Organizational Transmission of AI: Managerial Influence on Generative AI Adoption

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Abstract

Using longitudinal data from the Gallup Panel covering more than 30,000 U.S. employees surveyed from 2023 to 2025, I document heterogeneous adoption of generative AI and its "organizational transmission" within firms. First, I show that the share of active (occasional) AI users grew from 9% to 26% (10% to 19%). I subsequently document these patterns by organizational class of work, organizational hierarchy, income, industry, and occupation. Second, I show that perceived strategic clarity is the dominant correlate of frequent adoption: employees in clear-strategy organizations are roughly 26 percentage points more likely to report frequent use. Strategic clarity itself is tightly linked to managerial communication and credibility, including meaningful feedback and trust in leadership. Third, exploiting within-person variation, income-by-time controls, and a job-switcher design, I show that the relationship between AI use and worker outcomes is strongly contingent on organizational context. Frequent AI use is associated with substantially higher engagement and job satisfaction and with markedly lower burnout when organizations communicate a clear AI strategy, while these benefits are muted or reversed in low-clarity environments. These results are consistent with the predictions from a stylized theoretical model whereby workers are more likely to adopt and experiment with AI when they experience psychological safety.

Keywords: Generative AI; Technology Adoption; Managers; Trust; Communication; Organizational Complementarities; Panel data.

JEL Codes: O33; M15; M54.

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1 Introduction

Generative artificial intelligence (genAI) has rapidly emerged as a transformative technology in the workplace (Eloundou et al., 2024). Early experimental evidence indicates that integrating genAI tools can raise worker productivity, improving both the speed and quality of output (Noy and Zhang, 2023; Brynjolfsson et al., 2025). While there are suggestive positive signs of its impact on labor markets (e.g., Johnston and Makridis, 2025), its long-term effects will depend crucially on the speed and breadth of adoption (Brynjolfsson et al., 2021), consistent with historical findings that slow diffusion can delay the realization of productivity gains (Comin and Hobijn, 2010).

Recent evidence shows that genAI uptake has been strikingly fast (Bick et al., 2025). As of late 2024, nearly 40% of U.S. adults have used genAI, with about 23% of employed individuals using it for work at least once in the past week (Bick et al., 2025). This diffusion in genAI's first two years has matched or even outpaced that of past major innovations like personal computers and the internet. Despite this rapid overall growth, adoption remains uneven across workplaces and workers. Many employees are still on the sidelines of the "AI revolution," harboring skepticism about AI's impact on their jobs and its efficacy (Ray, 2024). Surveys show that a majority of workers express hesitancy or concern about AI—for instance, over half of U.S. employees worry that workplace AI could negatively affect their career opportunities. Such reservations underscore that swift technological progress does not guarantee universal adoption among the workforce.

A large literature suggests that managerial influence may be a decisive factor in technology uptake within firms.[1] Managers often serve as technology champions or gatekeepers, shaping their

[1]The industrial psychology literature finds that managers account for roughly 70% of the variance in team engagement (Beck and Harter, 2015).

teams' openness to new tools (Howell and Higgins, 1990; Rogers, 2003; Davenport, 2018). In addition, management practices—embodied through individual managers—are integral to unlocking the benefits of technology (Bresnahan et al., 2002; Bloom et al., 2012; Aral et al., 2012). This influence likely extends to shaping employees' willingness to experiment with innovations. Only about one-third of U.S. workers report that their organization has started integrating AI (Den Houter, 2024)—although another study places this as low as 18% (McElheran et al., 2024)—and a mere 15% strongly agree that their employer has communicated a clear AI strategy. When such a plan is in place, employees are nearly five times more likely to feel comfortable using AI. These patterns suggest that clear managerial communication and vision are critical in converting top-down AI investment into broad-based adoption on the ground. Trust in management is another potentially crucial element: employees who lack trust in their leaders may be especially reluctant to embrace new technologies and integrate them into their workflow. In short, leadership may make or break the "last-mile" of technological diffusion within organizations.

The primary contribution of this paper is to study how managers shape the internal diffusion of generative AI and how that diffusion maps into employee outcomes. Using longitudinal data from the Gallup Panel with more than 30,000 U.S. employees surveyed from 2023 to Q4:2025, I document rapid growth in workplace AI use alongside systematic heterogeneity that points to an organizational transmission mechanism. In the aggregate, adoption rose quickly—the share using AI often increased from 9% in 2023 to 26% in 2025, and the share using AI sometimes increased from 10% to 19%. But the deeper empirical regularity is that diffusion is structured by organizational conditions and managerial channels rather than only by individual characteristics: adoption follows the hierarchy, broadens even in the public sector, and remains widespread across the income distribution rather than strictly monotone in income. These patterns complement the

empirical evidence from Bick et al. (2025), e.g. the trend and the high uptake among managers.

Then, I study the cross-sectional determinants of AI adoption within organizations. A central empirical insight is that perceived clarity of an organization's AI strategy is the strongest and most economically meaningful correlate of frequent adoption. Employees who report that their organization has communicated a clear plan for integrating AI are substantially more likely to be frequent users, even after conditioning on demographics and time effects. Moreover, strategic clarity is robustly correlated with measures of managerial communication and credibility—especially trust in leadership and meaningful feedback—suggesting that employees experience "AI strategy" primarily through day-to-day managerial practices (e.g., how managers communicate and "legitimize" experimentation), rather than through formal policy statements alone.

Exploiting within-person variation over time, income × year controls, and a job-switcher design, I show that the association between AI use and outcomes is strongly contingent on organizational context. Frequent AI use is associated with higher engagement and job satisfaction and with lower burnout when employees perceive both a clear AI strategy and a high-trust environment, while these benefits are muted—and in some specifications reverse—when strategic direction is unclear and psychological safety is low. Put differently, the returns to genAI adoption appear to depend not only on access to the technology, but also on the managerial and cultural infrastructure that governs whether employees view experimentation as safe and worthwhile. These results are consistent with a stylized theoretical model in which workers adopt and experiment with genAI when expected gains exceed perceived costs, and managers influence both margins. Clear strategic communication reduces uncertainty about permissible use and raises the expected value of learning-by-doing, while trust and psychological safety reduce the perceived downside risk of experimentation (e.g., fear of punishment for mistakes, monitoring concerns, or reputational

penalties). The model predicts complementarities: adoption and its benefits should be strongest when clarity and psychological safety are jointly high, precisely as observed in the panel evidence.

This paper contributes primarily to the empirical management and organizational economics literature by providing new evidence on how managerial practices and workplace culture shape the within-firm diffusion of generative AI and its consequences for workers. A large body of research establishes that management quality is a central source of productivity differences across firms and countries (Bloom and Van Reenen, 2010; Bloom et al., 2013, 2017), and that the returns to digital technologies are larger when firms pair information technology (IT) with complementary organizational practices and skills (Bresnahan et al., 2002; Bloom et al., 2012; Aral et al., 2012).

To that end, AI has become the next frontier of the digital revolution, spurred by the zeitgeist of ChatGPT in 2022. Despite rapid growth in generative AI use (Bick et al., 2025) and accumulating evidence that it can raise output in specific work settings (Noy and Zhang, 2023; Brynjolfsson et al., 2025; Dell'Acqua et al., 2023, 2025; Cui et al., 2025), there is limited direct evidence on which organizational mechanisms govern whether employees experiment with AI, how quickly usage diffuses across colleagues, and whether adoption translates into better (or worse) workforce outcomes. Motivated by the "automation versus new tasks/augmentation" perspective (Autor, 2015; Acemoglu and Restrepo, 2019; Autor et al., 2022), my central premise is that the realized impact of genAI depends not only on tool availability, but also on the managerial infrastructure that reallocates tasks, legitimizes experimentation, and mitigates perceived downside risks.

A key contribution of the paper is measurement and identification at the organizational layer. The substantial within-firm heterogeneity in adoption and in the correlates of adoption matters for two reasons. First, it provides micro-level evidence consistent with the view that general-purpose technologies require intangible complements that are costly to build and slow to diffuse

(Brynjolfsson et al., 2021). Second, it suggests a mechanism through which AI could widen performance gaps across firms: organizations that pair genAI with strong managerial practices and high-trust climates appear better positioned to translate experimentation into sustained adoption and improved worker outcomes, while poorly aligned firms risk low uptake and muted (or adverse) effects. This mechanism complements firm-level evidence on who adopts AI and where (McElheran et al., 2024), by opening the black box of internal diffusion and showing that managerial conditions help explain why similar technologies yield very different realized impacts across workplaces.

The paper also contributes to the technology adoption literature by shifting emphasis from individual-level acceptance to organizational design and leadership. Classic acceptance frameworks center perceived usefulness and ease of use (Davis, 1989; Venkatesh et al., 2003). However, a growing body of evidence suggests that the returns to new digital technologies depend critically on organizational complements—especially the availability of complementary skills—rather than on user perceptions alone (Tambe, 2014). In the context of digital transformation, employees who trust their managers may be more willing to follow guidance to try unfamiliar technologies and less fearful of negative consequences (e.g., job loss) from automation. For example, Makridis and Han (2021) finds that the positive effects of technological change on employee empowerment and satisfaction are strongest in workplaces characterized by high trust in management and more directive (structured) managers. In other words, a trusting and well-led environment can help workers embrace and benefit from new technologies, rather than resist them. My results instead show that managerial communication and workplace norms—whether leaders provide clear guidance, whether employees trust managers, and whether feedback is candid and developmental—are first-order determinants of whether workers view AI experimentation as safe and worthwhile. This emphasis on internal learning and assimilation connects the adoption literature to organizational

change and trust research (Morgan and Zeffane, 2003) and to psychological safety and learning in organizations (Edmondson, 2019), and it is consistent with evidence that implementation outcomes hinge on work practices that facilitate employee learning during technology roll-outs (Avgar et al., 2018). These findings suggest that "soft" cultural factors materially condition the speed and breadth of diffusion of a new tool inside firms and explain the relatively high failure rate.[2]

A further contribution is to the literature on complementarities between technology and organizational practices. Prior work shows that technology investments deliver larger productivity gains when firms simultaneously adopt complementary workplace organization and incentive systems (Bresnahan et al., 2002; Aral et al., 2012). In the genAI setting, we identify specific complements—strategic clarity about AI use, trust/psychological safety, and feedback-rich management—that predict both adoption intensity and the direction of workforce outcomes (e.g., engagement, satisfaction, burnout). This evidence aligns with the "productivity J-curve" logic: realizing gains from a general-purpose technology often requires complementary investments in processes and organizational capital that may precede observable productivity improvements (Brynjolfsson et al., 2021). My contribution is to isolate and quantify particular cultural/managerial complements that operate as force multipliers for genAI diffusion and impact.

Finally, the paper offers a theoretical contribution by developing a stylized model of the "organizational transmission" of AI that disciplines the empirical analysis. Building on organizational

[2]A widely cited "MIT study" is often summarized as finding that "95% of AI pilots fail." In fact, the underlying source is a Project NANDA report that documents a sharp pilot-to-production drop-off in a *selected* sample of enterprise genAI initiatives (Challapally et al., 2025). The report's "95%" figure refers to organizations in its dataset reporting *no measurable return / no measurable P&L impact* from genAI efforts (and it separately labels this pattern a "95% failure rate"), not to a population-wide estimate of technical failure. The evidence is drawn from a systematic review of 300+ publicly disclosed initiatives, interviews with representatives from 52 organizations, and surveys of 153 senior leaders at industry conferences; the authors caution that deployment and "success" rates are directionally informative, based on interviews rather than audited reporting, and that definitions vary across organizations. Even with these limitations, the reported attrition from pilots to workflow-integrated production systems indicates a nontrivial implementation failure rate, consistent with the view that organizational complements (integration, change management, and employee adoption) are central determinants of whether pilots scale.

economics models of authority, communication, and coordination (Garicano, 2000; Dessein, 2002; Alonso et al., 2008; Crémer et al., 2007) and on relational incentives and credibility (Baker et al., 2002; Gibbons and Henderson, 2012), I build a simple model that formalizes how managers shape adoption through two interdependent choices: (i) complementary investments that lower the friction of integrating AI into workflows and (ii) the clarity and credibility of communication that governs whether employees perceive experimentation as valuable and safe. The model yields testable complementarities—adoption and its benefits should be strongest where clarity and psychological safety are jointly high—and provides a mechanism linking workplace culture to the equilibrium diffusion of a new technology within firms over time and space.

2 Modeling the Organizational Transmission of AI

This section provides a stylized framework that (i) clarifies the mechanisms through which management shapes GenAI adoption and (ii) delivers testable implications used to organize the empirical analysis. The model builds on core ideas in organizational economics that treat within-firm communication as a design choice that affects coordination and the use of dispersed information (e.g., Dessein, 2002; Alonso et al., 2008; Crémer et al., 2007), and on the view that many managerial "promises" are sustained by informal (relational) contracting rather than verifiable formal contracts (Baker et al., 2002; Gibbons and Henderson, 2012).

2.1 Setup

A firm consists of a unit mass of ex ante identical workers and a manager. Workers choose an intensity of generative AI (genAI) usage $a \in [0, 1]$, interpreted as the fraction of tasks completed

with genAI assistance (Eloundou et al., 2024). Using GenAI increases effective performance but requires experimentation and adjustment, generating private costs.

Let $E \in [0,1]$ denote the firm's "embedding" investment (training, workflow redesign, IT integration, and complementary inputs). Let S denote the clarity/precision of managerial communication about GenAI use (the "AI strategy"). The per-task gross return to GenAI is

$$B(E,S), \tag{1}$$

with $B_E > 0$, $B_S \geq 0$, and $B_{ES} > 0$ for complementarity between embedding and communication. Embedding investments are more productive when the organization has a shared, interpretable language and guidance about use-cases, standards, and responsibilities (Crémer et al., 2007).

Let θ index psychological safety/trust in the work environment. Higher θ reduces the perceived downside risk of experimentation and lowers the marginal cost of increasing genAI usage. Worker costs are given by

$$c(a;\theta), \tag{2}$$

with $c_a > 0$, $c_{aa} > 0$, $c_\theta < 0$, and $c(0;\theta) = 0$; θ captures the extent to which employees view experimentation (e.g., early mistakes) as safe and not career-damaging.

At the implementation stage, the firm chooses embedding E, and the manager chooses communication clarity S and takes actions shaping psychological safety θ. Workers then choose a after observing (E,S,θ). Conceptually, S corresponds to the informativeness/precision of internal communication and guidance: clearer communication improves alignment and coordination but can be constrained by organizational design and incentive conflicts in communication (Dessein,

2002; Alonso et al., 2008). The parameter θ captures the credibility of informal assurances around experimentation and learning, which are typically noncontractible (Baker et al., 2002).

Given (E, S, θ), a worker chooses a to maximize

$$\max_{a \in [0,1]} \; a \cdot B(E, S) - c(a; \theta). \tag{3}$$

An interior optimum satisfies

$$B(E, S) = c_a(a^*; \theta). \tag{4}$$

Lemma 1 (Adoption comparative statics)**.** *Suppose $c(\cdot; \theta)$ is strictly convex and $B(E, S)$ satisfies $B_E > 0$, $B_S \geq 0$, $B_{ES} > 0$. Then the equilibrium adoption intensity $a^*(E, S, \theta)$ is increasing in E, S, and θ, and the marginal effect of embedding is larger when strategy clarity is higher (i.e., $\partial^2 a^* / \partial E \partial S > 0$ under standard regularity conditions).*

Lemma 1 formalizes the idea that adoption is not "plug-and-play": both a higher return environment (via E and S) and lower experimentation costs (via θ) raise equilibrium GenAI usage. A closed-form example is provided in Section A.1.1 of the Online Appendix.

The central empirical implication concerns complementarities: the marginal effect of GenAI usage on performance and well-being depends on the managerial environment. Let W denote an organizational outcome of interest (e.g., productivity, engagement, burnout). We remain agnostic about the full mapping from (a, E, S, θ) to outcomes, but impose a complementarity structure:

$$\frac{\partial^2 W}{\partial a \partial \theta} > 0, \qquad \frac{\partial^2 W}{\partial a \partial S} > 0. \tag{5}$$

Intuitively, psychological safety increases the returns to experimentation with genAI, while clear

communication improves coordination and reduces role ambiguity, increasing the payoff to genAI usage. This aligns with a broader literature on complementarities between technology adoption and organizational practices (Milgrom and Roberts, 1990; Bresnahan et al., 2002).

Proposition 1 (Environment–adoption complementarity)**.** *Under* (5)*, the marginal effect of GenAI use on outcomes is larger in high-θ and high-S environments. In particular, holding E fixed, the slope of W with respect to a is increasing in θ and S.*

Section A.1.1 of the Online Appendix provides proofs and discusses how alternative microfoundations (e.g., communication as signal precision or "language" constraints) map into S, following Crémer et al. (2007) and strategic communication in Dessein (2002); Alonso et al. (2008).

The model delivers a set of hypotheses that guide the empirical analysis. Throughout, ClearAI proxies for S, trust/psychological safety proxies for θ, and embedding E is treated as partially observed (and absorbed by fixed effects and controls where appropriate).

H1 (Adoption levels). GenAI adoption intensity is increasing in embedding E, communication clarity S, and psychological safety θ (Lemma 1).

H2 (Complementarity in outcomes). The marginal association between GenAI usage and worker outcomes is more positive (or less negative) when ClearAI is high and when trust/psychological safety is high (Proposition 1).

H3 (Task interdependence amplifies the value of clarity). The outcome complementarity in H2 is stronger in jobs with higher task interdependence/coordination demands. The interaction between GenAI use and ClearAI is increasing in an occupation-level interdependence measure.

H4 (Credibility: trust strengthens the effect of clarity). The GenAI use × ClearAI interaction is larger when trust/psychological safety is high (a triple complementarity), consistent with interpreting θ as capturing the credibility of informal assurances around experimentation.

H5 (Composition of use). Conditional on adopting GenAI, ClearAI shifts usage toward more standardized, workflow-embedded applications (where alignment is valuable), while trust shifts usage toward more exploratory applications where experimentation costs are salient.

