How Organizations Use AI: Evidence from ChatGPT

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Abstract

We study how organizations use frontier generative AI by linking ChatGPT Enterprise account records to usage, worker roles, task classifications, and public-company financial data through March 2026. These linked data enable a privacy-preserving analysis of adoption, worker roles, and message-level tasks at scale: for instance, the worker-level sample we analyze at the six-month adoption horizon includes over 1,500 organizations and over 17 million messages. We document four facts about enterprise AI adoption and use. First, ChatGPT Enterprise usage has grown rapidly due to a combination of new firm adoption and growing intensity among existing adopters. Second, U.S.-based public company adoption is concentrated among larger, more valuable, and more R&D- and SG&A-intensive firms. Third, active use within adopting firms spans job functions and seniority levels, with especially high usage intensity among early-career workers. Fourth, ChatGPT Enterprise usage encompasses a broad range of knowledge work tasks, including writing, technical work, communication, and information synthesis. In aggregate, these results suggest that firms differ widely in the speed, breadth and purpose of their enterprise AI adoption, and that they are still actively learning how to integrate AI into organizational workflows.

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1 Introduction

Generative AI systems can perform a growing range of economically valuable tasks (Eloundou et al. 2024; Patwardhan et al. 2025), and individuals use consumer-facing generative AI chatbots for many work-related and personal activities (Chatterji et al. 2025; Handa et al. 2025). However, less is known about firm AI adoption: which workers account for observed use, how intensively active users engage with generative AI, and for which tasks. Understanding these patterns is important for interpreting recent findings about the impact of AI on productivity and employment (e.g., Brynjolfsson et al. 2025a; Brynjolfsson et al. 2025b). Most evidence on firm AI adoption comes from worker and firm surveys (McElheran et al. 2024; Bick et al. 2026a; Yotzov et al. 2026; Bonney et al. 2026). Although surveys provide broad coverage and can capture non-use, adoption barriers, and organizational context, self-reported usage is typically less detailed and may suffer from imperfect recall or reporting biases.

This paper studies workplace AI adoption using internal data from ChatGPT Enterprise, OpenAI's centrally administered workplace product.[2] We first examine firm adoption by decomposing enterprise growth into within- and between-firm components and linking ChatGPT Enterprise accounts to public company financial data. We then study within-firm heterogeneity by combining usage data with employee job title information and message-level task classifications, which tells us how usage intensity and task adoption varies across worker groups six months after organizational adoption.

We document four stylized facts about enterprise AI adoption and usage. First, enterprise AI usage is growing rapidly, reflecting both increased use among existing customers and the arrival of new adopters. Aggregate output tokens produced by ChatGPT Enterprise customers grew roughly sevenfold between June 2025 and March 2026, and by

[2]Over time, OpenAI's centrally administered workplace offering has expanded beyond ChatGPT to include additional products, such as Codex. For simplicity, and because ChatGPT accounts for the overwhelming majority of observed usage during our study period, we refer to this offering throughout as "ChatGPT Enterprise."

nearly fourfold within a consistent cohort of firms that adopted between January 2024 and June 2025. Thus, about half of the growth in token consumption over this period occurred within already-adopting firms. Second, among U.S.-based public companies, ChatGPT Enterprise adopters are larger, more valuable, and more R&D- and SG&A-intensive than non-adopters. This pattern suggests that early enterprise AI adoption is associated with greater prior investment in intangible and organizational capabilities.

Third, usage within adopting firms is broadly distributed across job title classes and seniority levels but with heterogeneous intensity. For example, marketing and communications workers send more messages than executives, and early-career workers send many more messages than more senior employees. Fourth, ChatGPT Enterprise use spans many different tasks across workers and organizations, rather than being concentrated in a single workflow. The most common use cases are writing, communication, and information synthesis, but usage is also common in tasks such as research, planning, data analysis, legal and regulatory work, finance, and many other applications. This breadth is consistent with generative AI functioning as a general purpose technology for knowledge work (Bresnahan and Trajtenberg 1995; Bresnahan 2024; Eloundou et al. 2024).

Taken together, these findings portray enterprise AI adoption as a broad but uneven organizational phenomenon. Adoption is concentrated among firms with greater scale and intangible investment, while use within adopting firms is distributed across many worker groups and knowledge work tasks but varies substantially in intensity. This heterogeneity highlights that the long-run economic value of enterprise AI adoption will depend on whether dispersed individual use develops into complementary organizational capabilities (Bresnahan and Greenstein 1996; Bresnahan et al. 2002; Brynjolfsson et al. 2021).

The remainder of the paper proceeds as follows: we first review the related literature and describe the data and measurement. We then follow the structure introduced above: Sections 4.1 and 4.2 examine adoption and usage across firms, while Sections 4.3 and 4.4

examine the distribution and task structure of use within adopting organizations. In Section 5, we conclude.

2 Related Literature

Our work contributes to four related literatures. First, we add to the literature on AI adoption and diffusion within firms. A central insight from research on general purpose technologies is that initial adoption does not imply effective deployment: realizing value requires experimentation, complementary investment, and organizational change, so use often diffuses gradually within firms (Bresnahan and Trajtenberg 1995; Bresnahan and Greenstein 1996; Bresnahan et al. 2002; Bresnahan 2024; Brynjolfsson et al. 2021; Mansfield 1963; Fuentelsaz et al. 2003). Consistent with this view, recent studies of digital technology adoption and use find that organizations continue to discover applications and improve their use after obtaining access (McElheran et al. 2024; Yotzov et al. 2026; Bick et al. 2026a; Bick et al. 2026b; Brand et al. 2024; Kim et al. 2026; Massenkoff et al. 2026a).[3] The most closely related paper to ours is Bonney et al. (2026), which distinguishes firm adoption from the subsequent deployment of AI across business functions and worker tasks. We advance this literature by examining which firm attributes predict enterprise AI adoption and, among adopters at a common point in their adoption cycles, measuring how deployment is distributed across workers and tasks.

Second, our paper contributes to research that measures AI usage with telemetry data. One strand uses data on the content of human–AI interactions to characterize the tasks, occupations, and modes of interaction represented in observed use (Handa et al. 2025; Appel et al. 2026; Massenkoff et al. 2026b; Chatterji et al. 2025; Tomlinson et al. 2025). A second strand uses API and product-activity data to characterize demand across applications and organizational settings and to examine how AI is incorporated into production workflows (Demirer et al. 2025; Fradkin 2025; Appel et al. 2025; Daniotti et al.

[3] Related studies connect firm-level AI investment and exposure to firm growth, product innovation, and market value (Babina et al. 2024; Eisfeldt et al. 2026; Yu et al. 2026).

2026; Chen and Stratton 2026; Demirer et al. 2026b). Two recent papers are particularly closely related to ours. Counts et al. (2026) use telemetry from Microsoft 365 Copilot to characterize aggregate workplace use and document how its task composition varies across occupations and industries. Johnston et al. (2026) use OpenAI telemetry data to study the shift from conversational to agentic AI, including how Codex adoption, usage intensity, and task composition vary across organizational settings, worker roles, and levels of seniority.

Third, we contribute to research on heterogeneous effects of AI across workers and tasks. This literature distinguishes between the activities for which AI is technically capable and the settings in which those capabilities translate into realized use and benefits. Early work takes a task-based approach and estimate potential exposure by comparing model capabilities with occupational task descriptions (Eloundou et al. 2024).[4] More recently, Patwardhan et al. (2025) evaluate frontier models on expert-constructed tasks spanning 44 occupations and nine sectors, providing evidence about where models can produce professional-quality deliverables. Experimental studies, in turn, show that AI's *realized* effects depend on the worker, the task, and how AI-generated output is evaluated and implemented (Noy and Zhang 2023; Brynjolfsson et al. 2025b; Dell'Acqua et al. 2026; Cui et al. 2026; Otis et al. 2026). We complement this work by documenting the deployment decisions that bridge the gap between capability and realized effects: which worker groups account for active use, how intensively users in each group engage with AI, and which tasks account for their activity.

Finally, our paper contributes to research on the relationship between AI, organizational structure, and the division of labor. Knowledge-based theories of the firm view organizational hierarchies as mechanisms for allocating problems among workers, managers, and specialized experts (Garicano 2000; Garicano and Rossi-Hansberg 2006).

[4] Subsequent work emphasizes that technical exposure need not translate directly into realized adoption, because workers vary in comparative advantage and in the costs of using and verifying AI output (Lindenlaub et al. 2026).

Technologies that change the cost of acquiring or communicating knowledge can therefore change where expertise is located and how tasks are divided within the firm (Bloom et al. 2014). Recent research applies this logic to AI by examining how it changes the value of expertise and which sequences of work can be delegated to AI (Autor and Thompson 2025; Demirer et al. 2026a), and within-firm evidence shows that intensive AI use can expand the range of tasks workers perform, accelerate learning, and shift work toward supervising and evaluating AI-generated output (Huang et al. 2025). The paper most closely related to ours in its organizational focus is Kim and Koning (2026), which shows that AI-native startups are smaller, flatter, and more engineering-intensive than comparable firms. Whereas much of this work examines AI-native organizations and highly technical workers, we study how AI is deployed within the existing structures of established firms across a wide range of industries. By comparing use across job functions, seniority levels, and managerial positions, we provide evidence on where a general purpose AI technology enters the organizational hierarchy and how its role varies across organizational contexts.

3 Data and Measurement

Our analysis draws on four related but distinct samples: an aggregate enterprise usage sample, a smaller sample with employee job title and firm industry information, a further time-limited subset of the job title and industry sample used for task-classification analysis, and a public company sample linked to the Compustat database from S&P Global Market Intelligence.[5] We describe the construction of each sample in the following subsections and summarize their relationships in Figure 1.

For our analysis of ChatGPT Enterprise usage data, we use de-identified data and report results only in aggregate. Message content is classified using automated systems, and job title metadata is mapped to broad job title class, seniority, and people manager categories. No researcher manually reviewed individual enterprise customer messages for this study. For our financial analysis of public companies, we securely link aggregate organizational usage data to public-company financial information from Compustat.

3.1 ChatGPT Enterprise Usage Data

Our primary data source is an organization-week panel of ChatGPT Enterprise adoption and usage, constructed from organizations whose ChatGPT Enterprise adoption dates range from January 1, 2024 to March 31, 2026. The data capture adoption of a paid, centrally administered ChatGPT Enterprise workspace, rather than use through personal accounts, the API, or other subscription plans. We observe each organization's enterprise account identifier, adoption date, and product usage over time.

Organizations enter the panel in the week they adopt ChatGPT Enterprise and they remain in the panel while their workspace is active. Organization-weeks with an active workspace but no observed product activity are retained with zero measured usage. For each organization-week, we measure messages sent, active users, and generated output tokens, including tokens generated through both ChatGPT and Codex. Weeks are indexed relative to each organization's adoption date. This aggregate ChatGPT Enterprise usage sample is used to measure adoption and product use over time.

3.2 Job Titles, Firm Industries, and Task Classifications

For analyses of usage by worker characteristics, we also construct a sample of ChatGPT Enterprise organizations for which we observe both firm industry and high-quality employee job title information. Starting from the ChatGPT Enterprise usage sample described above, we retain organizations that can be assigned to a broad industry category using NAICS classifications. We further require that at least some user activity within the organization can be linked to a non-empty administrative job title.[6] Because the corresponding analyses measure usage 6 months (26 weeks) after adoption, we additionally require an observed, active organization-week at that horizon. The resulting worker characteristics sample contains 1,764 organizations and 17,446,551 messages.

Within this sample, we normalize the available job title strings and classify them into broad job title classes, seniority levels, and people manager categories.[7] These user-title and firm-industry measures are then linked to ChatGPT Enterprise usage and aggregated by organization, week, and worker category. Appendix C describes the normalization, classification, and validation of our job title measures. Importantly, job title coverage within included organizations is incomplete. Active users without usable job title information remain in organization-level usage totals and denominators but are classified as missing or unclassified in analyses of heterogeneous use by worker type.

We also separately construct a task classification subsample of this dataset. We classify ChatGPT Enterprise messages into a taxonomy of work tasks using a message-level classifier that is available beginning on October 30, 2025. Appendix D provides information about the task taxonomy produced by this classifier. The task classification sample is restricted to organizations that satisfy the worker characteristics sample requirements above and have task classification data available at the week 26 horizon. This produces a task-classification sample of 973 organizations and 8,696,657 classified messages. We use this task classification sample for both analysis of the overall task distribution and for analyses of the task distributions by job title class, seniority level, people manager status, and industry.

[6] Job title information is observed at a single point in time and may therefore not capture changes in workers' roles over the full study period.

[7] Our main text analyses focus on job title class and seniority; results for people manager status appear in Appendix B.

3.3 Public Company Sample and Summary Statistics

For analyses of U.S. public company characteristics and financial outcomes, we begin with U.S. public firms in Compustat and identify ChatGPT Enterprise adopters by mapping ChatGPT Enterprise accounts to public-company identifiers using a combined curated and LLM-assisted account-to-ticker crosswalk.[8] We then draw a random sample from the resulting set of ChatGPT Enterprise accounts with public-company identifiers.[9] We define non-adopters as public firms with no ChatGPT Enterprise ticker-bridge match.[10] The resulting financial panel includes firm and fiscal-year identifiers as well as the Compustat variables reported in Table A1.[11]

We link weekly ChatGPT Enterprise activity to this panel by assigning each usage week to the Compustat fiscal year in which it falls and aggregating usage to the ticker-year level. For usage-intensity analyses, we measure weekly messages per employee, weekly output tokens per employee, and weekly active users (WAU) per employee. The first two measures capture usage volume relative to firm size, while WAU captures the breadth of participation in the ChatGPT Enterprise workspace.

This procedure yields a usage-linked panel of 521 ticker-year observations for 417 public-company tickers.[12] Of these usage-linked ticker-years, 509 observations, covering

[8]The public-company analyses are limited to U.S. firms because the Compustat data used here are restricted to U.S. public companies.

[9]We draw a random sample to limit disclosure of commercially sensitive information about OpenAI's enterprise business.

[10]We classify as non-adopters firms that we cannot match to a ChatGPT Enterprise account; this classification does not imply that they use no AI products. These firms may use enterprise language-model products from other providers or access ChatGPT outside an enterprise workspace. If such use is correlated with firm characteristics in the same direction as ChatGPT Enterprise adoption, this measurement error could attenuate estimated differences between adopters and non-adopters. We do exclude public firms that match OpenAI customer records for other products (like ChatGPT Business) but not a ChatGPT Enterprise account, which avoids the use of known OpenAI customers as untreated controls.

[11]Importantly, this public company sample does not require job title, industry, or task classification coverage. It is therefore distinct from the samples described in Section 3.2, although both begin with the ChatGPT Enterprise usage panel.

[12]We retain a usage-matched ticker only when at least one observed week of ChatGPT Enterprise usage falls within an observed Compustat fiscal-year window. Of 534 usage-matched domestic public-company tickers, 117 do not meet this condition: 50 have no observed Compustat fiscal-year window, and 67 have ChatGPT Enterprise usage only after the last available Compustat fiscal-year window.

410 tickers, have positive annual ChatGPT Enterprise message volume. The non-adopter comparison group contains 11,784 public-company tickers. These counts describe U.S.-based public-company adopters for which we observe matched ChatGPT Enterprise usage; sample sizes in regression tables may differ because the set of Compustat variables required as non-missing covariates varies across specifications.

4 Four Facts about Enterprise AI Usage

Using the datasets described above, we document four facts about the growth and composition of ChatGPT Enterprise use. First, aggregate use has grown rapidly, including within cohorts of organizations that adopted at different times. Second, early adoption is concentrated among larger, more productive firms with greater prior investment in intangible and organizational complements. Third, use is broadly distributed across job functions and seniority levels, but its intensity varies systematically across worker groups. Finally, ChatGPT Enterprise use spans a broad range of knowledge work tasks, while task mix varies across industries, job functions, and levels of seniority.

