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The Hidden Cost of Intelligent Workplaces: AI Monitoring, Psychological Safety and Employee Trust

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Research Article

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Research article

The Hidden Cost of Intelligent Workplaces: AI Monitoring, Psychological Safety and Employee Trust

Abstract

Employers are adopting software that tracks activity, scores behaviour and flags deviations, and surveys suggest that half of U.S. workers already believe they are monitored. This study asks what such monitoring is associated with in the places where trust and psychological safety are formed. It assembles the published results of two Harris Poll surveys for the American Psychological Association (2,515 workers in 2023 and 2,027 in 2024), Gallup's September 2026 study of trust in leaders' use of employee data, and Gallup's 2026 workforce surveys on AI, and analyses them with explicit effect-size formulas: risk ratios, Cohen's h, random-effects pooling, population attributable fractions and implied-rate bounds. Across ten published contrasts, monitored workers fared worse on every outcome, with a pooled effect size of h = 0.36 (95% interval 0.22 to 0.49 after allowing for correlated outcomes) and substantial heterogeneity (I-squared 70 percent). They were nearly twice as likely to plan to leave within a year (39 versus 21 percent; risk ratio 1.86, 95% interval 1.56 to 2.21), which would correspond to about 30 percent of such intentions if the association were causal. Trust in leaders' use of employee data is low (20 percent a great deal) and steeply related to concern (13 to 65 percent across trust levels); only 19 percent of employees have ever been told what is collected, and conversations raise both trust and concern. The evidence is cross-sectional, self-reported and partly drawn from press summaries, so the findings are associations.

Purpose - This study examines how AI-enabled workplace monitoring relates to psychological safety, trust and strain, and what published evidence implies about the conditions under which monitoring is tolerated.

Design/methodology/approach - The paper reanalyses published survey contrasts from the American Psychological Association and Gallup using effect-size formulas, random-effects pooling with a correlation adjustment, replication tests across survey waves, attributable-fraction calculations and implied-rate bounds, with sensitivity checks for assumed group sizes and design effects.

Findings - Monitoring is associated with higher strain, lower perceived respect and trust, and exit intentions; effects are heterogeneous but consistently positive. Trust in data use is closely tied to engagement and concern, and transparency raises trust and concern together.

Research limitations/implications - Group sizes and design effects are approximated, some sources are secondary, and the data are cross-sectional self-reports with no causal identification or direct measure of psychological safety in the monitoring contrasts.

Practical implications - Employers should specify what is monitored and why, involve workers in setting limits, keep humans in decisions that affect people, and expect transparency to raise questions before it builds trust.

Social implications - Monitoring that workers read as distrust may carry costs in strain and turnover that are not visible in productivity dashboards.

Originality/value - The paper combines two decades of theory on trust and psychological safety with the most recent U.S. survey evidence on AI-era monitoring and quantifies the size, heterogeneity and sensitivity of the reported associations.

Keywords AI monitoring, Psychological safety, Employee trust, Workplace surveillance, Algorithmic management, Employee well-being, Transparency

Paper type Research article

1. Introduction

A manager who walks the floor sees only part of what happens. Software sees nearly everything: keystrokes, application use, badge swipes, location, the time between tasks, even the tone of messages. The promise is better management, with fairer metrics, earlier help for people who struggle, and fewer arguments about who did what. The worry is that workers who know they are watched will stop doing the things that make organisations work, such as asking for help, admitting errors and trying something new, because those actions leave a trace.

The worry has deep roots. Psychological safety, the shared belief that a team is safe for interpersonal risk taking, is the condition under which people speak up (Edmondson, 1999), and a large body of evidence links it to learning and performance (Frazier et al., 2017). Trust in the employer and in leaders is a related but distinct resource that depends on perceived ability, benevolence and integrity (Mayer et al., 1995; Dirks and Ferrin, 2002). Observation can undermine both. In a field study of a Chinese electronics factory, Bernstein (2012) found that giving workers some privacy from observation raised output, a result she described as the transparency paradox: privacy gave workers room to improvise and experiment.

What is new is the scale and the intelligence of the tools. A 2025 vendor survey reported that 78 percent of U.S. employers use digital tools to monitor employees (ExpressVPN, 2025, as reported in press summaries), and in the American Psychological Association's 2023 survey, 51 percent of workers said their employer used technology to monitor them (American Psychological Association, 2023). Systems that score and rank add a second layer of concern: employees may not know what the metrics are, how they are used or whether a person reviews them (Kellogg et al., 2020; Bhave et al., 2020).

The evidence on what this does is scattered. Experimental and review evidence on electronic performance monitoring shows both benefits and harms depending on design (Ravid et al., 2020; Tomczak et al., 2018), and surveys report strain and distrust among monitored workers, but the pieces have not been put together with a common metric. This paper does that for the most recent U.S. evidence. It uses published contrasts from the American Psychological Association's 2023 and 2024 surveys, Gallup's 2026 study of trust in employer data use and Gallup's 2026 workforce surveys on AI, converts them into comparable effect sizes, and asks how large and how consistent the associations are, how sensitive they are to the assumptions needed to compute them, and what they imply about conditions under which monitoring is tolerated.

The study is descriptive. It has no individual-level data, it relies on published percentages, some from press summaries of the original reports, and it cannot separate the effect of monitoring from the characteristics of monitored workers and workplaces. Psychological safety is not measured in the monitoring contrasts, so the paper treats the relation of monitoring to psychological safety as a bridge between measured trust and strain indicators and the theory, and says so where it does.