H6 (Role clarity crossover). GenAI usage decreases role clarity when ClearAI is low (unmanaged adoption increases ambiguity), but increases role clarity when ClearAI is high (guidance clarifies expectations). Empirically, this predicts a sign change across clarity regimes.

3 Data and Measurement

3.1 Gallup Practice Panel

I primarily leverage data from the Gallup Practice Panel, a longitudinal survey of U.S. adults. The panel is probability based and surveys workers (18+) about workplace experiences, management, and well-being, with core questions repeated and new items added on emerging topics such as AI. For instance, the Q2 2024 wave was a web survey of 19,043 working adults drawn from this panel, with sampling weights calibrated to national demographics. Respondents span all major industries, occupations, and regions, which allows observation of AI adoption across a broad swath of the workforce. My analytic file restricts to employed respondents and links individuals across waves. The resulting sample includes 9,326 workers in 2023, 9,992 in 2024, and 30,815 in 2025.

Although the sample before 2025 each wave consists of roughly 20,000 respondents, not all workers are surveyed about their AI use. However, starting in Q2:2025, AI questions are asked quarterly.

The resulting Gallup Panel sample contains 30,530 unique respondents and 50,133 person wave observations across 2023 to 2025.[3] Of these, 14,029 respondents are observed in at least two waves. Among the multi wave sample, 38.4% (5,387/14,029) change their AI use category at least once over their observed panel. Considering adjacent wave transitions, there are 19,603 valid t-1 $\rightarrow$ t comparisons. Of these, 17.52% are adoptions (Never $\rightarrow$ Sometimes/Often) and 6.02% are cessations ((Sometimes/Often) $\rightarrow$ Never). The remaining 76.45% are either stable within category or movements between Sometimes and Often. Net flows favor adoption by 2,311 transitions, a ratio of roughly 3.01:1. Row percentages from the transition matrix for switchers indicate persistence and directional movement. Among those previously Never, 73.83% remain Never, 22.32% move to Sometimes, and 13.4% move to Often. Among those previously Sometimes, 48.04% remain Sometimes, 19.1% move to Often, and 16.84% revert to Never. Among those previously Often, 67.5% remain Often, 29.64% move to Sometimes, and 9.32% move to Never. These flows show that diffusion outpaces abandonment over the sample window and that movements up the intensity ladder are common, especially from Sometimes to Often.

3.1.1 AI Measurement

The primary outcome is an indicator of AI adoption at the individual level. In particular, I use answers to the question How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less

[3]Figure A.1 summarizes the longitudinal variation. The mean number of waves per person is 1.64, and 46% of respondents are observed in at least two waves. Tables A.1 and A.2 report the share of AI adopters and the transition matrix across AI use categories.

often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never). Before asking this question, respondents are given a definition of AI: Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." Figure 1 visualizes the time path of adoption and shows two distinct phases. From 2023 to 2024, adoption rises gradually, with a modest increase in frequent use and a larger expansion in occasional use. The trends intensify in 2025: often" rises from roughly 18% in Q2 to about 22% in Q3 and then jumps further to around 26% in Q4, while sometimes" remains elevated but comparatively flat (about 20% in Q2-Q3 and slightly lower in Q4).[4]

In some specifications, I also make use of another question on AI concern and expectations, namely: "How likely is it that the job you have now will be eliminated within the next five years as a result of new technology, automation, robots or artificial intelligence?" Respondents can choose among "very likely," "somewhat likely," "not too likely," "not at all likely," and "don't know or doesn't apply." I classify the last group as missing and focus on the other four, defining an indicator for fear that AI will replace the respondent's job based on reporting "very likely."

The Gallup Workplace Panel offers the most largest, high-frequency, nationally-representative data on not only the frequency, but also the composition of AI utilization. Nonetheless, it most closely aligns with the nationally representative evidence in Bick et al. (2025). In late 2024, they report that 23% of employed respondents used genAI for work at least once in the previous week and 9% used it every work day. In this data, the 2024 "often" share (daily or a few times per week) is about 12%, while "sometimes" use (a few times per month or year) is roughly 15%, implying that about 27% of workers use AI at least occasionally. The slight level differences are

[4]Table A.3 in the Online Appendix provides descriptive statistics on the sample by year.

consistent with definitional wedges: their headline "weekly" measure sits between my intensive "often" margin and my broader "often + sometimes" measure, while both series point to rapid diffusion among workers when measured in samples benchmarked to population targets.

By contrast, the adoption levels in Hartley et al. (2025) are less directly comparable for potentially several reasons. First, the core adoption concept is broader (e.g., "ever used genAI at work since tools became available"), which mechanically yields higher rates and is more sensitive to sporadic experimentation and sample composition. Second, the distinction between nationally representative designs and low-barrier online sampling is becoming first-order for measurement: Westwood (2025) shows that LLM-driven "synthetic respondents" can evade standard attention and quality checks at extremely high rates and can be deployed strategically to bias survey estimates. This evidence reinforces the value of probability-based sampling frames for tracking AI adoption, especially as LLM capabilities grow and the incentives to contaminate online panels rise.

3.2 Workplace Practices

In addition, I measure workplace (management) practices based on responses to the degree of agreement with the following statements on a 1-5 scale: (a) I feel connected to my organization's culture, (b) My organization consistently delivers on the promises it makes to customers, (c) I trust the leadership of this organization, (d) My organization cares about my overall wellbeing, (e) I have received meaningful feedback in the past week, and (f) I am treated with respect at work. We take the z-score of the average of these scores, but produce robustness results using them independently interacted with AI utilization.

3.3 Employee Engagement

I now turn to our outcome variables. The primary focus is on employee engagement, which is constructed as a z-score of the average across the "Q12" indicators—a set of 12 questions that have been validated by Gallup as defining employee engagement, including: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. We also focus on two other metrics: burnout and job satisfaction. The former is measured as follows: "Please indicate how often each of the following statements is true of your primary job (i.e., the job where you spend the most time working). I feel burned out at work: (a) Always, (b) Very often, (c) Sometimes, (d) Rarely, (e) Never." The latter is measured (ranked on a 1 to 5 scale) as follows: "How satisfied are you with your place of employment as a place to work?"

3.4 Individual Controls

The primary controls include: age, male, race (White, Black), full time and part time status, having children, and married. I also observe the employee's annual income bin, education, industry,

and occupational classification (using a mapping of job titles to SOC-codes), and tenure, although these latter variables are used only in robustness checks due to comparatively more missing values.

4 Descriptive Evidence on AI Utilization

4.1 Public v. Private Sector

Figure 2 compares AI adoption across federal, state/local, private, and non-profit workers. In 2023, frequent use is low and fairly similar in the federal, state/local, and private sectors (around 10%), with non-profits lower; occasional use is lowest among federal workers and higher in state/local, private, and non-profits. By 2024, adoption rises on both margins, but the increase is more visible on "sometimes" use in state/local and non-profits (near 18–20%) than in private. By Q2:2025, private and non-profit workers are already around one-fifth on "often" use, while federal and state/local are closer to the mid-teens; state/local also has the largest "sometimes" share (mid-20s). By Q4:2025, the private sector stands out for intensification—"often" reaches the high-20s while "sometimes" drops toward the high-teens—whereas state/local sustains a large pool of occasional users even as frequent use rises into the low-20s. Non-profits end 2025 with both high "often" and high "sometimes," and federal workers increase more gradually, remaining below private on frequent use. Non-profits and government do not appear to be persistent laggards in genAI use, which is striking given broader concerns about slow tech diffusion outside the private sector. A plausible reason is that genAI is relatively easy to trial (compared to traditional machine learning) and coordination-intensive tasks common in public and mission-driven work. The remaining gap is in *intensification*: the private sector converts experimentation into frequent use more quickly,

consistent with fewer compliance constraints and stronger organizational scaffolding.

4.2 Work Type

Figure 3 examines adoption by organizational role and shows a hierarchy gradient that widens over time. In 2023, frequent use is modest across the board—about 16% among senior leaders, 13% among supervisors, 11% among project managers, and 8% among individual contributors—while occasional use is roughly 17%, 15%, 14%, and 7%, respectively. By 2024, adoption rises in every role: frequent use reaches about 20% for senior leaders and roughly 12–13% for supervisors and project managers, with individual contributors around 11%. Occasional use also increases, with especially pronounced growth among senior leaders (high-20s) and project managers (low-20s).

These patterns accelerated in 2025, particularly at the top of the hierarchy. In Q2:2025, frequent use climbs to roughly 32% for senior leaders and about 24–25% for supervisors, with project managers and individual contributors in the low-20s; occasional use is similarly elevated, near 29% for senior leaders and the mid-20s for supervisors and project managers. In Q3:2025, frequent use rises further for senior leaders (mid-to-high 30s) and for project managers (high-20s), while individual contributors remain below 20%; occasional use stays high and relatively compressed across leadership and project-oriented roles. By Q4:2025, the gradient is most pronounced: senior leaders reach the low-40s in frequent use, project managers the mid-30s, supervisors around 30%, and individual contributors the low-20s, while occasional use remains elevated but does not increase proportionally. Diffusion is driven disproportionately by shifts toward frequent, embedded use, and that intensification is strongest in leadership and coordination-intensive roles, consistent with models that feature coordination costs (e.g., communication) (Lee and Makridis, 2023).

4.3 Income

Figure 4 tracks AI adoption by income and shows rapid growth across the distribution, with a clearer income gradient emerging by late 2025. In 2023, both "often" and "sometimes" use are low and fairly compressed across brackets: frequent use sits in the high single digits to low teens, while occasional use ranges from only a few percent at the bottom to around 10% in the upper-income groups. By 2024, adoption rises on both margins, with "often" generally in the low-to-mid teens and "sometimes" in the low-to-mid teens as well, leaving a modest advantage for higher earners.

In Q2:2025, frequent use increases markedly in most brackets, especially in the middle and upper parts of the distribution, and "sometimes" use also rises into the mid-teens to low-20s. By Q3:2025, the upper-income groups move into the low-30s on frequent use, while lower-income brackets increase more gradually; occasional use remains elevated but shows less dispersion than frequent use. By Q4:2025, the income gradient is sharpest: frequent use is highest in the upper brackets (around 30% to above 40%), while the lowest-income group remains closer to the low-20s. Occasional use stays high across the board but is comparatively flatter than "often."

4.4 Industries and Occupations

Starting with industries, Panel A in Figure 5 documents substantial cross-sectional heterogeneity in the intensity of workplace AI use. Technology/Math is the clear outlier on frequent use: roughly 45% report using AI often, compared to about 23% who use it sometimes. A second tier of information-intensive industries—notably FIRE and consulting—also exhibits high adoption, with often-use rates around 28–31% and sometimes-use rates around 20–23%. The public sector

is similarly elevated, with both "often" and "sometimes" close to one-quarter. Education and legal are different: often use is closer to the low-20s, while sometimes use is nearer to 25–27%, consistent with wider experimentation without the same depth of workflow integration. By contrast, several customer-facing or operational sectors sit lower in the distribution. Retail/Sales and Industrial/Extraction have often-use rates around the mid-teens, while Hospitality/Travel/Food is the laggard, with often close to 12–13% and sometimes around 10–12%. The cross-section is consistent with an exposure-based interpretation: industries centered on information production and knowledge work show deeper AI integration, while sectors with more in-person service and manual task content exhibit more limited adoption (Eloundou et al., 2024).

Panel B complements the cross-section by highlighting how quickly intensity is changing within industries during 2025 (percentage-point changes). Growth is concentrated in frequent use: the "often" series rises sharply in many sectors, including Arts/Entertainment/Media (roughly +15 pp), the public sector (about +13 pp), health care (about +12–13 pp), legal (about +10–11 pp), and FIRE (about +10 pp). Even industries with moderate baseline levels in Panel A therefore display rapid deepening of use over the year. Changes in "sometimes" are more mixed and, in several cases, negative—for example, Technology/Math shows a sizeable decline in "sometimes" alongside an increase in "often," consistent with a reallocation from occasional experimentation toward routinized use. A similar (though smaller) pattern appears in transportation/logistics and health care, where "often" rises while "sometimes" falls modestly. By contrast, legal stands out for broad-based expansion, with increases in both "often" and "sometimes," suggesting diffusion on both the extensive and intensive margins. In this sense, AI adoption in 2025 is not just spreading to new users, but shifting existing adopters toward more frequent, embedded usage, although the slowest-moving sectors (hospitality/food) showing comparatively limited growth on either margin.

Turning to occupations, Figure 6 reports both the cross-sectional distribution of AI-use intensity (Panel A) and the change in those shares over 2025 (Panel B). Panel A shows a pronounced gradient by task content. Computer/Math occupations are the clear leader on routinized use, with roughly 42% reporting AI use *often* and about 25% *sometimes*. Business/Finance is also high, with frequent use near 30% and occasional use in the low-20s. A broad middle tier—including Architecture/Engineering, Life/Physical/Social Science, Legal, Education, and Arts/Media—clusters around roughly 19–24% *often* and 21–29% *sometimes*. Within that tier, Education and Arts/Media stand out for a heavier tilt toward experimentation: sometimes-use is close to the high-20s while often-use is closer to one-fifth, suggesting relatively wide trial use without the same depth of routine integration. By contrast, occupations with more hands-on service content sit lower. Health-support and protective-service roles have frequent-use shares around 10–12%, while food service, building/grounds, and personal care are among the lowest on frequent use. Overall, the cross-section is consistent with an exposure-based interpretation: occupations centered on analytical, text-heavy, and information-processing tasks concentrate frequent AI use, while frontline and manual service roles adopt more slowly and, when they do, tend to do so at the occasional margin.

Panel B shows that diffusion in 2025 is occurring through both intensification and widening, with particularly large movements in a few occupations. Growth in *often* use is positive in most categories and is sizable in several white-collar groups (e.g., Business/Finance and Computer/Math) as well as in Office/Admin, where frequent use rises sharply. In parallel, some occupations exhibit notable growth in *sometimes* use, indicating expansion along the extensive margin of experimentation. Architecture/Engineering is the most striking example, showing very large increases in both sometimes and often, consistent with rapid diffusion and deepening within that occupational family. Several service-adjacent categories (e.g., health-support and personal care) also show increases

in sometimes use, suggesting that AI trial use is spreading even where baseline frequent-use rates remain lower. At the same time, some occupations show patterns consistent with upgrading from occasional to routine use: in a few analytic categories, sometimes use declines while often use rises, consistent with maturation from experimentation to embedded workflows. One notable exception is building/grounds, which shows declines, but could reflect sampling variability.

5 Empirical Strategy

5.1 Determinants of AI Adoption

To study correlates of AI adoption, I estimate regressions of the form:

$$AI_{it} = \zeta_1 \, ClearAI_{it} + \zeta_2 \, Trust_{it} + \zeta_3 W_{it} + \psi \, FEAR_{it} + \beta X_{it} + \lambda_t + \varepsilon_{it}, \tag{6}$$

where AI_{it} denotes whether individual i uses AI frequently for work (e.g., daily or a few times per week; normalized to the low/never-use group), $ClearAI_{it}$ is an indicator for whether the respondent reports that the organization has communicated a clear AI strategy for integrating AI into business practices, $Trust_{it}$ is a standardized index of trust in leadership, and W_{it} is a vector of workplace practice characteristics (measured as standardized z-scores of 1–5 items, with higher values denoting better practices). The term $FEAR_{it}$ denotes an indicator for whether the respondent believes AI will replace their job within five years, and X_{it} includes demographic and job characteristics. I include year fixed effects, λ_t, to address aggregate changes, weight observations using the survey weights, and cluster standard errors at the individual level.

Equation (6) is descriptive: it is designed to quantify whether clear organizational direction,

leadership credibility, and broader workplace practices are associated with higher adoption, above and beyond worker characteristics and AI-related anxiety. A central motivation is that experimentation with AI may be constrained not only by skills and perceived returns, but also by perceived organizational guardrails and the broader management environment. In particular, a clear AI strategy may reduce ambiguity about permissible use-cases and expected conduct, while trust in leadership and supportive workplace practices may shape whether employees view experimentation as career-safe and worth the effort required to integrate AI into day-to-day workflows.

5.2 Identifying Organizational Complementarities

The main empirical results study how AI utilization and organizational conditions interact in predicting employee outcomes. The baseline panel specification is:

$$y_{it} = \sum_{k \in \{\text{Often,Sometimes}\}} \gamma_k \, \mathbb{1}\{AI_{it} = k\} + \theta \, ClearAI_{it} + \sum_{k \in \{\text{Often,Sometimes}\}} \xi_k \Big(\mathbb{1}\{AI_{it} = k\} \times ClearAI_{it} \Big) + \beta X_{it} + \alpha_i + \lambda_t + \varepsilon_{it}. \tag{7}$$

where y_{it} denotes the standardized outcome of interest (employee engagement, burnout, or job satisfaction), $\mathbb{1}\{AI_{it} = k\}$ are indicators for AI use frequency relative to the low/never-use reference group, $ClearAI_{it}$ is the clear-strategy indicator, X_{it} includes time-varying controls, α_i are person fixed effects, and λ_t are year fixed effects. The coefficients of interest are the interaction terms ξ_k, which capture the complementarity hypothesis: whether the marginal association between AI use and outcomes is more favorable when organizations communicate a clear AI strategy.

5.3 Causal Inference and Interpretation

A key challenge is that neither AI use nor perceived organizational conditions are randomly assigned. Three threats are especially salient. First, there are selection effects. Individuals who adopt AI may differ systematically in ambition, task complexity at work, openness to change, or baseline optimism, and these traits could also correlate with how they rate their organization. Person fixed effects, α_i, address all time-invariant worker differences, exploiting within-person changes in AI utilization and perceived organizational context.

Second, there is the potential for reverse causality and simultaneity. Engagement could itself increase adoption (i.e., more motivated workers seek out new tools), and organizations may communicate AI strategy in response to adoption waves, performance pressures, or internal events that also affect engagement and burnout. Person and time fixed effects reduce these concerns but do not eliminate them when shocks are time-varying and jointly influence outcomes, AI use, and the communication of strategy. The heterogeneity analyses are helpful here.

Third, there are time-varying confounding macro and organizational level shocks. Aggregate shocks (e.g., industry cycles) or differential trends across groups could drive both AI adoption and outcomes. To address this, I implement specifications that flexibly control for heterogeneous macro dynamics by adding income group $\times$ time fixed effects, absorbing differential period shocks across income strata. I also experiment with industry $\times$ time fixed effects.