4.1 ChatGPT Enterprise usage has grown rapidly

We first study the growth of ChatGPT Enterprise usage, both overall and within fixed adoption cohorts. Using the organization-week panel described in Section 3.1, Figure 3 plots total output tokens relative to June 2025, overall and separately by quarter-year adoption cohorts.[13]

Aggregate output tokens increased sevenfold between June 2025 and March 2026. This growth was not driven solely by the addition of new organizations: output tokens also increased substantially within existing adoption cohorts. Among firms that had adopted by June 2025, for example, output tokens increased roughly fourfold over the

[13] ChatGPT Enterprise increasingly includes access to Codex as part of the product bundle. During our sample period, however, enterprise token output is overwhelmingly generated by ChatGPT and related non-agentic AI tools. Appendix Figure A1 shows that the aggregate growth documented here is driven primarily by non-Codex output. For an analysis of Codex usage within organizations, we refer the reader to Johnston et al. 2026.

same period. Thus, enterprise demand continued to deepen after organizations entered the product, alongside continued growth in the number of adopters. We also find that usage accelerated in early 2026 across all adoption cohorts. Because organizations that adopted at different times experienced this acceleration simultaneously, the increase appears to reflect developments affecting ChatGPT Enterprise customers broadly rather than only the normal expansion of use following adoption.

4.2 Early enterprise AI adopters are larger, more valuable, and more heavily invested in intangibles and organizational complements

We next examine how firms that adopt ChatGPT Enterprise differ from non-adopters and which firm characteristics are associated with usage intensity among adopters.

Figure 2 provides descriptive statistics from a comparison of 2024 firm characteristics for ChatGPT Enterprise adopters and non-adopters in the Compustat public-company sample. Across all measures, adopters are substantially larger. Median revenue is $2,275.1M for adopters versus $209.6M for non-adopters. Median total assets are $4,394.2M versus $667.6M, and median employment is 2,934 workers versus 424 workers. Adopters also have larger capital stocks, greater market valuations, and greater R&D spending. Median net property, plant, and equipment (PP&E) assets are $271.2M for adopters compared with $43.7M for non-adopters. Median market value is $4,997.2M versus $316.4M, and the median research and development expenses are $113.1M among adopters, compared with $9.9M among non-adopters. These patterns indicate that early ChatGPT Enterprise adopters are not representative of the average public firm; they are larger, more capitalized, more valuable, and more R&D-intensive.

4.2.1 Financial characteristics

These unadjusted differences motivate the regression analysis in Table 1, which relates ChatGPT Enterprise adoption to lagged financial characteristics measured at the public firm-year level. Importantly, our estimates describe conditional associations between these pre-adoption firm characteristics and the probability that a public firm is observed as a

ChatGPT Enterprise adopter, and should not be interpreted causally.

Across specifications, firms with higher revenue per employee are more likely to adopt ChatGPT Enterprise. A one-log-point increase in lagged revenue per employee is associated with roughly 0.4 to 0.9 percentage points higher adoption probability. This association remains positive and statistically significant after accounting for assets per employee, PP&E per employee, employment, year fixed effects, and industry fixed effects, indicating that it is not solely a difference between larger firms or more capital-intensive industries. Firm scale is also strongly associated with adoption: lagged log employment is positive and statistically significant in all specifications, including those with additional capital-intensity controls and finer NAICS4 industry fixed effects. By contrast, PP&E per employee is generally negatively associated with adoption conditional on scale and the other included financial characteristics. Thus, among otherwise comparable public firms, ChatGPT Enterprise adoption is less concentrated in firms with more physical-capital-intensive production. These patterns persist when excluding technology firms, indicating that they are not primarily driven by the information sector. In summary, ChatGPT Enterprise adoption is more likely among larger, higher revenue-per-worker public firms with relatively lower physical capital intensity.

4.2.2 Usage intensity among adopters

We next move from the extensive margin of adoption to the intensive margin, asking whether financial characteristics also vary with the level of ChatGPT Enterprise use among adopters. Figure 4 provides descriptive evidence by comparing the distribution of revenue per employee and market value per employee by adoption intensity, measured by weekly output tokens per employee. Panel A indexes each outcome to the non-adopter median. For both revenue per employee and market value per employee, high-intensity adopters are shifted to the right of non-adopters and low-intensity adopters. This indicates that, among public firms, the firms using ChatGPT Enterprise most intensively tend to have higher revenue productivity and higher market valuation per worker.

Panel B provides a covariate-adjusted version of this comparison, accounting for industry and firm size. This adjustment asks whether high-intensity adopters look different not only because they are in larger or more productive sectors, but also relative to observably similar firms in the same broad industry and size class. The rightward shift for high-intensity adopters remains visible, especially for market value per employee. Low-intensity adopters sit closer to non-adopters, while high-intensity adopters are more likely to appear in the upper part of the adjusted outcome distribution. Thus, the relationship between usage intensity and financial performance is not explained solely by firm size: conditional on adopting, more intensive ChatGPT Enterprise use is concentrated among firms with stronger per-employee financial outcomes.

Table 2 provides regression-based evidence, relating lagged financial characteristics to four measures of usage intensity among U.S.-based public-company adopters with positive ChatGPT Enterprise activity: messages per active usage week per employee, weekly active users per employee, output tokens per employee, and messages per weekly active user.[14] Revenue per employee has positive but imprecisely estimated associations with some usage margins. The point estimates are positive for messages per active usage week per employee and weekly active users per employee, but neither coefficient is statistically significant; revenue per employee is not meaningfully associated with output tokens per employee or messages per active user once other controls are included. The pattern is consistent with broader diffusion across employees and active weeks, but the estimates are too imprecise to support a strong conclusion. Firm size has the opposite association with per-employee usage intensity: lagged log employment is negative and statistically significant for messages per active week per employee, weekly active users per employee, and output tokens per employee. This pattern is consistent with a mechanical

[14] For usage intensity, no single measure captures the whole intensive margin. Messages per active week per employee captures how much use occurs when a firm is actively using the product; WAU per employee captures the breadth of adoption across the workforce; output tokens per employee captures the volume of model-generated work; and messages per WAU captures intensity among active users. Looking across these measures helps distinguish whether a firm's usage is broad-based, heavy among a small set of users, or concentrated in particular high-output workflows.

or organizational scaling effect: larger firms are more likely to adopt, but conditional on adoption, measured use per employee is lower.

4.2.3 Firm scale and adoption

Although larger firms have lower measured usage per employee conditional on adoption, they are more likely to adopt ChatGPT Enterprise in the first place. We next ask whether adoption is especially concentrated among the largest public firms. Table 3 shows that a one-log-point increase in lagged revenue is associated with a 1.1 percentage point higher probability of adoption. This relationship is most pronounced at the top of the revenue distribution: firms in the top revenue quartile are 6.9 percentage points more likely to adopt, and firms in the top 5 percent are 9.8 percentage points more likely to adopt.

This pattern is not simply a consequence of large firms operating in large industries. When scale is measured relative to other firms in the same industry-year cell, following the approach in Autor et al. 2020, firms in the top revenue quartile within their NAICS2-by-year cell are 7.2 percentage points more likely to adopt, while firms in the top 5 percent are 11.3 percentage points more likely to adopt. Thus, even within industries, adoption is more common among the largest firms. Importantly, these estimates are limited to U.S.-based public companies, which are already large relative to the broader population of businesses. They therefore describe variation among relatively large firms and do not establish how ChatGPT Enterprise adoption varies among small private firms, startups, or mid-market firms; the relationship could be steeper, flatter, or nonlinear elsewhere in that part of the firm-size distribution.

4.2.4 Pre-existing complements and enterprise adoption

Firm scale is unlikely to be the only reason some public firms are more likely to adopt ChatGPT Enterprise. Larger firms may also have accumulated organizational, technical, and managerial capabilities that help them identify valuable use cases, redesign workflows, train workers, and integrate the tool into existing business processes. Table 4 therefore examines whether ChatGPT Enterprise adoption is associated with pre-existing investments in organizational and intangible capital.

We measure these complements using stocks of SG&A, R&D, and capitalized software per employee, transformed as log one plus the employee-normalized stock. The measures capture accumulated investment in organizational capabilities, innovation, and software infrastructure, respectively—forms of intangible capital that have been emphasized as complements to computing in the broader literature (e.g., Brynjolfsson et al. 2021). We use stocks rather than one-year spending flows to capture capacity built up before ChatGPT Enterprise adoption. The adoption regressions cover fiscal years 2024–2025, while all complement stocks are measured in fiscal year 2021. For SG&A and R&D, we construct stocks by cumulating historical Compustat spending flows using a perpetual-inventory approach: SG&A expense is depreciated at 20 percent annually and R&D expense at 15 percent annually. Capitalized software is measured directly using the Compustat capitalized-software stock. Each stock is converted to dollars and normalized by employment before entering the regressions.

The strongest and most robust association is with SG&A stock per employee. In the full sample, its coefficient is 0.020 and statistically significant; in the sample excluding technology and high-R&D sectors, it remains positive at 0.010, though it is not statistically significant. R&D stock per employee is also positively associated with adoption in both samples, with coefficients of 0.004 in the full sample and 0.003 in the sample excluding technology and high-R&D sectors. Capitalized software is positive and statistically significant in the full sample, with a coefficient of 0.008, but is positive and imprecisely estimated in the non-tech/high-R&D-excluded sample, with a coefficient of 0.006.

Taken together, the results suggest that ChatGPT Enterprise adoption is associated not only with firm scale, but also with the organizational and intangible assets firms have accumulated beforehand. Alongside the earlier findings—that adoption rises with revenue productivity and especially firm scale, and that more productive adopters tend to use ChatGPT Enterprise more broadly per employee—this pattern is consistent with the view that generative AI, like other general purpose technologies, depends on complementary capabilities within firms. Larger and more organizationally intensive firms may be better positioned both to identify valuable use cases and to deploy and integrate the technology into existing workflows.

4.3 Enterprise AI use is broadly distributed across worker groups but uneven in intensity

We next examine the subset of firms for which we observe high-quality job title information, as described in Section 3.2. We focus on job title classes and seniority levels and study two margins: the share of weekly active users in each category and usage intensity conditional on active use.[15]

Two limitations of this approach are important for interpretation. First, job title coverage is not universal and varies across firms, so these estimates describe observed use within the covered job title sample rather than the full workforce of all adopting firms. Second, the composition of active users is not the same as a role-specific adoption rate, because we do not observe the denominator of all employees by role. Accordingly, the worker-composition results measure each category's share of observed weekly active users; they do not measure the share of employees in that category who adopt ChatGPT Enterprise or whether the category is overrepresented among users relative to its workforce share. Similarly, the usage-intensity estimates compare activity among active users and do not account for differences across categories in the probability of becoming active.

4.3.1 The Extensive Margin of Use Across Job Title Class and Seniority

Figure 5 reports two ways of summarizing active-user composition six months after organizational adoption. The population-level estimate pools weekly active users across organizations, giving greater weight to firms with more active users. The firm-level estimate first calculates each category's share within an organization and then averages

[15] In Figure A2, we also study how both of these margins vary with respect to whether or not a worker is a people manager.

those shares across organizations, giving each firm equal weight. The former describes the composition of observed active users in the sample as a whole, while the latter describes the composition of the average firm.

Panel A reports the distribution across job title classes. Both estimates show that observed active use extends across a range of organizational functions and is not confined to technical workers. At the average firm, engineering and technical practitioners account for approximately 11% of weekly active users after six months, while executives, founders, and partners account for 9%. Finance and accounting and marketing and communications each account for approximately 5%, and sales and account management accounts for approximately 4%. This broad functional distribution is consistent with ChatGPT being adopted across the organizational structure rather than within a single occupational domain.

Panel B reports the corresponding distribution across inferred seniority levels. At the average firm, managers and directors account for approximately 24% of weekly active users after six months, followed by individual contributors (ICs) and professionals at 15% and senior ICs and principals at 14%. Executives account for approximately 10%, while early-career workers and trainees account for 7%. The seniority distribution similarly shows that ChatGPT Enterprise use spans multiple levels of the organizational hierarchy, rather than being concentrated among either junior employees or senior leadership.

4.3.2 The Intensive Margin of Use Across Job Title Class and Seniority

Figure 6 reports differences in weekly ChatGPT Enterprise usage intensity across worker categories, measured as the difference in weekly messages per active user from the relevant baseline. Panel A reports differences by job title class, while Panel B reports differences by inferred seniority level. In each panel, the specifications without firm fixed effects compare each group to the average active user in the sample, while the firm fixed effects specifications absorb differences in average usage intensity across firms and compare workers to other active users within the same organization.

Panel A of Figure 6 reports variation in weekly messages per active user by job title class among active users. The results show that job title classes that account for larger shares of observed weekly active users are not necessarily those with the highest usage intensity conditional on active use. In particular, analysts and marketing and communications workers send more weekly messages than the average active user in their firms, even though they do not account for the largest shares of observed weekly active users (Figure 5, Panel A). By contrast, executives, founders, and partners send fewer messages than other active users within the same firm. These patterns indicate that active-user composition and usage intensity capture distinct dimensions of enterprise adoption.

Panel B of Figure 6 reports usage intensity by inferred seniority level. The clearest pattern is a strong negative seniority gradient in message volume. Among adopters, early-career workers and trainees send roughly eight to nine more weekly messages than the average active user within the same firm, while managers, directors, and executives send fewer messages. This pattern is especially relevant in light of recent evidence on generative AI and early-career labor-market outcomes (e.g. Brynjolfsson et al. 2025a), because it identifies early-career workers as particularly intensive users conditional on active use. At the same time, message volume should be interpreted as a measure of usage intensity rather than as a complete measure of economic importance.

Overall, high-intensity use appears both in specific functional groups, such as analysts and marketing and communications workers, and at particular points in the career hierarchy, especially among early-career workers and trainees.[16] This heterogeneity motivates the task-level analysis below, which examines whether these differences in usage intensity correspond to differences in the kinds of work for which employees use ChatGPT.

[16] In Figures A3-A5, we show how both the composition of ChatGPT Enterprise users and the intensity of usage covary across worker type and industry.

4.4 Enterprise AI use spans a broad set of knowledge work tasks within organizations

We now turn from who uses ChatGPT Enterprise to what kinds of work they use it for. We classify Enterprise messages into a task taxonomy using an automated classifier described in Appendix D and summarize task composition using two complementary measures. The first is the share of weekly active users who perform a task at least once during the week. This task-prevalence measure captures the breadth of exposure to each task category. Because users may perform multiple task types in the same week, the category shares are not mutually exclusive and therefore do not sum to one. The second is the share of weekly messages assigned to each task category. This message-share measure captures the intensity of use by task and shows which activities account for the largest share of observed interaction with ChatGPT Enterprise.

4.4.1 Overall Enterprise Task Composition

Figure 7 reports the overall task composition of ChatGPT Enterprise use. Panel A shows that more than half of active users perform documentation or technical-writing tasks, nearly half perform technical digital work, and large shares use ChatGPT Enterprise for messages, topic overviews, facts and figures, professional work, research, sales and marketing, planning, legal work, data analysis, and financial or tax tasks. The central pattern is not the dominance of a single application, but the breadth of task exposure among active users.

Panel B shows that message volume is more concentrated than task incidence. Documentation and technical writing, technical digital work, and message drafting account for large shares of total messages, while several categories that reach many users account for relatively small shares of message volume. Topic overviews, business and market research, legal and regulatory work, and financial and tax tasks are widespread but comparatively less message-intensive. This distinction matters for interpreting enterprise AI use. A task can be economically relevant because it reaches many workers, because it accounts for large amounts of usage, or both. User reach and usage depth are therefore separate margins of task-level diffusion. Panel B also shows a substantial residual category of other task classifications. This is useful evidence in itself, in that it indicates that ChatGPT Enterprise use has a long tail: workers apply the tool to many activities that do not fit cleanly into the largest task categories.