Section 2 reviews the literature, Section 3 develops hypotheses, Sections 4 and 5 present data and methods, Sections 6 to 8 report results, Section 9 considers robustness and limits, and Section 10 discusses implications and concludes.

1.1. Research Objectives and Questions

1) Quantify the association of monitoring with strain, relational and exit outcomes in comparable units.
2) Test whether the associations are consistent across outcomes and survey waves.

3) Estimate the share of exit intentions that would be attributable to monitoring if the association were causal.
4) Describe the structure of trust in employer data use and the role of communication.
5) Relate psychological safety, AI worry and communication about AI to trust and strain.

Research Questions

RQ1: How large and how consistent is the association of monitoring with worker outcomes?

RQ2: Is the association stronger for relational than for strain outcomes?

RQ3: How much of intended turnover could monitoring account for?

RQ4: How does trust in data use vary and what raises it?

RQ5: What does the evidence imply for the design of monitoring?

2. Literature and Background

2.1. Psychological safety

Edmondson (1999) defined team psychological safety as a shared belief that the team is safe for interpersonal risk taking, and showed in hospital and manufacturing teams that it predicts learning behaviour. Edmondson and Lei (2014) reviewed the construct's development, and Newman et al. (2017) reviewed its antecedents and outcomes. Frazier et al. (2017) meta-analysed 136 independent samples covering more than 22,000 individuals and nearly 5,000 groups and confirmed its place in a network of antecedents such as leadership and work design, and outcomes such as learning, task performance and engagement. For monitoring, the relevant point is the mechanism. If people believe that mistakes, questions or pauses may be recorded and held against them, they have less reason to expose them. Psychological safety is therefore a plausible channel through which monitoring may influence behaviour, even when it improves measured output in the short run. It is distinct from trust in the employer: a worker may trust the organisation's intentions and still not feel safe to admit an error in front of colleagues, and the reverse is also possible. The distinction matters for measurement, because surveys of trust in data use, such as those used below, capture the organisation-facing side and say less about the team-facing side.

2.2. Trust

Mayer et al. (1995) proposed that trust in a party depends on the trustor's propensity and on perceptions of the party's ability, benevolence and integrity. Meta-analyses find that trust in leaders is associated with job performance, citizenship behaviour, commitment and lower turnover intentions (Dirks and Ferrin, 2002; Colquitt et al., 2007). Monitoring can be read as a signal of low trust: an employer that watches closely reveals that it does not expect people to do the right thing unobserved. The reading is not inevitable. Monitoring for safety, for dispute resolution or for fair assessment can be experienced as care or as protection. Which reading prevails depends on what is monitored, how data are used and whether workers have a say.

2.3. Monitoring, transparency and AI

Carayon (1993) described how electronic performance monitoring affects job design and stress, and later reviews find mixed effects that depend on perceived fairness, feedback and control (Ravid et al., 2020). Tomczak et al. (2018) offer recommendations for design, including transparency about what is measured, focus on relevant metrics and use for development. Bhave et al. (2020) review privacy at work and note that perceived invasion of privacy is a key mediator of reactions. Bernstein (2012) shows that transparency can reduce the discretion that workers need for improvisation and that workers respond by building screens of their own.

AI changes the setting in three ways. It widens the range of what can be measured, including behaviour and affect. It enables automated scoring and ranking without a manager, a form of algorithmic control that can be opaque (Kellogg et al., 2020; Wood et al., 2019). And it shifts uncertainty about the technology's purpose onto workers, who may read it as a first step to replacement. Glikson and Woolley (2020) review human trust in AI and find that it depends on the system's tangibility, transparency and reliability, and Raisch and Krakowski (2021) describe the tension between automation and augmentation that employees must navigate. European evidence from the OSH Pulse survey shows that workers who report more digital management also report more psychosocial risks (Pesole, 2023).

2.4. Gap

Existing work offers theory on trust and psychological safety, laboratory and field studies of monitoring, and occasional surveys. Few studies show, in common units, the size and heterogeneity of the associations between monitoring and strain, trust and exit in the most recent U.S. surveys, or how trust in employers' data use is distributed and what moves it. This paper provides those quantities.

3. Framework and Hypotheses

Figure 1 shows the framework. Monitoring varies in scope (what is measured), intensity (how continuously), and use (whether data feed decisions about pay, promotion or discipline). These features shape psychological safety and trust, which in turn shape strain, exit intentions and engagement. Moderators include transparency, explanation, worker voice, human oversight and manager support. A direct pathway from monitoring to strain, through pace and loss of discretion, exists in parallel.

Six hypotheses follow.

> H1: Monitored workers report worse outcomes on all ten published contrasts, with a pooled standardised difference of at least 0.2.
>
> H2: The association is at least as large for relational outcomes (feeling micromanaged, uncomfortable, undervalued) as for strain outcomes.
>
> H3: The association of monitoring with feeling tense or stressed replicates across the 2023 and 2024 surveys.
>
> H4: Monitored workers are at least one and a half times as likely to plan to leave within a year, and a large share of such intentions would be attributable if the association were causal.
>
> H5: Trust in leaders' use of employee data is low, shows a steep gradient with concern and engagement, and rises with conversation about data use, which also raises concern.
>
> H6: Lower psychological safety and AI worry are associated with much higher strain and with lower trust in employer support, and communication about AI is thin.