In addition to the baseline specification containing person and time fixed effects, I also re-estimate (7) on the sample of job switchers, leveraging within-person changes around employer transitions, specifically two years before and two years after. This design increases plausibility that changes in exposure to organizational practices are causal because they isolate variation

within the same individual exposed to different organizational ecosystems. While job changes are not random and sorting into higher-quality firms remains a concern, the switchers results are useful because they isolate variation in organizational environment that is mechanically linked to changes in employer. Nonetheless, the empirical strategy is not a claim of causal identification from randomized exposure. Rather, it is a disciplined effort to (i) document robust complementarities between AI use and clear organizational strategy across increasingly demanding specifications, and (ii) evaluate whether these patterns survive within-person comparisons, flexible controls for macro heterogeneity, and variation induced by employer transitions.

6 Determinants of AI Adoption

Table 1 estimates correlates of using genAI often at work. Columns 1 through 6 enter each workplace practice separately; sample size varies because only subsets of respondents were asked particular workplace items.[5] In the single-item models, each practice is positively associated with frequent use, and all are precisely estimated: well-being (0.015, s.e. 0.003), connectedness (0.020, 0.003), feedback (0.029, 0.003), customer focus (0.008, 0.003), trust (0.019, 0.003), and respect (0.020, 0.004). Column 7 adds the clear AI strategy indicator, which is strongly predictive of adoption: reporting a clear strategy is associated with a 0.284 increase (s.e. 0.007) in the probability of using AI often, conditional on demographics and year fixed effects.

Column 8 includes all workplace practices jointly alongside the clear-strategy indicator. The key result is that clear AI strategy remains large and precisely estimated (0.262, s.e. 0.012), while the individual workplace-practice coefficients attenuate sharply and become statistically indistin-

[5] These differences reflect survey design (item routing) rather than non-response.

guishable from zero. This pattern suggests that, in the cross section, clear AI strategy captures the dominant organization-level correlate of frequent AI use, and that the bivariate associations between frequent use and broader workplace perceptions largely reflect common covariance with strategic clarity rather than independent predictive content. Column (8) coefficient implies that workers in clear-strategy organizations are about 26 percentage points more likely to report frequent AI use, holding constant demographics and year effects.[6]

Controls behave as expected and are stable across specifications. Frequent use rises strongly over time (the 2025 indicator is about 0.111–0.112 relative to 2023 in cols. 1–6). Age is negatively associated with frequent use (about −0.002 per year). Education loads positively and strongly: "college or more" is associated with roughly 9–13 percentage points higher frequent use depending on the specification, and remains sizable in the saturated model (0.107). Full-time status is also strongly positive (about 6–8pp), while men report higher frequent use (about 2pp). White respondents report lower frequent use (roughly 3–5pp), and being married or having children is associated with modestly higher adoption. R-squared values are about 0.06 in the single-item models, rising to 0.13 when adding clear strategy (col. 7), and 0.12 in the saturated model (col. 8); sample sizes range from about 23,000 to 50,000 depending on item availability.

Table A.5 in the Online Appendix also includes an indicator for whether an individual believes that AI is "very likely" to displace their job in the next five years. (It is included as robustness, rather than the baseline, because it is not part of the updated quarterly questions, e.g. in Q3:2025.) Perhaps counterintuitively, individuals who are worried that AI will displace their job are 10-17 percentage points more likely to use AI often. This could indicate that frequent AI users

[6]Does clear AI strategy just proxy for trust in leadership? Even when introducing person and time fixed effects, a regression of an indicator for having a clear AI strategy on a z-score for trust in leadership produces a coefficient of .037 (p-value = 0.002).

understand that their jobs—and jobs in the economy more broadly—are subject to evolution and that the nature of their work will simply change, but not go away.

Are these coefficients biased due to having too precise of a cutoff on AI utilization? Table A.4 in the Online Appendix replicates these results using the full distribution of AI utilization on a 0-10 scale: Daily=10, Few Times Week=8, Few Times Month=6, Few times Year=4, Once a Year=2, Less than Once a Year=1, Never/Other=0. Results are largely similar.

Table 2 subsequently explores the correlates of whether the respondent reports having a clear AI strategy, a yes/no response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." Columns (1)–(6) enter each workplace practice separately and show that perceived management quality is strongly associated with strategic clarity. The largest single-item associations are for feedback (0.055, s.e. 0.004), well-being (0.045, 0.004), and trust (0.046, 0.004), with connectedness (0.049, 0.004), customer focus (0.036, 0.004), and respect (0.037, 0.004) also positive and precisely estimated. Interpreted as linear probability estimates, a one standard deviation increase in feedback or trust is associated with roughly a 4–6 percentage point higher probability of reporting a clear AI strategy.

Column (7) includes all workplace practices jointly. First, feedback remains the most robust correlate of clear strategy (0.041, s.e. 0.006), suggesting that communication and performance dialogue are tightly linked to whether employees perceive their organization as having an articulated AI plan. Second, the coefficients on trust and connectedness remain positive but attenuate (0.017 and 0.020, respectively), while well-being, customer focus, and respect become small and statistically indistinguishable from zero. The saturated specification indicates that clear AI strategy is most closely linked to organizational communication and developmental feedback, with broader

positive workplace perceptions correlating with strategy primarily through shared covariance with those communication channels. Interestingly, however, as the main results in the next section will show, the complementarities are focused on trust (not feedback or connectedness).

The demographic gradients are stable across columns. Education is strongly predictive: "college or more" is associated with about 10–11 percentage points higher reported strategy clarity, and full-time workers are about 5–7pp more likely to report a clear strategy. Age loads negatively (roughly -0.002 per year), White respondents are less likely to report clear strategy (about 3–4pp), and Black respondents are more likely (about 4–5pp). These patterns underscore that reported strategic clarity is not purely an organization-level object; it also reflects heterogeneous exposure to communication and role context within firms.

7 Organizational Complementarities of AI Adoption

7.1 Main Results

Table 3 examines whether the relationship between employees' AI utilization and workplace outcomes depends on whether the organization has communicated a clear AI strategy. The baseline specification regresses standardized outcomes—employee engagement (Q12), burnout, and job satisfaction—on indicators for AI use frequency ("Often" and "Sometimes," relative to a low/never-use reference group), an indicator for whether the organization has articulated a clear AI strategy, and their interactions, alongside demographic controls and person and time fixed effects (baseline). The interaction terms capture complementarities: whether the marginal association of AI use with

outcomes is larger (or smaller) when a clear strategy is present.[7]

Across outcomes, the pooled baseline estimates with demographics (cols. (1), (5), and (9)) show a consistent pattern of complementarity. For employee engagement (Q12), AI use in isolation is weakly related to engagement, while the interaction with clear strategy is economically large and precisely estimated. In particular, "Often" AI use has a near-zero main effect (0.012 SD), whereas the "Often × Clear AI Strategy" coefficient is 0.226 SD, implying that frequent users in organizations with a clear strategy exhibit roughly 0.238 SD higher engagement relative to the low/never-use group. "Sometimes" use is positively associated with engagement (0.080 SD), and the corresponding interaction adds an additional 0.086 SD, yielding an implied association of approximately 0.166 SD when a clear strategy is present. Crucially, these cross-sectional regressions control for various potential confounders (e.g., age and education).

For burnout, the same complementarity appears with the opposite sign (i.e., mitigating burnout). "Often" AI use is associated with higher burnout (0.124 SD), but the interaction with clear strategy is negative (-0.086 SD), offsetting most of the increase. For "Sometimes" use, the main effect is 0.050 SD while the interaction is -0.093 SD, implying that moderate AI users in clear-strategy organizations experience slightly lower burnout on net (about -0.043 SD) relative to the low/never-use group. Job satisfaction mirrors the engagement results. "Often" AI use has a slightly negative main effect (-0.022 SD), but the "Often × Clear AI Strategy" interaction is strongly positive (0.198 SD), implying an overall association of roughly 0.176 SD for frequent users when a clear strategy is present. "Sometimes" use is modestly positive (0.040 SD), and the interaction adds 0.086 SD, implying about 0.126 SD higher satisfaction for moderate users in clear-strategy organizations.

[7]Figure A.2 in the Online Appendix documents robustness using the full distribution of AI utilization, rather than the indicators for frequent or sometimes users. For each outcome variable, employee outcomes are greatest among the daily AI users.

Cumulatively, the baseline estimates indicate that AI utilization is not uniformly associated with better employee outcomes; rather, its association is sharply more favorable in organizations that communicate a clear AI strategy. In this sense, a clear AI strategy appears to raise the marginal returns to AI use for workers—strengthening engagement and satisfaction while attenuating (and in some cases reversing) the burnout penalty associated with AI use absent such strategy.

Recognizing the potential for self-selection among more ambitious and productive individuals into using AI, columns (2), (6), and (10) introduce person and time fixed effects, absorbing all time-invariant worker heterogeneity and common period shocks. Once these fixed effects are included, the level association of having a clear AI strategy becomes small and statistically indistinguishable from zero across outcomes (e.g., 0.058 for engagement, -0.002 for burnout, and 0.069 for satisfaction). By contrast, the interaction terms remain economically large and precisely estimated, reinforcing the interpretation that the key channel is complementarity rather than additivity. For engagement, the "Often $\times$ Clear AI Strategy" coefficient is 0.183 SD and "Sometimes $\times$ Clear AI Strategy" is 0.188 SD (col. (2)), implying substantial gains in engagement among AI users when a clear strategy is present. For burnout, the interaction for frequent users is negative and sizeable (-0.147 in col. (6)), largely offsetting the positive main effect of frequent AI use (0.132), so that the implied net association for frequent users with a clear strategy is approximately zero. Job satisfaction exhibits the same pattern: the interaction terms are positive (0.130 for "Often" and 0.189 for "Sometimes" in col. (10)), converting otherwise small or negative main effects of AI use into meaningfully positive associations in clear-strategy organizations.

Columns (3), (7), and (11) augment the person and time fixed effects specification with income group $\times$ time fixed effects, flexibly controlling for differential trends and macro shocks across income strata. The results are essentially unchanged. For engagement, the complementarities

remain strong: 0.195 SD for "Often × Clear AI Strategy" and 0.190 SD for "Sometimes × Clear AI Strategy" (col. (3)). For burnout, the interaction for frequent users remains negative and statistically significant (−0.165 in col. (7)), again largely offsetting the positive main effect of frequent AI use (0.147). For job satisfaction, the interaction terms remain positive and statistically significant (0.156 for "Often" and 0.200 for "Sometimes" in col. (11)). In short, these estimates indicate that the complementarity is not an artifact of differential time trends by income group: conditioning on very flexible income-by-time shocks leaves the core pattern intact.

Finally, columns (4), (8), and (12) restrict the sample to job switchers and estimate the model using within-person variation around employer transitions (with person and time fixed effects). This specification exploits a potentially more exogenous source of variation, namely individual exposure to different company practices and management styles, although it still does not rule out non-random sorting into firms with better practices overall. The complementarity effects not only persist but become larger, consistent with the idea that the organizational environment conditions whether AI use translates into better worker outcomes. For engagement, the interaction coefficients rise to 0.299 SD ("Often") and 0.420 SD ("Sometimes") in col. (4), implying sizable engagement gains among AI users when the post-switch employer has a clear strategy. For burnout, the interactions remain negative (−0.192 for "Often" and −0.186 for "Sometimes" in col. (8)), indicating that clear strategy mitigates (and for moderate users can reverse) the burnout increases associated with AI use. For job satisfaction, the switchers estimates are again larger: 0.234 SD for "Often × Clear AI Strategy" and 0.384 SD for "Sometimes × Clear AI Strategy" (col. (12)). Overall, the switchers design strengthens the interpretation that the relevant variation is organizational: moving into (or out of) workplaces with clear AI strategy materially changes the marginal association between AI utilization and employee engagement, burnout, and satisfaction.

To understand the dimensions of employee engagement that are more heavily influenced by these complementarities, Table 4 replicates the baseline specification with each of the 12 engagement components. Two patterns stand out. First, the level association of having a clear AI strategy is generally small across items, with statistically detectable gains concentrated in forward-looking and growth-oriented dimensions: the strategy indicator is positive for "Development" (0.103) and "Progress" (0.217), while remaining imprecisely estimated for most other components. Second, and consistent with Table 4, the interaction terms indicate that the organizational strategy environment conditions how AI use maps into specific engagement margins. Absent the interaction, frequent AI use is negatively associated with the most "foundational" inputs to engagement—clarity of expectations and access to materials. For "Often" users, the coefficients are -0.138 for "Expectations" and -0.191 for "Materials." At the same time, frequent AI use is positively associated with several higher-order dimensions, including "Recognition" (0.146), "Development" (0.120), "Opinions" (0.135), and "Learn and grow" (0.173). "Sometimes" use exhibits a similar structure: negative for "Expectations" (-0.114), but positive for a broad set of items including "Recognition" (0.122), "Manager" (0.134), "Development" (0.120), "Opinions" (0.120), "Mission" (0.139), "Best friend" (0.126), "Progress" (0.191), and "Learn and grow" (0.273). The main effects suggest that AI use is associated with improvements in developmental and motivational dimensions even as it correlates with weaker role clarity and (in some cases) perceived resourcing.

The interaction terms show where complementarities are strongest. For role clarity ("Expectations"), the interaction is large and precisely estimated for both usage intensities: 0.183 for "Often $\times$ Clear AI Strategy" and 0.179 for "Sometimes $\times$ Clear AI Strategy." These estimates imply that a clear strategy largely offsets the negative main effects of AI use on expectations (e.g., for "Often" users, -0.138 + 0.183 $\approx$ 0.045). A similar, though less precisely estimated, pat-

tern appears for "Materials," where the interactions are positive (0.191 for "Often" and 0.203 for "Sometimes"). Complementarities emerge most clearly in voice, development, and quality. The interaction is positive for "Opinions" (0.124 for "Often" and 0.164 for "Sometimes"), indicating that AI use in clear-strategy organizations is more strongly associated with employees feeling that their views count. The "Sometimes" interaction is also positive for "Development" (0.138) and "Quality" (0.231), pointing to amplified associations between AI use and perceived growth support and commitment to high-quality work when a clear strategy is present. By con

Table 5 re-estimates the engagement baseline specification separately by demographic subgroup. The level effect of reporting a clear AI strategy is small and statistically indistinguishable from zero in every subgroup, consistent with the earlier fixed-effects results. Complementarities are most pronounced among respondents with at least a college education. Both interaction terms are positive and precisely estimated: "Often × Clear AI Strategy" is 0.184 (s.e. 0.066) and "Sometimes × Clear AI Strategy" is 0.171 (s.e. 0.067). The corresponding main effects of AI use are near zero or slightly negative ("Often" = −0.007; "Sometimes" = −0.018), implying that engagement gains from AI use accrue primarily when AI adoption is paired with clear organizational strategy (implied effects with strategy of ≈ 0.177 for frequent users and ≈ 0.153 for moderate users). By contrast, among respondents with less than a college education, the interaction terms are also positive (0.158 for "Often" and 0.177 for "Sometimes"), but imprecisely estimated (s.e. 0.167 and 0.168), making it difficult to rule out smaller complementarities in this group.

Among White respondents, the complementarities are large and statistically significant: 0.186 (s.e. 0.081) for "Often × Clear AI Strategy" and 0.244 (s.e. 0.080) for "Sometimes × Clear AI Strategy." Given small positive main effects of AI use (0.041 for "Often" and 0.066 for "Sometimes"), these estimates imply sizable engagement gains for AI users in clear-strategy workplaces

(roughly 0.23 SD for frequent users and 0.31 SD for moderate users). Among non-White respondents, the interaction terms are smaller and imprecisely estimated (0.072 and 0.056, respectively), suggesting that the strategy-conditioned marginal returns to AI use are weaker or harder to detect in this subsample. However, this attenuated effect could also be driven by the much smaller sample size. By sex, the evidence points to stronger direct associations of AI use for men, but less precisely estimated complementarities. For men, the main effects of AI use are positive (0.147 for "Often" and 0.112 for "Sometimes"), while the interaction terms are positive but not statistically distinguishable from zero (0.083 and 0.027). For women, the main effect of frequent AI use is slightly negative (-0.038), consistent with an alienation effect absent an AI strategy, and the interaction terms are positive (0.124 for "Often" and 0.174 for "Sometimes") but again imprecise.

Figure 7 plots comparable interaction coefficients between a clear AI strategy and AI utilization ("Often" and "Sometimes") on Q12 engagement, separately by age bracket, in the person- and time-fixed-effects specification. First, there is no simple monotonic age gradient in complementarities. Instead, the profile is somewhat hump-shaped/U-shaped: interaction effects are near zero (and occasionally slightly negative) for the youngest brackets, become more positive in the mid-to-late 30s (especially for "Sometimes" use), dip into negative territory in the early-to-mid 40s, and then turn positive again from roughly age 50 through the early 60s. In the older brackets (around 50–62), both "Clear AI × Often" and "Clear AI × Sometimes" are generally positive, suggesting that when older workers use AI, the presence of a clear organizational strategy is more consistently associated with higher engagement. Second, the uncertainty bands widen at the extremes—particularly at the oldest bracket—indicating smaller effective sample sizes and limiting statistical precision. Nonetheless, complementarities appear weakest (and sometimes negative) in the mid-career window around the 40s, and strongest in later career stages, where the

strategy environment more reliably conditions whether AI use maps into higher engagement. This pattern is consistent with the idea that organizational enablement and clarity may matter most for translating AI tools into productive, engagement-enhancing workflows among older workers, whereas in mid-career brackets the same tools may generate more heterogeneous experiences unless accompanied by clearer managerial and organizational scaffolding.

7.2 Credibility, Psychological Safety, and Realized Gains

Table 3 shows that AI use is not uniformly associated with better outcomes; instead, the association becomes sharply more favorable when the organization communicates a clear AI strategy, raising engagement and satisfaction and largely offsetting the burnout penalty that appears for adopters in low-clarity environments. A natural mechanism is psychological safety: strategy reduces ambiguity about purpose and guardrails, but employees still need to believe that experimentation is career-safe and that leadership will interpret early mistakes as learning rather than misuse.

