-9131.00	Postmasters and Mail Superintendents	10	17.4	100.0 (1)	77.6 (214)	22.4	0.0 (542)	22.4 (167)
416	29-1041.00	Optometrists	146	17.4	60.0 (371)	77.6 (213)	22.4	24.0 (77)	13.4 (413)
417	51-9198.00	Helpers–Production Workers	389	17.4	9.1 (618)	22.4 (629)	77.6	8.3 (441)	7.1 (590)
418	27-3091.00	Interpreters and Translators	189	17.4	87.5 (203)	77.7 (212)	22.3	10.9 (377)	19.6 (249)
419	19-1029.04	Biologists	13	17.3	66.7 (335)	77.7 (211)	22.3	22.2 (129)	14.9 (368)
420	17-2151.00	Mining and Geological Engineers, Including Mining Safety Engineers	10	17.3	88.9 (194)	77.7 (210)	22.3	9.9 (401)	19.8 (243)
421	29-1213.00	Dermatologists	45	17.3	75.0 (302)	77.7 (209)	22.3	18.8 (201)	16.7 (320)
422	29-1229.03	Urologists	51	17.3	64.3 (352)	77.8 (208)	22.2	23.0 (115)	14.3 (382)
423	19-1013.00	Soil and Plant Scientists	13	17.3	100.0 (1)	77.8 (207)	22.2	0.0 (542)	22.2 (174)
424	17-2199.07	Photonics Engineers	49	17.2	73.7 (314)	77.8 (206)	22.2	19.4 (195)	16.3 (332)
425	47-2042.00	Floor Layers, Except Carpet, Wood, and Hard Tiles	36	17.2	0.0 (654)	22.1 (630)	77.9	0.0 (542)	0.0 (654)
426	11-9021.00	Construction Managers	1,441	17.2	85.0 (227)	77.9 (205)	22.1	12.8 (340)	18.8 (269)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
427	51-7041.00	Sawing Machine Setters, Operators, and Tenders, Wood	14	17.2	10.0 (606)	22.1 (631)	77.9	9.0 (418)	7.8 (571)
428	13-2071.00	Credit Counselors	23	17.1	100.0 (1)	78.0 (204)	22.0	0.0 (542)	22.0 (180)
429	25-1065.00	Political Science Teachers, Postsecondary	21	17.1	78.9 (272)	78.1 (203)	21.9	16.6 (264)	17.3 (306)
430	49-9044.00	Millwrights	56	17.1	4.3 (652)	21.9 (632)	78.1	4.2 (536)	3.4 (653)
431	51-9022.00	Grinding and Polishing Workers, Hand	46	17.1	0.0 (654)	21.9 (633)	78.1	0.0 (542)	0.0 (654)
432	41-3031.00	Securities, Commodities, and Financial Services Sales Agents	255	17.1	100.0 (1)	78.1 (202)	21.9	0.0 (542)	21.9 (185)
433	35-3041.00	Food Servers, Nonrestaurant	170	17.0	15.4 (566)	21.8 (634)	78.2	13.0 (331)	12.0 (452)
434	29-1071.01	Anesthesiologist Assistants	31	17.0	40.0 (457)	21.7 (635)	78.3	24.0 (77)	31.3 (39)
435	13-2052.00	Personal Financial Advisors	494	17.0	94.1 (124)	78.4 (201)	21.6	5.5 (518)	20.4 (231)
436	39-5093.00	Shampooers	22	16.9	0.0 (654)	21.5 (636)	78.5	0.0 (542)	0.0 (654)
437	35-3011.00	Bartenders	904	16.9	25.0 (512)	21.5 (637)	78.5	18.8 (201)	19.6 (248)
438	39-5092.00	Manicurists and Pedicurists	85	16.9	11.1 (600)	21.5 (638)	78.5	9.9 (401)	8.7 (543)
439	51-7021.00	Furniture Finishers	40	16.8	0.0 (654)	21.3 (639)	78.7	0.0 (542)	0.0 (654)
440	47-2041.00	Carpet Installers	24	16.8	12.5 (588)	21.3 (640)	78.7	10.9 (377)	9.8 (511)
441	47-2181.00	Roofers	119	16.8	9.1 (618)	21.3 (641)	78.7	8.3 (441)	7.2 (589)
442	49-9043.00	Maintenance Workers, Machinery	46	16.7	17.6 (553)	21.2 (642)	78.8	14.5 (301)	13.9 (395)
443	43-4141.00	New Accounts Clerks	916	16.7	80.0 (265)	78.9 (200)	21.1	16.0 (273)	16.9 (317)
444	19-1031.00	Conservation Scientists	13	16.6	86.2 (221)	79.0 (199)	21.0	11.9 (361)	18.1 (287)
445	43-5032.00	Dispatchers, Except Police, Fire, and Ambulance	840	16.6	100.0 (1)	79.0 (198)	21.0	0.0 (542)	21.0 (212)
446	43-9061.00	Office Clerks, General	1,011	16.6	83.3 (243)	79.0 (197)	21.0	13.9 (305)	17.5 (303)
447	49-3053.00	Outdoor Power Equipment and Other Small Engine Mechanics	92	16.5	21.4 (535)	20.8 (643)	79.2	16.8 (253)	17.0 (312)
448	51-9195.00	Molders, Shapers, and Casters, Except Metal and Plastic	13	16.4	0.0 (654)	20.7 (644)	79.3	0.0 (542)	0.0 (654)
449	53-7062.00	Laborers and Freight, Stock, and Material Movers, Hand	1,264	16.3	0.0 (654)	20.5 (645)	79.5	0.0 (542)	0.0 (654)
450	19-1012.00	Food Scientists and Technologists	27	16.3	69.2 (330)	79.5 (196)	20.5	21.3 (160)	14.2 (389)
451	21-2011.00	Clergy	178	16.2	47.6 (427)	20.3 (646)	79.7	24.9 (23)	37.9 (8)
452	19-3051.00	Urban and Regional Planners	99	16.2	94.7 (121)	79.7 (195)	20.3	5.0 (526)	19.2 (258)
453	47-4071.00	Septic Tank Servicers and Sewer Pipe Cleaners	94	16.2	10.0 (606)	20.3 (647)	79.7	9.0 (418)	8.0 (564)
454	15-1231.00	Computer Network Support Specialists	191	16.1	80.8 (263)	79.9 (194)	20.1	15.5 (286)	16.3 (335)
455	19-1021.00	Biochemists and Biophysicists	39	16.1	80.0 (265)	79.9 (193)	20.1	16.0 (273)	16.1 (341)
456	43-1011.00	First-Line Supervisors of Office and Administrative Support Workers	1,030	16.0	89.5 (189)	79.9 (192)	20.1	9.4 (412)	18.0 (291)
457	51-6092.00	Fabric and Apparel Patternmakers	12	16.0	81.2 (259)	80.0 (191)	20.0	15.2 (290)	16.3 (334)
458	29-1031.00	Dietitians and Nutritionists	329	16.0	100.0 (1)	80.0 (190)	20.0	0.0 (542)	20.0 (236)
459	49-3093.00	Tire Repairers and Changers	347	16.0	0.0 (654)	19.9 (648)	80.1	0.0 (542)	0.0 (654)
460	19-1029.02	Molecular and Cellular Biologists	165	16.0	78.9 (272)	80.1 (189)	19.9	16.6 (264)	15.7 (349)
461	41-3021.00	Insurance Sales Agents	2,617	15.9	100.0 (1)	80.1 (188)	19.9	0.0 (542)	19.9 (240)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
462	53-7121.00	Tank Car, Truck, and Ship Loaders	85	15.9	11.1 (600)	19.8 (649)	80.2	9.9 (401)	8.9 (538)
463	41-3011.00	Advertising Sales Agents	371	15.9	89.5 (189)	80.2 (187)	19.8	9.4 (412)	17.7 (298)
464	11-3031.00	Financial Managers	668	15.8	100.0 (1)	80.3 (186)	19.7	0.0 (542)	19.7 (246)
465	51-9195.03	Stone Cutters and Carvers, Manufacturing	14	15.8	14.3 (573)	19.7 (650)	80.3	12.2 (347)	11.5 (463)
466	11-2022.00	Sales Managers	1,439	15.7	92.3 (152)	80.5 (185)	19.5	7.1 (472)	18.0 (289)
467	39-3093.00	Locker Room, Coatroom, and Dressing Room Attendants	48	15.7	12.5 (588)	19.5 (651)	80.5	10.9 (377)	10.1 (506)
468	41-9022.00	Real Estate Sales Agents	722	15.7	87.0 (212)	80.6 (184)	19.4	11.3 (374)	16.9 (315)
469	51-6021.00	Pressers, Textile, Garment, and Related Materials	18	15.6	0.0 (654)	19.4 (652)	80.6	0.0 (542)	0.0 (654)
470	47-2082.00	Tapers	29	15.5	0.0 (654)	19.2 (653)	80.8	0.0 (542)	0.0 (654)
471	51-3022.00	Meat, Poultry, and Fish Cutters and Trimmers	24	15.4	0.0 (654)	19.0 (654)	81.0	0.0 (542)	0.0 (654)
472	49-9098.00	Helpers–Installation, Maintenance, and Repair Workers	114	15.4	7.1 (634)	19.0 (655)	81.0	6.6 (486)	5.8 (615)
473	39-2021.00	Animal Caretakers	673	15.4	45.5 (436)	19.0 (656)	81.0	24.8 (37)	36.8 (14)
474	27-4031.00	Camera Operators, Television, Video, and Film	115	15.2	77.8 (284)	81.2 (183)	18.8	17.3 (243)	14.6 (373)
475	13-1151.00	Training and Development Specialists	1,025	15.2	100.0 (1)	81.2 (182)	18.8	0.0 (542)	18.8 (270)
476	19-2041.00	Environmental Scientists and Specialists, Including Health	138	15.2	100.0 (1)	81.3 (181)	18.7	0.0 (542)	18.7 (271)
477	11-9121.00	Natural Sciences Managers	269	15.2	100.0 (1)	81.3 (180)	18.7	0.0 (542)	18.7 (274)
478	43-4031.00	Court, Municipal, and License Clerks	272	15.2	96.0 (115)	81.3 (179)	18.7	3.8 (538)	17.9 (292)
479	13-1075.00	Labor Relations Specialists	32	15.2	92.0 (160)	81.4 (178)	18.6	7.4 (471)	17.2 (310)
480	29-1224.00	Radiologists	91	15.2	100.0 (1)	81.4 (177)	18.6	0.0 (542)	18.6 (275)
481	17-2199.05	Mechatronics Engineers	244	15.1	86.7 (215)	81.4 (176)	18.6	11.6 (365)	16.1 (342)
482	41-9021.00	Real Estate Brokers	14	15.1	100.0 (1)	81.4 (175)	18.6	0.0 (542)	18.6 (276)
483	51-9124.00	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	203	15.1	6.2 (643)	18.5 (657)	81.5	5.9 (509)	5.1 (635)
484	53-7061.00	Cleaners of Vehicles and Equipment	563	15.0	13.3 (583)	18.5 (658)	81.5	11.6 (365)	10.9 (480)
485	43-5061.00	Production, Planning, and Expediting Clerks	604	15.0	88.9 (194)	81.6 (174)	18.4	9.9 (401)	16.3 (331)
486	49-3021.00	Automotive Body and Related Repairers	277	15.0	9.1 (618)	18.3 (659)	81.7	8.3 (441)	7.4 (579)
487	47-2081.00	Drywall and Ceiling Tile Installers	29	14.8	9.1 (618)	18.1 (660)	81.9	8.3 (441)	7.4 (578)
488	39-9011.01	Nannies	959	14.8	16.7 (555)	18.0 (661)	82.0	13.9 (305)	13.7 (405)
489	11-9199.11	Brownfield Redevelopment Specialists and Site Managers	24	14.8	90.0 (181)	82.0 (173)	18.0	9.0 (418)	16.2 (336)
490	19-1041.00	Epidemiologists	133	14.7	90.9 (169)	82.0 (172)	18.0	8.3 (441)	16.3 (330)
491	13-2053.00	Insurance Underwriters	174	14.7	100.0 (1)	82.1 (171)	17.9	0.0 (542)	17.9 (293)
492	17-2111.02	Fire-Prevention and Protection Engineers	28	14.6	100.0 (1)	82.2 (170)	17.8	0.0 (542)	17.8 (296)
493	35-2021.00	Food Preparation Workers	1,222	14.6	4.3 (652)	17.8 (662)	82.2	4.2 (536)	3.6 (652)
494	33-9021.00	Private Detectives and Investigators	106	14.6	80.0 (265)	82.3 (169)	17.7	16.0 (273)	14.2 (390)
495	47-2131.00	Insulation Workers, Floor, Ceiling, and Wall	36	14.5	10.0 (606)	17.6 (663)	82.4	9.0 (418)	8.2 (555)
496	17-2111.00	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	48	14.5	87.0 (212)	82.4 (168)	17.6	11.3 (374)	15.3 (360)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
497	45-2093.00	Farmworkers, Farm, Ranch, and Aquacultural Animals	98	14.5	10.0 (606)	17.6 (664)	82.4	9.0 (418)	8.2 (554)
498	29-2055.00	Surgical Technologists	510	14.4	7.1 (634)	17.5 (665)	82.5	6.6 (486)	5.9 (613)
499	53-7063.00	Machine Feeders and Offbearers	82	14.4	11.1 (600)	17.4 (666)	82.6	9.9 (401)	9.2 (533)