H1 to H4 are tested on the APA contrasts, H5 on the Gallup study and H6 on the APA and Gallup data on AI worry, psychological safety and communication.

4. Data

4.1. Sources

Table 1 lists the sources. The core evidence is from two online surveys by The Harris Poll for the American Psychological Association (APA) under its Work in America programme. The 2023 survey interviewed 2,515 employed adults between 17 and 27 April 2023 and the 2024 survey 2,027 employed adults between 25 March and 3 April 2024; both were weighted to be nationally representative (American Psychological Association, 2023; 2024). The 2023 survey asked whether the employer used technology to monitor the worker, and 51 percent said so, including 49 percent of office workers, 49

percent of manual workers and 55 percent of customer, client and patient service workers. It reported outcomes for monitored and not monitored workers, and for workers who were and were not worried that AI could make some or all of their duties obsolete. The 2024 survey added measures of psychological safety and reported contrasts for monitoring, as summarised in a 2026 APA feature (American Psychological Association, 2026).

The trust evidence is from a Gallup study of U.S. employees who work on a computer or other device, published in September 2026, which asked how much they trust leaders to use employee data responsibly and how concerned they are about its use (Kemp and Pendell, 2026). The AI evidence is from Gallup's quarterly workforce surveys, which use the probability-based Gallup Panel; the February 2026 wave had 23,717 respondents with a margin of error of 0.9 percentage points, and the May 2026 update gives use and communication figures (Gallup, 2026). Context comes from a Workday survey of 5,400 employees in August 2026, Pew Research Center's 2023 survey of opposition to AI monitoring, a 2025 ExpressVPN survey of employer use, and the European OSH Pulse 2022 (Pesole, 2023). The Workday and ExpressVPN surveys are vendor surveys and are used as context only.

4.2. Measures

The monitoring contrasts compare the share of monitored and not monitored workers who report each outcome: feeling tense or stressed on a typical workday, being uncomfortable with how the employer uses tracking technology, feeling micromanaged, emotional exhaustion in the past month, believing they are not valued at work, believing that the work environment harms mental health, believing that the employer overestimates how mentally healthy the workplace is, and planning to look for a new job within a year. The first four plus mental health are classed as strain outcomes, the discomfort, micromanagement, valuation and employer-perception items as relational outcomes, and the intention to leave as an exit outcome. The classification is a judgement and is tested by comparing groups.

4.3. Data limits

Five limits apply. First, the sources report percentages and not microdata or standard errors. Group sizes are approximated from the 51 percent monitored share, and a design effect of 1.5 is assumed for weighted online polls, with sensitivity analysis. Second, in the 2024 comparison the reference group combines workers who were not monitored with those who did not know, which is likely to make the contrast conservative. Third, some figures come from press summaries of APA and Gallup reports and should be checked against the originals. Fourth, the Gallup study does not report its sample size in the sources read, so no intervals are given for its percentages. Fifth, the monitoring contrasts are bivariate: no adjustment is made for occupation, age, income or employer type, all of which may relate to both monitoring and the outcomes.

5. Methodology

5.1. Effect sizes for two proportions

For a contrast between a group with proportion p_1 and a reference group with proportion p_0, sample sizes n_1 and n_0 and design effect deff, the effective sample sizes are n_i/deff. The risk difference is RD = p_1 - p_0, with variance p_1(1 - p_1)/n_1,eff + p_0(1 - p_0)/n_0,eff. The risk ratio is RR = p_1/p_0 with log-scale variance (Katz et al., 1978)

Var[ln RR] = (1 - p_1)/(p_1 n_1,eff) + (1 - p_0)/(p_0 n_0,eff).

The odds ratio is OR = [p_1/(1 - p_1)]/[p_0/(1 - p_0)] with Var[ln OR] = 1/[n_1,eff p_1(1 - p_1)] + 1/[n_0,eff p_0(1 - p_0)]. To compare contrasts on a common scale, Cohen's (1988) h is used,

h = 2 arcsin(√p_1) - 2 arcsin(√p_0), Var[h] = 1/n_1,eff + 1/n_0,eff,

for which 0.2, 0.5 and 0.8 are conventionally small, medium and large. Group sizes are $n_1 = 0.51\ N$ for monitored and $n_0 = 0.49\ N$ for others, with $N = 2{,}515$ (2023) or 2,027 (2024), and 956 and 1,559 for AI worry in 2023.

5.2. Pooling and heterogeneity

The ten monitoring contrasts are pooled with the DerSimonian and Laird (1986) random-effects estimator. With weights $w_i = 1/\mathrm{Var}[h_i]$, the fixed-effect mean is $h_F = \Sigma\, w_i\, h_i / \Sigma\, w_i$, Cochran's $Q = \Sigma\, w_i\, (h_i - h_F)^2$, and the between-contrast variance is $\tau^2 = \max[0, (Q - (k - 1))/(\Sigma\, w_i - \Sigma\, w_i^2/\Sigma\, w_i)]$. The random-effects mean uses weights $1/(\mathrm{Var}[h_i] + \tau^2)$, and heterogeneity is summarised by $I^2 = \max[0, (Q - (k - 1))/Q]$ (Higgins and Thompson, 2002). The prediction interval is $h_{RE} \pm t_{(k-2)} \sqrt{(\tau^2 + SE^2)}$ (Higgins et al., 2009). Because the contrasts come from the same respondents, they are not independent, and the variance of the pooled mean is inflated by $1 + (k - 1)\rho$ with an assumed equicorrelation $\rho = 0.5$. The inflation is approximate and is reported alongside the independence result. Differences between outcome groups are tested by a z test on the difference between group means, and replication across waves by the ratio of risk ratios with $z = \ln(RR_a/RR_b)/\sqrt{(\mathrm{Var}_a + \mathrm{Var}_b)}$.