Table 6 indicates that workplace trust is a first-order correlate of employee well-being, and that it meaningfully conditions how AI adoption maps into engagement in several specifications. Across outcomes, the trust index enters with the expected signs and is large in magnitude: higher trust is strongly associated with higher engagement and job satisfaction and with lower burnout. The trust coefficients remain sizable when adding person and time fixed effects (and, where applicable, income-group-by-time fixed effects), suggesting that changes in perceived trust track changes in these outcomes within workers over time.

The interaction terms provide more nuanced evidence on psychological-safety mechanisms. For employee engagement, the AI-use-by-trust interactions are small in the pooled-with-demographics

specification (col. (1)), but become positive and statistically significant once person and time fixed effects are introduced (cols. (2)–(3)). In particular, the interaction for frequent users is positive (0.062 in col. (2) and 0.056 in col. (3)), and the interaction for moderate users is positive in the richer specification (0.047 in col. (3)). This pattern implies that, holding constant worker fixed effects and common time shocks, AI use is more strongly associated with higher engagement in higher-trust workplaces. In other words, trust appears to amplify the engagement returns to AI adoption, consistent with the idea that employees are more willing to experiment, share failures, and integrate AI into workflows when leadership is perceived as fair and supportive.

For burnout, the interaction terms are generally small and statistically indistinguishable from zero in the fixed-effects specifications, indicating limited evidence that trust systematically moderates the AI–burnout relationship in this table. For job satisfaction, the evidence of moderation is also weaker: while one pooled specification shows a positive interaction for frequent users (col. (9)), the interaction estimates attenuate and become imprecise after introducing person and time fixed effects (cols. (10)–(11)). The switchers designs, which are noisier due to smaller samples, do not deliver as much robustness as the main results with clear AI strategy.

In this sense, Table 6 complements Table 3 by showing that psychological safety, proxied here by workplace trust, is tightly linked to baseline levels of engagement and satisfaction and is plausibly an enabling condition for translating AI use into higher engagement once individual heterogeneity is absorbed. The moderation evidence is strongest for engagement and weaker for burnout and job satisfaction, suggesting that trust primarily affects whether AI adoption feels motivating and empowering, rather than directly offsetting burnout in the way a clear strategy appears to do.

Table 7 examines a candidate mechanism by linking workplace trust to employees' perceived productivity gains from genAI. In pooled cross sections, frequent users report substantially higher

perceived AI productivity: 0.907 s.d. (s.e. =0.206) for the z-score outcome and 0.242 (s.e. =0.020) for the "5/5" indicator in cols. 1 and 4. Introducing person fixed effects and year controls attenuates these main effects toward zero in cols. 2-3 and 5-6 (e.g., 0.336 and 0.387 for the z-score outcome; 0.125 and 0.151 for the binary outcome), consistent with selection into frequent use.

By contrast, interactions with workplace trust are large and stable for frequent users. For the z-score outcome, the "often" $\times$ trust coefficient equals 0.240 (0.199) in the pooled model and rises sharply once person fixed effects are introduced, to 0.939 (0.366) and 0.853 (0.312) in cols. 2–3. For the "5/5" indicator, the corresponding interactions are 0.091 (0.025), 0.563 (0.152), and 0.522 (0.166) in cols. 4-6. Interactions for "sometimes" users are smaller and less robust in the z-score specifications—0.137 (0.198), 0.699 (0.488), and 0.514 (0.313) in cols. 1-3—but they are positive

Consistent with this hypothesis of psychological safety, better communication and trust should also shift how employees use AI—not just whether they use it. After restricting the sample to those who use AI at least sometimes, Figure 8 examines how the composition of AI use-cases varies based on whether respondents report their firm having a clear AI strategy, or whether they report high trust in senior leadership; the sample is restricted to respondents who use AI at least sometimes. In Panel A, respondents who report that their firm has communicated a clear AI strategy are more likely to use AI across a broad set of concrete work tasks. Relative to adopters in low-clarity environments, they are more likely to report using AI to automate basic tasks, identify problems, and learn new things, and they also exhibit notably higher shares in more workflow-integrative use cases such as collaborating with others, setting up/operating/monitoring devices, consolidating information, and making predictions. By contrast, the residual "Other" category is smaller for the clear-strategy group, consistent with strategy shifting AI use away from idiosyncratic or hard-to-classify experimentation and toward more standardized, legible applications.

Panel B indicates a related but more selective pattern for trust in leadership. High-trust adopters are disproportionately more likely to report using AI for learning new things and for idea generation (and are modestly higher on several interpersonal or outward-facing applications such as collaboration and customer interaction), while differences in routine applications such as basic task automation or problem identification are comparatively small. Taken together, the figure is consistent with a psychological-safety mechanism in which clearer strategy and stronger trust are associated not simply with *more* AI use, but with a tilt toward higher-value, more exploratory, and more organization-embedded AI use cases among those already adopting.

8 Conclusion

How has generative AI adoption evolved in the United States, and when does adoption translate into better workplace outcomes? Using nationally representative longitudinal data from 2023–2025, I document rapid diffusion of AI use at work. Frequent use rose from single digits to nearly one-quarter of employees, and occasional use expanded in parallel. Adoption is not confined to a narrow slice of the labor market: while diffusion is fastest in analytic and information-processing roles, it is visible across sectors and throughout the income distribution, intensifying heavily among active users in 2025. Importantly, diffusion is structured by organizational hierarchy. Senior leaders report the highest intensity of use, with supervisors and project managers close behind, consistent with an internal transmission process in which adoption spreads through managerial channels rather than arriving solely as individual experimentation.

A central result is that managerial and organizational context is not peripheral to AI diffusion—it is predictive of both who adopts and what adoption delivers. In the cross section, per-

ceived clarity of an organization's AI strategy is the dominant correlate of frequent AI use, even after controlling for demographics and time effects. Moreover, employees' perceptions of strategic clarity are most strongly associated with managerial communication and credibility—especially developmental feedback and trust in leadership—suggesting that "strategy" is experienced on the ground through managerial practice rather than through formal policy alone. These patterns motivate the paper's broader framing: generative AI diffuses inside firms through an organizational transmission mechanism shaped by what managers communicate, model, and legitimize.

The most relevant finding is that adoption does not mechanically improve employee outcomes, helping to explain low adoption rates and high failure rates of AI pilots. Using within-person designs, I show strong complementarities between AI use and organizational conditions. When organizations communicate a clear AI strategy, AI adoption is associated with meaningfully higher engagement and job satisfaction and with a substantial attenuation of the burnout penalty that appears among adopters in low-clarity environments. These results are robust to exploiting variation among job switchers who are exposed to different managerial environments. Complementary evidence indicates that psychological safety—proxied by trust in leadership—amplifies the engagement returns to adoption and is strongly related to whether adopters report realizing productivity gains and using AI for higher-value, more exploratory tasks (e.g., learning and idea generation) rather than narrow automation alone. In this sense, the realized returns to generative AI are jointly determined by technology and governance: workers are more likely to integrate AI into productive workflows when leadership provides clear direction and credible support for experimentation.

These findings have practical implications for firms and public-sector organizations seeking AI-enabled productivity gains. Investments in tools and infrastructure are unlikely to be sufficient without complementary investments in managerial capacity—communication, feedback, and trust-

building—that shape how employees interpret guardrails and whether they view experimentation as career-safe. Future research can extend this work by linking adoption patterns more directly to objective performance measures, tracing the distinct role of middle management in scaling use cases, and studying how governance choices (training, monitoring, incentives, and risk frameworks) affect both productivity and worker well-being over longer horizons.

Tables and Figures

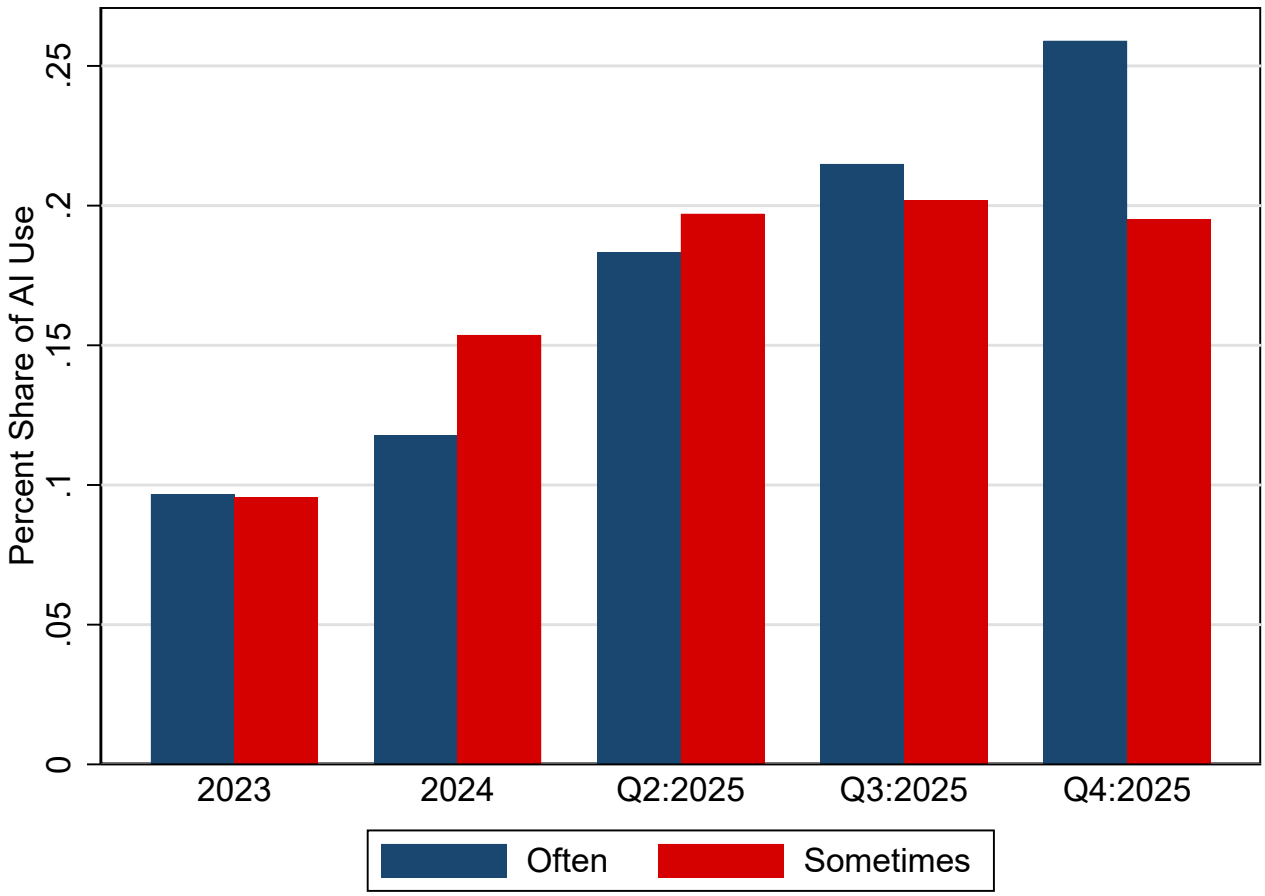


Figure 1: Time Series Adoption of AI, 2023-2025

Notes.—Sources: Gallup Panel, 2023-2025. The figure plots the share of respondents who answer the question "How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never). Before asking this question, respondents are given a definition of AI: "Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." The sample is restricted to full and part time workers, and the observations are weighted.

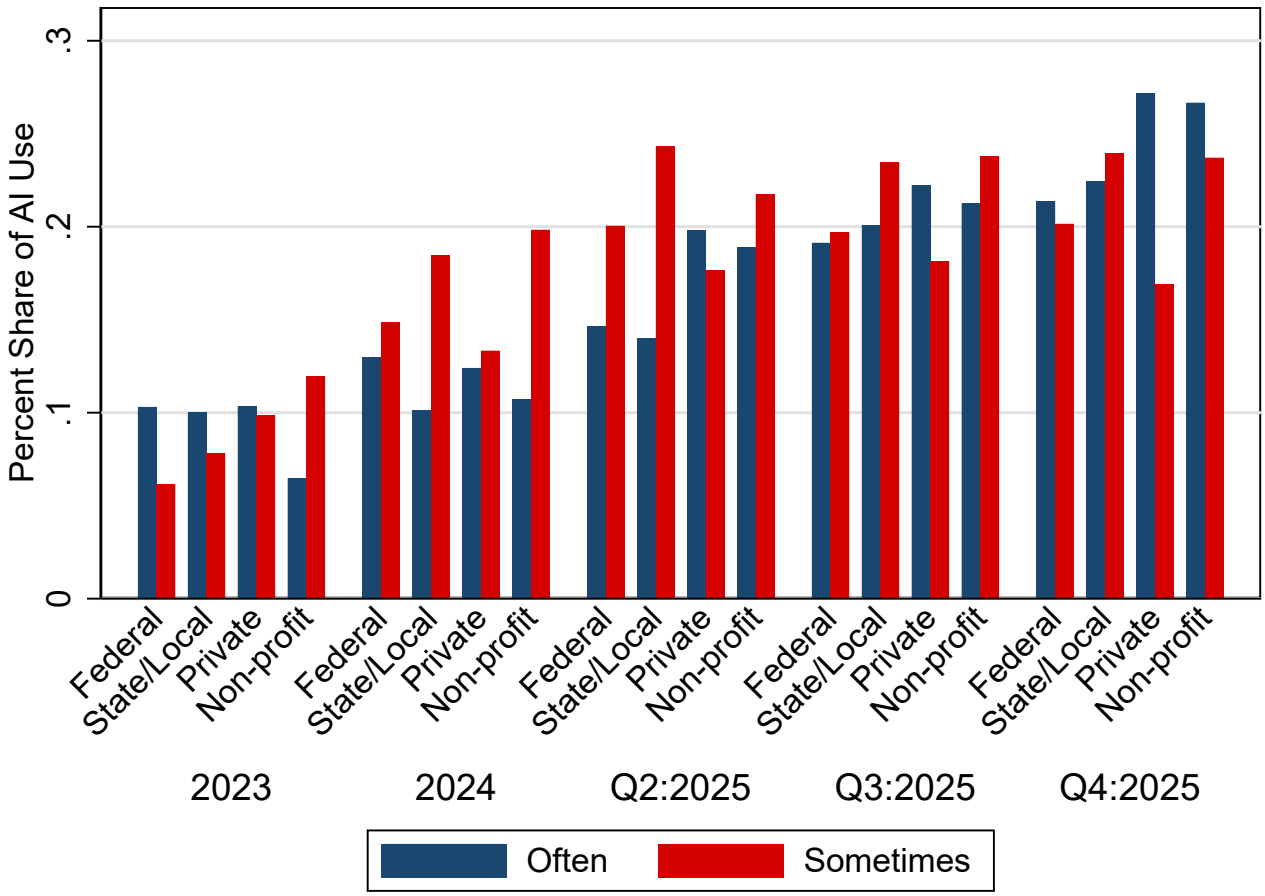


Figure 2: AI Adoption Across Public and Private Sectors, 2023-2025

Notes.—Sources: Gallup Panel, 2023-2025. The figure plots the share of respondents separately for federal, state, and private sector employees who answer the question "How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never). Before asking this question, respondents are given a definition of AI: "Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." The sample is restricted to full and part time workers, and the observations are weighted.

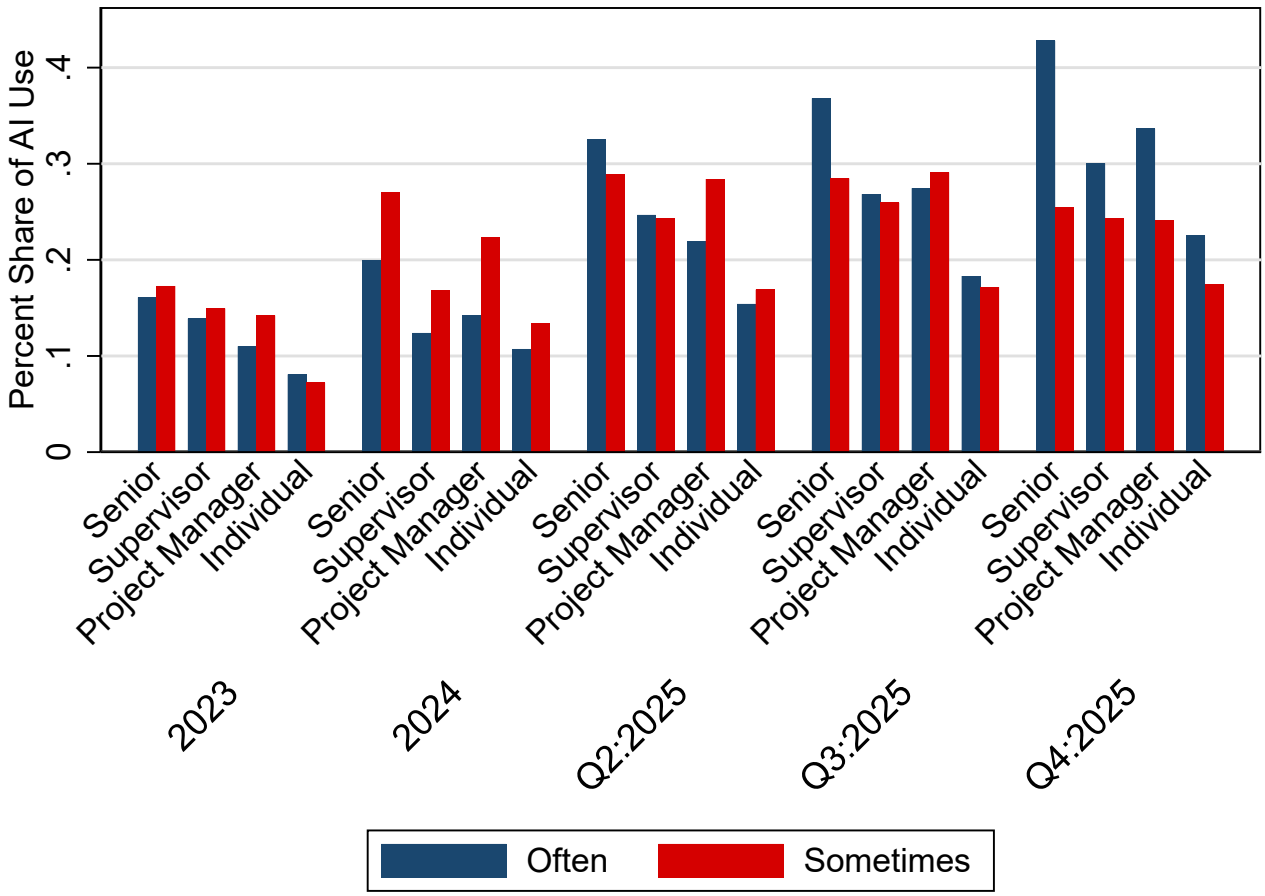


Figure 3: AI Adoption Across Employee Hierarchical Structure, 2023-2025

Notes.—Sources: Gallup Panel, 2023-2025. The figure plots the share of respondents separately for employees at different parts of the hierarchical structure who answer the question "How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never). Before asking this question, respondents are given a definition of AI: "Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." The hierarchy is based on the answer to the following: "Which of the following best describes your role or job responsibilities within your organization? (a) Senior leader - I am a senior leader, or a leader who manages other managers, (b) Manager/Supervisor - I am a manager or supervisor whose main responsibilities are the work output of other people, (c) Project Manager - I am a project manager who is responsible for other people's work, (d) Individual Contributor - I am responsible for my own work or output." The sample is restricted to full and part time workers, and the observations are weighted.