4.4.2 Task Differences Across Industries

Figure 8 examines task composition by two-digit NAICS sector (referred to hereafter as "industry"), separately for task prevalence and message shares. Panel A reports the share of weekly active users in each industry who use ChatGPT Enterprise for a given task at least once, while Panel B reports the share of weekly messages in each industry assigned to each task.

Panel A shows both commonality and industry variation. The broad task structure is similar across industries: documentation and technical writing, technical digital work, and communication are among the most common tasks in every major industry group. At the same time, task prevalence varies in ways that are consistent with differences in the underlying task content of work across industries. For example, financial and tax-related tasks are substantially more prevalent in finance and insurance than in other industries, business and market research is also especially common in finance and insurance, and sales and marketing tasks are more prevalent in arts, entertainment, and recreation, information, and retail trade than in manufacturing. Panel B shows that these industry differences are more muted when tasks are weighted by message volume. Across industries, messages are concentrated in a similar set of categories, especially documentation and technical writing, technical digital work, and communication. In other words, industry differences appear more strongly on the extensive task margin, i.e., which tasks active users try at least once, than on the intensive task margin, i.e., which tasks account for the largest shares of total messages.

4.4.3 *Task Differences by Job Title Class and Seniority*

Figures 9 and 10 examine task composition by job title class and inferred seniority, respectively.[17] As above, Panel A in each figure reports the share of active users in each group who use ChatGPT Enterprise for a task at least once during the week, while Panel B reports the share of messages assigned to each task.

Figure 9 shows both broad commonality and role-specific specialization. Documentation and technical writing, communication, and technical or digital tasks appear across many job title classes. At the same time, task prevalence varies in ways that align with job responsibilities: engineering and technical practitioners are especially likely to use ChatGPT Enterprise for technical digital work and debugging, finance and accounting workers for financial and tax tasks, and sales, account, marketing, and communications roles for sales and marketing tasks. The message-share panel shows a related pattern, but also makes clear that these role-specific tasks do not overpower the small set of core tasks that are performed by all roles.

Figure 10 shows a similar structure across the organizational hierarchy. Workers at different seniority levels use overlapping task categories, but with different relative emphasis. Early-career workers, individual contributors, managers, and executives all use ChatGPT Enterprise for common categories such as documentation and technical writing, technical digital work, communication, and information-oriented tasks. At the same time, seniority is associated with differences in the breadth and mix of task use. For instance, early-career workers and individual contributors have high prevalence in several common production-oriented categories, whereas executives are relatively more represented in categories such as topic overviews, facts and figures, legal and regulatory work, and financial or tax-related tasks.

[17] We report task composition across people manager status in Figure A8.

5 Conclusion

A growing literature argues that AI, and especially large language models, have the characteristics of a general purpose technology (Goldfarb et al. 2023; Eloundou et al. 2024). For such technologies to affect production, firms must do more than obtain access: they must discover valuable use cases, encourage use across workers, and integrate the technology into existing workflows. This paper studies that process using administrative data from ChatGPT Enterprise. One central message is that access to the same underlying system does not imply uniform use: firms differ in whether and when they adopt, workers differ in how intensively they use the tool, and task use varies across industries, job title classes, and seniority levels.

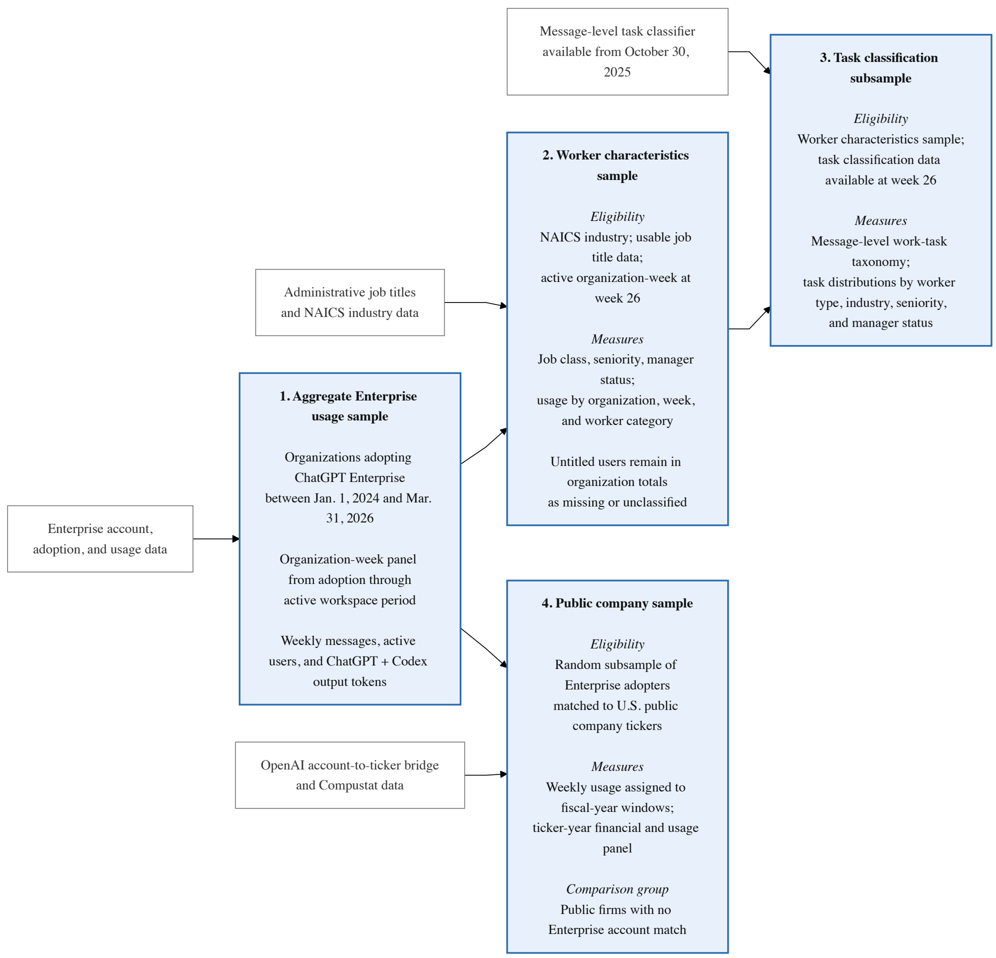
This interpretation has several implications. First, the earliest U.S.-based public company adopters are not average firms; they are larger, more intangible-intensive, and more highly valued. The relationship between adoption and firm capabilities also points toward the importance of complements. Firms with greater scale and accumulated intangible investments may be better positioned to identify valuable applications, support workers in using the technology, and integrate it into business processes. Second, diffusion may initially reinforce existing firm heterogeneity. If larger and more intangible-intensive firms adopt earlier and are better positioned to integrate the technology into work, generative AI could widen differences in productivity or value creation across firms even when the underlying models are broadly available. Third, adopting firms differ substantially in the breadth of participation, the intensity of use, and the task mix to which the technology is applied. These margins matter because the economic role of generative AI depends not only on whether a firm has access, but also on where the technology enters the organization of work.

Importantly, these results should be interpreted in light of the scope of the data. The analyses measure usage only within OpenAI's ChatGPT Enterprise product, not usage of other AI systems, API-based tools, internally built applications, or personal accounts. The worker-level results are based on observed administrative job titles, which are incomplete and do not provide denominators for the full workforce in each role. The task results are based on classified message content and do not measure downstream work products, productivity effects, or changes in organizational routines. Finally, the public company analyses are limited to the selected subset of U.S.-based enterprise organizations that can be linked to financial data. Future work should connect enterprise AI telemetry to measures of output, organizational change, and longer-run firm performance, and should examine how adoption, usage intensity, worker composition, and task mix evolve as generative AI continues to become more widespread.

Even with these limitations, the patterns documented in this paper point to a central feature of enterprise AI diffusion: adoption is only the beginning of deployment. The rapid adoption of generative AI by firms should therefore not be equated with immediate productivity transformation. General purpose technologies rarely generate immediate, economy-wide gains; their impact unfolds through a slower process of co-invention in which firms discover use cases, invest in complements, and reorganize production so that a new capability becomes reliable in everyday work (Griliches 1957; Mansfield 1961; Hall and Khan 2003; Jovanovic and Rousseau 2005; Bresnahan and Trajtenberg 1995). We are still in the early stages of that process. Firms are not merely deciding whether to use generative AI; they are learning where it belongs in their organizational workflow. The economic effects of generative AI will depend on how that learning and decision-making process unfolds across firms, workers, and tasks.

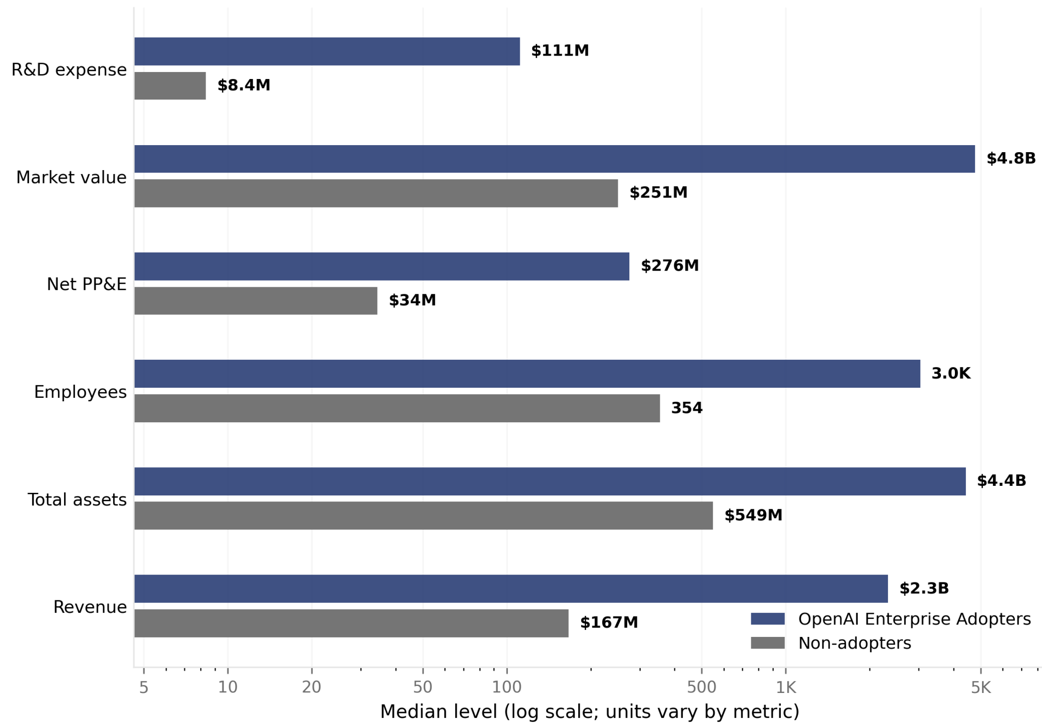
6 Figures

Fig. 1: CONSTRUCTION OF CHATGPT ENTERPRISE ADOPTION AND USAGE SAMPLES



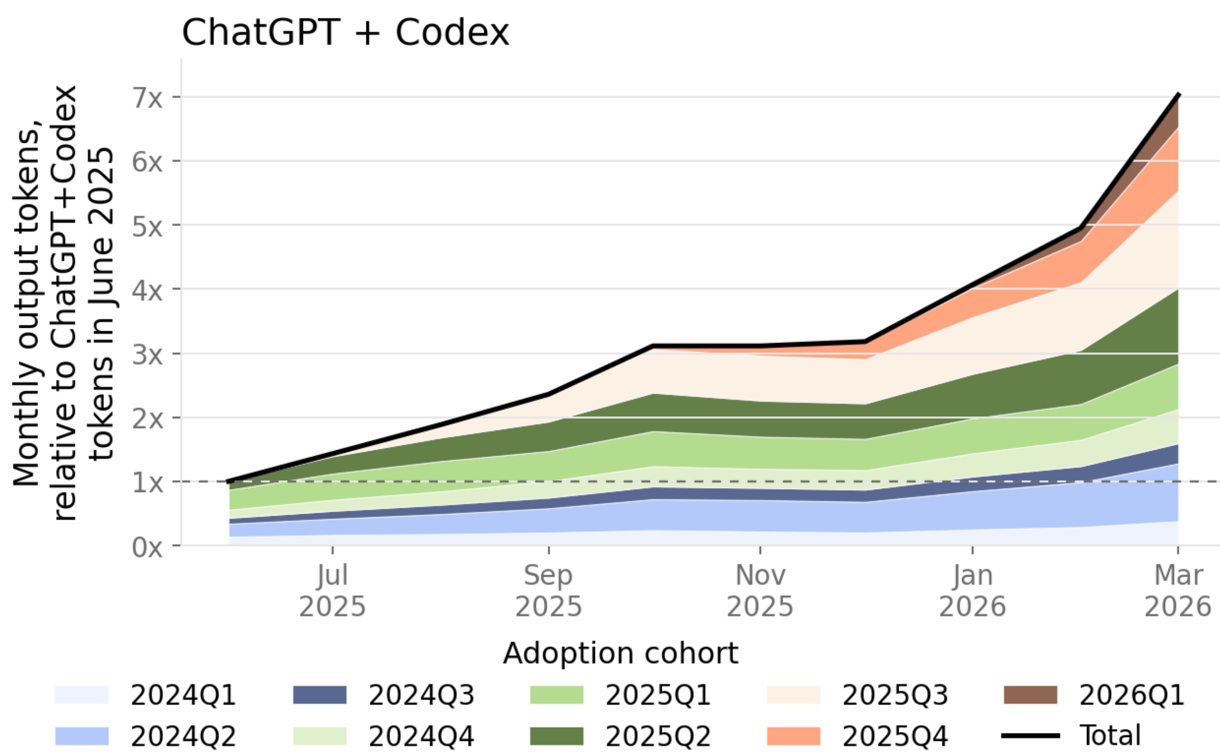
Note: This figure summarizes the construction of the four samples used in the analysis. Blue boxes denote analysis samples, while white boxes denote additional data sources used to construct or augment them. Arrows indicate sample restrictions and data linkages.

Fig. 2: SUMMARY STATISTICS: COMPARISON OF CHATGPT ENTERPRISE ADOPTERS WITH OTHER PUBLIC FIRMS



Note: This figure compares median 2024 Compustat firm characteristics for public firms linked to ChatGPT Enterprise accounts with those of other public firms. Dollar-denominated variables are reported in millions of dollars, and employment is measured in workers. The underlying data combine Compustat annual business metrics with ChatGPT Enterprise account-to-ticker matches.