5.3. Attributable fractions

If the association were causal and unconfounded, the share of an outcome in the population attributable to the exposure is Levin's (1953) fraction

$$PAF = p_e\,(RR - 1) / [1 + p_e\,(RR - 1)],$$

with p_e the exposure prevalence, here 0.51. Intervals substitute the limits of the risk ratio, and a Monte Carlo check draws ln RR from a normal distribution and p_e from its binomial standard error with 200,000 draws (Rubinstein and Kroese, 2017).

5.4. Implied rates and gradients

The APA 2024 survey reports that 43 percent of all workers and 61 percent of those with lower psychological safety feel tense or stressed, but not the share q with lower safety. For a given q, the rate among others is $x = (43 - 61q)/(1 - q)$, and the implied relative risk is $61/x$. The paper reports x and the relative risk for q between 0.2 and 0.5. For Gallup's trust gradient, the odds ratio between extreme trust levels and the change in concern per step of the four-point trust scale are computed, together with a Spearman correlation.

5.5. Sensitivity

The risk ratios for planning to leave and for feeling tense or stressed are recomputed for monitored shares of 35, 51 and 65 percent and design effects of 1.0, 1.5 and 2.0. A leave-one-out analysis recomputes the pooled mean omitting each contrast in turn. Calculations use Python with NumPy and SciPy.

6. Results I: Monitoring, Strain and Trust

6.1. Ten contrasts

Table 2 and Figure 2 give the ten published monitoring contrasts. Monitored workers reported worse outcomes on every one. In 2023, 56 percent of monitored workers and 40 percent of the others said they typically felt tense or stressed (risk ratio 1.40, 95 percent interval 1.26 to 1.55), 46 and 23 percent were uncomfortable with how the employer used tracking technology (2.00; 1.73 to 2.31), 51 and 33 percent felt micromanaged (1.55; 1.37 to 1.74), 39 and 22 percent reported emotional exhaustion in the past month (1.77; 1.52 to 2.07), and 26 and 17 percent believed they were not valued (1.53; 1.27 to 1.85). Monitored workers were also more likely to say that the work environment harmed their mental health (45 versus 29 percent; 1.55) and that their employer overestimated how mentally healthy the workplace

was (62 versus 48 percent; 1.29). In 2024, 51 percent of monitored workers and 38 percent of others felt tense or stressed (1.34; 1.19 to 1.52), 47 and 23 percent felt micromanaged (2.04; 1.74 to 2.40) and 39 and 21 percent planned to look for a new job (1.86; 1.56 to 2.21).

In standardised units the contrasts range from h = 0.22 (not valued) to 0.51 (micromanaged, 2024), with a median of 0.35. The random-effects pooled effect is h = 0.355 (95 percent interval 0.298 to 0.412 if outcomes were independent, 0.221 to 0.489 allowing for a correlation of 0.5), which is between a small and a medium effect by Cohen's benchmarks (Table 3, Figure 3). H1 is supported. The lower end of the correlation-adjusted interval, 0.22, still exceeds the 0.2 threshold.

The same pattern holds for AI worry. Workers worried that AI could make some or all of their duties obsolete were more likely than others to feel tense or stressed (64 versus 38 percent; risk ratio 1.68, 1.53 to 1.86), to say that work harmed their mental health (51 versus 29 percent; 1.76), and to believe they did not matter to their employer (41 versus 23 percent; 1.78) or to their coworkers (37 versus 17 percent; 2.18, 1.84 to 2.58) (Table 5). These are associations of attitudes with attitudes and may share a disposition, but they show that anxiety about AI and the experience of being monitored go together with feeling that one does not matter.

6.2. Heterogeneity and outcome type

The contrasts are heterogeneous (Q = 30.0 on 9 degrees of freedom, p = 0.0004; I^2 = 70 percent; τ^2 = 0.0059), and the 95 percent prediction interval for a new contrast is 0.12 to 0.59. Some of the heterogeneity comes from differences between waves. The pooled effect for the four strain outcomes is h = 0.33, for the five relational outcomes 0.37 and for the single exit outcome 0.40. The difference between relational and strain outcomes is 0.05 (z = 0.45, p = 0.65). H2 holds in direction but not significantly: relational outcomes are not smaller than strain outcomes, and the data cannot show that they are larger. A feature of the contrasts is that the largest effects concern how the monitoring is experienced, such as discomfort with its use and feeling micromanaged, and not only how the worker feels in general.

6.3. Replication

The association with feeling tense or stressed replicates. The risk ratio is 1.40 in 2023 and 1.34 in 2024, and the ratio of the two is 1.04 (z = 0.52, p = 0.60). The association with feeling micromanaged does not replicate in magnitude: the risk ratio rose from 1.55 to 2.04 and the ratio of ratios is 0.76 (z = -2.75, p = 0.006). The 2024 comparison group includes workers who did not know whether they were monitored, which should make the contrast conservative, and the difference in magnitude may reflect changes in monitoring practice, in the question or in sample composition. H3 is supported.