500	29-1217.00	Neurologists	101	14.3	90.9 (169)	82.7 (167)	17.3	8.3 (441)	15.8 (347)
501	19-3094.00	Political Scientists	99	14.3	90.0 (181)	82.8 (166)	17.2	9.0 (418)	15.5 (354)
502	43-6013.00	Medical Secretaries and Administrative Assistants	4,540	14.2	100.0 (1)	82.8 (165)	17.2	0.0 (542)	17.2 (309)
503	13-1011.00	Agents and Business Managers of Artists, Performers, and Athletes	10	14.2	88.9 (194)	82.8 (164)	17.2	9.9 (401)	15.3 (361)
504	17-2051.00	Civil Engineers	409	14.1	81.8 (254)	83.0 (163)	17.0	14.9 (293)	13.9 (392)
505	53-7062.04	Recycling and Reclamation Workers	80	14.1	0.0 (654)	17.0 (667)	83.0	0.0 (542)	0.0 (654)
506	13-1041.03	Equal Opportunity Representatives and Officers	43	14.1	81.8 (254)	83.0 (162)	17.0	14.9 (293)	13.9 (396)
507	11-9199.10	Wind Energy Development Managers	12	14.1	100.0 (1)	83.1 (161)	16.9	0.0 (542)	16.9 (313)
508	53-7021.00	Crane and Tower Operators	51	14.0	25.0 (512)	16.9 (668)	83.1	18.8 (201)	20.8 (222)
509	19-2012.00	Physicists	23	14.0	100.0 (1)	83.2 (160)	16.8	0.0 (542)	16.8 (319)
510	43-4051.00	Customer Service Representatives	2,206	13.9	100.0 (1)	83.3 (159)	16.7	0.0 (542)	16.7 (322)
511	13-1041.00	Compliance Officers	154	13.9	100.0 (1)	83.3 (158)	16.7	0.0 (542)	16.7 (323)
512	13-1131.00	Fundraisers	335	13.9	91.7 (161)	83.4 (157)	16.6	7.6 (459)	15.3 (363)
513	43-4011.00	Brokerage Clerks	215	13.8	100.0 (1)	83.4 (156)	16.6	0.0 (542)	16.6 (324)
514	33-9091.00	Crossing Guards and Flaggers	132	13.8	14.3 (573)	16.6 (669)	83.4	12.2 (347)	11.9 (455)
515	23-1011.00	Lawyers	1,061	13.8	83.3 (243)	83.5 (155)	16.5	13.9 (305)	13.8 (398)
516	45-2092.00	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	122	13.8	16.7 (555)	16.5 (670)	83.5	13.9 (305)	13.9 (393)
517	47-3012.00	Helpers–Carpenters	68	13.7	0.0 (654)	16.5 (671)	83.5	0.0 (542)	0.0 (654)
518	11-3051.01	Quality Control Systems Managers	449	13.7	96.2 (114)	83.6 (154)	16.4	3.7 (540)	15.8 (345)
519	35-2014.00	Cooks, Restaurant	2,358	13.7	11.8 (597)	16.4 (672)	83.6	10.4 (395)	9.8 (510)
520	41-9031.00	Sales Engineers	736	13.7	84.2 (236)	83.6 (153)	16.4	13.3 (322)	13.8 (400)
521	27-3092.00	Court Reporters and Simultaneous Captioners	28	13.7	100.0 (1)	83.6 (152)	16.4	0.0 (542)	16.4 (329)
522	43-6014.00	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	2,617	13.7	90.0 (181)	83.7 (151)	16.3	9.0 (418)	14.7 (372)
523	47-5022.00	Excavating and Loading Machine and Dragline Operators, Surface Mining	17	13.6	0.0 (654)	16.3 (673)	83.7	0.0 (542)	0.0 (654)
524	41-9041.00	Telemarketers	356	13.6	100.0 (1)	83.7 (150)	16.3	0.0 (542)	16.3 (333)
525	13-2072.00	Loan Officers	734	13.6	100.0 (1)	83.8 (149)	16.2	0.0 (542)	16.2 (337)
526	43-5053.00	Postal Service Mail Sorters, Processors, and Processing Machine Operators	38	13.6	0.0 (654)	16.2 (674)	83.8	0.0 (542)	0.0 (654)
527	35-2015.00	Cooks, Short Order	288	13.6	0.0 (654)	16.2 (675)	83.8	0.0 (542)	0.0 (654)
528	19-2032.00	Materials Scientists	45	13.5	84.6 (232)	83.9 (148)	16.1	13.0 (331)	13.7 (404)
529	19-3099.01	Transportation Planners	36	13.5	95.2 (118)	83.9 (147)	16.1	4.5 (532)	15.3 (359)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
530	47-4061.00	Rail-Track Laying and Maintenance Equipment Operators	21	13.5	0.0 (654)	16.1 (676)	83.9	0.0 (542)	0.0 (654)
531	47-2141.00	Painters, Construction and Maintenance	230	13.4	6.2 (643)	16.0 (677)	84.0	5.9 (509)	5.3 (630)
532	43-4151.00	Order Clerks	719	13.4	100.0 (1)	84.0 (146)	16.0	0.0 (542)	16.0 (344)
533	47-2132.00	Insulation Workers, Mechanical	13	13.3	11.1 (600)	15.9 (678)	84.1	9.9 (401)	9.3 (525)
534	13-1081.00	Logisticians	158	13.3	90.9 (169)	84.1 (145)	15.9	8.3 (441)	14.4 (376)
535	47-3013.00	Helpers–Electricians	77	13.3	0.0 (654)	15.8 (679)	84.2	0.0 (542)	0.0 (654)
536	25-9031.00	Instructional Coordinators	377	13.3	60.0 (371)	84.3 (144)	15.7	24.0 (77)	9.4 (522)
537	17-2131.00	Materials Engineers	26	13.3	85.0 (227)	84.3 (143)	15.7	12.8 (340)	13.4 (414)
538	19-2043.00	Hydrologists	13	13.2	87.0 (212)	84.4 (142)	15.6	11.3 (374)	13.5 (408)
539	11-9041.00	Architectural and Engineering Managers	803	13.1	92.9 (143)	84.5 (141)	15.5	6.6 (486)	14.4 (378)
540	25-4011.00	Archivists	16	13.1	92.3 (152)	84.5 (140)	15.5	7.1 (472)	14.3 (380)
541	43-5011.00	Cargo and Freight Agents	239	13.1	100.0 (1)	84.5 (139)	15.5	0.0 (542)	15.5 (355)
542	47-2021.00	Brickmasons and Blockmasons	21	13.1	8.3 (626)	15.4 (680)	84.6	7.6 (459)	7.0 (591)
543	35-2011.00	Cooks, Fast Food	489	13.0	0.0 (654)	15.4 (681)	84.6	0.0 (542)	0.0 (654)
544	43-3061.00	Procurement Clerks	246	13.0	100.0 (1)	84.6 (138)	15.4	0.0 (542)	15.4 (358)
545	17-2041.00	Chemical Engineers	80	13.0	84.6 (232)	84.7 (137)	15.3	13.0 (331)	13.0 (421)
546	17-1022.00	Surveyors	47	13.0	85.7 (222)	84.7 (136)	15.3	12.2 (347)	13.1 (418)
547	17-2081.00	Environmental Engineers	60	12.9	100.0 (1)	84.7 (135)	15.3	0.0 (542)	15.3 (362)
548	11-3012.00	Administrative Services Managers	163	12.9	60.0 (371)	84.7 (134)	15.3	24.0 (77)	9.2 (534)
549	17-2051.01	Transportation Engineers	175	12.9	100.0 (1)	84.7 (133)	15.3	0.0 (542)	15.3 (364)
550	29-9092.00	Genetic Counselors	12	12.9	89.5 (189)	84.8 (132)	15.2	9.4 (412)	13.6 (406)
551	11-3121.00	Human Resources Managers	672	12.9	91.7 (161)	84.8 (131)	15.2	7.6 (459)	14.0 (391)
552	17-2199.06	Microsystems Engineers	18	12.8	100.0 (1)	84.9 (130)	15.1	0.0 (542)	15.1 (367)
553	17-2141.02	Automotive Engineers	105	12.8	96.0 (115)	84.9 (129)	15.1	3.8 (538)	14.5 (375)
554	17-2071.00	Electrical Engineers	414	12.7	80.0 (265)	85.1 (128)	14.9	16.0 (273)	11.9 (454)
555	43-4071.00	File Clerks	81	12.6	93.3 (136)	85.3 (127)	14.7	6.2 (497)	13.8 (401)
556	11-3031.03	Investment Fund Managers	28	12.6	100.0 (1)	85.3 (126)	14.7	0.0 (542)	14.7 (371)
557	11-3131.00	Training and Development Managers	287	12.5	90.0 (181)	85.4 (125)	14.6	9.0 (418)	13.1 (417)
558	17-2161.00	Nuclear Engineers	18	12.4	85.0 (227)	85.4 (124)	14.6	12.8 (340)	12.4 (446)
559	27-3031.00	Public Relations Specialists	851	12.4	93.3 (136)	85.5 (123)	14.5	6.2 (497)	13.5 (410)
560	17-2011.00	Aerospace Engineers	256	12.3	90.0 (181)	85.6 (122)	14.4	9.0 (418)	12.9 (426)
561	47-2073.00	Operating Engineers and Other Construction Equipment Operators	507	12.3	5.6 (647)	14.3 (682)	85.7	5.2 (524)	4.8 (640)
562	47-3015.00	Helpers–Pipelayers, Plumbers, Pipefitters, and Steamfitters	71	12.2	0.0 (654)	14.3 (683)	85.7	0.0 (542)	0.0 (654)
563	17-2051.02	Water/Wastewater Engineers	158	12.2	92.6 (149)	85.7 (121)	14.3	6.9 (483)	13.2 (416)
564	47-4051.00	Highway Maintenance Workers	240	12.2	0.0 (654)	14.3 (684)	85.7	0.0 (542)	0.0 (654)
565	23-1012.00	Judicial Law Clerks	11	12.2	100.0 (1)	85.7 (120)	14.3	0.0 (542)	14.3 (383)
566	47-4031.00	Fence Erectors	45	12.2	5.3 (648)	14.3 (685)	85.7	5.0 (526)	4.5 (645)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
567	27-2012.00	Producers and Directors	160	12.2	70.6 (323)	85.8 (119)	14.2	20.8 (173)	10.0 (508)
568	13-1199.06	Online Merchants	109	12.2	87.5 (203)	85.8 (118)	14.2	10.9 (377)	12.4 (445)
569	47-5071.00	Roustabouts, Oil and Gas	11	12.1	0.0 (654)	14.1 (686)	85.9	0.0 (542)	0.0 (654)
570	17-2072.00	Electronics Engineers, Except Computer	467	12.1	84.6 (232)	86.0 (117)	14.0	13.0 (331)	11.9 (456)
571	15-1241.01	Telecommunications Engineering Specialists	168	12.0	90.5 (178)	86.0 (116)	14.0	8.6 (437)	12.7 (437)
572	11-9121.01	Clinical Research Coordinators	428	12.0	88.5 (200)	86.0 (115)	14.0	10.2 (400)	12.4 (447)
573	47-2221.00	Structural Iron and Steel Workers	32	12.0	6.7 (639)	13.9 (687)	86.1	6.2 (497)	5.7 (617)
574	19-1029.03	Geneticists	12	12.0	78.9 (272)	86.1 (114)	13.9	16.6 (264)	11.0 (476)
575	17-2141.00	Mechanical Engineers	527	12.0	93.3 (136)	86.1 (113)	13.9	6.2 (497)	13.0 (423)
576	47-2151.00	Pipelayers	61	11.9	7.1 (634)	13.9 (688)	86.1	6.6 (486)	6.2 (608)
577	15-1232.00	Computer User Support Specialists	1,585	11.9	81.8 (254)	86.2 (112)	13.8	14.9 (293)	11.3 (468)
578	17-2112.03	Manufacturing Engineers	486	11.9	91.3 (168)	86.2 (111)	13.8	7.9 (457)	12.6 (440)
579	17-2199.08	Robotics Engineers	63	11.9	75.0 (302)	86.2 (110)	13.8	18.8 (201)	10.3 (497)
580	53-5011.00	Sailors and Marine Oilers	30	11.8	5.3 (648)	13.7 (689)	86.3	5.0 (526)	4.5 (644)
581	27-1022.00	Fashion Designers	42	11.7	75.0 (302)	86.4 (109)	13.6	18.8 (201)	10.2 (504)
582	17-2199.03	Energy Engineers, Except Wind and Solar	44	11.7	100.0 (1)	86.5 (108)	13.5	0.0 (542)	13.5 (409)
583	27-1025.00	Interior Designers	122	11.7	100.0 (1)	86.5 (107)	13.5	0.0 (542)	13.5 (412)
584	43-6011.00	Executive Secretaries and Executive Administrative Assistants	1,218	11.6	93.3 (136)	86.6 (106)	13.4	6.2 (497)	12.5 (443)
585	49-9051.00	Electrical Power-Line Installers and Repairers	88	11.6	0.0 (654)	13.4 (690)	86.6	0.0 (542)	0.0 (654)
586	51-9192.00	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	103	11.6	12.5 (588)	13.4 (691)	86.6	10.9 (377)	10.8 (481)
587	19-3032.00	Industrial-Organizational Psychologists	42	11.6	90.0 (181)	86.7 (105)	13.3	9.0 (418)	12.0 (453)
588	19-1042.00	Medical Scientists, Except Epidemiologists	89	11.3	87.5 (203)	87.0 (104)	13.0	10.9 (377)	11.4 (465)