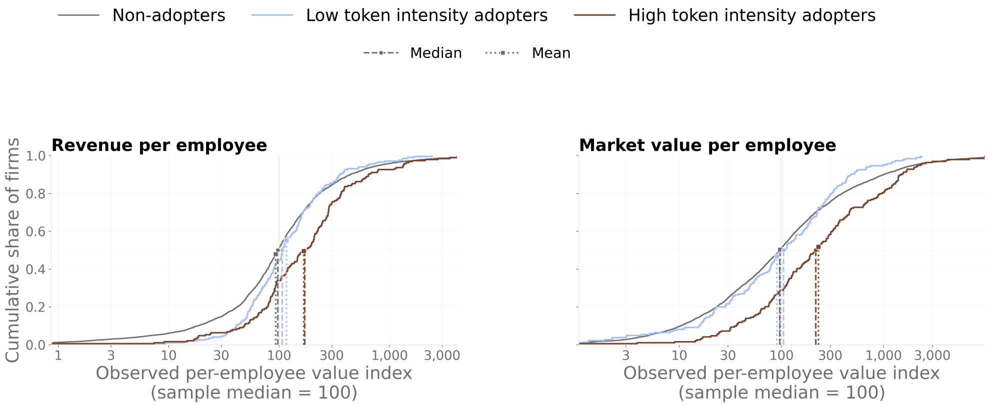
Fig. 3: ENTERPRISE OUTPUT TOKEN GROWTH



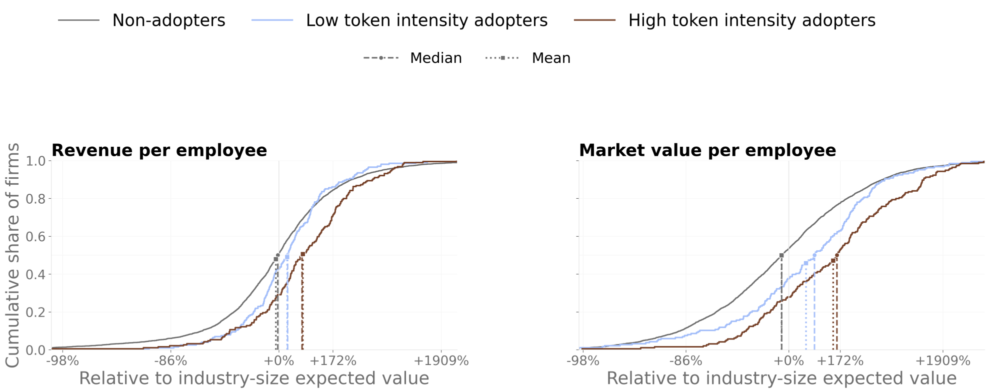
Note: This figure plots monthly ChatGPT and Codex output tokens for firms in the ChatGPT Enterprise analysis sample, stacked by the quarter in which each firm first adopted ChatGPT Enterprise. Tokens are counted only after each firm's ChatGPT Enterprise adoption date. Values are indexed to total combined ChatGPT and Codex output tokens in June 2025, with the dashed horizontal line marking 1.0 and the black line showing the aggregate total across cohorts.

Fig. 4: FINANCIAL MEASURES BY USAGE INTENSITY: ECDF

Panel A. Distribution of observed-value index



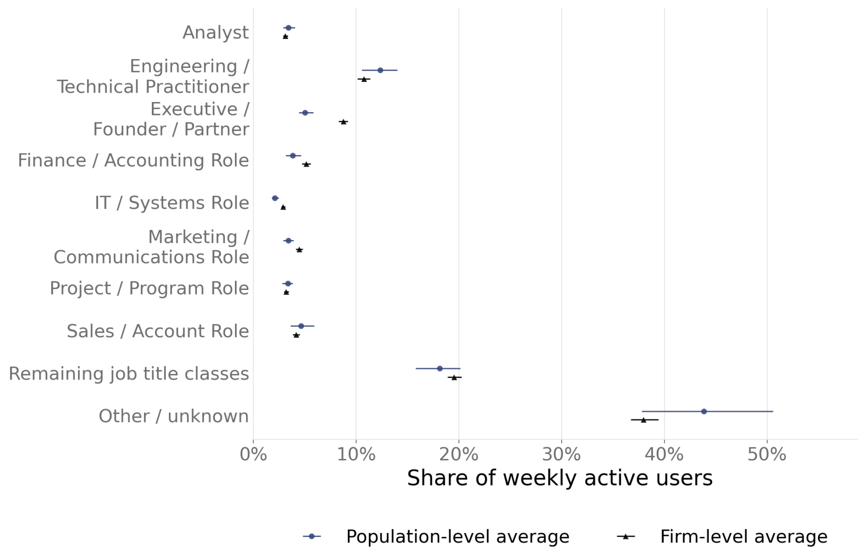
Panel B. Distribution of industry-size-adjusted residuals



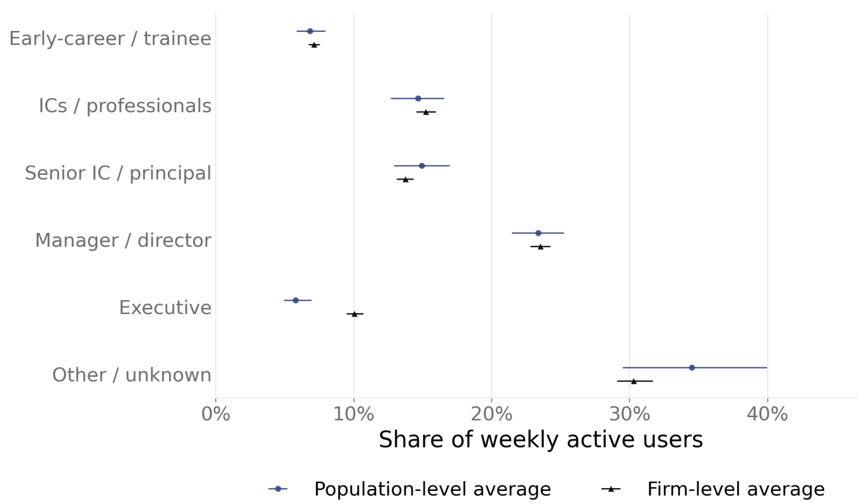
Note: This figure compares 2025 financial outcomes across public firms by ChatGPT Enterprise usage intensity. Non-adopters are public firms not linked to a ChatGPT Enterprise account. Among adopters with positive observed usage, low- and high-intensity groups are defined using a median split of weekly output tokens per employee. Panel A reports per-employee financial outcomes indexed to the sample median, which is set to 100. Panel B reports outcomes after adjusting for industry and firm-size. Step functions show empirical CDFs; dashed and dotted vertical lines indicate group medians and means, respectively. The underlying data combine the ChatGPT Enterprise usage panel with Compustat annual business metrics.

Fig. 5: COMPOSITION OF ACTIVE USERS BY WORKER TYPE

Panel A. Job title class



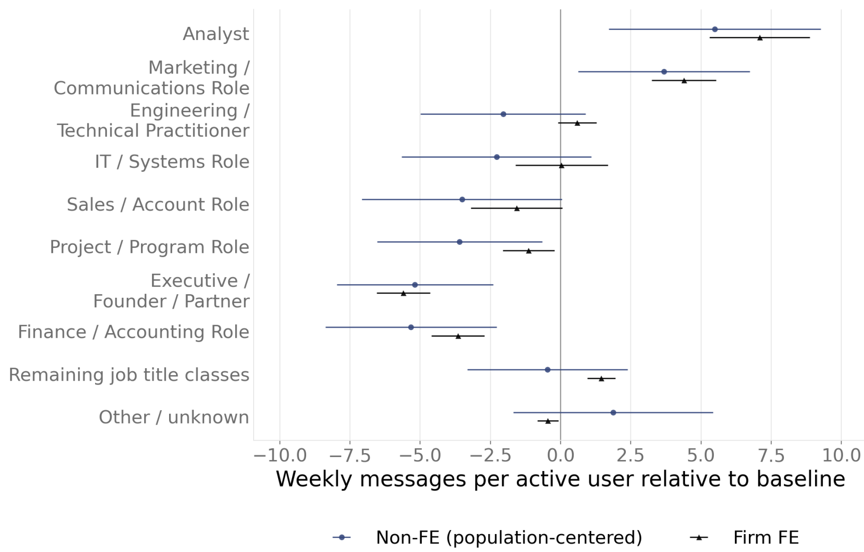
Panel B. Seniority level



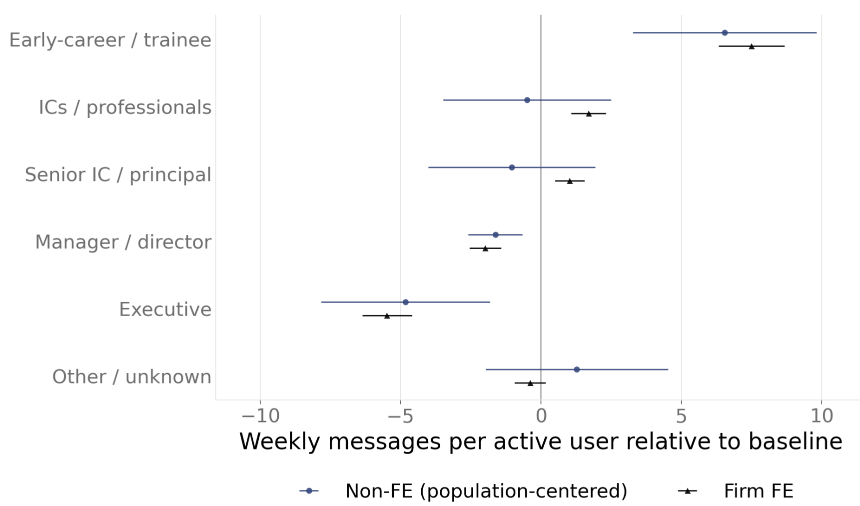
Note: This figure reports the distribution of weekly active ChatGPT Enterprise users across worker categories six months after firm adoption. Panel A groups users by inferred job title class. Panel B groups users by inferred seniority level. Blue points report the population-level average, computed as each category's share of all weekly active users across firms. Black points report the firm-level average, computed as each category's share of weekly active users within each firm and then averaged across firms, giving each firm equal weight. Horizontal bars show 95% firm-bootstrap confidence intervals. "Remaining job title classes" pools inferred job title classes outside the individually displayed categories. "Other / unknown" includes users with missing, ambiguous, malformed, or otherwise low-information job titles that cannot be assigned to a substantive class. "IC" denotes an individual contributor.

Fig. 6: DIFFERENCES IN AI USAGE INTENSITY ACROSS WORKER ROLES

Panel A. Job title class



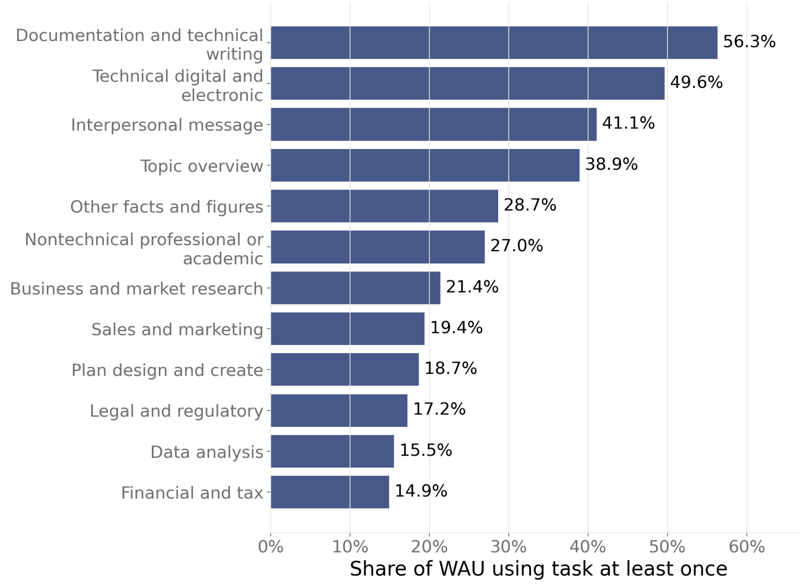
Panel B. Seniority level



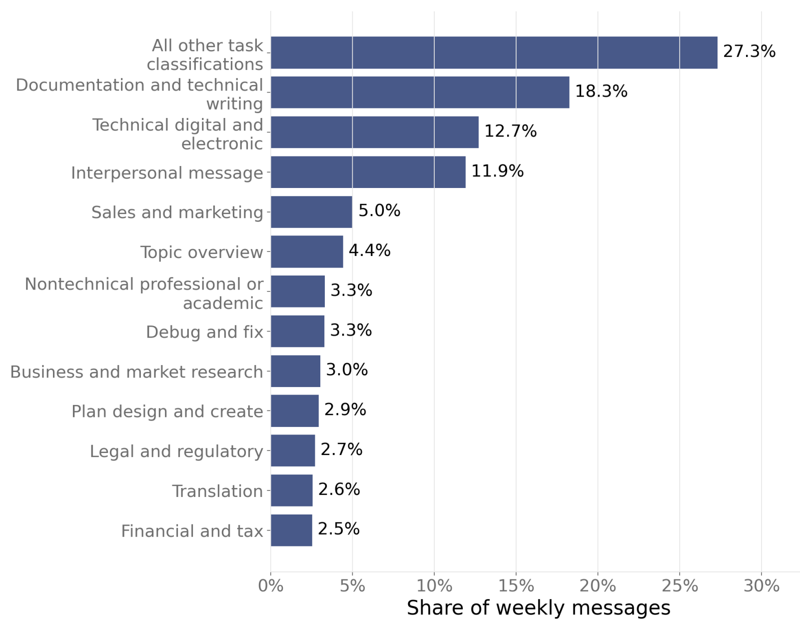
Note: This figure reports differences in weekly ChatGPT Enterprise usage intensity across worker categories six months after firm adoption. Panel A groups users by inferred job title class. Panel B groups users by inferred seniority level. Usage intensity is measured as weekly messages per active user within each worker category. Blue points report population-level estimates, comparing each worker category to the average active user across firms. Black points report firm fixed effect estimates, comparing each worker category to other active users within the same firm. Positive values indicate more messages per active user than the relevant baseline; negative values indicate fewer. Horizontal bars show 95% confidence intervals with firm-clustered standard errors. "Remaining job title classes" pools inferred job title classes outside the individually displayed categories. "Other / unknown" includes users with missing, ambiguous, malformed, or otherwise low-information job titles that cannot be assigned to a substantive class. "IC" denotes an individual contributor.

Fig. 7: DISTRIBUTION OF AI USE ACROSS TASKS

Panel A. Task Prevalence Among Active Users



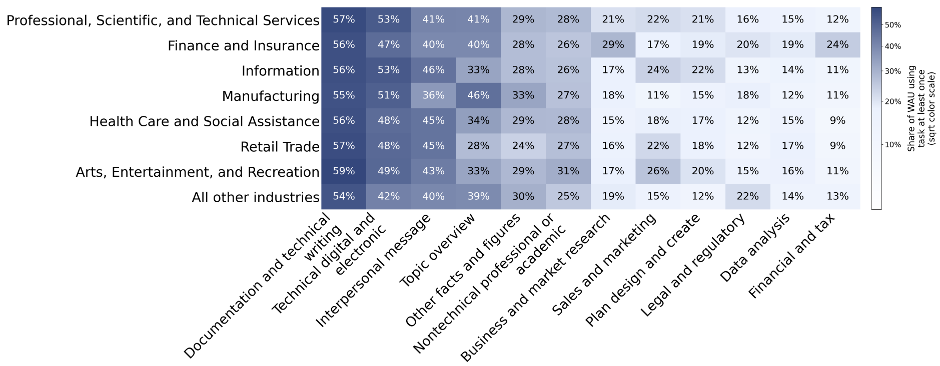
Panel B. Distribution of Messages Across Tasks



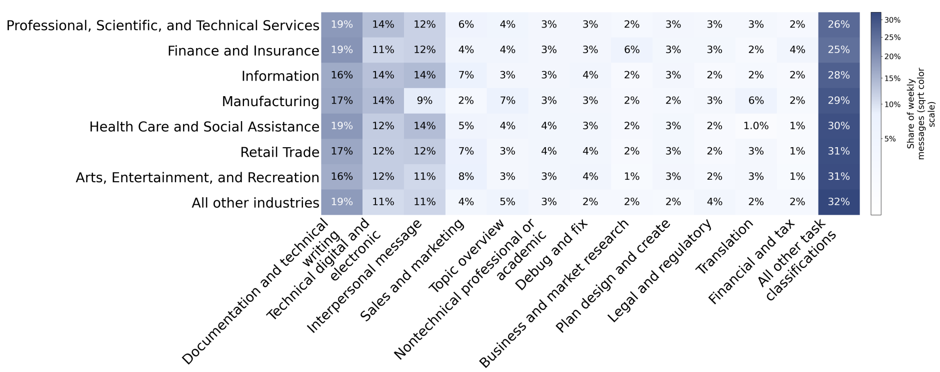
Note: The figure describes the distribution of ChatGPT Enterprise use across tasks among ChatGPT Enterprise firms with task-classification data, measured six months after adoption. Each message is assigned to one of 60 task categories using the classifier described in the text. Panel A reports the share of weekly active users who submitted at least one message in each of the 12 task categories with the greatest user reach. Because users may use ChatGPT for multiple tasks during the same week, these shares are not mutually exclusive and do not sum to 100 percent. Panel B reports the share of classified weekly messages assigned to the 12 largest task categories by message volume. "All other task classifications" pools the remaining categories. Categories are selected separately in each panel based on the corresponding measure.