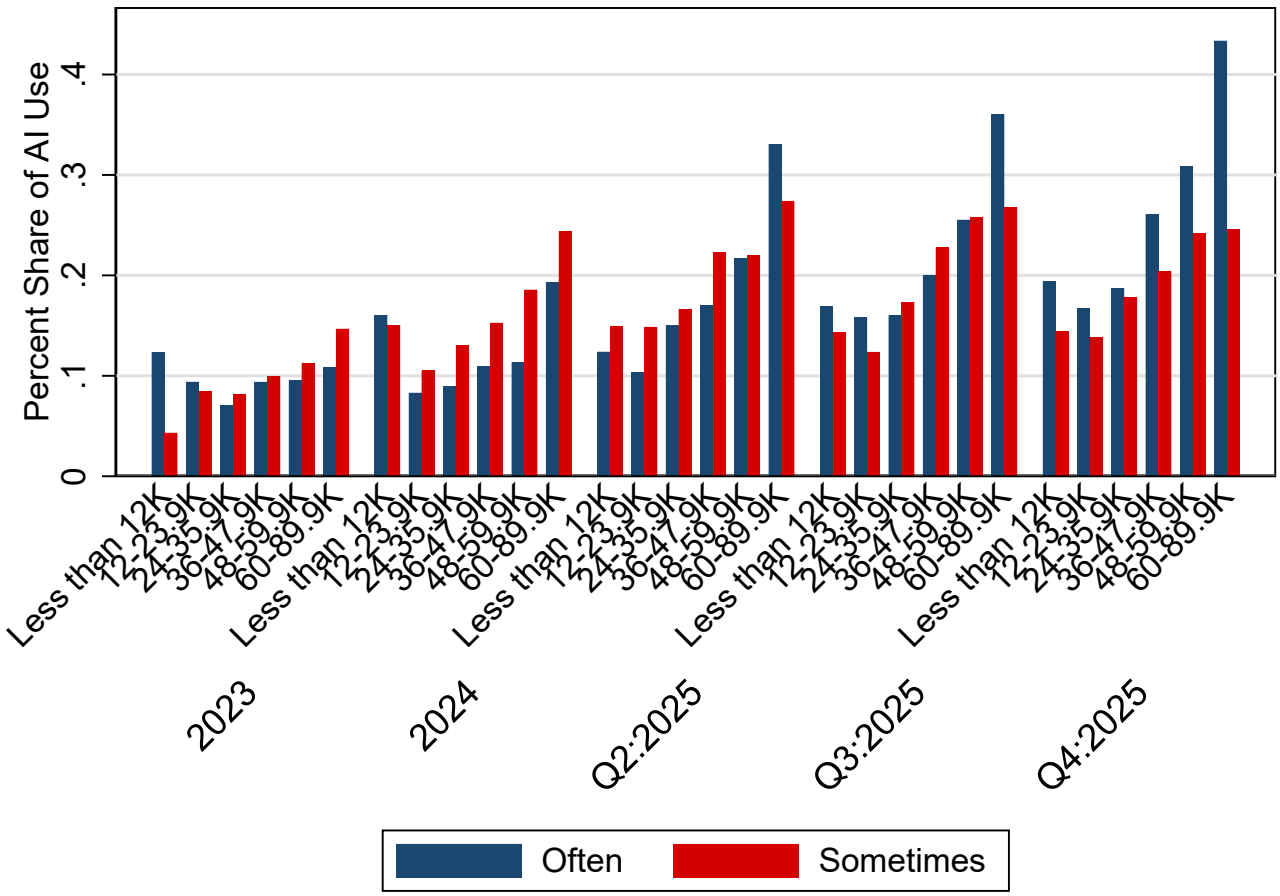
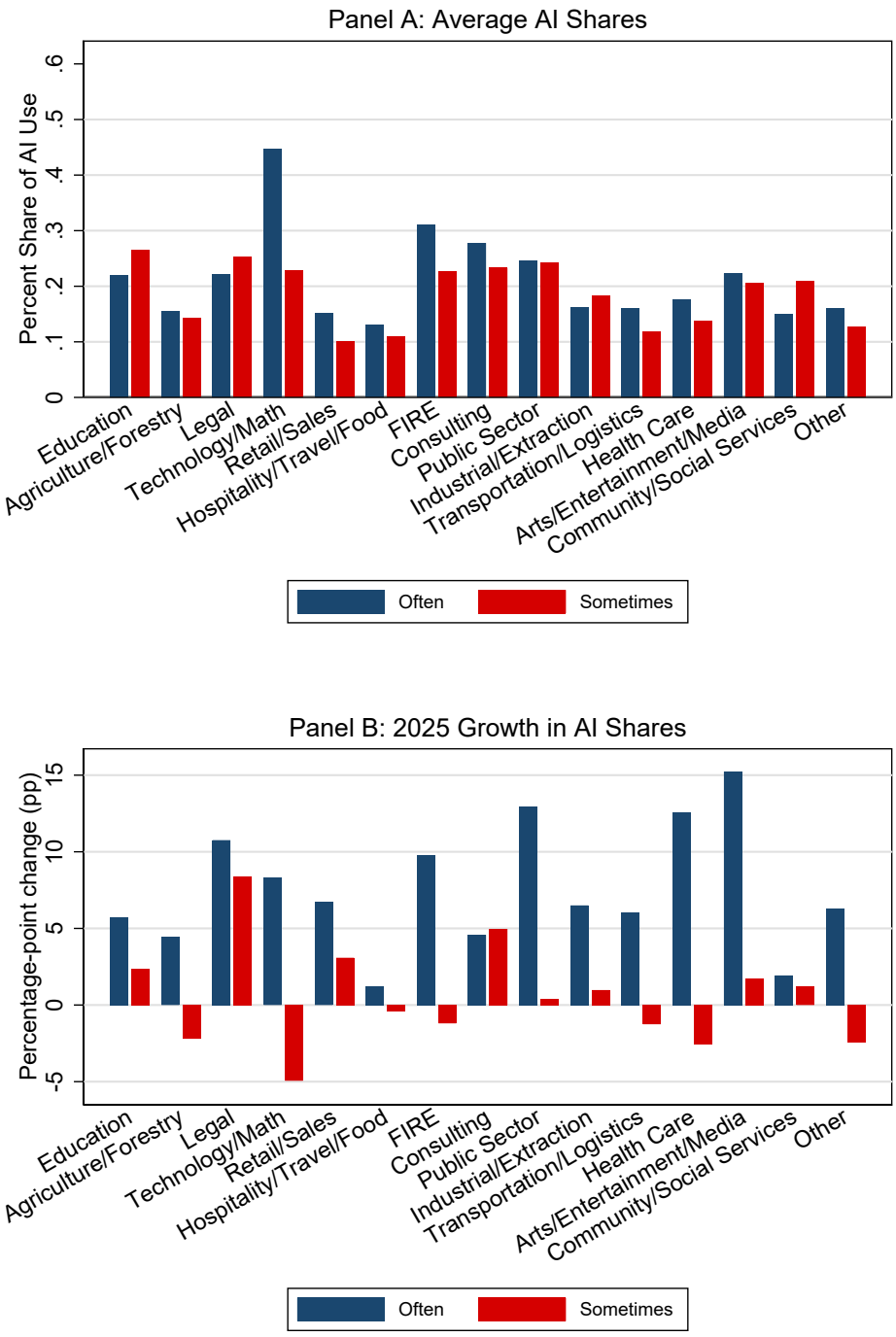


Figure 4: AI Adoption Across Income Groups, 2023-2025

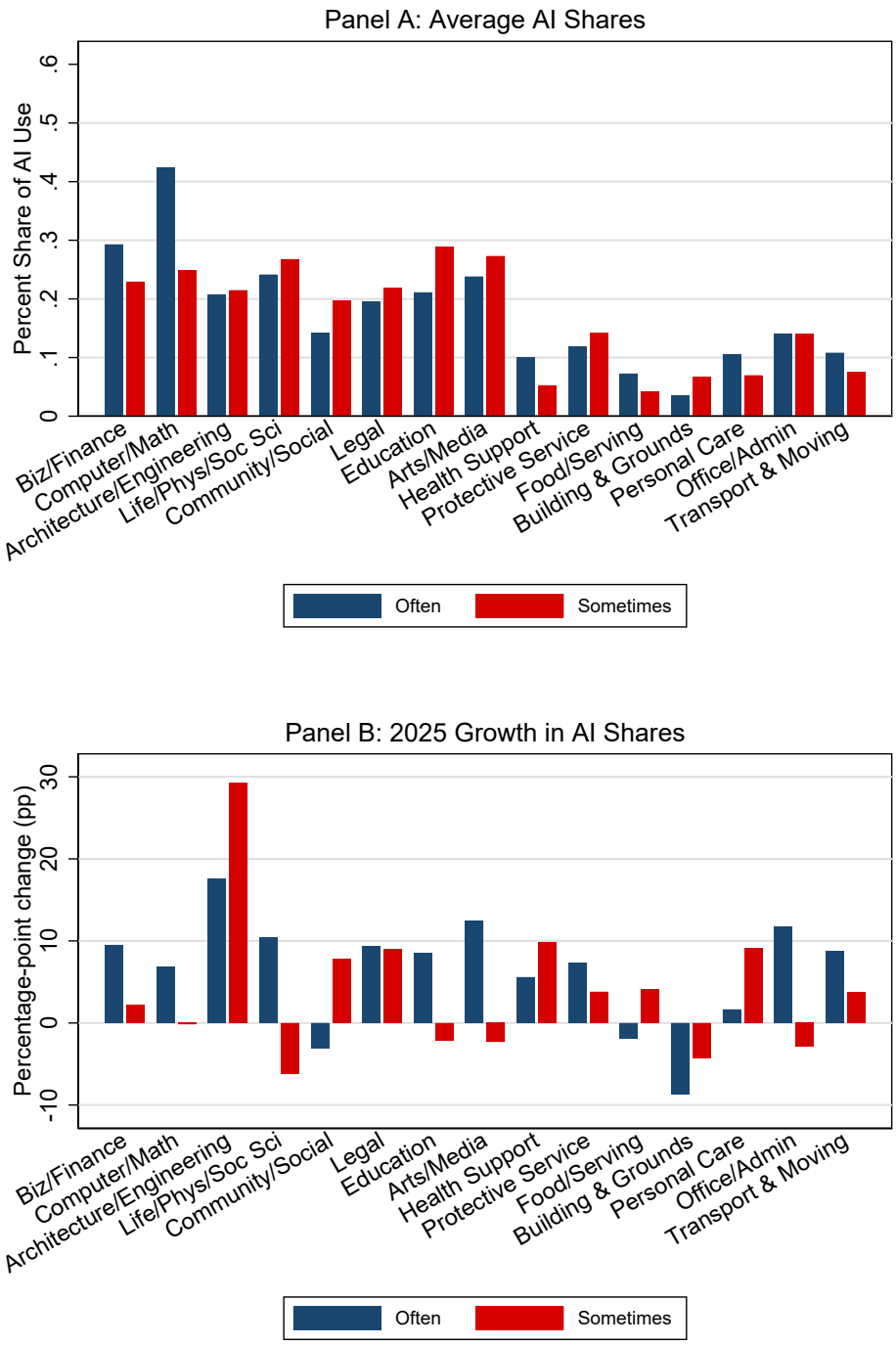
Notes.—Sources: Gallup Panel, 2023-2025. The figure plots the share of respondents separately for employees at income levels who answer the question "How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never). Before asking this question, respondents are given a definition of AI: "Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." The sample is restricted to full and part time workers, and the observations are weighted.

Figure 5: Cross-sectional and Time Series Variation Across Industries



Notes.—Sources: Gallup Panel, 2023-2025. Panel A plots the share of respondents who answer the question "How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never), separately by two-digit occupation. Before asking this question, respondents are given a definition of AI: "Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." Panel B plots the percentage point change between Q2:2025 and Q4:2025. The sample is restricted to full and part time workers, occupations with at least 300 respondents-period, and the observations are weighted.

Figure 6: Cross-sectional and Time Series Variation Across Occupations



Notes.—Sources: Gallup Panel, 2023-2025. Panel A plots the share of respondents who answer the question "How often do you use artificial intelligence in your role," which include: (a) daily, (b) a few times a week, (c) a few times a month, (d) few times a year, (e) once a year, (f) less often than once a year, and (g) never. I consolidate these answers into three groups: often (daily and a few times a week), sometimes (a few times a month, a few times a year), and never (once a year, less often than once a year, and never), separately by two-digit industry. Before asking this question, respondents are given a definition of AI: "Artificial intelligence is when a computer does or enhances a task that is normally performed by a person." Panel B plots the percentage point change between Q2:2025 and Q4:2025. The sample is restricted to full and part time workers, industries with at least 300 respondents-period, and the observations are weighted.

Table 1: Predicting High AI Utilization Using Workplace Practices

Dep. var. =	Use AI Often (1/0)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C: Well-being	.015***							-.010
	[.003]							[.008]
C: Connected		.020***						.007
		[.003]						[.007]
C: Feedback			.029***					.007
			[.003]					[.006]
C: Customers				.008***				-.006
				[.003]				[.006]
C: Trust					.019***			.011
					[.003]			[.008]
C: Respect						.020***		.007
						[.004]		[.006]
Has Clear AI Strategy							.284***	.262***
							[.007]	[.012]
Age	-.002***	-.003***	-.002***	-.002***	-.002***	-.002***	-.001***	-.002***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Some College	.012	.009	.030***	.008	.012	.027***	.030***	.015
	[.010]	[.010]	[.010]	[.010]	[.010]	[.010]	[.008]	[.013]
College or More	.093***	.090***	.129***	.093***	.094***	.120***	.124***	.107***
	[.009]	[.009]	[.010]	[.009]	[.009]	[.009]	[.007]	[.012]
Male	.024***	.024***	.018**	.022***	.025***	.021***	.026***	.018**
	[.007]	[.007]	[.007]	[.007]	[.007]	[.007]	[.005]	[.009]
White	-.043***	-.044***	-.042***	-.046***	-.045***	-.045***	-.032***	-.030***
	[.009]	[.009]	[.009]	[.009]	[.009]	[.009]	[.007]	[.011]
Black	.012	.008	.027*	.012	.011	.022	.012	.025
	[.014]	[.014]	[.015]	[.015]	[.014]	[.015]	[.011]	[.018]
Full time	.064***	.064***	.067***	.066***	.066***	.077***	.068***	.062***
	[.008]	[.008]	[.009]	[.009]	[.008]	[.008]	[.007]	[.012]
Has Children	.024***	.024***	.025***	.023***	.024***	.023***	.019***	.018*
	[.007]	[.008]	[.008]	[.008]	[.007]	[.008]	[.006]	[.010]
Is Married	.016**	.017**	.025***	.019***	.016**	.022***	.023***	.032***
	[.007]	[.007]	[.008]	[.007]	[.007]	[.008]	[.006]	[.010]
Year = 2024	.016*	.015	-.092***	.016*	.015			
	[.009]	[.010]	[.008]	[.010]	[.009]			
Year = 2025	.111***	.112***		.111***	.112***	.092***	.000	
	[.008]	[.008]		[.008]	[.008]	[.008]	[.]	
R-squared	.06	.06	.06	.06	.06	.06	.13	.12
Sample Size	38814	38431	28365	37227	38927	30901	50302	18050
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of an indicator for whether the respondent uses AI daily or frequently during the week (zero otherwise) on a vector of workplace perceptions and whether the firm has a clear AI strategy, and individual covariates and year fixed effects. Workplace (management) practices are based on responses to the degree of agreement with the following statements on a 1-5 scale: (a) I feel connected to my organization's culture, (b) My organization consistently delivers on the promises it makes to customers, (c) I trust the leadership of this organization, (d) My organization cares about my overall wellbeing, (e) I have received meaningful feedback in the past week, and (e) I am treated with respect at work. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, and college or more). The sample is restricted to full and part time workers, and the observations are weighted.