589	43-9111.00	Statistical Assistants	10	11.3	100.0 (1)	87.0 (103)	13.0	0.0 (542)	13.0 (424)
590	43-3011.00	Bill and Account Collectors	458	11.3	100.0 (1)	87.1 (102)	12.9	0.0 (542)	12.9 (428)
591	11-3071.04	Supply Chain Managers	215	11.3	100.0 (1)	87.1 (101)	12.9	0.0 (542)	12.9 (429)
592	11-2011.00	Advertising and Promotions Managers	375	11.2	100.0 (1)	87.1 (100)	12.9	0.0 (542)	12.9 (431)
593	15-1211.01	Health Informatics Specialists	48	11.1	100.0 (1)	87.2 (99)	12.8	0.0 (542)	12.8 (434)
594	37-2012.00	Maids and Housekeeping Cleaners	2,752	11.1	0.0 (654)	12.7 (692)	87.3	0.0 (542)	0.0 (654)
595	51-6011.00	Laundry and Dry-Cleaning Workers	301	11.1	0.0 (654)	12.7 (693)	87.3	0.0 (542)	0.0 (654)
596	31-9094.00	Medical Transcriptionists	97	11.0	92.3 (152)	87.4 (98)	12.6	7.1 (472)	11.7 (458)
597	39-4021.00	Funeral Attendants	35	10.9	10.5 (605)	12.5 (694)	87.5	9.4 (412)	9.2 (531)
598	43-9022.00	Word Processors and Typists	31	10.9	76.5 (295)	87.5 (97)	12.5	18.0 (226)	9.5 (520)
599	13-1199.05	Sustainability Specialists	44	10.9	100.0 (1)	87.5 (96)	12.5	0.0 (542)	12.5 (444)
600	17-2031.00	Bioengineers and Biomedical Engineers	74	10.9	88.9 (194)	87.6 (95)	12.4	9.9 (401)	11.1 (473)
601	11-3021.00	Computer and Information Systems Managers	1,014	10.8	93.8 (129)	87.6 (94)	12.4	5.9 (509)	11.6 (460)
602	17-2199.11	Solar Energy Systems Engineers	13	10.8	83.3 (243)	87.6 (93)	12.4	13.9 (305)	10.3 (498)
603	45-2091.00	Agricultural Equipment Operators	77	10.8	0.0 (654)	12.3 (695)	87.7	0.0 (542)	0.0 (654)
604	11-1011.03	Chief Sustainability Officers	22	10.8	94.4 (123)	87.7 (92)	12.3	5.2 (524)	11.6 (461)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
605	43-4161.00	Human Resources Assistants, Except Payroll and Timekeeping	715	10.8	100.0 (1)	87.7 (91)	12.3	0.0 (542)	12.3 (449)
606	43-6012.00	Legal Secretaries and Administrative Assistants	286	10.7	100.0 (1)	87.8 (90)	12.2	0.0 (542)	12.2 (450)
607	47-2071.00	Paving, Surfacing, and Tamping Equipment Operators	37	10.7	0.0 (654)	12.2 (696)	87.8	0.0 (542)	0.0 (654)
608	35-9011.00	Dining Room and Cafeteria Attendants and Bartender Helpers	1,110	10.6	0.0 (654)	12.1 (697)	87.9	0.0 (542)	0.0 (654)
609	41-3041.00	Travel Agents	138	10.6	100.0 (1)	87.9 (89)	12.1	0.0 (542)	12.1 (451)
610	13-1071.00	Human Resources Specialists	1,565	10.3	94.7 (121)	88.3 (88)	11.7	5.0 (526)	11.1 (472)
611	43-4131.00	Loan Interviewers and Clerks	547	10.3	100.0 (1)	88.3 (87)	11.7	0.0 (542)	11.7 (459)
612	17-1011.00	Architects, Except Landscape and Naval	163	10.2	89.5 (189)	88.5 (86)	11.5	9.4 (412)	10.3 (496)
613	19-4061.00	Social Science Research Assistants	95	10.2	100.0 (1)	88.5 (85)	11.5	0.0 (542)	11.5 (462)
614	13-1111.00	Management Analysts	1,372	10.1	70.0 (326)	88.6 (84)	11.4	21.0 (166)	8.0 (565)
615	47-5081.00	Helpers–Extraction Workers	24	10.1	0.0 (654)	11.4 (698)	88.6	0.0 (542)	0.0 (654)
616	13-2041.00	Credit Analysts	193	10.0	100.0 (1)	88.7 (83)	11.3	0.0 (542)	11.3 (467)
617	37-3011.00	Landscaping and Groundskeeping Workers	870	10.0	0.0 (654)	11.3 (699)	88.7	0.0 (542)	0.0 (654)
618	17-3012.00	Electrical and Electronics Drafters	101	10.0	100.0 (1)	88.8 (82)	11.2	0.0 (542)	11.2 (470)
619	27-1011.00	Art Directors	158	10.0	92.3 (152)	88.8 (81)	11.2	7.1 (472)	10.4 (495)
620	49-9096.00	Riggers	22	10.0	0.0 (654)	11.2 (700)	88.8	0.0 (542)	0.0 (654)
621	11-9199.02	Compliance Managers	867	9.8	95.0 (120)	89.0 (80)	11.0	4.8 (530)	10.4 (493)
622	43-9021.00	Data Entry Keyers	653	9.8	100.0 (1)	89.0 (79)	11.0	0.0 (542)	11.0 (477)
623	43-9041.00	Insurance Claims and Policy Processing Clerks	571	9.7	100.0 (1)	89.1 (78)	10.9	0.0 (542)	10.9 (478)
624	27-2012.03	Media Programming Directors	22	9.7	93.8 (129)	89.1 (77)	10.9	5.9 (509)	10.2 (501)
625	47-2061.00	Construction Laborers	638	9.6	25.0 (512)	10.7 (701)	89.3	18.8 (201)	22.3 (170)
626	43-3031.00	Bookkeeping, Accounting, and Auditing Clerks	2,140	9.6	100.0 (1)	89.3 (76)	10.7	0.0 (542)	10.7 (484)
627	17-2112.02	Validation Engineers	398	9.6	90.0 (181)	89.3 (75)	10.7	9.0 (418)	9.6 (515)
628	13-2099.04	Fraud Examiners, Investigators and Analysts	165	9.5	90.5 (178)	89.4 (74)	10.6	8.6 (437)	9.6 (516)
629	19-2021.00	Atmospheric and Space Scientists	25	9.4	100.0 (1)	89.5 (73)	10.5	0.0 (542)	10.5 (489)
630	13-1199.04	Business Continuity Planners	55	9.4	100.0 (1)	89.5 (72)	10.5	0.0 (542)	10.5 (492)
631	43-9031.00	Desktop Publishers	26	9.3	100.0 (1)	89.6 (71)	10.4	0.0 (542)	10.4 (494)
632	43-3021.00	Billing and Posting Clerks	599	9.3	83.3 (243)	89.7 (70)	10.3	13.9 (305)	8.6 (546)
633	11-3061.00	Purchasing Managers	449	9.2	94.1 (124)	89.8 (69)	10.2	5.5 (518)	9.6 (517)
634	13-1081.02	Logistics Analysts	233	9.2	100.0 (1)	89.8 (68)	10.2	0.0 (542)	10.2 (503)
635	15-1244.00	Network and Computer Systems Administrators	924	9.2	94.1 (124)	89.8 (67)	10.2	5.5 (518)	9.6 (518)
636	47-3016.00	Helpers–Roofers	22	9.2	0.0 (654)	10.2 (702)	89.8	0.0 (542)	0.0 (654)
637	17-2112.00	Industrial Engineers	182	9.1	100.0 (1)	89.8 (66)	10.2	0.0 (542)	10.2 (505)
638	17-3013.00	Mechanical Drafters	189	9.1	92.9 (143)	89.9 (65)	10.1	6.6 (486)	9.4 (523)
639	27-1021.00	Commercial and Industrial Designers	38	9.0	91.7 (161)	89.9 (64)	10.1	7.6 (459)	9.2 (530)
640	13-2061.00	Financial Examiners	101	8.8	93.8 (129)	90.2 (63)	9.8	5.9 (509)	9.2 (532)
641	23-2011.00	Paralegals and Legal Assistants	778	8.8	87.5 (203)	90.2 (62)	9.8	10.9 (377)	8.5 (549)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
642	33-3021.06	Intelligence Analysts	206	8.7	100.0 (1)	90.3 (61)	9.7	0.0 (542)	9.7 (512)
643	13-2082.00	Tax Preparers	390	8.7	100.0 (1)	90.3 (60)	9.7	0.0 (542)	9.7 (513)
644	13-2011.00	Accountants and Auditors	3,367	8.7	100.0 (1)	90.4 (59)	9.6	0.0 (542)	9.6 (514)
645	19-3041.00	Sociologists	17	8.7	92.3 (152)	90.4 (58)	9.6	7.1 (472)	8.9 (539)
646	11-2021.00	Marketing Managers	1,355	8.7	91.7 (161)	90.4 (57)	9.6	7.6 (459)	8.8 (542)
647	15-2031.00	Operations Research Analysts	102	8.6	100.0 (1)	90.4 (56)	9.6	0.0 (542)	9.6 (519)
648	27-4032.00	Film and Video Editors	70	8.6	100.0 (1)	90.5 (55)	9.5	0.0 (542)	9.5 (521)
649	13-1141.00	Compensation, Benefits, and Job Analysis Specialists	292	8.5	85.7 (222)	90.6 (54)	9.4	12.2 (347)	8.0 (562)
650	17-3011.00	Architectural and Civil Drafters	230	8.5	95.5 (117)	90.7 (53)	9.3	4.3 (535)	8.9 (540)
651	47-3014.00	Helpers–Painters, Paperhangers, Plasterers, and Stucco Masons	47	8.4	0.0 (654)	9.3 (703)	90.7	0.0 (542)	0.0 (654)
652	13-1051.00	Cost Estimators	585	8.4	100.0 (1)	90.7 (52)	9.3	0.0 (542)	9.3 (528)
653	13-1031.00	Claims Adjusters, Examiners, and Investigators	507	8.4	95.2 (118)	90.7 (51)	9.3	4.5 (532)	8.8 (541)
654	43-4041.00	Credit Authorizers, Checkers, and Clerks	18	8.4	100.0 (1)	90.8 (50)	9.2	0.0 (542)	9.2 (529)
655	15-1211.00	Computer Systems Analysts	2,662	8.3	91.7 (161)	90.8 (49)	9.2	7.6 (459)	8.4 (551)
656	15-2011.00	Actuaries	148	8.3	100.0 (1)	90.9 (48)	9.1	0.0 (542)	9.1 (535)
657	47-2051.00	Cement Masons and Concrete Finishers	104	8.3	0.0 (654)	9.1 (704)	90.9	0.0 (542)	0.0 (654)
658	23-2093.00	Title Examiners, Abstractors, and Searchers	38	8.2	90.9 (169)	90.9 (47)	9.1	8.3 (441)	8.2 (556)
659	43-5011.01	Freight Forwarders	63	8.2	100.0 (1)	91.0 (46)	9.0	0.0 (542)	9.0 (536)
660	11-3031.01	Treasurers and Controllers	926	8.1	93.8 (129)	91.1 (45)	8.9	5.9 (509)	8.3 (553)
661	15-1299.09	Information Technology Project Managers	2,070	7.9	100.0 (1)	91.3 (44)	8.7	0.0 (542)	8.7 (545)
662	15-1212.00	Information Security Analysts	301	7.9	100.0 (1)	91.4 (43)	8.6	0.0 (542)	8.6 (547)
663	37-3013.00	Tree Trimmers and Pruners	224	7.8	6.7 (639)	8.5 (705)	91.5	6.2 (497)	6.1 (609)
664	17-2061.00	Computer Hardware Engineers	193	7.7	93.3 (136)	91.6 (42)	8.4	6.2 (497)	7.8 (570)
665	37-2011.00	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	3,124	7.6	0.0 (654)	8.3 (706)	91.7	0.0 (542)	0.0 (654)
666	15-1299.03	Document Management Specialists	148	7.5	100.0 (1)	91.8 (41)	8.2	0.0 (542)	8.2 (557)
667	43-4021.00	Correspondence Clerks	20	7.5	100.0 (1)	91.8 (40)	8.2	0.0 (542)	8.2 (558)
668	15-1299.02	Geographic Information Systems Technologists and Technicians	131	7.4	100.0 (1)	91.9 (39)	8.1	0.0 (542)	8.1 (560)
669	27-1014.00	Special Effects Artists and Animators	62	7.4	100.0 (1)	92.0 (38)	8.0	0.0 (542)	8.0 (561)
670	15-1299.08	Computer Systems Engineers/Architects	2,704	7.3	100.0 (1)	92.1 (37)	7.9	0.0 (542)	7.9 (566)
671	27-3023.00	News Analysts, Reporters, and Journalists	142	7.3	100.0 (1)	92.1 (36)	7.9	0.0 (542)	7.9 (567)
672	11-3111.00	Compensation and Benefits Managers	137	7.3	92.9 (143)	92.1 (35)	7.9	6.6 (486)	7.3 (582)
673	13-1161.00	Market Research Analysts and Marketing Specialists	399	7.2	100.0 (1)	92.1 (34)	7.9	0.0 (542)	7.9 (568)
674	15-1241.00	Computer Network Architects	409	7.1	93.5 (135)	92.3 (33)	7.7	6.0 (508)	7.2 (588)
675	13-2081.00	Tax Examiners and Collectors, and Revenue Agents	39	7.0	100.0 (1)	92.5 (32)	7.5	0.0 (542)	7.5 (577)
676	13-1041.07	Regulatory Affairs Specialists	216	6.8	100.0 (1)	92.6 (31)	7.4	0.0 (542)	7.4 (580)