Fig. 8: DIFFERENCES IN AI TASK USE ACROSS INDUSTRIES

Panel A. Task Prevalence Among Active Users



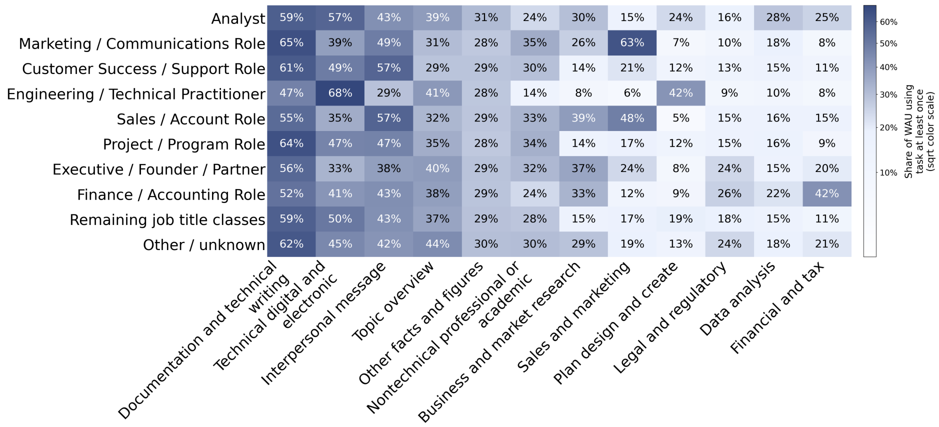
Panel B. Distribution of Messages Across Tasks



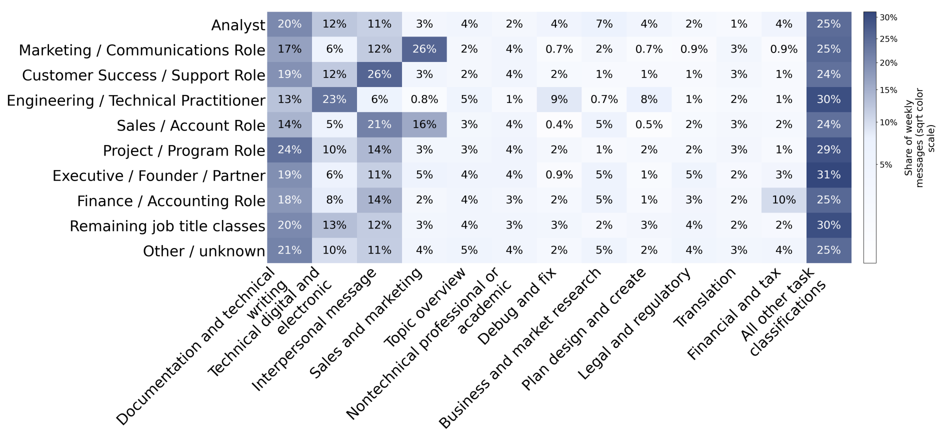
Note: The figure compares the distribution of ChatGPT Enterprise use across tasks and two-digit NAICS sectors among ChatGPT firms with task-classification data, measured six months after adoption. Each message is assigned to one of 60 task categories using the classifier described in the text. Panel A reports the share of weekly active users in each industry who submitted at least one message in each of the 12 task categories with the greatest user reach. Because users may use ChatGPT for multiple tasks during the same week, the shares in each row are not mutually exclusive and do not sum to 100 percent. Panel B reports the share of classified weekly messages in each industry assigned to the 12 largest task categories by message volume. "All other task classifications" pools the remaining task categories, while "All other industries" pools NAICS two-digit sectors not displayed separately. Task categories are selected separately in each panel based on the corresponding measure.

Fig. 9: DIFFERENCES IN AI TASK USE ACROSS JOB TITLE CLASSES

Panel A. Task Prevalence Among Active Users



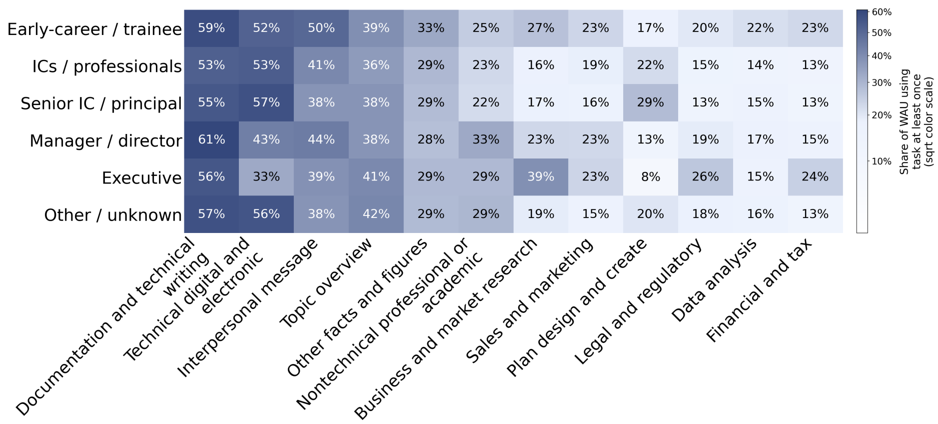
Panel B. Distribution of Messages Across Tasks



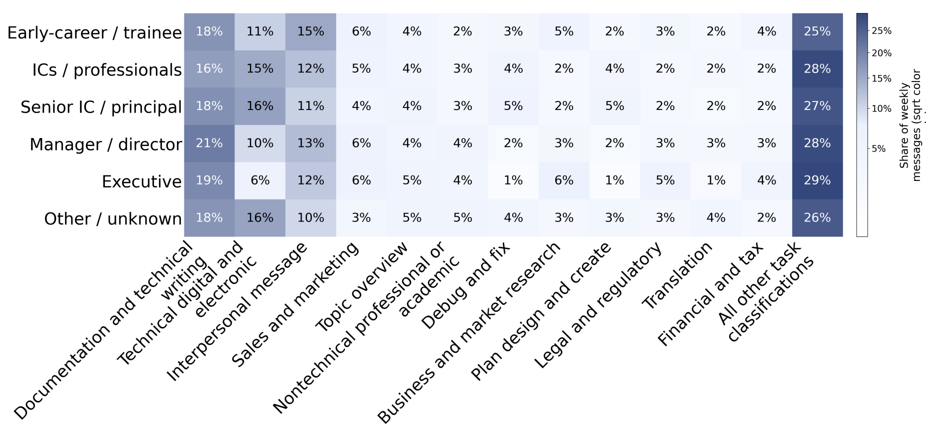
Note: The figure compares the distribution of ChatGPT Enterprise use across tasks and inferred job title classes among firms with task-classification and job title data, measured six months after adoption. Each message is assigned to one of 60 task categories using the classifier described in the text. Panel A reports the share of weekly active users in each job title class who submitted at least one message in each of the 12 task categories with the greatest user reach. Because users may use ChatGPT for multiple tasks during the same week, the shares in each row are not mutually exclusive and do not sum to 100 percent. Panel B reports the distribution of classified weekly messages across the 12 largest task categories by message volume within each job title class. "All other task classifications" pools the remaining task categories. "Remaining job title classes" pools substantive inferred job title classes outside the individually displayed categories, while "Other / unknown" includes users whose job titles are missing, ambiguous, malformed, or otherwise cannot be assigned to a substantive class. Task categories are selected separately in each panel using their prevalence in the full task-classification sample.

Fig. 10: DIFFERENCES IN AI TASK USE ACROSS SENIORITY LEVELS

Panel A. Task Prevalence Among Active Users



Panel B. Distribution of Messages Across Tasks



Note: The figure compares the distribution of ChatGPT Enterprise use across tasks and inferred seniority levels among firms with task-classification and job title data, measured six months after adoption. Each message is assigned to one of 60 task categories using the classifier described in the text. Panel A reports the share of weekly active users at each seniority level who submitted at least one message in each of the 12 task categories with the greatest user reach. Because users may use ChatGPT for multiple tasks during the same week, the shares in each row are not mutually exclusive and do not sum to 100 percent. Panel B reports the distribution of classified weekly messages across the 12 largest task categories by message volume within each seniority group. “All other task classifications” pools the remaining task categories. “Contractor / Temporary” identifies users whose job titles indicate employment status rather than a conventional seniority level. “Other / unknown” includes users whose job titles are missing, ambiguous, malformed, or otherwise do not provide enough information to infer seniority. “IC” denotes an individual contributor. Task categories are selected separately in each panel using their prevalence in the full task classification sample.

7 Tables

Table 1: FINANCIAL CHARACTERISTICS AND ENTERPRISE ADOPTION

	(1)	(2)	(3)	(4)
DV	Adopter	Adopter	Adopter	Adopter
Controls	Base.	Addl.	Addl.	Addl.
Sample	All	All	All	No tech
L. log rev./emp.	0.009***	0.006***	0.004*	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
L. log assets/emp.		0.010***	0.013***	0.009***
		(0.003)	(0.003)	(0.003)
L. log PP&E/emp.		-0.007***	-0.001	-0.007***
		(0.002)	(0.002)	(0.002)
L. log emp.	0.013***	0.015***	0.019***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
Obs.	8,229	8,229	8,229	7,379
R^2	0.053	0.055	0.109	0.046
FYs	2024-2025	2024-2025	2024-2025	2024-2025
Year FE	Yes	Yes	Yes	Yes
Ind. FE	NAICS2	NAICS2	NAICS4	NAICS2

Note: Each column reports a linear probability model estimated on public firm-years with positive lagged employment and positive lagged firm-characteristic values. The dependent variable equals one when a public firm's first OpenAI Enterprise adoption date falls in the current fiscal year; controls are public firm-years not linked through the OpenAI ticker bridge. The table reports the industry fixed-effect level used in each column. Baseline columns control for lagged log employment. Additional-control columns additionally control for lagged log assets per employee, lagged log positive PP&E per employee, and indicators for no positive and missing lagged PP&E; the indicator coefficients are included in the model but omitted from the table. The no-tech column excludes firms with two-digit NAICS code 51. Standard errors clustered by Compustat gvkey are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 2: FINANCIAL CHARACTERISTICS AND USAGE INTENSITY

	(1)	(2)	(3)	(4)
DV	Msgs/ act. wk/emp	WAU/emp	Tokens/emp	Msgs/WAU
L. log rev./emp.	0.062	0.006	0.036	-0.014
	(0.044)	(0.007)	(0.094)	(0.021)
L. log assets/emp.	0.061	0.012*	0.107	0.008
	(0.045)	(0.008)	(0.099)	(0.019)
L. log PP&E/emp.	-0.079**	-0.010*	-0.087	-0.018
	(0.033)	(0.006)	(0.070)	(0.014)
L. log emp.	-0.266***	-0.032***	-0.667***	-0.002
	(0.019)	(0.003)	(0.048)	(0.008)
Obs.	478	478	396	482
R^2	0.480	0.362	0.471	0.100
FYs	2024-2025	2024-2025	2024-2025	2024-2025
Year FE	Yes	Yes	Yes	Yes
Ind. FE	NAICS2	NAICS2	NAICS2	NAICS2

Note: Each column reports an OLS regression of transformed current fiscal-year Enterprise usage intensity on lagged public-company financial characteristics, estimated on public tickers with positive fiscal-year Enterprise usage, positive lagged employment, and positive lagged firm-characteristic values. Dependent variables are transformed as log one plus usage intensity. Msgs/act. wk/emp is messages per active usage week per employee; WAU/emp is mean weekly active users per employee; Tokens/emp is mean weekly output tokens per employee; Msgs/WAU is messages per weekly active user. Output-token usage is measured over weeks with complete output-token coverage. All columns control for lagged log employment, lagged log assets per employee, lagged log positive PP&E per employee, and indicators for no positive and missing lagged PP&E; the indicator coefficients are included in the model but omitted from the table. Standard errors clustered by Compustat gvkey are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 3: FIRM SCALE AND ENTERPRISE ADOPTION

	(1)	(2)	(3)	(4)	(5)
DV	Adopter	Adopter	Adopter	Adopter	Adopter
Scale	Revenue	Revenue	Revenue	Ind.-yr rev.	Ind.-yr rev.
L. log revenue	0.011***				
	(0.001)				
Top 25% by L. rev.		0.069***			
		(0.007)			
Top 5% by L. rev.			0.098***		
			(0.016)		
Top 25% by L. rev., ind.-yr				0.072***	
				(0.006)	
Top 5% by L. rev., ind.-yr					0.113***
					(0.017)
Obs.	9,391	9,391	9,391	9,391	9,391
R^2	0.051	0.046	0.035	0.048	0.040
FYs	2024-2025	2024-2025	2024-2025	2024-2025	2024-2025
Year FE	Yes	Yes	Yes	Yes	Yes
Ind. FE	NAICS2	NAICS2	NAICS2	NAICS2	NAICS2

Note: Each column reports a linear probability model estimated on public firm-years with positive lagged scale values. The dependent variable equals one when a public firm's first OpenAI Enterprise adoption date falls in the current fiscal year; controls are public firm-years not linked through the OpenAI ticker bridge. Column 1 uses lagged log revenue. Columns 2–5 use indicators for being in the top tail of lagged revenue, computed within fiscal year using lagged total revenue; industry-year indicators are computed within fiscal-year and two-digit NAICS cells. All columns include fiscal-year and two-digit NAICS industry fixed effects. Standard errors clustered by Compustat gvkey are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Table 4: INTANGIBLE ASSETS AND ENTERPRISE ADOPTION

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Adopter	Adopter	Adopter	Adopter	Adopter	Adopter
Complement measure	SG&A stock	R&D stock	Capitalized software	SG&A stock	R&D stock	Capitalized software
Sample	All	All	All	No tech/ high R&D	No tech/ high R&D	No tech/ high R&D
Log(1 + comp./emp.)	0.020***	0.004***	0.008**	0.010	0.003***	0.006
	(0.005)	(0.001)	(0.003)	(0.007)	(0.001)	(0.006)
L. log revenue/emp.	0.006**	0.008***	0.012	0.010	0.019***	0.021
	(0.003)	(0.002)	(0.009)	(0.007)	(0.006)	(0.019)
L. log assets/emp.	0.004	0.010***	0.020	0.002	-0.001	0.005
	(0.004)	(0.003)	(0.012)	(0.007)	(0.006)	(0.020)
L. log PP&E/emp.	-0.005**	-0.005**	-0.017**	-0.005	-0.005*	-0.010
	(0.002)	(0.002)	(0.008)	(0.003)	(0.003)	(0.012)
L. log employment	0.020***	0.015***	0.017***	0.017***	0.015***	0.023***
	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)	(0.007)
Observations	5,943	7,117	1,076	3,247	4,029	477
R^2	0.064	0.058	0.075	0.055	0.057	0.085
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	NAICS2	NAICS2	NAICS2	NAICS2	NAICS2	NAICS2