Table 2: Predicting Having a Clear AI Strategy Using Workplace Practices

Dep. var. =	Has Clear AI Strategy (1/0)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
C: Well-being	.045***						-.005
	[.004]						[.009]
C: Connected		.049***					.020***
		[.004]					[.008]
C: Feedback			.055***				.041***
			[.004]				[.006]
C: Customers				.036***			.004
				[.004]			[.006]
C: Trust					.046***		.017**
					[.004]		[.008]
C: Respect						.037***	.002
						[.004]	[.007]
Age	-.002***	-.002***	-.002***	-.002***	-.002***	-.002***	-.002***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Some College	.025**	.024*	.038***	.027**	.025**	.036***	.036**
	[.012]	[.012]	[.012]	[.012]	[.012]	[.012]	[.014]
College or More	.101***	.097***	.111***	.107***	.102***	.102***	.111***
	[.011]	[.011]	[.011]	[.011]	[.011]	[.011]	[.013]
Male	.016*	.015*	.006	.013	.014*	.010	.006
	[.008]	[.008]	[.009]	[.009]	[.008]	[.008]	[.010]
White	-.034***	-.034***	-.032***	-.036***	-.036***	-.035***	-.035***
	[.011]	[.011]	[.011]	[.011]	[.011]	[.011]	[.012]
Black	.048***	.041**	.049***	.050***	.046***	.048***	.041**
	[.018]	[.017]	[.018]	[.018]	[.017]	[.017]	[.020]
Full time	.066***	.067***	.051***	.066***	.071***	.063***	.053***
	[.012]	[.012]	[.012]	[.012]	[.012]	[.011]	[.015]
Has Children	.012	.012	.009	.016*	.013	.011	.014
	[.009]	[.009]	[.010]	[.010]	[.009]	[.009]	[.011]
Is Married	.003	-.000	.006	.000	.004	.004	-.005
	[.009]	[.009]	[.009]	[.009]	[.009]	[.009]	[.010]
R-squared	.04	.04	.05	.04	.04	.04	.05
Sample Size	25634	25379	23850	24613	25680	26059	18050
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of an indicator for whether the respondent says the firm has a clear AI strategy on a vector of workplace perceptions and whether the firm has a clear AI strategy, and individual covariates and year fixed effects. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." Workplace (management) practices are based on responses to the degree of agreement with the following statements on a 1-5 scale: (a) I feel connected to my organization's culture, (b) My organization consistently delivers on the promises it makes to customers, (c) I trust the leadership of this organization, (d) My organization cares about my overall wellbeing, (e) I have received meaningful feedback in the past week, and (e) I am treated with respect at work. Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, and college or more). The sample is restricted to full and part time workers, and the observations are weighted.

Table 3: Effects of AI Utilization and Clear AI Strategy on Employee Engagement

Dep. var. =	Employee Engagement (Q12)				Burnout				Job Satisfaction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Has Clear AI Strategy	.163***	.058	.043	-.036	-.029	-.002	.004	.069	.134***	.069	.042	-.020
	[.033]	[.048]	[.049]	[.078]	[.034]	[.047]	[.047]	[.074]	[.031]	[.047]	[.048]	[.077]
AI Use - Often	.012	.043	.030	.030	.124***	.132***	.147***	.140**	-.022	-.016	-.037	-.080
	[.026]	[.037]	[.038]	[.054]	[.025]	[.044]	[.045]	[.061]	[.026]	[.040]	[.041]	[.058]
× Clear AI Strategy	.226***	.183***	.195***	.299***	-.086*	-.147**	-.165**	-.192*	.198***	.130**	.156**	.234**
	[.044]	[.065]	[.065]	[.104]	[.045]	[.064]	[.065]	[.098]	[.043]	[.065]	[.066]	[.105]
AI Use - Sometimes	.080***	.058*	.053	-.049	.050**	.082**	.088**	.107*	.040*	.013	-.000	-.094
	[.022]	[.035]	[.035]	[.056]	[.023]	[.036]	[.036]	[.061]	[.022]	[.035]	[.036]	[.060]
× Clear AI Strategy	.086*	.188***	.190***	.420***	-.093**	-.075	-.070	-.186*	.086**	.189***	.200***	.384***
	[.044]	[.065]	[.065]	[.103]	[.046]	[.067]	[.068]	[.106]	[.043]	[.070]	[.071]	[.109]
R-squared	.03	.72	.72	.67	.04	.72	.72	.67	.03	.70	.70	.66
Sample Size	43668	20578	19837	8055	36711	15567	15074	5893	43407	20379	19643	7976
Demographics	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Person FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Income x Time FE	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Sample	Pooled	Pooled	Pooled	Switchers	Pooled	Pooled	Pooled	Switchers	Pooled	Pooled	Pooled	Switchers

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of a z-score for average Q12 employee engagement scores, a z-score of burnout, and a z-score of job satisfaction on an indicator for whether the organization has articulated a clear AI strategy, indicators of AI utilization, their interactions, and conditional on individual covariates and fixed effects. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; the normalization is relative to those who use it once a year, less than once a year, or never. The regressions with switchers restricts the sample to respondents who had just switched employers, looking two periods before and two after. Employee engagement is defined as a z-score of the average across the Q12 indicators: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. Burnout is a z-score to: "Please indicate how often each of the following statements is true of your primary job (i.e., the job where you spend the most time working). I feel burned out at work: (a) Always, (b) Very often, (c) Sometimes, (d) Rarely, (e) Never" from (5=always) to (1=never). Job satisfaction is similarly defined: "How satisfied are you with your place of employment as a place to work?" Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, and college or more). The sample is restricted to full and part time workers, and the observations are weighted.

Table 4: Effects of AI Utilization and Clear AI Strategy on Q12 Employee Engagement

Dep. var. =	Expectations	Materials	Do Best	Recognition	Manager	Development	Opinions	Mission	Quality	Best Friend	Progress	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Has Clear AI Strategy	-.027	.042	.038	.149	.086	.103**	.015	.105	.087	.119	.217**	.132
	[.043]	[.097]	[.049]	[.118]	[.118]	[.052]	[.048]	[.118]	[.085]	[.106]	[.096]	[.095]
AI Use - Often	-.138***	-.191***	-.029	.146*	-.044	.120***	.135***	-.001	-.058	.043	.147	.173**
	[.038]	[.073]	[.035]	[.077]	[.073]	[.039]	[.039]	[.070]	[.071]	[.081]	[.090]	[.075]
× Clear AI Strategy	.183***	.191	.090	-.060	.052	.084	.124*	.015	.172	-.038	.108	.045
	[.061]	[.145]	[.065]	[.151]	[.147]	[.069]	[.066]	[.148]	[.122]	[.143]	[.142]	[.136]
AI Use - Sometimes	-.114***	-.091	-.046	.122*	.134**	.120***	.120***	.139**	.062	.126*	.191**	.273***
	[.033]	[.067]	[.035]	[.070]	[.065]	[.035]	[.036]	[.063]	[.064]	[.071]	[.075]	[.066]
× Clear AI Strategy	.179***	.203	.126*	.030	.057	.138*	.164**	.020	.231*	-.310**	.121	.086
	[.066]	[.136]	[.073]	[.163]	[.153]	[.075]	[.066]	[.159]	[.127]	[.152]	[.139]	[.139]
R-squared	.69	.63	.70	.63	.65	.70	.70	.65	.65	.63	.64	.65
Sample Size	20441	5130	20294	4394	4776	18770	19917	4950	4924	4206	4154	4590
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of a z-score of 12 employee engagement scores on an indicator for whether the firm has a clear AI strategy, indicators of AI utilization, their interactions, and conditional on individual covariates and fixed effects. The Q12 include: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; the normalization is relative to those who use it once a year, less than once a year, or never. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, and college or more). The sample is restricted to full and part time workers, and the observations are weighted.

Table 5: Heterogeneous Effects of AI Utilization and Clear AI Strategy on Employee Engagement

Dep. var. =	Employee Engagement (Q12, z-score)					
	(1)	(2)	(3)	(4)	(5)	(6)
Has Clear AI Strategy	.076	.096	.034	-.004	.026	.053
	[.076]	[.086]	[.052]	[.108]	[.061]	[.095]
AI Use - Often	.147**	-.038	-.007	.049	.041	.082
	[.062]	[.063]	[.042]	[.099]	[.042]	[.108]
× Clear AI Strategy	.083	.124	.184***	.158	.186**	.072
	[.106]	[.111]	[.066]	[.167]	[.081]	[.147]
AI Use - Sometimes	.112*	.052	-.018	.067	.066	.009
	[.058]	[.048]	[.038]	[.095]	[.044]	[.085]
× Clear AI Strategy	.027	.174	.171**	.177	.244***	.056
	[.097]	[.106]	[.067]	[.168]	[.080]	[.135]
R-squared	.76	.76	.69	.80	.74	.80
Sample Size	8073	6873	11340	4153	12925	3338
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Male	Female	>College	<College	White	Non-white

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of a z-score for the average Q12 employee engagement score on an indicator for whether the firm has a clear AI strategy, indicators of AI utilization, their interactions, and conditional on individual covariates and fixed effects, separately by group. AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; the normalization is relative to those who use it once a year, less than once a year, or never. Employee engagement is defined as a z-score of the average across the Q12 indicators: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." The sample is restricted to full and part time workers, and the observations are weighted.

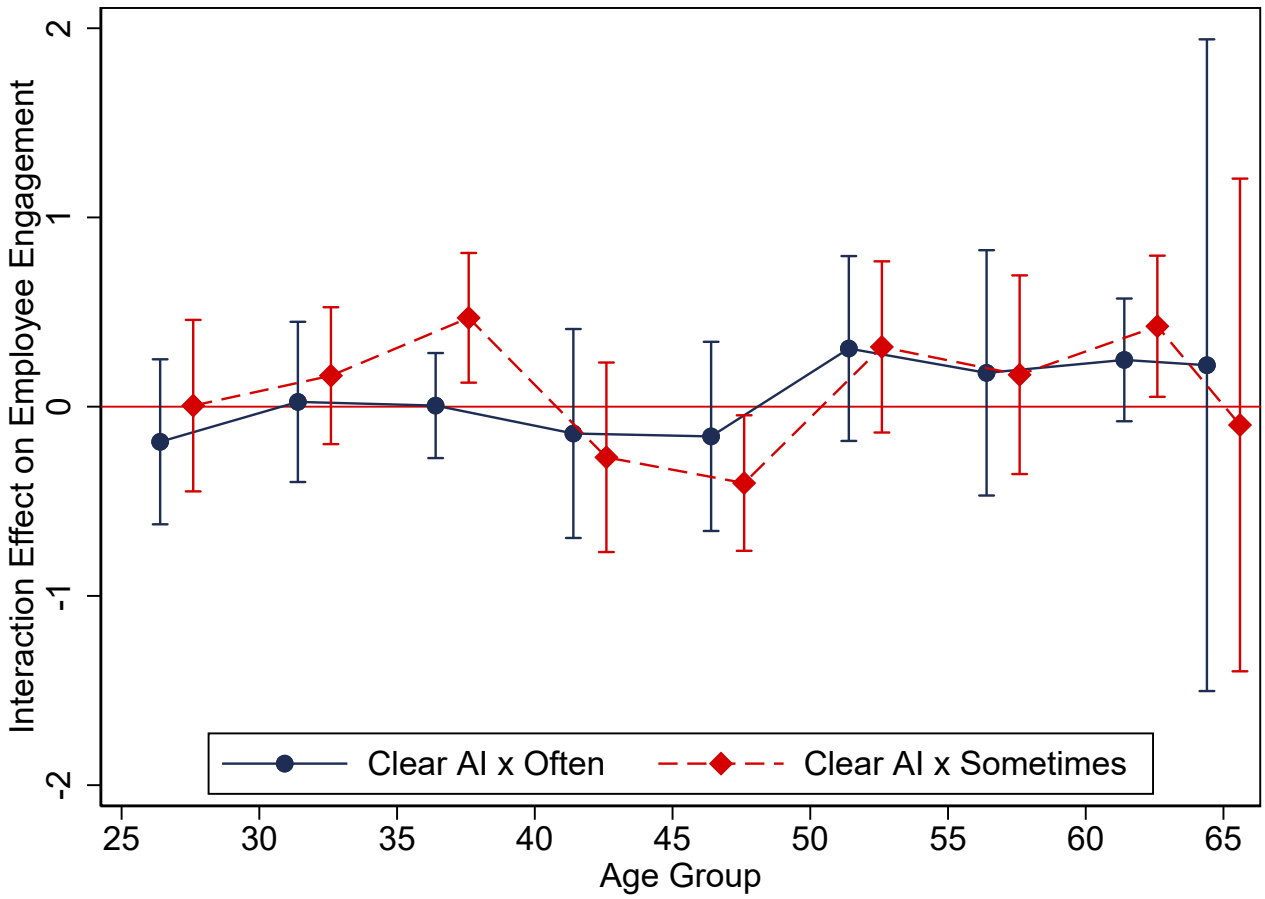


Figure 7: Heterogeneous Effects of Complementarities by Age Bracket

Notes.—Sources: Gallup Panel, 2023-2025. The figure reports the coefficients associated with regressions of a z-score for average Q12 employee engagement scores on an indicator for whether the organization has articulated a clear AI strategy, indicators of AI utilization, their interactions, separately by age bracket, conditional on person and time fixed effects. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; the normalization is relative to those who use it once a year, less than once a year, or never. The regressions with switchers restricts the sample to respondents who had just switched employers, looking two periods before and two after. Employee engagement is defined as a z-score of the average across the Q12 indicators: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. The sample is restricted to full and part time workers, and the observations are weighted.

Table 6: Effects of AI Utilization and Workplace Trust on Employee Engagement

Dep. var. =	Employee Engagement (Q12)				Burnout				Job Satisfaction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Workplace Trust	.672***	.450***	.448***	.449***	-.394***	-.279***	-.276***	-.377***	.642***	.497***	.499***	.505***
	[.009]	[.020]	[.020]	[.050]	[.013]	[.024]	[.025]	[.068]	[.010]	[.021]	[.022]	[.072]
AI Use - Often	.075***	.039	.041	.036	.116***	-.004	-.006	.049	-.016	.009	-.002	-.004
	[.020]	[.036]	[.035]	[.075]	[.027]	[.037]	[.035]	[.098]	[.019]	[.031]	[.032]	[.094]
× Workplace Trust	-.023	.062*	.056*	-.005	.003	-.048	-.047	-.029	.055**	.038	.034	-.152*
	[.023]	[.032]	[.031]	[.056]	[.028]	[.035]	[.034]	[.081]	[.022]	[.031]	[.032]	[.085]
AI Use - Sometimes	.042**	-.031	-.024	-.157*	.049**	-.011	-.006	-.063	-.028	-.011	-.021	-.089
	[.018]	[.027]	[.027]	[.082]	[.022]	[.031]	[.030]	[.107]	[.017]	[.026]	[.026]	[.070]
× Workplace Trust	-.070***	.035	.047*	.078	.039	-.020	-.034	.064	.008	.014	.021	-.011
	[.019]	[.026]	[.027]	[.070]	[.025]	[.028]	[.028]	[.082]	[.018]	[.027]	[.027]	[.085]
R-squared	.44	.86	.86	.86	.20	.82	.82	.83	.45	.83	.83	.82
Sample Size	33240	16566	15830	2205	27671	12287	11823	1670	33069	16458	15730	2189
Demographics	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No
Person FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Income x Time FE	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Sample	Pooled	Pooled	Pooled	Switchers	Pooled	Pooled	Pooled	Switchers	Pooled	Pooled	Pooled	Switchers

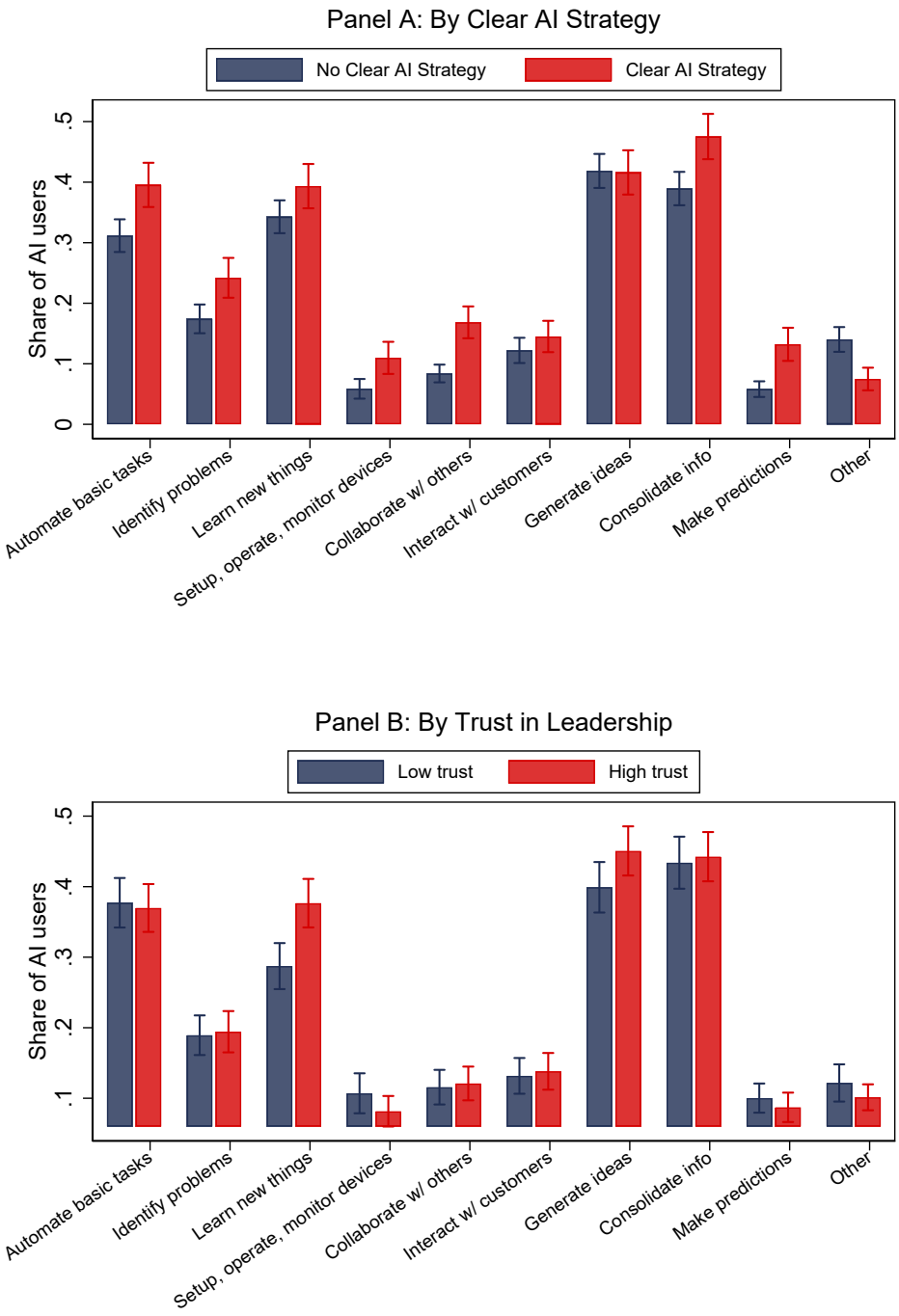
Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of a a z-score for average Q12 employee engagement scores, a z-score of burnout, and a z-score of job satisfaction on a z-score of trust in senior leadership, indicators of AI utilization, their interactions, and conditional on individual covariates and fixed effects. AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; the normalization is relative to those who use it once a year, less than once a year, or never. Employee engagement is defined as a z-score of the average across the Q12 indicators: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. Burnout is a z-score to: "Please indicate how often each of the following statements is true of your primary job (i.e., the job where you spend the most time working). I feel burned out at work: (a) Always, (b) Very often, (c) Sometimes, (d) Rarely, (e) Never" from (5=always) to (1=never). Job satisfaction is similarly defined: "How satisfied are you with your place of employment as a place to work?" Trust in leadership is defined on a 1-5 scale in response to: "I trust the leadership of this organization." Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, and college or more). The sample is restricted to full and part time workers, and the observations are weighted.