Full notes at the end of the table.

Table E.1, continued

Rank	O*NET-SOC	Occupation	Postings (thousands)	Pressure	Catalog exposure (rank)	Posting exposure (rank)	AI-infeasible share	Catalog-only pressure (rank)	Hybrid pressure (rank)
677	15-1251.00	Computer Programmers	101	6.8	100.0 (1)	92.6 (30)	7.4	0.0 (542)	7.4 (581)
678	15-1221.00	Computer and Information Research Scientists	162	6.8	90.9 (169)	92.6 (29)	7.4	8.3 (441)	6.7 (597)
679	27-1024.00	Graphic Designers	448	6.8	100.0 (1)	92.7 (28)	7.3	0.0 (542)	7.3 (583)
680	15-2051.02	Clinical Data Managers	67	6.8	100.0 (1)	92.7 (27)	7.3	0.0 (542)	7.3 (584)
681	19-3022.00	Survey Researchers	38	6.7	100.0 (1)	92.8 (26)	7.2	0.0 (542)	7.2 (586)
682	19-3011.00	Economists	84	6.5	100.0 (1)	93.0 (25)	7.0	0.0 (542)	7.0 (592)
683	13-1081.01	Logistics Engineers	49	6.5	100.0 (1)	93.0 (24)	7.0	0.0 (542)	7.0 (593)
684	13-1041.08	Customs Brokers	45	6.3	100.0 (1)	93.2 (23)	6.8	0.0 (542)	6.8 (595)
685	43-9081.00	Proofreaders and Copy Markers	14	6.1	100.0 (1)	93.5 (22)	6.5	0.0 (542)	6.5 (600)
686	43-3051.00	Payroll and Timekeeping Clerks	407	6.0	100.0 (1)	93.6 (21)	6.4	0.0 (542)	6.4 (601)
687	13-2031.00	Budget Analysts	268	5.9	100.0 (1)	93.7 (20)	6.3	0.0 (542)	6.3 (603)
688	15-2041.01	Biostatisticians	114	5.9	100.0 (1)	93.7 (19)	6.3	0.0 (542)	6.3 (604)
689	11-9199.01	Regulatory Affairs Managers	88	5.8	100.0 (1)	93.8 (18)	6.2	0.0 (542)	6.2 (607)
690	19-1029.01	Bioinformatics Scientists	65	5.7	100.0 (1)	93.9 (17)	6.1	0.0 (542)	6.1 (610)
691	19-2099.01	Remote Sensing Scientists and Technologists	27	5.6	90.9 (169)	94.0 (16)	6.0	8.3 (441)	5.5 (623)
692	27-3041.00	Editors	183	5.5	92.3 (152)	94.1 (15)	5.9	7.1 (472)	5.4 (624)
693	17-2112.01	Human Factors Engineers and Ergonomists	80	5.5	87.5 (203)	94.2 (14)	5.8	10.9 (377)	5.1 (634)
694	15-2051.01	Business Intelligence Analysts	1,526	5.4	100.0 (1)	94.2 (13)	5.8	0.0 (542)	5.8 (616)
695	15-1243.00	Database Architects	552	5.4	100.0 (1)	94.3 (12)	5.7	0.0 (542)	5.7 (620)
696	27-3042.00	Technical Writers	237	5.1	93.3 (136)	94.6 (11)	5.4	6.2 (497)	5.0 (636)
697	47-3011.00	Helpers–Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	15	5.1	0.0 (654)	5.4 (707)	94.6	0.0 (542)	0.0 (654)
698	13-1161.01	Search Marketing Strategists	673	5.1	100.0 (1)	94.6 (10)	5.4	0.0 (542)	5.4 (626)
699	27-3043.00	Writers and Authors	211	5.0	100.0 (1)	94.7 (9)	5.3	0.0 (542)	5.3 (627)
700	13-2099.01	Financial Quantitative Analysts	76	5.0	100.0 (1)	94.7 (8)	5.3	0.0 (542)	5.3 (629)
701	15-2041.00	Statisticians	33	5.0	100.0 (1)	94.8 (7)	5.2	0.0 (542)	5.2 (631)
702	15-1253.00	Software Quality Assurance Analysts and Testers	862	4.9	96.3 (113)	94.9 (6)	5.1	3.6 (541)	4.9 (638)
703	15-1243.01	Data Warehousing Specialists	632	4.7	100.0 (1)	95.0 (5)	5.0	0.0 (542)	5.0 (637)
704	35-9021.00	Dishwashers	1,397	4.7	0.0 (654)	4.9 (708)	95.1	0.0 (542)	0.0 (654)
705	15-1299.01	Web Administrators	83	4.6	100.0 (1)	95.2 (4)	4.8	0.0 (542)	4.8 (639)
706	15-1255.01	Video Game Designers	13	4.5	100.0 (1)	95.3 (3)	4.7	0.0 (542)	4.7 (642)
707	15-1254.00	Web Developers	817	4.4	100.0 (1)	95.4 (2)	4.6	0.0 (542)	4.6 (643)
708	15-1242.00	Database Administrators	225	4.2	100.0 (1)	95.6 (1)	4.4	0.0 (542)	4.4 (646)