Note: Each column reports a linear probability model estimated on public firm-years with positive employment and finite nonnegative complement stock per employee. The dependent variable equals one when a public firm's first OpenAI Enterprise adoption date falls in the current fiscal year; controls are public firm-years not linked through the OpenAI ticker bridge. Entries report coefficients from regressions of adoption on log one plus complement stock per employee, lagged log revenue per employee, lagged log employment, lagged log assets per employee, lagged log positive PP&E per employee, indicators for no positive and missing lagged PP&E, fiscal-year fixed effects, and two-digit NAICS industry fixed effects. The no-tech/high-R&D columns exclude NAICS2 sectors 32, 33, 51; high-R&D sectors are selected using fiscal-year 2021 sector median R&D stock per employee. Fiscal years: 2024-2025. Complement variables are measured in fiscal year 2021. SG&A and R&D stocks are accumulated from Compustat flow variables: SG&A uses `xsga` with 20% annual depreciation, and R&D uses `xrd` with 15% annual depreciation. Capitalized software uses the Compustat `capsft` level joined from the capitalized-software extract. Complement values are converted to dollars, divided by employees, and transformed as log one plus the employee-normalized value before entering the model. Complement-stock opening stock: zero-growth steady-state opening stock. Missing SG&A and negative flows are left missing; missing R&D and observed zero flows are treated as zero investment. Standard errors clustered by Compustat gvkey are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

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A Additional Tables

Table A1: Compustat measures used in the analysis

Measure	Source field(s)	Construction	Used for
Revenue	`revt`	Annual Compustat revenue, reported in millions of dollars	Firm scale and revenue-per-employee outcomes
Total assets	`at`	Annual Compustat total assets, reported in millions of dollars	Firm scale and balance-sheet comparison
Employees	`emp`	Compustat employment, converted from thousands to workers	Denominator for per-employee measures
Net PP&E	`ppent`	Annual Compustat net property, plant, and equipment, reported in millions of dollars	Physical capital comparison
Market value	`mkvalt`	Annual Compustat market value, reported in millions of dollars	Market-value and market-value-per-employee outcomes
R&D expense	`xrd`	Annual Compustat research and development expense, reported in millions of dollars	Intangible investment comparison
Revenue per employee	`revt`, `emp`	Revenue divided by employees	Financial distribution and regression outcome
Market value per employee	`mkvalt`, `emp`	Market value divided by employees	Financial distribution and regression outcome
Enterprise usage intensity	`annual_total messages`, `active_weeks`, `emp`	Messages per active usage week per employee	Usage-level financial comparisons
WAU per employee	`mean_weekly active_users`, `emp`	Mean weekly active users divided by employees	Industry usage-intensity coefficient figure

Note: Financial variables are drawn from the Compustat annual business metrics panel. Dollar-denominated Compustat variables are reported in millions of dollars. Employment is converted from thousands of workers to workers before constructing per-employee measures. Enterprise usage measures are aggregated to ticker-fiscal-year observations before merging to the financial panel.

Table A2: Top 5 actual job titles by job title class

Job title class	Actual job title	User share
Administrative / executive support	Executive assistant	15.4%
Administrative / executive support	Administrative assistant	4.5%
Administrative / executive support	Student assistant	3.4%
Administrative / executive support	Senior executive assistant	2.6%
Administrative / executive support	Office manager	2.0%
Analyst	Analyst	7.9%
Analyst	Business analyst	3.9%
Analyst	<redacted>	2.8%
Analyst	Senior analyst	2.2%
Analyst	Senior business analyst	1.9%
Consultant / professional services	Consultant	19.2%
Consultant / professional services	Senior consultant	6.4%
Consultant / professional services	Management consultant	6.0%
Consultant / professional services	Management consulting manager	4.1%
Consultant / professional services	Associate consultant	3.1%
Contractor / temporary	Contractor	36.0%
Contractor / temporary	Contingent worker	9.4%
Contractor / temporary	Contingent worker hourly	6.3%
Contractor / temporary	Temporary worker	5.5%
Contractor / temporary	Contractor - <redacted>	2.5%
Customer success / support role	Customer success manager	2.6%
Customer success / support role	Senior customer success manager	1.5%
Customer success / support role	Customer service specialist	1.2%

Job title class	Actual job title	User share
Customer success / support role	Senior customer service representative	1.1%
Customer success / support role	Customer service representative	0.9%
Data / analytics practitioner	Data engineer	4.9%
Data / analytics practitioner	Senior data scientist	4.4%
Data / analytics practitioner	Data scientist	4.4%
Data / analytics practitioner	Senior data engineer	4.1%
Data / analytics practitioner	Machine learning engineer	2.3%
Design / creative role	Senior product designer	4.3%
Design / creative role	Product designer	3.7%
Design / creative role	Graphic designer	2.1%
Design / creative role	Designer	1.9%
Design / creative role	Senior designer	1.7%
Education / academic role	Student	67.1%
Education / academic role	Student worker	3.2%
Education / academic role	Professor	3.2%
Education / academic role	Undergraduate	2.5%
Education / academic role	Associate professor	2.4%
Engineering / technical practitioner	Software engineer	8.6%
Engineering / technical practitioner	Senior software engineer	7.1%
Engineering / technical practitioner	Staff software engineer	1.8%
Engineering / technical practitioner	Software engineer II	1.5%
Engineering / technical practitioner	<redacted>	1.1%
Executive / founder / partner	Partner	14.6%
Executive / founder / partner	Managing director	7.1%

Job title class	Actual job title	User share
Executive / founder / partner	Executive director	1.8%
Executive / founder / partner	Associate partner	1.7%
Executive / founder / partner	General manager	1.2%
Finance / accounting role	Senior accountant	1.7%
Finance / accounting role	Portfolio manager	1.2%
Finance / accounting role	Finance manager	1.1%
Finance / accounting role	Accountant	1.0%
Finance / accounting role	Trader	0.9%
Generic rank / seniority only	Associate	12.3%
Generic rank / seniority only	Senior associate	10.0%
Generic rank / seniority only	Manager	8.1%
Generic rank / seniority only	Director	5.7%
Generic rank / seniority only	Senior manager	5.2%
Healthcare / clinical role	CRA	5.6%
Healthcare / clinical role	<redacted>	3.0%
Healthcare / clinical role	Physician	1.4%
Healthcare / clinical role	<redacted>	1.2%
Healthcare / clinical role	<redacted>	1.2%
IT / systems role	IT specialist	1.3%
IT / systems role	Systems administrator	0.9%
IT / systems role	IT manager	0.9%
IT / systems role	<redacted>	0.8%
IT / systems role	IT support specialist	0.7%
Legal role	Associate attorney	2.8%

Job title class	Actual job title	User share
Legal role	Legal counsel	2.7%
Legal role	Paralegal	2.6%
Legal role	Senior legal counsel	2.4%
Legal role	Counsel	2.1%
Marketing / communications role	Marketing manager	1.7%
Marketing / communications role	Product marketing manager	0.8%
Marketing / communications role	Senior marketing manager	0.6%
Marketing / communications role	Senior product marketing manager	0.6%
Marketing / communications role	Technical writer	0.6%
People / recruiting role	Recruiter	2.2%
People / recruiting role	HR business partner	1.7%
People / recruiting role	Senior recruiter	1.7%
People / recruiting role	Talent acquisition partner	1.2%
People / recruiting role	HR manager	1.0%
Product role	Senior product manager	10.5%
Product role	Product manager	10.3%
Product role	Product owner	3.3%
Product role	Principal product manager	2.1%
Product role	Director, product management	1.9%
Project / program role	Project manager	6.3%
Project / program role	Senior project manager	3.7%
Project / program role	Project leader	2.6%
Project / program role	Program manager	1.7%
Project / program role	Senior program manager	1.0%

Job title class	Actual job title	User share
Research / scientist role	Senior CRA	4.3%
Research / scientist role	Principal CRA	2.3%
Research / scientist role	Research assistant	2.1%
Research / scientist role	Senior scientist	2.1%
Research / scientist role	Research associate	1.9%
Sales / account role	Account executive	3.3%
Sales / account role	Account manager	3.0%
Sales / account role	Senior account executive	1.8%
Sales / account role	Senior account manager	1.6%
Sales / account role	Sales development representative	1.3%
Security role	Security engineer	3.4%
Security role	Senior security engineer	2.5%
Security role	Chief information security officer	1.3%
Security role	<redacted>	1.1%
Security role	Security analyst	1.0%

Note: Percentages are shares of title-user observations within each classifier value in the full SCIM job-title classification universe. Unknown and malformed classifier values are omitted. Normalized title variants are combined before applying the publication rule. Job-title detail observed in fewer than 2 workspaces is redacted. Ties are ordered alphabetically by actual job title.

Table A3: Top 5 actual job titles by seniority level

Seniority level	Actual job title	User share
C-suite / founder / owner / partner	Partner	29.1%
C-suite / founder / owner / partner	Managing director	14.1%
C-suite / founder / owner / partner	Executive director	3.5%
C-suite / founder / owner / partner	Managing director and partner	2.4%
C-suite / founder / owner / partner	Chief financial officer	1.8%
Contractor / temporary	Contractor	34.3%
Contractor / temporary	Contingent worker	9.0%
Contractor / temporary	Contingent worker hourly	6.0%
Contractor / temporary	Temporary worker	5.2%
Contractor / temporary	IT BST outside consultant	2.9%
Director / head	Director	7.6%
Director / head	Senior manager	6.6%
Director / head	Associate director	1.0%
Director / head	Associate partner	0.8%
Director / head	Senior director	0.8%
Entry / associate	Associate	15.2%
Entry / associate	Analyst	3.7%
Entry / associate	Business analyst	1.8%
Entry / associate	<redacted>	1.3%
Entry / associate	Associate consultant	1.2%
Individual contributor / professional	Software engineer	6.5%
Individual contributor / professional	Consultant	3.8%
Individual contributor / professional	Executive assistant	1.4%

Seniority level	Actual job title	User share
Individual contributor / professional	Project manager	1.3%
Individual contributor / professional	Management consultant	1.2%
Manager / team lead	Manager	7.0%
Manager / team lead	Management consulting manager	1.2%
Manager / team lead	Engineering manager	1.0%
Manager / team lead	[non-Latin text]	0.8%
Manager / team lead	Project leader	0.8%
Senior IC / principal	Senior associate	6.3%
Senior IC / principal	Senior software engineer	5.5%
Senior IC / principal	Principal	1.4%
Senior IC / principal	Staff software engineer	1.4%
Senior IC / principal	Senior consultant	1.3%
Student / trainee / intern	Student	61.4%
Student / trainee / intern	Intern	6.1%
Student / trainee / intern	Student worker	3.0%
Student / trainee / intern	Undergraduate	2.3%
Student / trainee / intern	Assistant professor	2.0%
VP / senior executive	Vice president	14.2%
VP / senior executive	Senior vice president	2.9%
VP / senior executive	Corporate vice president	2.8%
VP / senior executive	Assistant vice president	1.2%
VP / senior executive	VP	0.6%

Note: Percentages are shares of title-user observations within each classifier value in the full SCIM job-title classification universe. Unknown and malformed classifier values are omitted. Normalized title variants are combined before applying the publication rule. Job-title detail observed in fewer than 2 workspaces is redacted. Ties are ordered alphabetically by actual job title.

Table A4: Top 5 actual job titles by manager status

Manager status	Actual job title	User share
Likely individual contributor	Student	6.7%
Likely individual contributor	Associate	3.5%
Likely individual contributor	Software engineer	3.0%
Likely individual contributor	Senior associate	2.9%
Likely individual contributor	Senior software engineer	2.5%
Likely people manager	Manager	3.6%
Likely people manager	Director	2.6%
Likely people manager	Partner	2.5%
Likely people manager	Senior manager	2.3%
Likely people manager	Vice president	1.4%
Manager title but ambiguous	Project manager	2.2%
Manager title but ambiguous	Senior product manager	1.9%
Manager title but ambiguous	Product manager	1.8%
Manager title but ambiguous	<redacted>	1.4%
Manager title but ambiguous	Account executive	1.4%

Note: Percentages are shares of title-user observations within each classifier value in the full SCIM job-title classification universe. Unknown and malformed classifier values are omitted. Normalized title variants are combined before applying the publication rule. Job-title detail observed in fewer than 2 workspaces is redacted. Ties are ordered alphabetically by actual job title.

Table A5: Task classifier values

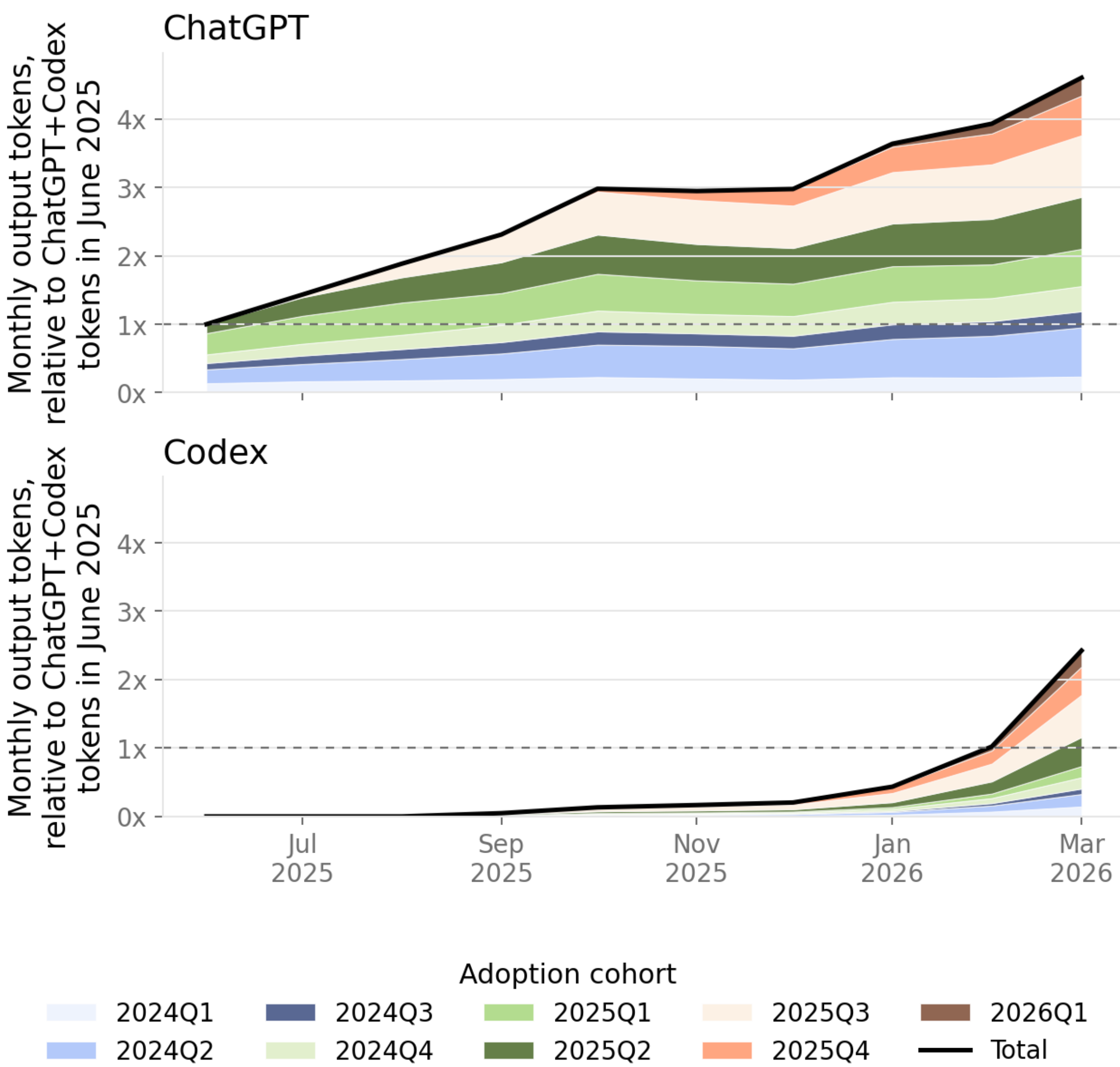
First-level category	Second-level value
`advice`	`career`
	`academic`
	`legal and regulatory`
	`financial and tax`
	`beauty`
	`cooking and recipes`
	`spirituality`
`analysis and calculations`	`data analysis`
	`scientific math and engineering computation`
`coding`	`plan design and create`
	`debug and fix`
	`modify and extend`
	`interpret and explain`
`commerce`	`product specs`
	`product reviews and recommendations`
	`facilitate purchase`
`creative media`	`generate image`
	`edit image`
	`video audio or other`
`education and learning`	`review and develop academic essay`
	`help with homework assignment`
`health and wellness`	`triage and symptoms`