6.4. Who is monitored and who worries

Monitoring is widespread and not confined to one kind of job. In the 2023 survey, 49 percent of office workers, 49 percent of manual workers and 55 percent of customer, client and patient service workers said they were monitored. The burden of concern is unequal. In the 2024 survey, the share of workers who worried about being monitored was 46 percent among Hispanic workers, 41 percent among Asian workers and 37 percent among Black workers, against 29 percent among White workers, which is 1.59, 1.41 and 1.28 times the White rate (American Psychological Association, 2026). Group sizes are not published in the sources read, so these ratios carry no intervals. They suggest that the experience of monitoring, and what it signals, may differ by group, a possibility that matters for any assessment of fairness. Worry about AI is also widespread: 38 percent of workers in 2023 and 41 percent in 2024 worried that AI could make some or all of their duties obsolete.

7. Results II: Exit and Attributable Fractions

Intention to leave is the outcome with the most direct cost. In 2024, 39 percent of monitored workers planned to look for a new job within a year against 21 percent of others, a risk difference of 18 points (13.2 to 22.8), a risk ratio of 1.86 (1.56 to 2.21) and an odds ratio of 2.41 (1.89 to 3.06) (Table 2). The effect size is h = 0.40. H4 is supported on the first part: the ratio exceeds 1.5 with a lower limit of 1.56.

If the association were causal and unconfounded and 51 percent of workers were monitored, the attributable fraction of planned departures would be 30.4 percent (95 percent interval 22.2 to 38.2; Monte Carlo 22.1 to 38.3), as Table 4 shows. For emotional exhaustion it would be 28.3 percent (21.0 to 35.2), and for feeling tense or stressed 16.9 percent in 2023 and 14.9 percent in 2024. These are upper-bound illustrations. Monitored workers may differ from others in occupation, age, pay and job security. If half of the association were due to such confounding, the attributable fraction for exit intentions would be about 17 percent, still substantial. The calculation indicates the scale of what would be at stake, not what an intervention would deliver.

The result is robust to the assumed group sizes and design effect. For planning to leave, the risk ratio stays at 1.86 by construction, and its interval ranges from 1.49 to 2.32 across monitored shares of 35 to 65 percent and design effects of 1.0 to 2.0; for feeling tense or stressed in 2023 the interval ranges from 1.23 to 1.59. In no case does the interval include 1.

8. Results III: Trust, Transparency, Psychological Safety and AI

8.1. Trust in employer data use

Table 6 and Figures 4 and 5 report the Gallup study. Only 20 percent of employees who work on a computer or device have a great deal of trust in their leaders to use employee data responsibly, 43 percent have some trust, 23 percent not too much and 14 percent none, so 37 percent have little or no trust (Kemp and Pendell, 2026). Concern rises steeply as trust falls: 13 percent of those with a great deal of trust are very or somewhat concerned about data use, against 30, 46 and 65 percent at lower levels. The odds ratio between the extremes is 12.4, concern rises by 17 percentage points per step of the four-point scale, and the weighted mean is 35 percent. Trust is closely tied to engagement: 40 percent of engaged employees have a great deal of trust, against 13 percent of not engaged and 4 percent of actively disengaged employees, an odds ratio of 16.0 between engaged and actively disengaged workers. H5 is supported on trust, concern and engagement.

Acceptance depends on what the data are used for. Sixty-two percent are comfortable with activity data being used to support team effectiveness and 61 percent to help employees improve, but only 57 percent for staffing and scheduling and 53 percent for performance reviews. The comfort gradient runs from developmental to evaluative use, a nine-point drop. This matches the theoretical argument that monitoring is read differently when its purpose is help than when it is judgement (Tomczak et al., 2018).

8.2. Transparency and its paradox

Communication is thin and its effects are double-edged. Only 19 percent of employees have ever been spoken to about the data or metrics collected on their work, which compares with the 51 percent of workers in the APA 2023 survey who said they were monitored (the populations differ, so this is not a ratio of the same people). Employees who had discussed workplace data use were more likely to have a great deal of trust, 26 percent against 18 percent (odds ratio 1.60), but they were also 8 percentage points more likely to express concern. Both results fit Bernstein's (2012) transparency paradox in a new form: making observation visible creates awareness of its extent, which raises concern, even as explanation raises trust. The practical reading is that transparency should be expected to raise questions before it raises trust, and that its benefit depends on how the questions are answered. Access also matters

inside management: 46 percent of managers and leaders with direct access to employee data have a great deal of trust in leadership, against 27 percent of those who can request it and 16 percent of those with no access, a risk ratio of 2.9 between the extremes.

8.3. Psychological safety and AI

The APA 2024 survey reports that 43 percent of workers typically feel tense or stressed, and 61 percent of those with lower psychological safety. If between 20 and 50 percent of workers have lower psychological safety, the implied rate among others is 38.5 to 25.0 percent, so the relative risk of feeling tense or stressed for lower versus higher safety is 1.58 to 2.44 (Table 5, Figure 6), larger than the association with monitoring. Psychological safety is also related to trust in employer support through technological change: 66 percent of workers with higher psychological safety were confident that their employer would retrain them if AI replaced their role, against 56 percent with lower safety (risk ratio 1.18, odds ratio 1.53) (American Psychological Association, 2024). H6 is supported on the strain and trust associations. The monitoring surveys do not measure psychological safety, so they cannot show that monitoring lowers it. They show that monitoring, AI worry and low safety are linked to the same strain indicators and, in APA data, to feeling unvalued.