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold, binary at the task level. Catalog exposure is the AI-feasible share of the occupation's core O*NET tasks, equally weighted; posting exposure is the AI-feasible share of its posted task mentions. Pressure is posting exposure times one minus posting exposure. The AI-infeasible share is one minus posting exposure. The catalog-only benchmark is catalog exposure times one minus catalog exposure. Hybrid pressure is catalog exposure times the AI-infeasible share from postings. All scores are on a 0–100 scale. Occupations are sorted by postings-only pressure. Ranks in parentheses rank occupations by the exposure or pressure measure in that column, among the same 708 occupations. Ranks use unrounded scores, with rank 1 assigned to the highest value and ties sharing the minimum rank; subsequent ranks are skipped. Occupation code orders exact ties. Identical displayed scores can have different ranks because scores are rounded. All 708 occupations are ranked. The lowest catalog-exposure rank is 654 because 55 occupations tie at zero exposure. Differences between catalog and posting exposure can reflect matching error and errors in assigning postings to occupations, as well as the work employers advertise (Sections 3.3 and 6). O*NET-SOC is the detailed O*NET occupation code. Specialties that share its first six digits are separate occupations.

Table E.2: The 100 AI-infeasible tasks with the highest average pressure

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
1	Discuss data presentation requirements with clients	373	102	89.9	0.039	1
2	Implement or test design solutions	303	64	87.9	0.024	3
3	Discuss project goals, equipment requirements, or methodologies with colleagues or team members	379	103	86.8	0.038	4
4	Confer with realtors, lending institution personnel, buyers, sellers, contractors, surveyors, and courthouse personnel to exchange title-related information or to resolve problems	191	58	85.2	0.021	10
5	Direct and participate in formal and informal meetings with bank directors, trustees, senior management, counsels, outside accountants, and consultants to gather information and discuss findings	233	64	84.3	0.023	6
6	Supervise legal assistants	126	63	84.3	0.022	7
7	Present project plans or designs to public stakeholders, such as government agencies or community groups	382	68	84.0	0.024	9
8	Consult with, or serve as, technical liaison between business, industry, government, and union officials	585	497	83.7	0.175	11
9	Supervise technical personnel and postdoctoral research fellows	411	99	83.5	0.035	12
10	Meet with job search committees or coordinators to explain the role of the equal opportunity coordinator, to provide resources for advertising, or to explain expectations for future contacts	391	59	83.4	0.021	17
11	Conduct field demonstrations of new products, techniques, or services	323	67	83.2	0.023	16
12	Test experimental models under simulated operating conditions, for purposes such as development, standardization, or feasibility of design	239	51	82.8	0.018	
13	Supervise loan personnel	117	69	82.5	0.024	8
14	Prepare manuals and train workers in use of new forms, reports, procedures or equipment, according to organizational policy	480	107	81.5	0.037	18
15	Confer with board members, organization officials, or staff members to discuss issues, coordinate activities, or resolve problems	515	116	81.4	0.040	19
16	Confer with sales and management executives or with clients to discuss design ideas	288	80	81.2	0.028	26
17	Meet with clients' other advisors, such as attorneys, accountants, trust officers, or investment bankers, to fully understand clients' financial goals and circumstances	228	185	81.2	0.063	14
18	Maintain or coordinate the maintenance of network peripherals, such as printers	272	80	81.2	0.027	40
19	Represent clients in court or before government agencies	324	129	80.9	0.044	24
20	Consult with clients to determine functional or spatial requirements of structures	402	77	80.5	0.026	23

Full notes at the end of the table.

Table E.2, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
21	Set up equipment for employee use, performing or ensuring proper installation of cables, operating systems, or appropriate software	455	295	80.3	0.100	44
22	Supervise or train project team members, as necessary	545	386	80.2	0.130	22
23	Conduct interviews for broadcasts	358	55	80.2	0.019	
24	Establish and maintain effective working relationships with clients, government officials, and media representatives and use these relationships to develop new business opportunities	582	727	80.1	0.245	15
25	Obtain and serve subpoenas	167	52	80.0	0.018	
26	Conduct information sharing sessions, such as in-service workshops for other professionals, potential client groups, or the general community	446	121	79.9	0.041	21
27	Visit sites to observe environmental problems, to consult with contractors, or to monitor construction activities	427	76	79.8	0.026	38
28	Mentor graduate students and junior colleagues	582	257	79.4	0.086	31
29	Observe, interview, and survey employees and conduct focus group meetings to collect job, organizational, and occupational information	346	77	79.2	0.026	39
30	Meet with clients, such as district or regional councils, farmers, and developers, to discuss their needs	438	97	79.1	0.032	20
31	Develop new styles and techniques	495	68	79.0	0.023	109
32	Participate in public meetings or hearings to explain planning proposals, to gather feedback from those affected by projects, or to achieve consensus on project designs	450	86	78.8	0.029	33
33	Accompany buyers during visits to and inspections of property, advising them on the suitability and value of the homes they are visiting	103	62	78.6	0.020	
34	Meet with managers, vendors, and others to solicit cooperation and resolve problems	531	134	78.5	0.044	27
35	Train users in details of system operation	524	260	78.5	0.086	71
36	Supervise professional, technical, and clerical personnel	413	69	78.2	0.023	47
37	Assemble prototypes or models of circuits, instruments, and systems for use in testing	282	64	77.9	0.021	
38	Supervise, train, and direct professional staff and interns	415	129	77.8	0.042	25
39	Confer with personnel concerned to ensure successful functioning of newly implemented systems or procedures	581	186	77.7	0.061	37
40	Address employee relations issues, such as harassment allegations, work complaints, or other employee concerns	488	424	77.6	0.138	58
41	Confer with managerial or technical personnel, other departments, or contractors to resolve problems or to coordinate activities	623	283	77.3	0.092	41
42	Receive and screen telephone calls and visitors	361	175	77.3	0.057	62

Full notes at the end of the table.

Table E.2, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
43	Meet with other departmental leaders to establish organizational goals, strategic plans, and objectives, as well as make decisions about personnel, resources, and space or equipment needs	421	74	77.2	0.024	29
44	Supervise administrative staff and provide training and orientation to new staff	308	64	77.1	0.021	35
45	Represent company at trade association meetings to promote products	471	186	77.1	0.060	43
46	Consult with clients to assess risks and to determine security requirements	400	182	77.0	0.059	32
47	Talk to clients and study instructions, plans, or diagrams to establish work requirements	485	88	76.9	0.028	52
48	Conduct or direct mining experiments to test or prove research findings	385	99	76.8	0.032	36
49	Preside over, or serve on, boards of directors, management committees, or other governing boards	346	57	76.4	0.018	49
50	Attend trade shows and seminars to promote products or to learn about industry developments	507	418	76.1	0.134	30
51	Represent work unit at meetings or conferences and serve as liaison for requests or complaints	559	129	76.1	0.041	50
52	Represent their government at local, national, and international meetings and conferences	485	151	76.1	0.048	48
53	Oversee or provide expertise on manufacturing, assembly, or fabrication processes	306	51	75.5	0.016	
54	Coach senior executives and managers on leadership and performance	407	247	75.3	0.078	63
55	Collaborate with other offices and agencies to exchange information and coordinate activities*	688	673	75.2	0.213	45
56	Hold public meetings with government officials, social scientists, lawyers, developers, the public, or special interest groups to formulate, develop, or address issues regarding land use or community plans	351	54	75.1	0.017	
57	Visit establishments to evaluate needs or to promote product or service sales	389	81	75.0	0.026	46
58	Discuss production requirements with clients	380	60	75.0	0.019	56
59	Develop and maintain liaisons and effective working relations with groups and individuals, agencies, and the public to encourage cooperative management strategies or to develop information and interpret findings*	679	615	75.0	0.194	54
60	Teach personal development skills, such as goal setting, independence, and self-advocacy	463	165	75.0	0.052	86
61	Direct technicians, engineering designers or other technical support personnel as needed	417	80	74.8	0.025	68
62	Contact individuals to be interviewed at home, place of business, or field location, by telephone, mail, or in person	372	58	74.7	0.018	130
63	Train faculty and media staff on the use of software and audio-visual equipment	417	99	74.6	0.031	55
64	Participate in fieldwork	614	187	74.5	0.059	74

Full notes at the end of the table.

Table E.2, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
65	Develop and maintain liaisons with municipalities, county departments, and similar entities to facilitate plan development, response effort coordination, and exchanges of personnel and equipment	396	69	74.5	0.022	59
66	Confer with officials of public health and law enforcement agencies to coordinate interdepartmental activities	481	64	74.5	0.020	42
67	Obtain informed consent of research subjects or their guardians	212	88	74.3	0.027	164
68	Collect, count, and disburse money, do basic bookkeeping, and complete banking transactions	208	55	74.2	0.017	73
69	Supervise or coordinate the work of physicians, nurses, statisticians, or other professional staff members	303	54	74.0	0.017	57
70	Perform teller duties as required	132	374	73.9	0.116	65
71	Confer with personnel, such as management, engineering, quality control, customer, or union workers' representatives, to coordinate work activities, resolve employee grievances, or identify and review resource needs	597	184	73.9	0.057	51
72	Sort incoming and outgoing mail, according to type and destination, by hand or by operating electronic mail-sorting and scanning devices	185	57	73.9	0.018	
73	Perform general office or clerical work, such as filing materials, operating duplicating machines, or running errands	513	106	73.8	0.033	132
74	Serve on professional panels and committees	486	69	73.6	0.021	53
75	Interview clients to obtain information about employment history, educational background, and career goals, and to identify barriers to employment	331	71	73.4	0.022	
76	Conduct seminars and training sessions for sales agents to improve sales techniques	337	430	73.3	0.133	60
77	Network within communities to find and attract new business	584	899	73.0	0.276	72
78	Inspect project sites to monitor progress and ensure conformance to design specifications and safety or sanitation standards	449	215	72.8	0.066	88
79	Sort and route incoming mail, and collect outgoing mail, using carts as necessary	199	74	72.8	0.023	
80	Manage and direct the construction, operations, or maintenance activities at project site	456	312	72.7	0.095	96
81	Serve on committees or in professional societies	425	57	72.7	0.018	
82	Receive and count daily inventories of cash, drafts, and travelers' checks	200	59	72.7	0.018	94
83	Supervise, train, or mentor junior team members*	691	1,821	72.5	0.556	82
84	Train demonstrators to present a company's products or services	367	117	72.5	0.036	64
85	Provide technical direction or support to installation teams during installation, start-up, testing, system commissioning, or performance monitoring	439	193	72.4	0.059	67

Full notes at the end of the table.