First-level category	Second-level value
	tests and results
	care and treatments
	nutrition and diet
	fitness and exercise
	mental and emotional
how to and procedural guidance	technical digital and electronic
	technical mechanical and vehicle
	technical other
	nontechnical personal
	nontechnical professional or academic
information	topic overview
	entertainment and sports
	current events and news
	local travel and weather
	business and market research
	people
	find file or document
	other facts and figures
support	goal setting and coaching
	relationships
	self disclosure and companionship
writing and communication	fiction
	games and role play
	private personal message

First-level category	Second-level value
	public personal message
	documentation and technical writing
	instructional content
	sales and marketing
	career and job search
	persuasion and argumentation
	translation

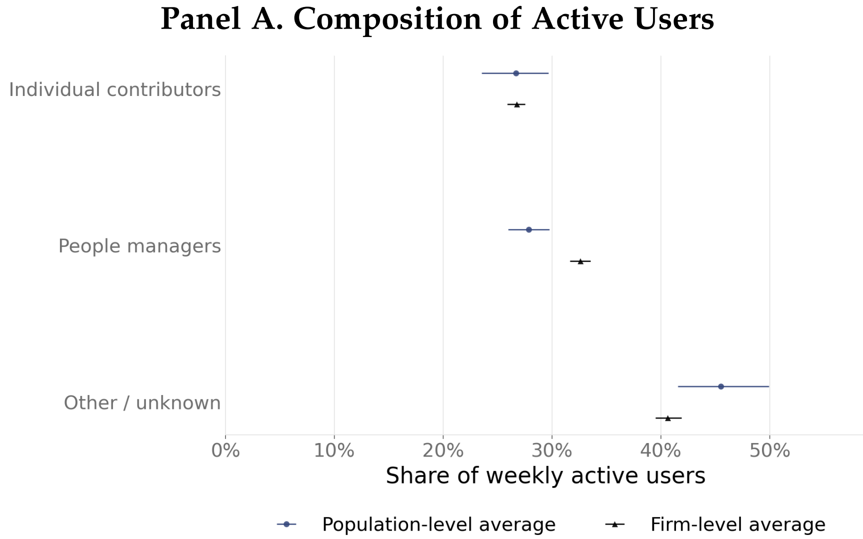
B Additional Figures

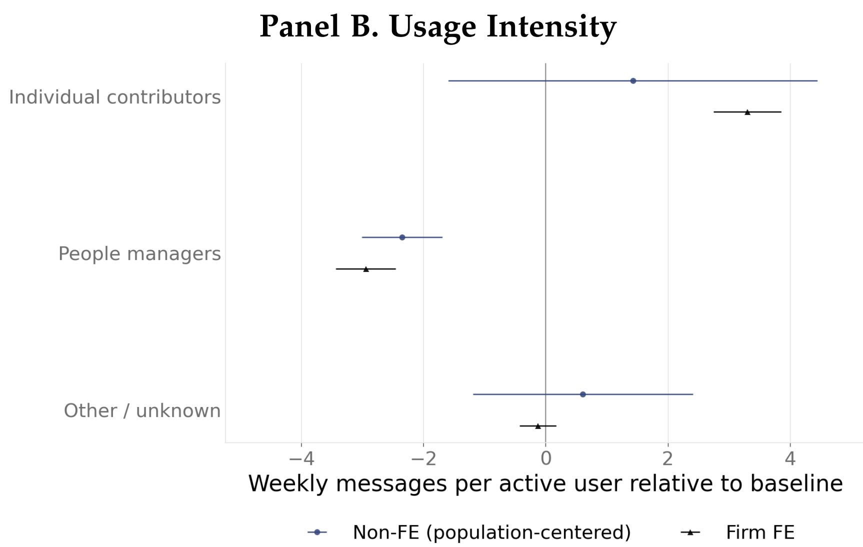
Fig. A1: ENTERPRISE OUTPUT TOKEN GROWTH BY PRODUCT



Note: This figure plots monthly ChatGPT and Codex output tokens for firms in the ChatGPT Enterprise analysis sample, shown separately by product and stacked by the quarter in which each firm first adopted ChatGPT Enterprise. Tokens are counted only after each firm's ChatGPT Enterprise adoption date. Values in both panels are indexed to total combined ChatGPT and Codex output tokens in June 2025, with the dashed horizontal line marking 1.0 and the black line in each panel showing the aggregate total across cohorts for that product.

Fig. A2: COMPOSITION AND INTENSITY OF AI USE BY PEOPLE MANAGER STATUS

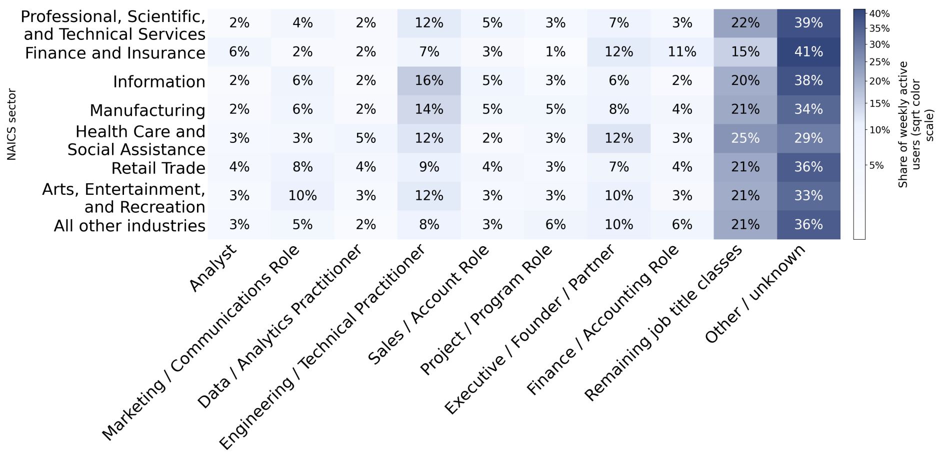




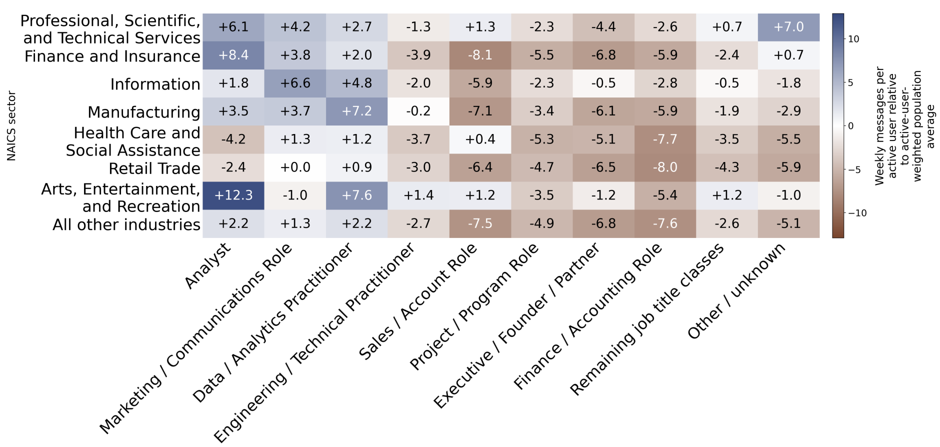
Note: This figure compares ChatGPT Enterprise use among individual contributors, people managers, and users whose manager status cannot be inferred, measured six months after firm adoption. Manager status is inferred from normalized job titles. Panel A reports each group's share of weekly active users. Blue points report the population-level average, computed as each group's share of all weekly active users across firms. Black points report the firm-level average, computed as each group's share of weekly active users within each firm and then averaged across firms, giving each firm equal weight. Horizontal bars show 95% firm-bootstrap confidence intervals. Panel B reports differences in weekly messages per active user. Blue points report population-level estimates, comparing each group to the average active user across firms. Black points report firm fixed effect estimates, comparing each group to other active users within the same firm. Positive values indicate more intensive use than the relevant baseline; negative values indicate less intensive use. Horizontal bars in Panel B show 95% confidence intervals with firm-clustered standard errors. "Other / unknown" includes users whose job titles are missing, ambiguous, malformed, or otherwise do not provide enough information to infer manager status.

Fig. A3: DIFFERENCES IN AI USE ACROSS INDUSTRIES AND JOB TITLE CLASSES

Panel A. Composition of Active Users



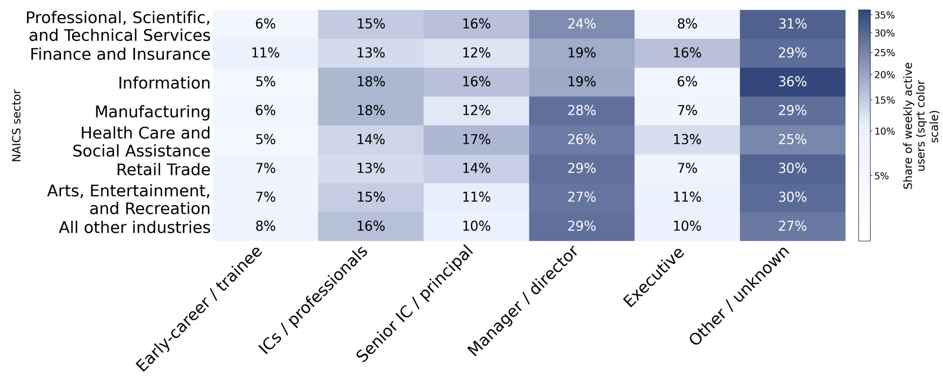
Panel B. Usage Intensity



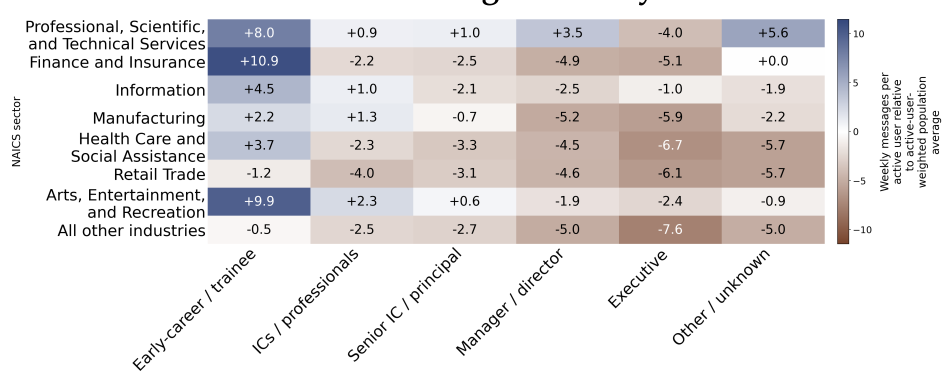
Note: The figure compares ChatGPT Enterprise use across two-digit NAICS sectors and inferred job title classes six months after firm adoption. Panel A reports the average share of weekly active users in each job title class within each industry; darker cells indicate that a larger share of active users in that industry come from that worker type. Panel B reports usage intensity for the same industry-by-role cells, measured as weekly messages per active user relative to the overall average active user in the sample. Positive values indicate more intensive use than average; negative values indicate less intensive use. "Remaining job title classes" pools inferred job title classes outside the individually displayed top categories. "Other / unknown" includes users with missing, ambiguous, malformed, or otherwise low-information job titles that cannot be assigned to a substantive class. A version of Panel B that accounts for firm fixed effects can be found in Panel A of Figure A6.

Fig. A4: DIFFERENCES IN AI USE ACROSS INDUSTRIES AND SENIORITY LEVELS

Panel A. Composition of Active Users



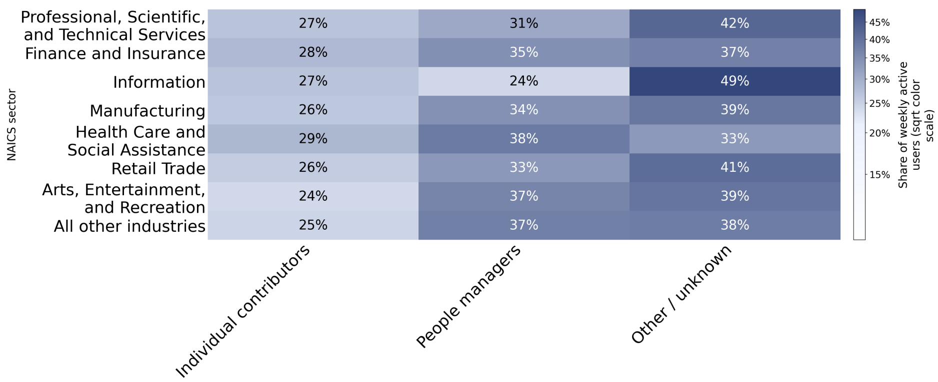
Panel B. Usage Intensity



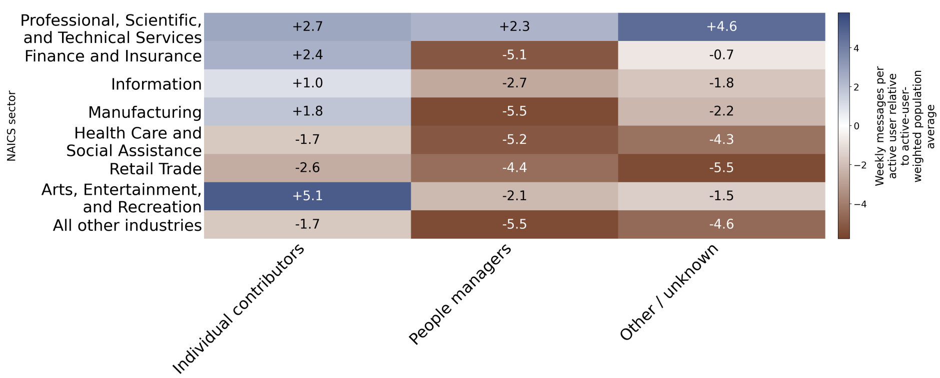
Note: The figure compares ChatGPT Enterprise use across two-digit NAICS sectors and inferred seniority levels six months after firm adoption. Panel A reports the average share of weekly active users at each seniority level within each industry; darker cells indicate that a larger share of active users in that industry belong to that seniority group. Panel B reports usage intensity for the same industry-by-seniority cells, measured as weekly messages per active user relative to the overall average active user in the sample. Positive values indicate more intensive use than average; negative values indicate less intensive use. “Other / unknown” includes users whose job titles are missing, ambiguous, malformed, indicate contractor or temporary status without conveying seniority, or otherwise do not provide enough information to infer a seniority level. “IC” denotes an individual contributor. A version of Panel B that accounts for firm fixed effects can be found in Panel B of Figure A6.