Table 7: Effects of AI Utilization and Workplace Trust on Perceived Productivity from AI

Dep. var. =	Perceived AI Productivity (z-score)			Perceived AI Productivity (1/0)		
	(1)	(2)	(3)	(4)	(5)	(6)
Workplace Trust	.042	-.644**	-.628**	-.012	-.488***	-.444***
	[.194]	[.311]	[.281]	[.016]	[.142]	[.158]
AI Use - Often	.907***	.336	.387	.242***	.125	.151
	[.206]	[.531]	[.475]	[.020]	[.259]	[.261]
× Workplace Trust	.240	.939**	.853***	.091***	.563***	.522***
	[.199]	[.366]	[.312]	[.025]	[.152]	[.166]
AI Use - Sometimes	.388*	.236	.354	.044***	.066	.070
	[.203]	[.516]	[.420]	[.012]	[.251]	[.254]
× Workplace Trust	.137	.699	.514	.031*	.463***	.399**
	[.198]	[.488]	[.313]	[.019]	[.148]	[.165]
R-squared	.16	.74	.79	.13	.80	.79
Sample Size	3054	314	290	3054	314	290
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Person FE	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
Income x Year FE	No	No	Yes	No	No	Yes

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of perceived productivity on AI on a z-score of trust in the workplace, indicators of AI utilization, their interactions, and conditional on individual covariates and fixed effects. AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; the normalization is relative to those who use it once a year, less than once a year, or never. Perceived AI productivity is measured as a z-score of a 1-5 index, as well as an indicator based on a 5/5, in response to the following question: "What type of impact do you think these artificial intelligence (AI) tools will have on your individual productivity and efficiency at work?" The responses on perceived AI productivity range from extremely negative to extremely positive. Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, and college or more). The sample is restricted to full and part time workers, and the observations are weighted.

Figure 8: Composition of AI Use-cases by Employees, 2024-2025



Notes.—Sources: Gallup Panel, 2024-2025. The figure plots the share of respondents across different AI applications distinguishing among respondents who report having a clear AI strategy at their firm (Panel A), and high versus low trust in leadership, i.e. a score of 4/5 or 5/5 (Panel B). Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." Trust in leadership is defined on a 1-5 scale in response to: "I trust the leadership of this organization." The sample is restricted to full and part time workers, those who use AI at least somewhat, and the observations are weighted.

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A Online Appendix

A.1 Extensions of the Stylized Model

A.1.1 Closed-form Example, Corner Solutions, and Comparative Statics

Consider the commonly used quadratic cost specification

$$c(a;\theta) = \frac{a^2}{2\theta}, \qquad \theta > 0, \tag{8}$$

and let the per-task benefit be linear in embedding with a complementarity between embedding and managerial clarity:

$$B(E,S) = \alpha + \beta E + \gamma SE, \qquad \alpha, \beta, \gamma \geq 0, \tag{9}$$

where $S \in \{0,1\}$ (or $S \in [0,1]$ in a continuous interpretation).

Interior solution. For $a \in (0,1)$, the first-order condition (4) becomes

$$B(E,S) = \frac{a^*}{\theta}, \tag{10}$$

so the interior optimum is

$$a^*(E,S,\theta) = \theta\, B(E,S). \tag{11}$$

Corner solutions. Because $a \in [0, 1]$, the equilibrium is

$$a^*(E, S, \theta) = \min\{1,\ \theta B(E, S)\}. \tag{12}$$

Thus, full adoption occurs when $\theta B(E, S) \geq 1$.

Comparative statics in closed form. On the interior region $\theta B(E, S) < 1$, we have

$$\frac{\partial a^*}{\partial \theta} = B(E, S) > 0, \tag{13}$$

$$\frac{\partial a^*}{\partial E} = \theta(\beta + \gamma S) > 0, \tag{14}$$

$$\frac{\partial a^*}{\partial S} = \theta\gamma E \geq 0, \tag{15}$$

$$\frac{\partial^2 a^*}{\partial E \partial S} = \theta\gamma > 0 \quad \text{(complementarity)}. \tag{16}$$

Closed-form outcome examples. The main text imposes a complementarity structure for outcomes. Two simple specifications show how these cross-partials arise naturally.

First, let per-worker productivity be

$$Y = Y_0 + a \cdot B(E, S). \tag{17}$$

Under (11), this becomes $Y = Y_0 + \theta[B(E, S)]^2$ on the interior region, so the realized productivity gains from embedding and clarity scale with psychological safety through equilibrium adoption.

Second, let an employee outcome (e.g., engagement) be

$$G = G_0 + \eta\, a\, \theta + \zeta\, a\, S, \qquad \eta, \zeta > 0, \tag{18}$$

which implies $\partial^2 G/\partial a\,\partial\theta = \eta > 0$ and $\partial^2 G/\partial a\,\partial S = \zeta > 0$ as in (5). This toy specification is useful for interpretation (e.g., adoption is more beneficial when experimentation is safe and guidance is clear) without restricting the empirical analysis to a particular functional form.

A.1.2 Proof of Lemma 1

Proof of Lemma 1. Let $a^*(E, S, \theta)$ denote an interior solution to (3). The first-order condition (4) is

$$F(a, E, S, \theta) \equiv c_a(a; \theta) - B(E, S) = 0.$$

Strict convexity implies $c_{aa}(a; \theta) > 0$, so $F_a = c_{aa} > 0$. By the Implicit Function Theorem, a^* is continuously differentiable in (E, S, θ) locally and

$$\frac{\partial a^*}{\partial E} = -\frac{F_E}{F_a} = \frac{B_E(E, S)}{c_{aa}(a^*; \theta)} > 0, \tag{19}$$

$$\frac{\partial a^*}{\partial S} = -\frac{F_S}{F_a} = \frac{B_S(E, S)}{c_{aa}(a^*; \theta)} \geq 0, \tag{20}$$

$$\frac{\partial a^*}{\partial \theta} = -\frac{F_\theta}{F_a} = -\frac{c_{a\theta}(a^*; \theta)}{c_{aa}(a^*; \theta)} > 0, \tag{21}$$

where the last inequality uses $c_{a\theta} < 0$ (higher psychological safety lowers the marginal cost of adoption). For the complementarity between embedding and clarity, differentiate (19) with respect to S:

$$\frac{\partial^2 a^*}{\partial S \partial E} = \frac{B_{ES}(E, S)}{c_{aa}(a^*; \theta)} - \frac{B_E(E, S)\, c_{aaa}(a^*; \theta)}{[c_{aa}(a^*; \theta)]^2} \cdot \frac{\partial a^*}{\partial S}. \tag{22}$$

A sufficient (and standard) condition for $\partial^2 a^*/\partial S \partial E > 0$ is $B_{ES} > 0$ together with either (i) c_{aaa} small relative to c_{aa} in the relevant region, or (ii) $c_{aaa} \leq 0$ (weakly decreasing curvature), or (iii)

the quadratic benchmark (8) where $c_{aaa} \equiv 0$, yielding

$$\frac{\partial^2 a^*}{\partial S \partial E} = \frac{B_{ES}(E,S)}{c_{aa}(a^*;\theta)} > 0.$$

This establishes the claims. □

A.1.3 Proof of Proposition 1

Proof of Proposition 1. Let $W = W(a, E, S, \theta)$ be twice continuously differentiable in (a, S, θ) for fixed E and suppose (5) holds. Fix E and S. Consider the marginal effect of adoption on outcomes:

$$M(\theta) \equiv \frac{\partial W(a, E, S, \theta)}{\partial a}.$$

Then

$$\frac{dM(\theta)}{d\theta} = \frac{\partial^2 W(a, E, S, \theta)}{\partial a \, \partial \theta} > 0,$$

so $\partial W/\partial a$ is increasing in θ. An identical argument with S in place of θ implies $\partial W/\partial a$ is increasing in S when $\partial^2 W/\partial a \, \partial S > 0$. Hence, the marginal effect of GenAI usage is larger in high-θ and high-S environments. □

A.1.4 Microfoundation for S as Communication Precision

This subsection provides a reduced-form microfoundation for interpreting S as the precision of internal communication about GenAI use-cases, constraints, and standards, consistent with the view that communication inside firms is a design choice and is shaped by organizational frictions

(Dessein, 2002; Alonso et al., 2008) and by language/communication costs (Crémer et al., 2007).

Let the productivity gain from using GenAI depend on whether usage is aligned with a firm-specific "target" practice τ (e.g., approved tools, data-handling rules, quality standards). Suppose workers choose a and also (implicitly) a practice x; misalignment yields a coordination loss. Let x be a worker's belief/action about "how to use GenAI." The manager sends a message m about τ; workers observe a noisy signal

$$x = \tau + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, \sigma^2(S)),$$

where higher clarity S reduces noise, $\sigma'(S) < 0$. If the expected per-task gross benefit is $\bar{b}(E)$ but misalignment reduces effective benefit by $\kappa E[(x-\tau)^2] = \kappa\sigma^2(S)$, then the net per-task return becomes

$$B(E, S) = \bar{b}(E) - \kappa\sigma^2(S). \tag{23}$$

If embedding increases the underlying return $\bar{b}(E)$ and also reduces the marginal cost of coordination (e.g., by standardizing workflows), then $\kappa = \kappa(E)$ with $\kappa'(E) < 0$. In that case,

$$B_{ES}(E, S) = -\kappa'(E)\,\sigma^{2\prime}(S) > 0,$$

since $\kappa'(E) < 0$ and $\sigma^{2\prime}(S) < 0$. Thus, clearer communication and embedding are complements in returns, as assumed in the main text.

A.1.5 Task Interdependence and Clarity (H3)

To connect more to H3, let $\tau \geq 0$ index task interdependence/coordination intensity at the occupation (or team) level. Suppose the coordination loss from unclear guidance scales with τ:

$$B(E, S; \tau) = \bar{b}(E) - \tau\, \kappa(E)\, \sigma^2(S), \tag{24}$$

with $\kappa'(E) < 0$ and $\sigma^{2\prime}(S) < 0$ as above. Then

$$\frac{\partial B}{\partial S} = -\tau\, \kappa(E)\, \sigma^{2\prime}(S) > 0, \qquad \frac{\partial^2 B}{\partial S\, \partial \tau} = -\kappa(E)\, \sigma^{2\prime}(S) > 0,$$

so the marginal return to clarity S is larger in high-interdependence jobs. Under the quadratic benchmark (8)–(9), this implies larger $\partial a^*/\partial S$ and larger outcome interactions (e.g., larger AI $\times$ ClearAI) at higher τ, which motivates the triple-interaction test in H3.

A.1.6 Credibility and the Triple Complementarity (H4)

To formalize the idea that trust increases the *effectiveness* of communication (beyond shifting experimentation costs), let the manager's clarity choice be "discounted" when trust is low. A parsimonious way is to let effective clarity be $S \cdot g(\theta)$, where g is increasing and concave, $g'(\theta) > 0$, $g(0) = 0$, and $g(1) = 1$. Then

$$B(E, S, \theta) = \alpha + \beta E + \gamma E \cdot S \cdot g(\theta). \tag{25}$$

Under (8), equilibrium adoption is $a^* = \theta B(E, S, \theta)$ (interior). Differentiating yields

$$\frac{\partial^2 a^*}{\partial S \, \partial \theta} = \gamma E \left[g(\theta) + \theta g'(\theta) \right] > 0,$$

and outcome complementarities become naturally triple-interaction objects. This extension provides a structural rationale for why the AI × ClearAI interaction should be strongest when trust is high (H4).

A.1.7 Role Clarity via Ambiguity Costs (H6)

To generate the sign-switching prediction in H6 within the model, let worker well-being/role clarity include an ambiguity term that increases with adoption when guidance is unclear. For example, let an outcome R (role clarity) be

$$R = R_0 + \underbrace{\rho_1 a S}_{\text{guided adoption clarifies}} - \underbrace{\rho_0 a (1 - S)}_{\text{unguided adoption confuses}}, \qquad \rho_0, \rho_1 > 0. \tag{26}$$

Then

$$\frac{\partial R}{\partial a} = \begin{cases} +\rho_1 & \text{if } S = 1, \\ -\rho_0 & \text{if } S = 0, \end{cases}$$

which produces the crossover interaction: adoption increases role clarity under high clarity and decreases it under low clarity.

A.1.8 Composition of AI Utilization (H5)

To rationalize H5, consider two GenAI application types: a standardized/workflow-embedded use a_s and an exploratory/learning use a_e, with $a_s + a_e \leq 1$. Let returns satisfy

$$\text{standardized: } B_s(E,S) \text{ with } \frac{\partial B_s}{\partial S} \text{ large (alignment-intensive)}, \qquad \text{exploratory: } B_e(E) \text{ with } \frac{\partial B_e}{\partial S} \approx 0,$$

and let costs be

$$c(a_s, a_e; \theta) = \frac{a_s^2}{2\theta_s(\theta)} + \frac{a_e^2}{2\theta_e(\theta)},$$

where $\theta_e'(\theta) > \theta_s'(\theta) \geq 0$ (psychological safety disproportionately reduces the marginal cost of exploratory experimentation). Then, conditional on adopting ($a_s + a_e > 0$), higher S tilts usage toward a_s (since it raises B_s), while higher θ tilts usage toward a_e (since it lowers the marginal cost of exploration more). This generates the composition predictions in H5 (and maps directly into use-case heterogeneity tests).

A.1.9 Endogenous (E, S, θ) and Organizational Complementarities

The main text treats (E, S, θ) as given when characterizing worker adoption. If desired, one can endogenize these choices to formalize organizational complementarities (in the spirit of Milgrom and Roberts, 1990; Bresnahan et al., 2002). Let the firm choose E and the manager choose (S, θ)

to maximize

$$\Pi(E,S,\theta) = \underbrace{\Omega(a^*(E,S,\theta),E,S,\theta)}_{\text{gross surplus}} - K_E(E) - K_S(S) - K_\theta(\theta),$$

with convex costs $K_\cdot$. When a^* is increasing in each argument and $B_{ES} > 0$, standard supermodularity conditions imply that optimal choices are complementary: higher S raises the marginal return to E, and higher θ raises the marginal return to both E and S (especially under the credibility formulation (25)). This delivers an additional interpretation of observed cross-firm heterogeneity: firms that invest in embedding are also those that tend to communicate clearly and cultivate psychological safety, because these choices are jointly optimal in environments where the technology is valuable.

A.2 Additional Details on Data and Measurement

Table A.1: Descriptive Evidence on Switchers in the Panel

	Count	Percent
Unique persons	39899	.
Persons observed in ≥2 waves	18797	.
Ever switchers among ≥2 waves	10226	54.4
Valid adjacent-wave transitions	29602	.
Adoptions: Never → (Sometimes/Often)	6925	23.39
Cessations: (Sometimes/Often) → Never	3657	12.35

Notes.—Sources: Gallup Panel. The table reports descriptive statistics on the number of respondents under different thresholds in the data, particularly around "AI switchers."

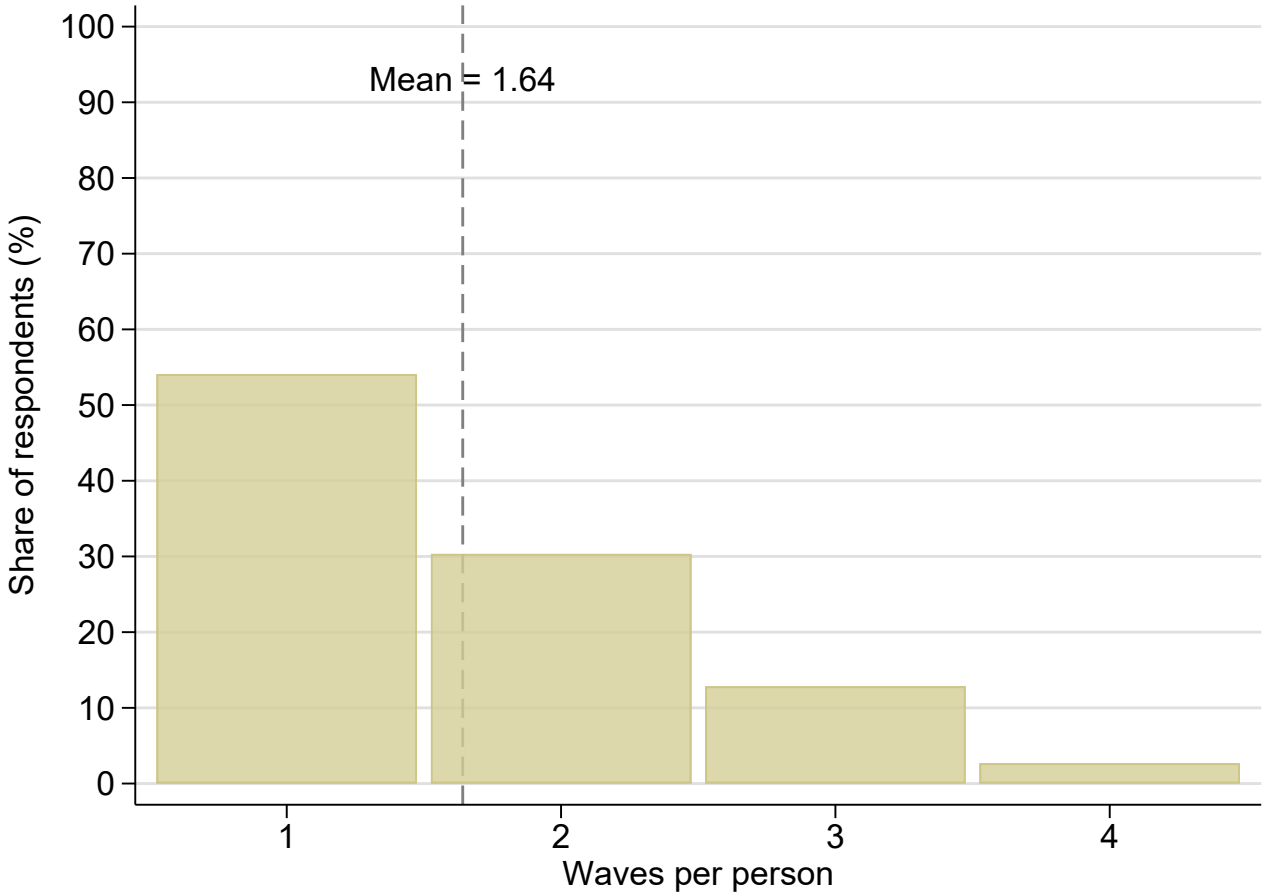


Figure A.1: Descriptive Evidence on Longitudinal Variation

Notes.—Sources: Gallup Panel, 2023-2025. The figure plots the share of respondents across the potential number of waves in the data.