Table E.2, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
86	Promote the university by participating in community, state, and national events or meetings, and by developing partnerships with industry and secondary education institutions	426	145	72.2	0.044	69
87	Compound and dispense medications as prescribed by doctors and dentists, by calculating, weighing, measuring, and mixing ingredients, or oversee these activities	89	116	72.1	0.035	102
88	Process incoming or outgoing mail, packages, or deliveries	340	225	72.0	0.068	162
89	Attend or participate in conferences, community events, and promotional events related to products or technologies	563	311	72.0	0.094	76
90	Distribute product samples or literature that details products or services	403	67	72.0	0.020	61
91	Mentor and support administrative staff members, such as superintendents and principals	441	91	71.9	0.028	90
92	Display commercial, industrial, agricultural, and residential properties to clients and explain their features	133	52	71.8	0.016	
93	Print and make copies of work	417	66	71.7	0.020	110
94	Operate office equipment, such as fax machines, copiers, or phone systems and arrange for repairs when equipment malfunctions	611	433	71.6	0.130	124
95	Participate in campus and community events, such as giving presentations to the public	520	102	71.5	0.031	81
96	Represent institutions at community and campus events, in meetings with other institution personnel, and during accreditation processes	506	214	71.3	0.064	84
97	Allocate and manage laboratory space and resources	385	53	71.2	0.016	
98	Plan and conduct new employee orientation to foster positive attitude toward organizational objectives	349	174	71.2	0.052	85
99	Participate in staffing decisions and direct training of subordinates	633	497	71.1	0.149	83
100	Maintain communication between governing boards, medical staff, and department heads by attending board meetings and coordinating interdepartmental functioning	615	526	71.1	0.157	78

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold, binary at the task level. The table lists AI-infeasible tasks with at least 50,000 postings, ranked by average pressure. Average pressure P_t averages the posting exposure of the occupations that post the task, weighted by postings; share of all pressure is the task's posting-weighted pressure as a share of the total across all tasks. In the last column, we show the task's rank among AI-infeasible tasks with at least 100,000 postings when medium-confidence matches are also included. We leave the entry blank for tasks below that floor. The two audited statements ("Climb trees…" and "Perform physically demanding tasks…") are excluded from the ranking (Appendix C). Task text is the O*NET task statement; *marks statements posted in at least 650 of the 708 occupations, which Table 4, Panel A, leaves out. Occupations counts each occupation whose job postings include the task at least once. 163 of the 192 distinct tasks ranked in Table 4 and Appendix Tables E.2 and E.3 are not on the O*NET list of the occupation that posts them most, so a statement's wording is BGI's top-ranked catalog match for those responsibility lines rather than a verified duty. The 192 tasks are the union of the two top-100 lists, which share eight tasks. Table 4 is a subset. For AI-infeasible composite statements, like "general office or clerical work (filing, duplicating, errands)," the whole statement carries one GPT-4 rating from Eloundou et al. (2024). Consequently, a matched job-posting line describing only the feasible part of the task may inherit the infeasible label from the composite O*NET task statement.

Table E.3: The 100 AI-infeasible tasks with the largest share of total pressure

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
1	Develop and maintain client relationships*	705	6,015	68.7	1.741	1
2	Greet customers and make them feel welcome*	667	5,246	41.2	0.911	3
3	Follow ethical codes that protect the confidentiality of information*	703	3,347	63.1	0.889	4
4	Maintain cleanliness of work area*	699	5,846	33.3	0.820	9
5	Comply with all applicable standards, policies, or procedures, such as safety procedures or the maintenance of a clean work area*	702	4,205	41.0	0.726	5
6	Collaborate with other health care professionals and service providers to ensure optimal patient care	372	2,698	60.1	0.682	6
7	Learn and follow safety regulations*	704	4,049	38.3	0.653	12
8	Provide workers with assistance in performing duties as necessary to meet deadlines*	708	2,716	54.5	0.623	2
9	Attend meetings, educational conferences, and training workshops, and serve on committees*	706	2,310	62.0	0.603	15
10	Keep storage areas and carts well-stocked, clean, and tidy	559	3,333	40.2	0.565	10
11	Supervise, train, or mentor junior team members*	691	1,821	72.5	0.556	13
12	Attend staff meetings and serve on committees as required*	702	2,349	54.7	0.541	19
13	Participate in the work of subordinates to facilitate productivity or to overcome difficult aspects of work*	707	2,247	51.4	0.487	8
14	Follow established safety rules and regulations and maintain a safe and clean environment*	694	2,783	39.4	0.462	17
15	Maintain and follow standard quality, safety, environmental, and infection control policies and procedures*	688	2,224	47.3	0.444	14
16	Perform sales floor work, such as greeting or assisting customers, stocking shelves, or taking inventory	437	2,386	42.3	0.425	7
17	Maintain and clean work and inventory areas*	651	2,746	35.4	0.410	31
18	Adhere to safety practices and procedures, such as checking equipment regularly and erecting barriers around work areas*	699	2,384	40.1	0.403	30
19	Confer with customers to assess customer needs or obtain feedback	644	1,567	58.3	0.385	22
20	Monitor the facility to ensure that it remains safe, secure, and well-maintained*	667	1,883	47.2	0.374	25
21	Stock shelves, racks, cases, bins, and tables with new or transferred merchandise	380	2,117	41.7	0.372	28
22	Receive, unload, open, unpack, or issue sales floor merchandise	382	2,089	40.9	0.360	18
23	Perform general cleaning duties in the store to ensure the shop is clean and tidy	369	2,170	38.9	0.356	40
24	Report and document safety hazards, potentially hazardous conditions, and unsafe practices and procedures*	703	1,993	41.6	0.349	48
25	Direct, supervise, assess, and communicate with supportive personnel*	705	1,259	64.7	0.343	11

Full notes at the end of the table.

Table E.3, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
26	Establish and maintain standards of behavior to create safe, orderly, and effective environments for learning	611	1,463	54.0	0.333	33
27	Refer guest problems or complaints to supervisors	503	1,757	44.7	0.331	43
28	Develop and maintain relationships with community referral sources, such as schools or community groups	561	1,278	60.6	0.327	46
29	Attend staff meetings and serve on committees, as required*	699	1,369	55.3	0.319	45
30	Operate safety equipment and use safe work habits*	691	2,063	34.1	0.296	37
31	Participate in patients' care meetings and conferences	419	1,124	60.7	0.287	55
32	Provide assistance or direction to other stockroom, warehouse, or storage yard workers	612	1,624	41.9	0.286	24
33	Inspect and clean food preparation areas, such as equipment, work surfaces, and serving areas, to ensure safe and sanitary food-handling practices	382	2,394	28.0	0.282	36
34	Network within communities to find and attract new business	584	899	73.0	0.276	34
35	Maintain clean working environments, according to clean room standards*	670	1,499	42.1	0.266	56
36	Perform or assist with cleaning duties as necessary*	703	1,772	34.8	0.260	20
37	Train and supervise subordinates and other staff*	668	965	63.8	0.260	66
38	Respond to emergency situations on an on-call basis	646	1,309	47.0	0.259	61
39	Coordinate work with nurses, social workers, rehabilitation therapists, pharmacists, psychologists, and other health care providers	438	962	63.5	0.257	38
40	Assist with duties in other areas of the store, such as monitoring fitting rooms or bagging and carrying out customers' items	396	1,371	43.2	0.249	35
41	Administer medications to patients and monitor patients for reactions or side effects	237	1,053	56.0	0.248	76
42	Train new employees*	692	983	59.6	0.247	81
43	Establish and maintain effective working relationships with clients, government officials, and media representatives and use these relationships to develop new business opportunities	582	727	80.1	0.245	49
44	Maintain sanitation, health, and safety standards in work areas*	666	1,846	30.7	0.239	58
45	Load or unload trucks that deliver or pick up food or supplies	426	1,671	32.9	0.232	79
46	Advocate for patients' and families' needs, or provide emotional support for patients and their families	381	920	59.5	0.231	74
47	Enforce safety, health, and security rules*	669	1,060	51.5	0.230	67
48	Greet customers and help them locate merchandise	343	1,285	40.6	0.220	65
49	Confer with department supervisors or other personnel to assess progress and discuss needed changes*	686	737	69.8	0.217	47
50	Answer customers' questions about merchandise and advise customers on merchandise selection	285	1,180	43.2	0.215	50
51	Inventory stock to ensure that supplies and equipment are available in adequate amounts	579	1,070	47.5	0.214	69

Full notes at the end of the table.

Table E.3, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
52	Collaborate with other offices and agencies to exchange information and coordinate activities*	688	673	75.2	0.213	62
53	Respond to critical incidents, such as catastrophic events, violent weather, or civil disorders*	654	1,019	49.3	0.212	87
54	Greet incoming guests and escort them to their rooms	380	1,334	37.2	0.209	54
55	Perform maintenance duties, such as sweeping, painting, and yard work to keep facilities clean and in order	581	1,604	30.6	0.207	92
56	Greet customers and ascertain what each customer wants or needs	531	1,066	46.0	0.206	29
57	Check and maintain equipment to ensure that it is in working order*	667	1,160	42.0	0.205	108
58	Supervise or train staff members on daily tasks, such as visual merchandising	283	887	54.8	0.205	23
59	Establish and maintain relationships with other agencies and organizations in community to meet community needs and to ensure that services are not duplicated	583	811	59.8	0.204	63
60	Perform cleaning duties, such as sweeping, mopping, and washing dishes, to keep equipment and facilities sanitary	584	2,296	21.1	0.204	99
61	Move heavy furniture, equipment, or supplies, either manually or with hand trucks*	691	1,320	36.6	0.204	53
62	Operate office machines, such as photocopiers and scanners, facsimile machines, voice mail systems, and personal computers*	674	685	70.4	0.203	115
63	Interview and hire staff, and oversee staff training	585	696	68.5	0.201	100
64	Attend sales meetings, industry trade shows, and training seminars to gather information, promote products, expand network of contacts, and increase knowledge	428	673	70.6	0.200	64
65	Demonstrate products to clients	464	833	56.7	0.199	93
66	Enforce safety rules and ensure careful adherence to physicians' orders	592	770	60.0	0.195	41
67	Develop and maintain liaisons and effective working relations with groups and individuals, agencies, and the public to encourage cooperative management strategies or to develop information and interpret findings*	679	615	75.0	0.194	39
68	Coordinate and direct work of nurses, medical technicians, and other health care providers	323	718	63.8	0.193	52
69	Participate in faculty and college committee activities	535	665	68.9	0.193	106
70	Prepare patients for and assist with examinations or treatments	255	875	52.3	0.193	97
71	Pack and unpack items to be stocked on shelves in stockrooms, warehouses, or storage yards	494	1,213	37.4	0.191	71
72	Communicate and collaborate with other healthcare professionals involved with the care of a patient	373	745	60.8	0.191	85
73	Establish and enforce operating procedures and work standards that will ensure adequate performance and personnel safety*	673	851	52.5	0.188	77

Full notes at the end of the table.