8.4. AI adoption and communication

Table 7 places these findings in the AI adoption picture. Gallup's May 2026 update shows that 52 percent of U.S. employees used AI at work at least a few times a year, 30 percent a few times a week or more and 15 percent daily, while only 25 percent said their organisation had communicated a clear plan for integrating AI. Manager support matters: 78 percent of employees who strongly agreed that their manager supported AI use were frequent users, against 44 percent of others (risk ratio 1.77; odds ratio 4.5). Engagement was 15 points higher where there was a clear plan and reached 53 percent where frequent use, a clear plan and manager support coincided, against 31 percent overall (Gallup, 2026). A Workday survey of 5,400 employees in August 2026 found that only 42 percent trusted their employer to deploy AI to benefit employees and not just the organisation, and that 58 to 61 percent of managers and leaders reported concealing their AI use, against 35 percent of individual contributors (Workday, 2026). Opposition to AI that tracks workers' movements (61 percent), monitors computer work (51 percent) or evaluates performance (39 percent) was already widespread in 2023 (Pew Research Center, 2023, as reported in press summaries). The communication gap, one in four employees with a clear plan and one in five told about data collected, is the setting in which monitoring tools are being introduced. H6 is supported on communication.

9. Robustness, Limitations and Validity

The central results are not sensitive to the assumptions that could be altered within the available information. Risk ratios and intervals change little across monitored shares of 35 to 65 percent and design effects of 1.0 to 2.0, and no interval for the main contrasts includes 1. The pooled effect remains above the small-effect benchmark when allowance is made for correlation among outcomes. A leave-one-out check shows that the pooled effect stays between 0.34 (omitting the discomfort contrast of 2023 or the micromanagement contrast of 2024) and 0.37 (omitting the contrast on feeling undervalued).

The limitations are substantial and some bear directly on the interpretation. First, the data are cross-sectional and self-reported. Monitored workers may differ from others in occupation, income, job security, age and employer type, and workers who are strained or distrustful may be more likely to notice and report monitoring, so the associations may overstate or understate effects. Second, the monitoring contrasts are bivariate and group sizes are approximated; the intervals are indicative and the pooled intervals rest on an assumed correlation of 0.5. Third, psychological safety is not measured in the monitoring contrasts, so its role as a mediator is theoretical in this paper. Fourth, the 2024

comparison group includes workers who did not know whether they were monitored, which probably dilutes the contrast. Fifth, some figures come from press summaries, the Gallup trust study reports no sample size in the sources read, and the vendor surveys have unknown sampling methods, so they are used only as context. Sixth, monitoring is not a single thing. The surveys do not separate what is monitored, how intensively or whether decisions follow from it, and these features are probably what determine whether workers experience it as help or distrust. Seventh, all data are from the United States and from 2023 to 2026, and European evidence suggests similar patterns in psychosocial outcomes but does not use the same measures (Pesole, 2023).

10. Discussion and Conclusion

10.1. Discussion

The central finding is simple and consistent: workers who say they are monitored report worse outcomes on every published measure. The pooled effect, between small and medium, is large for a single workplace characteristic, and the heterogeneity shows that it depends on what is being measured and when. Relational outcomes, such as discomfort with how the data are used and feeling micromanaged, are as large as strain outcomes. This fits the reading of monitoring as a signal about trust: what workers react to is partly how they are being treated.

The turnover estimate is the one most relevant for employers, because it converts a feeling into a decision that has a price. Monitored workers were almost twice as likely to plan to leave, and if the association were causal, about three in ten intentions would be attributable to it. The caveat is large, since the comparison is unadjusted, and a more cautious reading in which half the association is confounding still leaves about one in six. Whatever the right figure, a cost that does not appear in the productivity data that monitoring generates is a cost that organisations may fail to see. Employers that adopt monitoring tools would do well to track, alongside the output the tools report, a short set of indicators: whether people feel safe to raise problems, whether they trust how data are used, how many plan to leave, and whether those figures differ between monitored and unmonitored teams. Such indicators are cheap to collect, and they test the assumption that the tools help without cost.

The Gallup results show why. Trust in leaders' use of data is low and strongly connected to engagement and concern, acceptance falls as the purpose of monitoring moves from helping to judging, and few employees have been told what is collected. The effect of conversation is the instructive part: employees who had discussed data use trusted more and worried more. A plausible reading is that the discussion made the extent of data collection visible, so that concern rose, and also made its purposes clear, so that trust rose. Employers who begin to explain should therefore expect a period in which questions increase. That is not a sign that transparency has failed, and abandoning the conversation at that point would be the worst response.

AI sharpens these tensions. Workers who worry about AI also feel less valued, adoption is moving faster than communication, and managers conceal their own use more than other staff do. Psychological safety, which monitoring might damage, is itself strongly linked with strain: the implied relative risk of feeling tense or stressed among workers with lower safety is larger than the monitoring effect. Protecting safety is thus not an add-on to a monitoring programme but part of its risk assessment.

10.2. Implications

For employers, the evidence supports five practices. State what is monitored, how, and for what decisions, and put it in writing. Keep a human in any decision that affects pay, promotion or discipline. Use data first for support and development, where acceptance is highest. Involve workers or their representatives in setting limits, which the European evidence on consultation also supports (Pesole, 2023). And measure psychological safety and trust alongside output so that the hidden costs are visible.