Table A.2: Descriptive Evidence on Transition Matrix for Switchers

	Never	Sometimes	Often
Never	63.59	19.29	17.12
Sometimes	36.08	36.61	27.3
Often	32.94	21.09	45.97

Notes.—Sources: Gallup Panel. The table reports descriptive statistics on transition matrix for "AI switchers."

Table A.3: Summary Statistics on the Gallup Workplace Panel

	2023		2024		2025	
	(1)		(2)		(3)	
	mean	sd	mean	sd	mean	sd
AI Use - Often	0.10	0.30	0.12	0.32	0.21	0.40
AI Use - Sometimes	0.10	0.29	0.15	0.36	0.20	0.40
AI Use - Never	0.81	0.39	0.73	0.44	0.53	0.50
AI Will Displace Job	0.14	0.35	0.15	0.35	0.15	0.35
Hours Worked/Week	38.4	12.6	37.7	12.2	39.1	11.4
Age	43.9	13.8	43.1	14.3	43.7	13.9
Male	0.53	0.50	0.53	0.50	0.52	0.50
White	0.67	0.47	0.73	0.44	0.66	0.47
Black	0.12	0.32	0.10	0.30	0.12	0.32
Full-time	0.78	0.41	0.77	0.42	0.81	0.39
Part-time	0.22	0.41	0.23	0.42	0.19	0.39
Has Children	0.35	0.48	0.33	0.47	0.35	0.48
Married	0.60	0.49	0.53	0.50	0.52	0.50
Less than HS	0.32	0.47	0.28	0.45	0.31	0.46
Some College	0.26	0.44	0.29	0.46	0.26	0.44
College or More	0.42	0.49	0.42	0.49	0.43	0.49
Observations	9322		9966		31651	

Notes.—Sources: Gallup Panel, 2023-2025. The table reports summary statistics on the key variables by year. AI Use - Often is based on using AI daily or a few times a week; AI Use - Sometimes is based on using AI a few times a month or a few times a year; AI Use - Never is based on using AI once a year, less than once a year, or never. AI Will Displace Job is an indicator for believing that AI is "very likely" to replace their job in the next five years. Demographics include: age, race (White, Black), full-time status, having children, and being married. The sample is restricted to full and part time workers, and the observations are weighted.

A.3 Robustness to the Main Results

Table A.4: Robustness: Workplace Determinants of AI Utilization (Full Distribution)

Dep. var. =	Use AI Often or Sometimes (1/0)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C: Well-being	.196***							-.043
	[.028]							[.068]
C: Connected		.255***						.138**
		[.030]						[.060]
C: Feedback			.310***					.111**
			[.032]					[.051]
C: Customers				.068**				-.150***
				[.030]				[.051]
C: Trust					.219***			.108*
					[.029]			[.065]
C: Respect						.193***		.030
						[.033]		[.056]
Has Clear AI Strategy							3.045***	2.874***
							[.059]	[.096]
Age	-.030***	-.031***	-.030***	-.029***	-.030***	-.032***	-.018***	-.026***
	[.002]	[.002]	[.003]	[.002]	[.002]	[.002]	[.002]	[.003]
Some College	.215**	.186**	.369***	.173*	.208**	.342***	.381***	.239**
	[.089]	[.091]	[.099]	[.091]	[.088]	[.096]	[.070]	[.115]
College or More	1.420***	1.377***	1.770***	1.399***	1.408***	1.716***	1.693***	1.520***
	[.083]	[.085]	[.092]	[.085]	[.083]	[.089]	[.065]	[.107]
Male	.303***	.304***	.261***	.282***	.306***	.278***	.271***	.216***
	[.060]	[.060]	[.068]	[.062]	[.060]	[.065]	[.047]	[.077]
White	-.434***	-.433***	-.385***	-.449***	-.443***	-.424***	-.279***	-.209**
	[.083]	[.084]	[.088]	[.085]	[.083]	[.085]	[.060]	[.094]
Black	.081	.054	.292**	.084	.082	.219	.089	.239
	[.127]	[.127]	[.138]	[.130]	[.126]	[.133]	[.092]	[.153]
Full time	.767***	.762***	.805***	.787***	.795***	.918***	.797***	.737***
	[.078]	[.079]	[.088]	[.080]	[.077]	[.081]	[.061]	[.106]
Has Children	.313***	.313***	.346***	.310***	.316***	.334***	.321***	.305***
	[.067]	[.067]	[.076]	[.069]	[.067]	[.074]	[.054]	[.087]
Is Married	.217***	.209***	.285***	.233***	.209***	.269***	.270***	.341***
	[.062]	[.063]	[.073]	[.065]	[.062]	[.070]	[.051]	[.084]
Year = 2024	-.279***	-.290***	-1.103***	-.292***	-.299***			
	[.084]	[.084]	[.074]	[.087]	[.083]			
Year = 2025	.845***	.868***		.850***	.860***	1.106***	.000	
	[.066]	[.067]		[.069]	[.067]	[.071]	[.]	
R-squared	.10	.10	.11	.10	.10	.11	.22	.21
Sample Size	38814	38431	28365	37227	38927	30901	50294	18050
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of a 0-10 index of AI utilization on a vector of workplace perceptions and whether the firm has a clear AI strategy, and individual covariates and year fixed effects. The frequency count is defined as follows: Daily=10, Few Times Week=8, Few Times Month=6, Few times Year=4, Once a Year=2, Less than Once a Year=1, Never/Other=0. Workplace (management) practices based on responses to the degree of agreement with the following statements on a 1-5 scale: (a) I feel connected to my organization's culture, (b) My organization consistently delivers on the promises it makes to customers, (c) I trust the leadership of this organization, (d) My organization cares about my overall wellbeing, (e) I have received meaningful feedback in the past week, and (e) I am treated with respect at work. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." Demographics include: age, race (White, Black), full-time status, having children, and being married. The sample is restricted to full and part time workers, and the observations are weighted.

Table A.5: Workplace Determinants of AI Utilization (With Displacement Risk)

Dep. var. =	Use AI Often (1/0)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AI Will Displace Job	.137***	.139***	.118***	.134***	.137***	.111***	.083***	
	[.019]	[.019]	[.020]	[.019]	[.019]	[.019]	[.014]	
C: Well-being	.014***							-.011
	[.004]							[.007]
C: Connected		.019***						.005
		[.005]						[.006]
C: Feedback			.030***					.010*
			[.005]					[.005]
C: Customers				.007				-.005
				[.005]				[.005]
C: Trust					.017***			.012*
					[.005]			[.007]
C: Respect						.024***		.006
						[.006]		[.006]
Has Clear AI Strategy							.258***	.272***
							[.014]	[.011]
Age	-.002***	-.002***	-.002***	-.002***	-.002***	-.002***	-.002***	-.002***
	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]	[.000]
Some College	-.006	-.010	.031*	-.008	-.006	.033**	.012	.010
	[.014]	[.014]	[.016]	[.014]	[.014]	[.015]	[.011]	[.011]
College or More	.048***	.042***	.106***	.048***	.047***	.102***	.066***	.089***
	[.013]	[.014]	[.015]	[.013]	[.013]	[.014]	[.010]	[.011]
Male	.021**	.021**	.012	.020**	.022**	.015	.024***	.013
	[.009]	[.009]	[.011]	[.009]	[.009]	[.011]	[.008]	[.008]
White	-.048***	-.049***	-.061***	-.051***	-.050***	-.059***	-.033***	-.044***
	[.016]	[.016]	[.016]	[.016]	[.016]	[.015]	[.011]	[.010]
Black	-.015	-.022	.015	-.017	-.018	.012	-.003	.018
	[.022]	[.022]	[.026]	[.023]	[.022]	[.025]	[.017]	[.017]
Full time	.054***	.053***	.065***	.054***	.057***	.076***	.040***	.060***
	[.012]	[.012]	[.014]	[.012]	[.012]	[.012]	[.010]	[.010]
Has Children	.024**	.023**	.017	.025**	.024**	.015	.011	.018**
	[.011]	[.011]	[.012]	[.011]	[.011]	[.012]	[.009]	[.009]
Is Married	.002	.003	.020*	.003	.003	.019*	.025***	.030***
	[.009]	[.010]	[.012]	[.010]	[.010]	[.011]	[.008]	[.008]
Year = 2024	.016*	.015	-.064***	.016	.015			
	[.009]	[.009]	[.011]	[.010]	[.009]			
Year = 2025	.095***	.099***		.094***	.094***	.063***	.051***	
	[.011]	[.011]		[.011]	[.011]	[.010]	[.007]	
R-squared	.06	.06	.07	.06	.06	.07	.13	.13
Sample Size	16775	16621	8397	16064	16828	8974	17958	22188
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

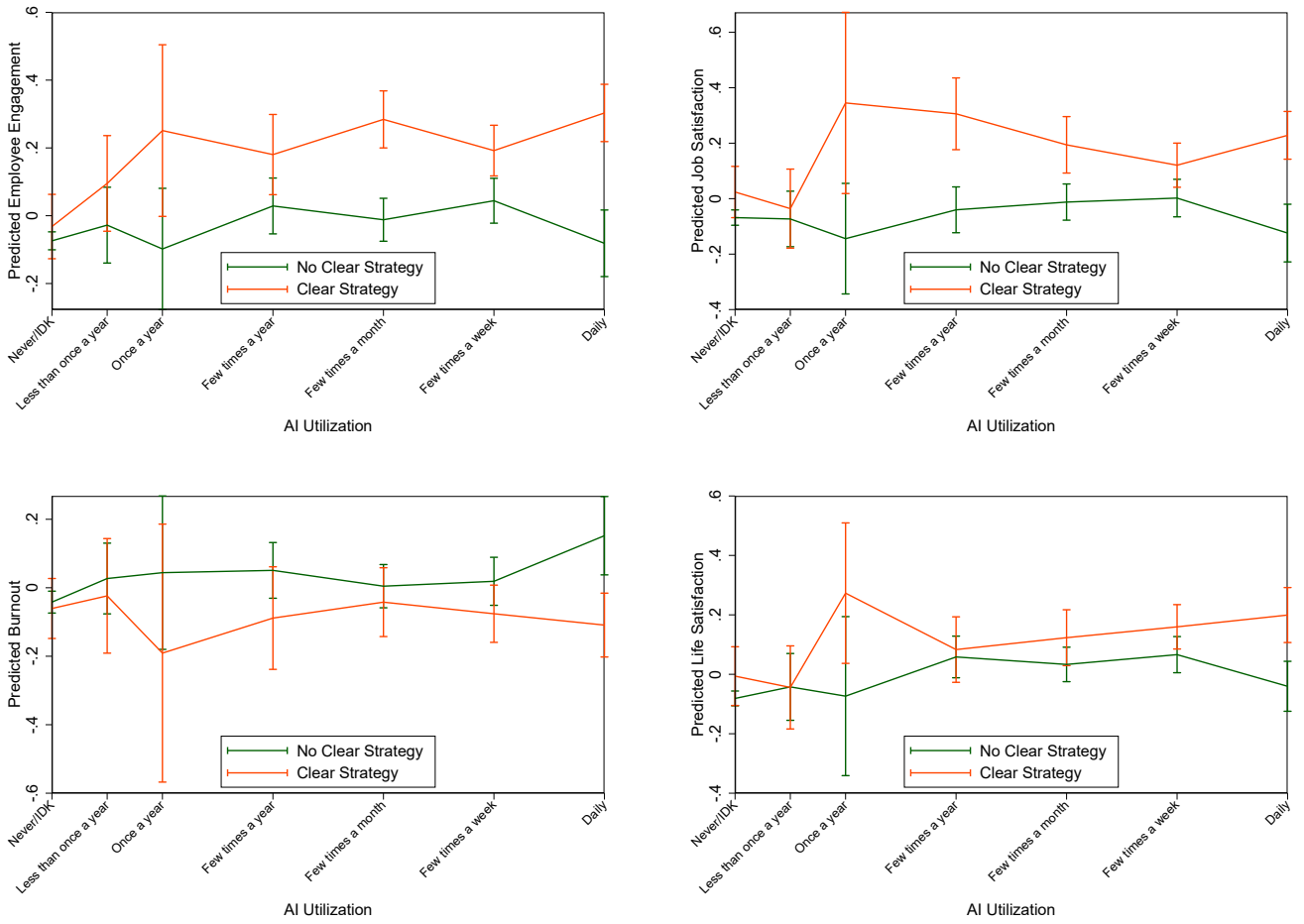
Notes.—Sources: Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of an indicator for whether the respondent uses AI daily or frequently during the week (zero otherwise) on a vector of workplace perceptions and whether the firm has a clear AI strategy, an indicator for believing that AI is "very likely" or "somewhat likely" to replace their job in the next five years, and individual covariates and year fixed effects. Workplace (management) practices based on responses to the degree of agreement with the following statements on a 1-5 scale: (a) I feel connected to my organization's culture, (b) My organization consistently delivers on the promises it makes to customers, (c) I trust the leadership of this organization, (d) My organization cares about my overall wellbeing, (e) I have received meaningful feedback in the past week, and (e) I am treated with respect at work. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." The wording for the replacement of jobs question is: "How likely is it that the job you have now will be eliminated within the next five years as a result of new technology, automation, robots or artificial intelligence?" Demographics include: age, race (White, Black), full-time status, having children, and being married. The sample is restricted to full and part time workers, and the observations are weighted.

Table A.6: Exposure to genAI and AI Utilization

Dep. var. =	AI Use - Often		AI Use - Sometimes	
	(1)	(2)	(3)	(4)
Displacement Exposure	.052***	.047***	.031***	.029***
	[.012]	[.010]	[.006]	[.006]
Augmentation Exposure	.015	-.000	.035***	.028***
	[.012]	[.011]	[.006]	[.006]
R-squared	.07	.10	.05	.06
Sample Size	13210	12681	13210	12681
Demographics	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Time x Income FE	No	Yes	No	Yes

Notes.—Sources: Eloundou et al. (2024) and Gallup Panel, 2023-2025. The table reports the coefficients associated with regressions of an indicator for whether the respondent uses AI daily or frequently during the week (zero otherwise) on the displacement (beta) and augmentation-based exposure at a six-digit occupational level from Eloundou et al. (2024), and individual covariates and time (year and quarter when the survey switches quarterly in 2025) fixed effects. Demographics include: age, race (White, Black), full-time status, having children, and being married. The sample is restricted to full and part time workers, and the observations are weighted.

Figure A.2: Effects of Clear AI Strategy on Employee Outcomes Across AI Utilization



Notes.—Sources: Gallup Panel, 2023-2025. The figures reports the predicted coefficients associated with regressions of z-scores for average Q12 employee engagement scores, burnout, job satisfaction, and life satisfaction on an indicator for whether the organization has articulated a clear AI strategy, a 0-10 index of AI utilization, their interactions, and conditional on individual covariates and fixed effects. Clear AI strategy is a binary in response to: "Has your organization communicated a clear plan or strategy for integrating artificial intelligence (AI) technology or tools into current business practices? (e.g., to increase productivity, efficiency, and quality)." The frequency count is defined as follows: Daily=10, Few Times Week=8, Few Times Month=6, Few times Year=4, Once a Year=2, Less than Once a Year=1, Never/Other=0. Employee engagement is defined as a z-score of the average across the Q12 indicators: (1) I know what is expected of me at work, (2) I have the materials and equipment I need to do my work right, (3) At work, I have the opportunity to do what I do best every day, (4) In the last seven days, I have received recognition or praise for doing good work, (5) My supervisor, or someone at work, seems to care about me as a person, (6) There is someone at work who encourages my development, (7) At work, my opinions seem to count, (8) The mission or purpose of my organization makes me feel my job is important, (9) My associates or fellow employees are committed to doing quality work, (10) I have a best friend at work, (11) In the last six months, someone at work has talked to me about my progress, (12) This last year, I have had opportunities at work to learn and grow. Burnout is a z-score to: "Please indicate how often each of the following statements is true of your primary job (i.e., the job where you spend the most time working). I feel burned out at work: (a) Always, (b) Very often, (c) Sometimes, (d) Rarely, (e) Never" from (5=always) to (1=never). Job satisfaction is similarly defined: "How satisfied are you with your place of employment as a place to work?" Life satisfaction is defined as a 0-10 score in response to: "Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time?" Demographics include: age, race (White, Black), full-time status, having children, being married, and education (some college, college or more). The sample is restricted to full and part time workers, and the observations are weighted.