Table E.3, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
74	Prepare treatment rooms for patient examinations, keeping the rooms neat and clean	288	877	50.8	0.188	131
75	Restock storage areas, replenishing items on shelves	470	1,320	33.7	0.187	91
76	Establish or maintain cooperative relationships with representatives of community, consumer, employee, or public interest groups*	658	668	66.2	0.186	73
77	Direct, coordinate, or supervise the patient care activities of nursing or support staff	218	719	61.1	0.185	75
78	Transport patients to and from treatment areas, lifting and transferring them according to positioning requirements	372	890	48.5	0.182	120
79	Adhere to local, state, and federal laws, regulations, and statutes*	662	735	57.2	0.177	104
80	Greet customers entering establishments	436	962	43.6	0.177	141
81	Consult with, or serve as, technical liaison between business, industry, government, and union officials	585	497	83.7	0.175	59
82	Inspect condition of premises, and arrange for necessary maintenance or notify owners of maintenance needs	446	956	43.2	0.174	96
83	Confer with medical personnel to better understand the backgrounds and needs of individual residents	294	730	56.0	0.172	80
84	Observe nurses and visit patients to ensure proper nursing care	188	710	56.6	0.169	16
85	Conduct routine and special inspections as required by regulations	611	784	51.1	0.169	129
86	Check vehicles to ensure that mechanical, safety, and emergency equipment is in good working order	526	1,243	32.2	0.169	133
87	Operate cash registers to accept payment from customers	257	941	42.1	0.167	140
88	Greet customers and ask about the quality of service they are receiving	572	849	46.5	0.166	21
89	Attend community events, meetings, or conferences to promote organizational goals or solicit donations or sponsorships	615	582	66.7	0.164	116
90	Operate cash register to process cash or credit sales	236	911	42.2	0.162	101
91	Maintain communication between governing boards, medical staff, and department heads by attending board meetings and coordinating interdepartmental functioning	615	526	71.1	0.157	51
92	Train other workers or coordinate their work, as necessary*	697	724	50.9	0.155	32
93	Perform other clerical duties, such as answering telephone, sorting and distributing mail, running errands or sending faxes*	698	617	59.3	0.154	27
94	Confer with parents and staff to discuss educational activities, policies, and student behavior or learning problems	377	614	58.3	0.151	178
95	Demonstrate or explain products, methods, or services to persuade customers to purchase products or use services	443	577	61.9	0.150	70
96	Participate in staffing decisions and direct training of subordinates	633	497	71.1	0.149	84
97	Supply, operate, or maintain personal protective equipment*	653	831	42.5	0.149	144

Full notes at the end of the table.

Table E.3, continued

	Task	Occupations	Postings (thousands)	Average pressure P_t	Share of all pressure (%)	Rank, medium included
98	Coordinate activities with other departments to ensure that services are provided in an efficient and timely manner*	673	549	64.1	0.148	89
99	Attend community meetings or health fairs to understand community issues or build relationships with community members	551	551	63.7	0.148	163
100	Hire, supervise, and work with extended coaching staff	546	579	59.1	0.144	82

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026, with BGI's recommended filters for analysis over time, in the 708 detailed O*NET occupations with a catalog exposure score. Only posting lines describing responsibilities are matched to O*NET task statements; a line's top-ranked match is kept only if it meets BGI's internal high-confidence threshold, and a posting counts once per task. AI feasibility is the GPT-4 rating of Eloundou et al. (2024) at the broad threshold, binary at the task level. The table lists AI-infeasible tasks ranked by their share of total pressure. Average pressure P_t averages the posting exposure of the occupations that post the task, weighted by postings; share of all pressure is the task's posting-weighted pressure as a share of the total across all tasks. The last column gives the task's rank when medium-confidence matches are also kept. The two audited statements ("Climb trees…" and "Perform physically demanding tasks…") are excluded from the ranking (Appendix C). Task text is the O*NET task statement; *marks statements posted in at least 650 of the 708 occupations, which Table 4, Panel A, leaves out. Occupations counts each occupation whose job postings include the task at least once. 163 of the 192 distinct tasks ranked in Table 4 and Appendix Tables E.2 and E.3 are not on the O*NET list of the occupation that posts them most, so a statement's wording is BGI's top-ranked catalog match for those responsibility lines rather than a verified duty. The 192 tasks are the union of the two top-100 lists, which share eight tasks. Table 4 is a subset. We identify O*NET statements that are listed more than once, often with just differences in punctuation (e.g., attending staff meetings and serving on committees). There are 27 such pairs of tasks and we rank them separately. Merging the pairs whose variants are all rated AI-infeasible, and counting a posting once per merged statement while keeping posting exposure fixed, leaves all 20 highest-contributing tasks represented in the top 20. The pair with conflicting feasibility ratings is kept separate: "Operate diagnostic imaging equipment to produce contrast[-]enhanced radiographs of heart and cardiovascular system." The hyphenated variant is rated infeasible and the unhyphenated variant feasible. The pair's 9,232 mentions account for less than 0.001 percent of labeled mentions. When we merge the pair and assign either feasibility label, while recomputing posting exposure, occupation pressure changes by at most 0.017 points on the 0–100 scale. Membership of the top-20 occupation set and both top-100 task lists remains unchanged.

F Changes over time

This appendix shows how bottleneck pressure and job posting patterns have evolved from 2018 to the first half of 2026, holding feasibility ratings fixed (Figure F.3).

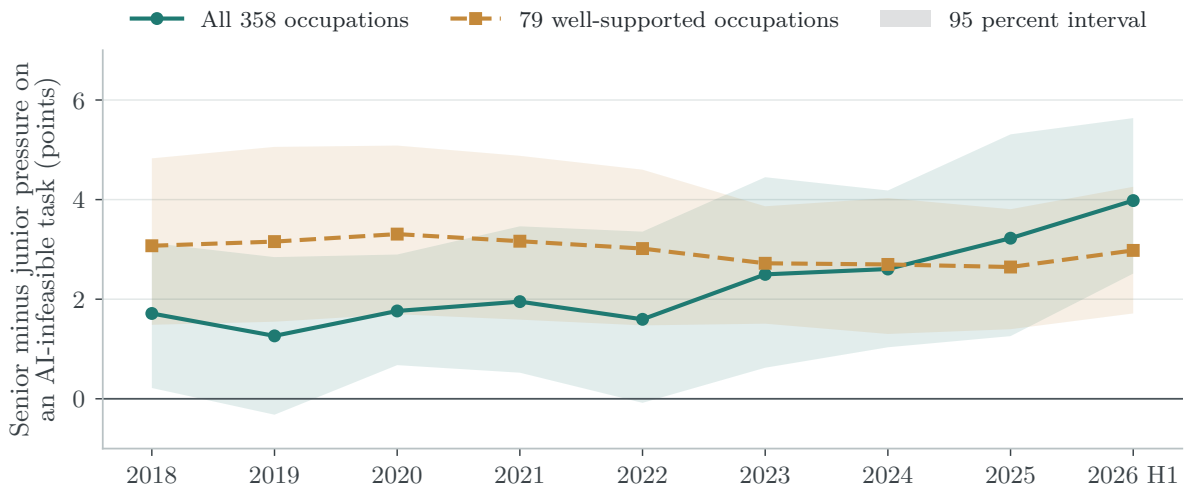


Figure F.1: The junior–senior gap in pressure on AI-infeasible tasks, 2018 to 2026 H1

Notes: BGI harmonized U.S. job postings, high-confidence matches only, for the 358 occupations with at least 100 labeled task mentions in both junior postings (0–3 years of experience required) and senior postings (7 or more) in every year from 2018 to 2026 (2026 covers January–June). Each point is the difference between senior and junior postings in the pressure an AI-infeasible task faces, which equals the difference in their AI-feasible shares, averaged across occupations with fixed 2021 weights. The dashed line restricts to the 79 occupations with at least 1,000 labeled postings in both groups in 2026, with the same weights rescaled. The shaded bands denote 95% confidence intervals from resampling occupations, with 2,000 draws.

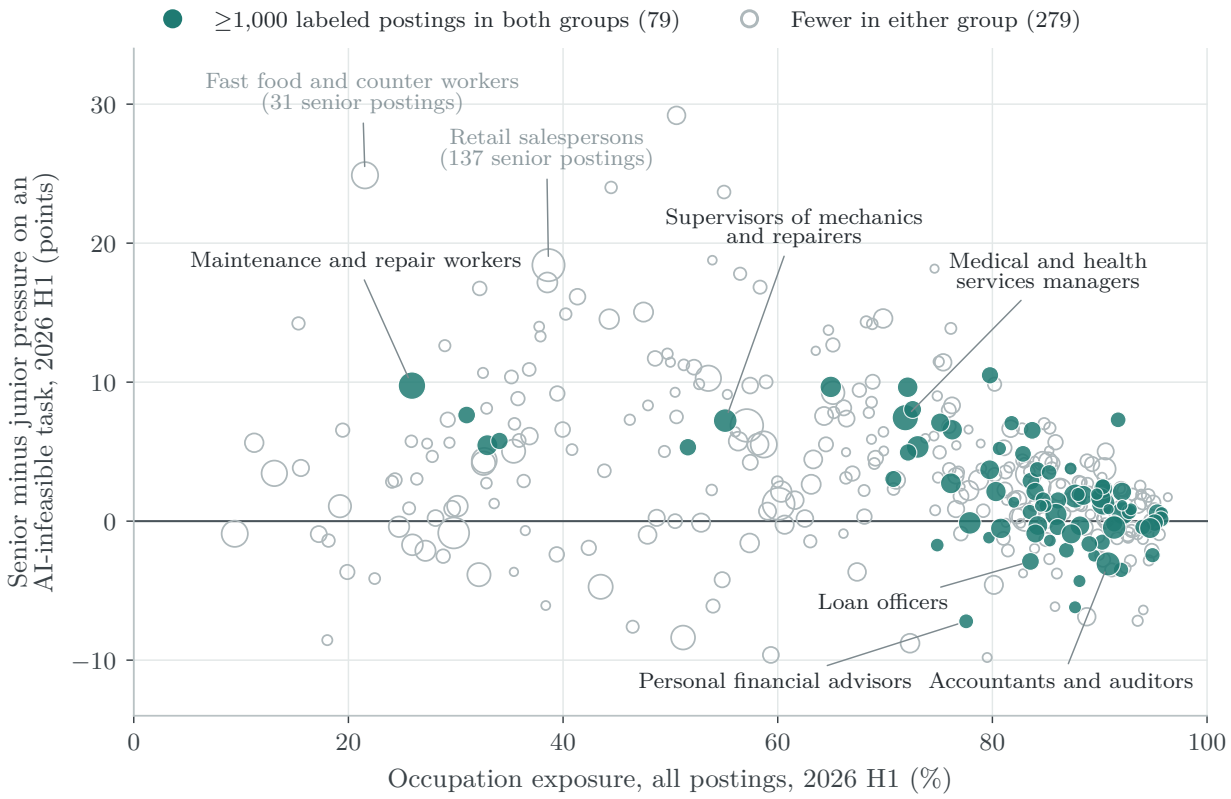


Figure F.2: The junior–senior gap by occupation, 2026 H1

Notes: BGI harmonized U.S. job postings, high-confidence matches only, for the same 358 occupations as Figure F.1. Each circle is an occupation, with area increasing with its fixed 2021 weight. The horizontal axis is the occupation's exposure in 2026 H1, computed across all its postings, including those requiring 4–6 years of experience or stating no requirement. Filled circles have at least 1,000 labeled postings in both groups. Labels mark the three largest positive and three largest negative contributions to the average gap among filled circles and, in grey, the two largest contributions overall, which rest on few senior postings.