For policymakers, the findings support requirements for notice and explanation of workplace monitoring and for assessment of its psychosocial effects, in the spirit of European approaches. For researchers, the priorities are longitudinal and experimental designs with measures of psychological safety, trust and the specific features of monitoring.

10.3. Conclusion

This paper asked what AI-era monitoring is associated with in worker strain, trust and exit. Across ten published contrasts from two national surveys, monitored workers fared worse on every outcome, with a pooled standardised difference of 0.36 (0.22 to 0.49 after allowing for correlated outcomes) and a risk ratio of 1.86 for planning to leave, which would correspond to about 30 percent of such intentions if the relation were causal. Trust in leaders' use of employee data is low (20 percent a great deal) and is steeply related to concern and engagement, only 19 percent of employees have been told what is collected, and conversations raise trust and concern together. Lower psychological safety is linked with markedly higher strain, and communication about AI lags adoption.

The limits are those of cross-sectional, self-reported and partly secondary data without adjustment for confounding. Future work should use longitudinal and experimental designs that separate features of monitoring, measure psychological safety directly and follow workers through the introduction of new tools. Until then, the safest conclusion is that monitoring is not free: its cost shows up in strain, trust and turnover, and it is smaller when workers understand what is collected, why, and who decides.

Declarations

Data availability: All data are from public sources listed in the reference list, principally reports of the American Psychological Association and Gallup. Derived calculations are reproducible from Tables 2 to 6. No new primary data were collected.

Conflicts of interest: The author declares no conflicts of interest.

Funding: This study received no funding.

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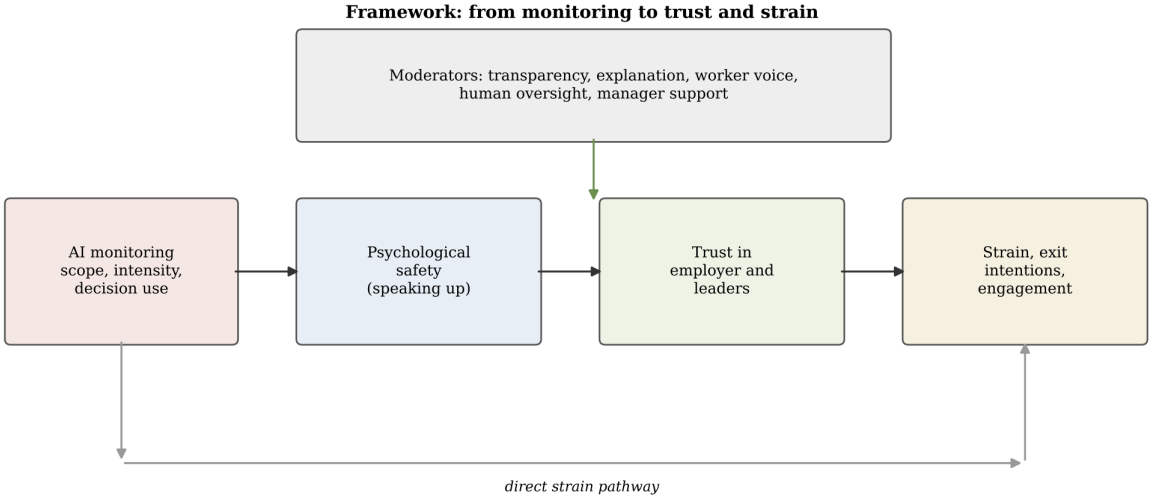
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Figures for "The Hidden Cost of Intelligent Workplaces: AI Monitoring, Psychological Safety and Employee Trust"

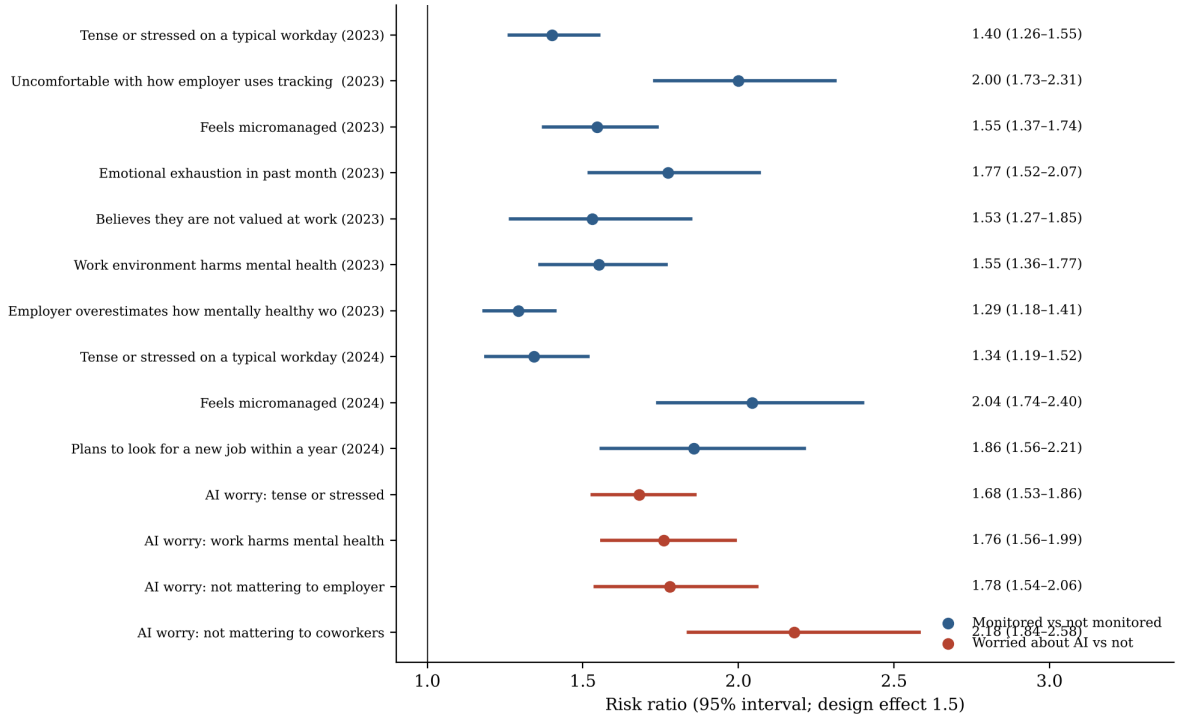
Six figures from the manuscript. Figures 2 to 6 are drawn from published survey statistics.