Fig. A5: DIFFERENCES IN AI USE ACROSS INDUSTRIES AND PEOPLE MANAGER STATUS

Panel A. Composition of Active Users



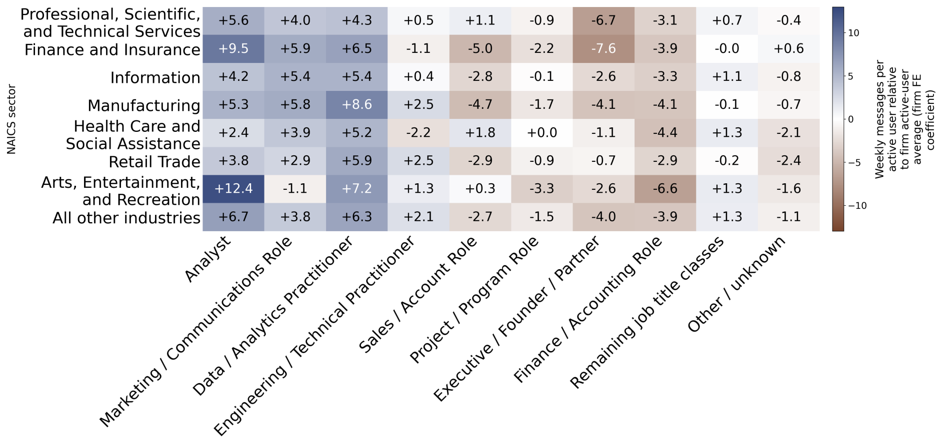
Panel B. Intensity of Usage



Note: This figure compares ChatGPT Enterprise use across two-digit NAICS sectors and inferred people manager status groups among firms with job title data, measured six months after adoption. Manager status is inferred from normalized job titles. Panel A reports the average share of weekly active users in each people manager status group within each industry; darker cells indicate that a larger share of active users belong to that group. Panel B reports usage intensity for the same industry-by-people-manager-status cells, measured as weekly messages per active user relative to the overall average active user in the sample. Positive values indicate more intensive use than average, while negative values indicate less intensive use. "Other / unknown" includes users whose job titles are missing, ambiguous, malformed, or otherwise do not provide enough information to infer manager status. "All other industries" pools two-digit NAICS sectors not displayed separately. Cell labels report percentages in Panel A and differences from the overall average in Panel B. A version of Panel B that accounts for firm fixed effects can be found in Figure A7.

Fig. A6: WITHIN-FIRM DIFFERENCES IN AI USAGE INTENSITY BY INDUSTRY, JOB TITLE CLASS AND SENIORITY LEVEL

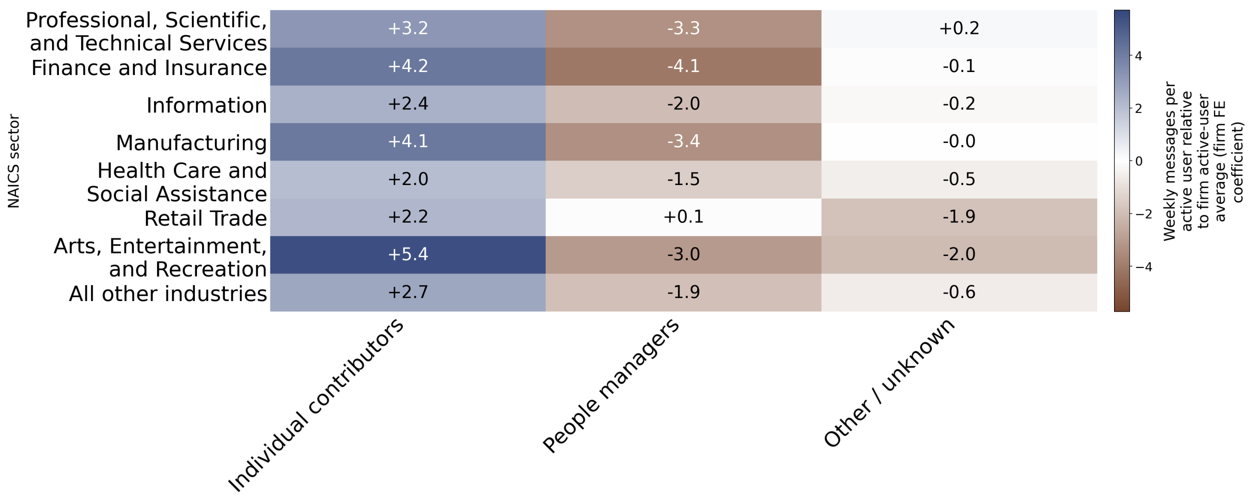
Panel A. Job title class



Panel B. Seniority level

Note: This figure compares weekly ChatGPT Enterprise usage intensity across worker categories within firms and separately by two-digit NAICS sector, measured six months after adoption. Usage intensity is measured as weekly messages per active user. Panel A groups users by inferred job title class, while Panel B groups users by inferred seniority level. Each cell reports how usage intensity for that worker category differs from the average among active users at the same firm. Positive values indicate more intensive use than the within-firm average, while negative values indicate less intensive use. The estimates remove differences in overall usage intensity across firms and therefore describe within-firm differences across worker types, rather than differences in average usage across industries. “Remaining job title classes” pools substantive inferred classes outside the individually displayed categories. “Other / unknown” includes users whose job titles do not provide enough information to assign the relevant worker classification. “IC” denotes an individual contributor. “All other industries” pools two-digit NAICS sectors not displayed separately.

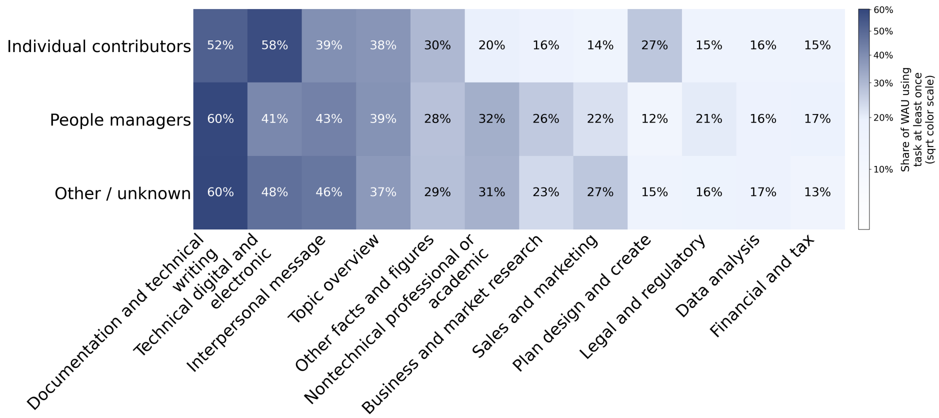
Fig. A7: WITHIN-FIRM DIFFERENCES IN AI USAGE INTENSITY BY INDUSTRY AND PEOPLE MANAGER STATUS



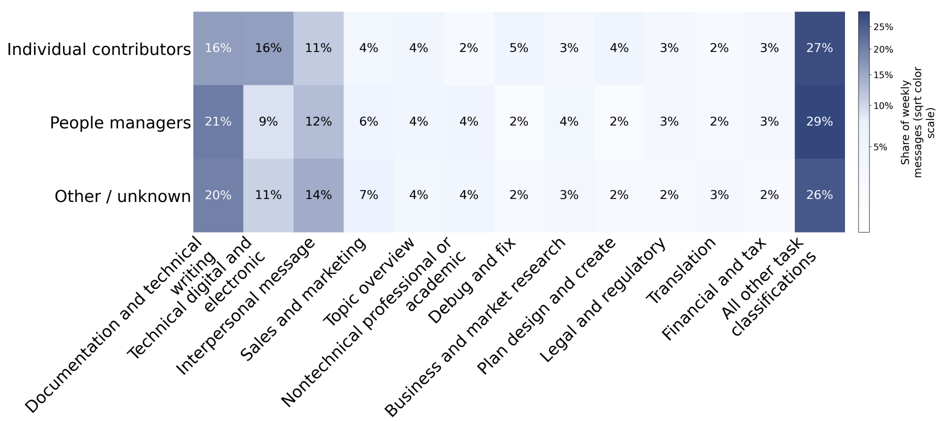
Note: This figure compares weekly ChatGPT Enterprise usage intensity across people manager status groups within firms and separately by NAICS two-digit sector, measured six months after adoption. People manager status is inferred from normalized job titles. Each cell reports how weekly messages per active user for that group differ from the average among active users at the same firm. Positive values indicate more intensive use than the within-firm average, while negative values indicate less intensive use. The estimates remove differences in overall usage intensity across firms and therefore describe within-firm differences by manager status, rather than differences in average usage across industries. “Other / unknown” includes users whose job titles are missing, ambiguous, malformed, or otherwise do not provide enough information to infer manager status. “All other industries” pools two-digit NAICS sectors not displayed separately.

Fig. A8: DIFFERENCES IN AI TASK USE BY PEOPLE MANAGER STATUS

Panel A. Task Prevalence Among Active Users



Panel B. Distribution of Messages Across Tasks



Note: This figure compares the distribution of ChatGPT Enterprise use across tasks and inferred people manager status groups among firms with task classification and job title data, measured six months after adoption. Each message is assigned to one of 60 task categories using the classifier described in the text, and manager status is inferred from normalized job titles. Panel A reports the share of weekly active users in each manager-status group who submitted at least one message in each of the 12 task categories with the greatest user reach. Because users may use ChatGPT for multiple tasks during the same week, the shares in each row are not mutually exclusive and do not sum to 100 percent. Panel B reports the distribution of classified weekly messages across the 12 largest task categories by message volume within each manager-status group. "All other task classifications" pools the remaining task categories. "Other / unknown" includes users whose job titles do not provide enough information to infer manager status. Task categories are selected separately in each panel using their prevalence in the full task-classification sample.

C Job Title Classification

In this appendix, we detail the classifier that we use to classify organizational users' job titles. Note that this same classifier was used in Johnston et al. (2026), and a nearly verbatim copy of this appendix appears in that paper as well.

We use the gpt-5-mini model with minimal reasoning effort to classify organizational users' job titles. The classifier uses only the supplied job title, and returns structured outputs for inferred department, seniority, people manager status, and cleaned job title class. In the prompt below, we include only the definitions used for each field.

C.1 Job Title Classification Prompt

```
Classify this enterprise ChatGPT user job title. Use only the title below.

Field definitions:
- inferred_department is the likely department, function, or substantive work
↪ area. It is not seniority and it is not the literal title family.
- role_level is seniority or rank. It should be classified even when
↪ inferred_department is Other / Unknown.
- people_manager_signal is the likelihood that the title implies managing people.
↪ It is separate from role_level because many titles with Manager do not imply
↪ people management.
- job_title_class is the cleaned-up occupation or title-family wording. It should
↪ preserve generic occupations like Consultant and Analyst even when
↪ inferred_department remains Other / Unknown.

Allowed inferred_department labels:
- Financial Markets + Corporate Finance
- Sales
- Marketing
- Data Science
```

```
- Biz Ops
- Engineering
- Design
- User Ops / Customer Support
- Legal
- Product Management
- Project Management
- Healthcare / Life Sciences
- Education
- Policy
- Security
- People & Recruiting
- IT
- Partnerships
- Comms
- Research
- Other / Unknown

Inferred-department guidelines:
- Financial Markets + Corporate Finance: finance, accounting, audit, treasury,
↪ FP&A, investment, portfolio, banking, tax, controller, CFO roles.
- Sales: sales, account executive, account manager, business development, revenue,
↪ SDR/BDR, sales engineering when primarily commercial.
- Marketing: brand, growth, demand generation, content marketing, product
↪ marketing, SEO, lifecycle, communications only when clearly marketing.
- Data Science: data scientist, data analyst, analytics engineer, machine learning
↪ scientist, BI, quantitative analyst when primarily data or ML.
- Biz Ops: operations, strategy, chief of staff, business analyst, general
↪ management, consulting, program operations, administrative roles.
```

```
- Engineering: software, hardware, infrastructure, platform, systems, DevOps, QA, site reliability, technical engineering roles.
- Design: product design, UX, UI, visual design, creative design, design research.
- User Ops / Customer Support: customer success, support, customer experience, implementation, solutions, technical account management, help desk.
- Legal: legal, counsel, compliance legal, contracts, privacy counsel.
- Product Management: product manager, product owner, product lead, product strategy.
- Project Management: project manager, program manager, delivery manager, scrum master, agile coach, PMO.
- Healthcare / Life Sciences: clinical, medical, physician, nurse, pharmaceutical, biotech, lab, hospital, health science, life science research.
- Education: student, teacher, professor, instructor, faculty, academic, dean, curriculum, school administration.
- Policy: public policy, government affairs, trust and safety policy, regulatory policy, public affairs when policy-focused.
- Security: cybersecurity, information security, security engineering, GRC, threat, risk when security-specific.
- People & Recruiting: HR, people ops, talent, recruiting, compensation, benefits, learning and development.
- IT: IT, systems administration, enterprise applications, workplace technology, service desk, network administration.
- Partnerships: partnerships, alliances, partner management, ecosystem, channel partnerships.
- Comms: communications, PR, media relations, internal comms, corporate communications.
- Research: researcher, scientist, research engineer, research associate, lab research, academic research unless clearly healthcare or education.
```

```
- Other / Unknown: seniority-only, malformed, vague, or titles without enough
↪ department/function signal.

Allowed role_level labels:
- Student / Trainee / Intern
- Entry / Associate
- Individual Contributor / Professional
- Senior IC / Principal
- Manager / Team Lead
- Director / Head
- VP / Senior Executive
- C-suite / Founder / Owner / Partner
- Contractor / Temporary
- Unknown

Allowed people_manager_signal labels:
- Likely people manager
- Manager title but ambiguous
- Likely individual contributor
- Unknown

Allowed job_title_class labels:
- Consultant / Professional Services
- Analyst
- Engineering / Technical Practitioner
- Data / Analytics Practitioner
- Product Role
- Project / Program Role
- Sales / Account Role
```

```
- Customer Success / Support Role
- Finance / Accounting Role
- Legal Role
- Healthcare / Clinical Role
- Education / Academic Role
- Research / Scientist Role
- Design / Creative Role
- Administrative / Executive Support
- People / Recruiting Role
- IT / Systems Role
- Marketing / Communications Role
- Security Role
- Executive / Founder / Partner
- Generic Rank / Seniority Only
- Contractor / Temporary
- Placeholder / Malformed
- Unknown
```

The classifier returns a JSON object with the following fields: inferred_department, confidence, evidence_source, rationale, role_level, role_level_confidence, people_manager_signal, people_manager_signal_confidence, role_rationale, job_title_class, job_title_class_confidence, and job_title_class_rationale.

Throughout the paper, before plotting, we collapse several fine-grained job title classifier outputs into coarser display categories and then recompute all totals at the collapsed-category level. For the job title class dimension, Unknown, Generic Rank / Seniority Only, Placeholder / Malformed, Contractor / Temporary, and missing or unclassified job titles are displayed as Other / unknown, while all other job title classes are left unchanged. For the seniority dimension, Student / Trainee / Intern and Entry / Associate are mapped to Early-career / trainee; Individual Contributor / Professional is mapped to ICs / professionals; Senior IC / Principal is mapped to Senior IC / principal; Manager / Team Lead and Director / Head are mapped to Manager / director; VP / Senior Executive and C-suite / Founder / Owner / Partner are mapped to Executive; and Unknown, Contractor / Temporary, and missing or unclassified job titles are displayed as Other / unknown. For the people manager status dimension, Likely individual contributor is mapped to Individual contributors, Likely people manager is mapped to People managers, and Manager title but ambiguous, Unknown, and missing or unclassified job titles are displayed as Other / unknown.

C.2 Job Title Classifier Validation

To provide some validation of the values assigned by our job title classifier, we report below the top five most common job titles for each unique inferred job title class, seniority level, and people manager status. To limit disclosure risk, we apply a pre-specified suppression rule to raw job title strings: after normalizing superficial title variants, we display a title only if it is observed in at least two distinct non-OpenAI organizations or in OpenAI's internal sample. Titles that do not satisfy this rule are redacted. We do not report titles for the labels "Unknown" and "Placeholder / Malformed," because their most common values often contained sensitive or identifying information.

D Task Classifier Details

The task classifier assigns each ChatGPT turn to exactly one value in a two-level taxonomy. The first level identifies the broad domain of the user request, and the second level identifies the more specific task type within that domain. The task classifier has been evaluated against an internal benchmark of human- and model-labelled ChatGPT conversations. Table A5 lists the possible classifier values.