Figure F.3: Change in mean occupation pressure, 2018 to 2026 H1

Notes: BGI harmonized U.S. job postings, January 2018 to June 2026 (2026 covers January–June), 708 occupations, high-confidence matches only, with feasibility ratings held fixed. Panel A uses a weighted average of occupations by their task mentions in each year or 2021. Its vertical axis starts at 17.4. Panel B splits the total change into within and across occupation components. The across occupation change focuses on changes in the occupation mix, which, for each group, sums each occupation's change in mention share times its midpoint pressure relative to the weighted mean (18.14), and so shrinking low-pressure occupations raise the average. The right-hand column shows the change, in percentage points, in each group's share of labeled mentions.

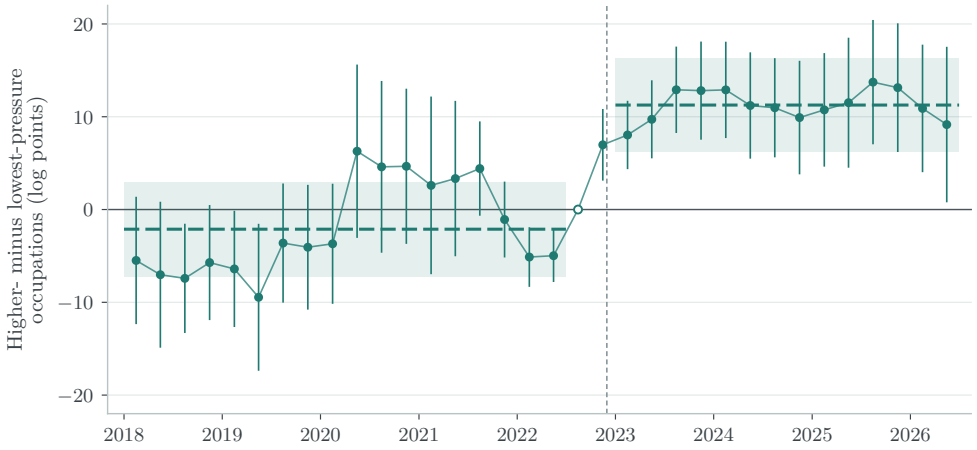


Figure F.4: Posting growth in higher- versus lowest-pressure occupations, by quarter

Notes: BGI harmonized U.S. job postings, 2018 Q1 to 2026 Q2 (2026 covers January–June), with BGI's recommended filters for analysis over time. Each point is a quarterly coefficient from the regression behind Table F.3, Panel A. The coefficients show the difference in log(1 + eligible postings) between occupations in the upper three quartiles of baseline occupation pressure and occupations in the lowest quartile, in log points, relative to 2022 Q3 (hollow point). Vertical bars denote 95 percent intervals, and the thin line connects the quarterly coefficients. We cluster by occupation. Dashed lines are the averages of the coefficients over 2018 Q1–2022 Q2 and 2023 Q1–2026 Q2, with the shaded bands denoting 95% confidence intervals, which allow for correlation between quarters, and 2022 Q4 enters neither average. The vertical dashed line marks the public release of ChatGPT on November 30, 2022. The pre-period coefficients are jointly different from zero (Table F.3).

Table F.1: The same AI-infeasible task across occupations

	Coefficient	Cells	Tasks	Occupations
All supported tasks	0.023	58,316	1,837	668
	(0.047)			
Broadly shared tasks	0.071	17,161	99	650
	(0.085)			

Notes: BGI harmonized U.S. job postings, with BGI's recommended filters for analysis over time, high-confidence matches only. Each observation is an AI-infeasible task in an occupation. The outcome is the change in the log of the task's share of the occupation's labeled task mentions from 2018–2021 to 2023–2025, and the regressor is the occupation's posting exposure in 2018–2021 on a 0–1 scale, which equals the pressure on the task there. We measure exposure in one random half of postings and the outcome in the other, then the reverse. All specifications include task fixed effects, so each coefficient compares the same task across occupations, and weight cells by their 2018–2021 mentions. We cluster by occupation and task. For all supported tasks, a cell needs at least 100 mentions in each half in both periods, and a task needs at least 10 such occupations. Broadly shared tasks, selected on 2018–2021 data only, appear in at least 100 occupations and have a 90th-minus-10th percentile exposure spread of at least 0.30. A coefficient of 0.1 means about 1 percent faster growth in the task's share for each 10 percentage points of exposure.

Table F.2: Exposure, bottleneck pressure and posting growth after 2022

	Exposure	Pressure
A. Log postings, average post-period coefficient relative to 2022 Q3		
Exposure only	2.31	
	(2.49)	
Pressure only		4.48
		(1.31)
Both	4.21	5.11
	(2.38)	(1.25)
Both, excluding largest 10% of employers	3.36	4.31
	(2.13)	(1.42)
Both, excluding computer and mathematical	4.06	5.16
	(2.38)	(1.26)
B. Other estimators, both regressors		
Static post versus 2018–2022	3.62	6.69
	(2.36)	(1.18)
Poisson on posting counts	1.18	5.84
	(2.01)	(1.33)
Poisson on posting counts, 2021 weights	10.83	6.71
	(2.14)	(1.34)
C. Placebos on data before 2022 Q3, both regressors		
Fake start in 2020 Q1, relative to 2019 Q4	−4.01	1.21
	(2.51)	(1.41)
Fake start in 2019 Q1, relative to 2018 Q4	0.45	0.51
	(2.46)	(1.12)

Notes: BGI harmonized U.S. job postings, 2018 Q1 to 2026 Q2 (2026 covers January–June), with BGI's recommended filters for analysis over time. The outcome is log(1 + eligible postings) in each of the 14,223 occupation × industry cells with postings in 2021, by quarter, as in Table F.3. Exposure is each occupation's 2021 posting exposure E_o, and pressure is its 2021 occupation pressure $E_o(1 - E_o)$. Panels A and C interact each with every quarter, while Panel B uses single post-period interactions. All regressions include cell, industry × quarter and occupation group × quarter fixed effects, with 2021 postings as weights except in the first Poisson row. Coefficients are in log points per one standard deviation across the 708 occupations, 0.26 for exposure and 0.059 for pressure. We cluster by occupation. Figure F.5 plots the third row by quarter.

Table F.3: Posting growth by baseline occupation pressure, 2023–June 2026

	Quartile versus Q1			Q2–Q4	Above
Firms	Q2	Q3	Q4	versus Q1	median
A. Average post-period coefficient, relative to 2022 Q3					
All firms	9.85	15.13	10.74	11.26	6.02
	(3.07)	(4.41)	(3.07)	(2.57)	(3.38)
Excluding largest 1%	7.39	15.56	12.49	10.65	8.84
	(3.35)	(4.26)	(3.21)	(2.84)	(3.10)
Excluding largest 5%	5.02	12.71	9.74	8.06	7.68
	(3.66)	(4.59)	(3.42)	(3.07)	(3.37)
Excluding largest 10%	4.22	12.17	7.90	7.02	6.99
	(3.94)	(4.92)	(3.68)	(3.27)	(3.67)
B. Static post versus 2018–2022 interaction					
All firms				12.82	7.60
				(2.37)	(3.49)
Excluding largest 10%				10.83	5.03
				(3.41)	(4.17)
p, Q2 = Q3 = Q4, all firms		0.435			
p, no pre-period differences, all firms				<0.001	<0.001
Occupation × industry fixed effects	✓	✓	✓	✓	✓
Industry × quarter fixed effects	✓	✓	✓	✓	✓
Occupation group × quarter fixed effects	✓	✓	✓	✓	✓
Weighted by 2021 postings in each cell	✓	✓	✓	✓	✓

Notes: BGI harmonized U.S. job postings, 2018 Q1 to 2026 Q2 (2026 covers January–June), with BGI's recommended filters for analysis over time. The outcome is log(1 + eligible postings) in each occupation × industry × quarter cell, for the 14,223 cells in the 708 occupations and 21 industries with postings in 2021. Occupations are split into quartiles or halves by their 2021 pressure, and each coefficient is the log-point difference from the lowest group. We cluster by occupation. Figure F.4 plots the quarterly coefficients behind the Q2–Q4 column. Firm exclusions drop employers in the largest 1, 5 or 10 percent of the 2021 employer ranking by postings, keeping the 2021 cells and weights.

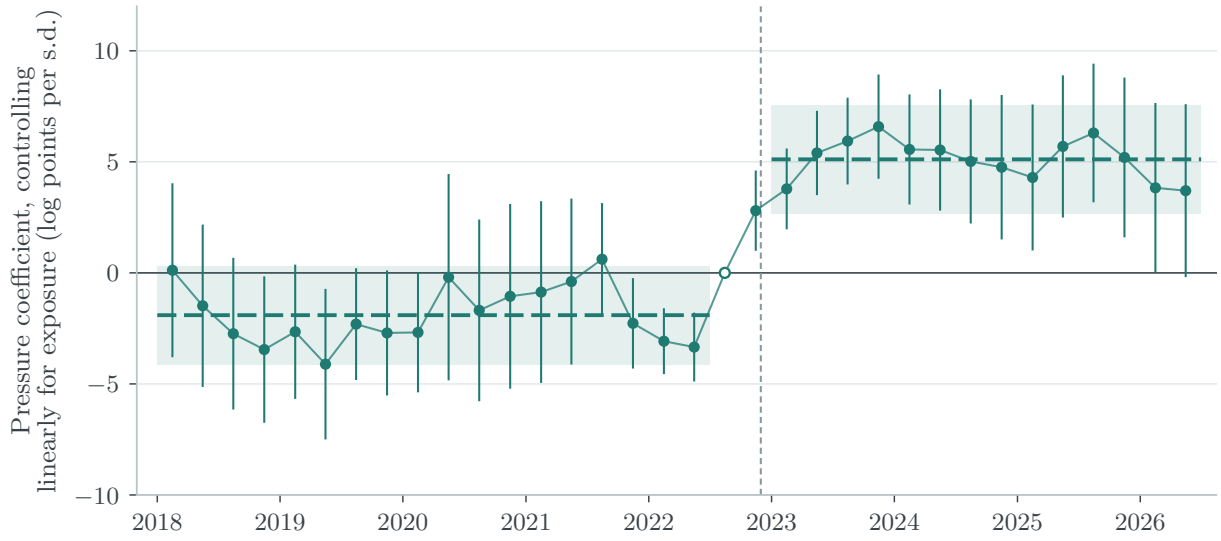


Figure F.5: Pressure and posting growth, controlling linearly for exposure, by quarter

Notes: BGI harmonized U.S. job postings, 2018 Q1 to 2026 Q2 (2026 covers January–June). Each point is the quarterly coefficient on 2021 occupation pressure from the regression in Table F.2, Panel A, third row, which controls linearly for 2021 exposure. The coefficients are in log points per one standard deviation of pressure, relative to 2022 Q3 (hollow point). Vertical bars denote 95 percent intervals, and the thin line connects the quarterly coefficients. We cluster by occupation. Dashed lines are the averages of the coefficients over 2018 Q1–2022 Q2 and 2023 Q1–2026 Q2, with the shaded bands denoting 95% confidence intervals. The vertical dashed line marks the public release of ChatGPT on November 30, 2022.