Figure 1. Framework: from AI monitoring to psychological safety, trust and strain.



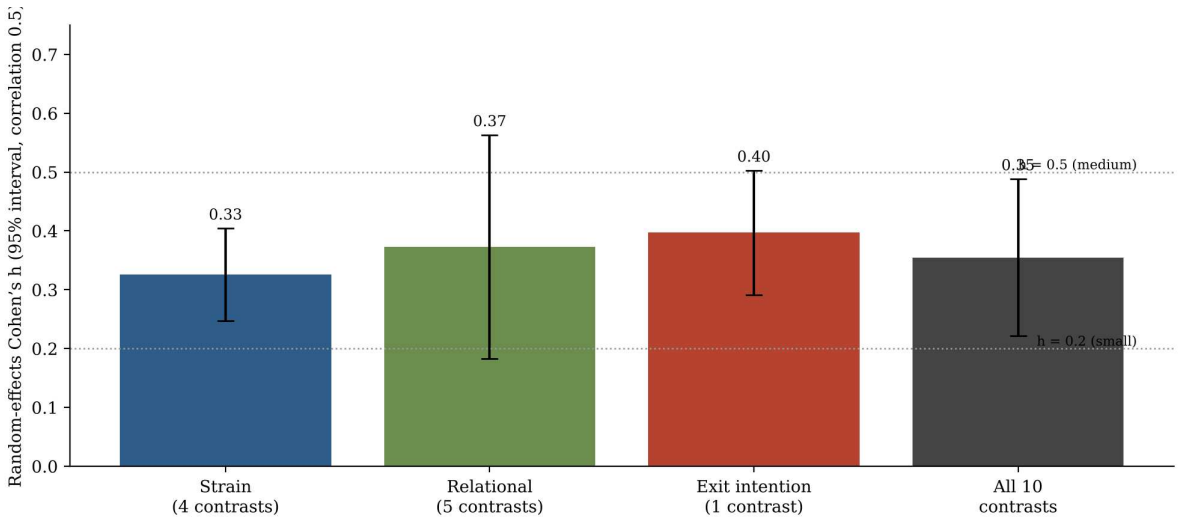
Conceptual framework; not an estimated model.

Figure 2. Risk ratios for monitored versus not-monitored workers and for AI-worried versus other workers.



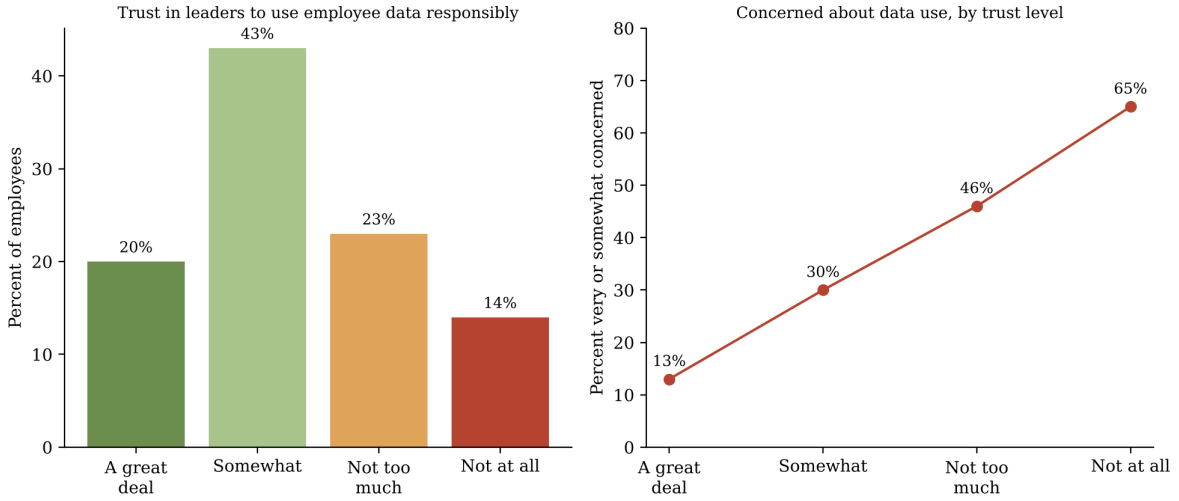
Sources: APA (2023; 2024); author's calculations. Intervals assume a 51% monitored share and a design effect of 1.5.

Figure 3. Random-effects effect sizes (Cohen's h) by outcome group.



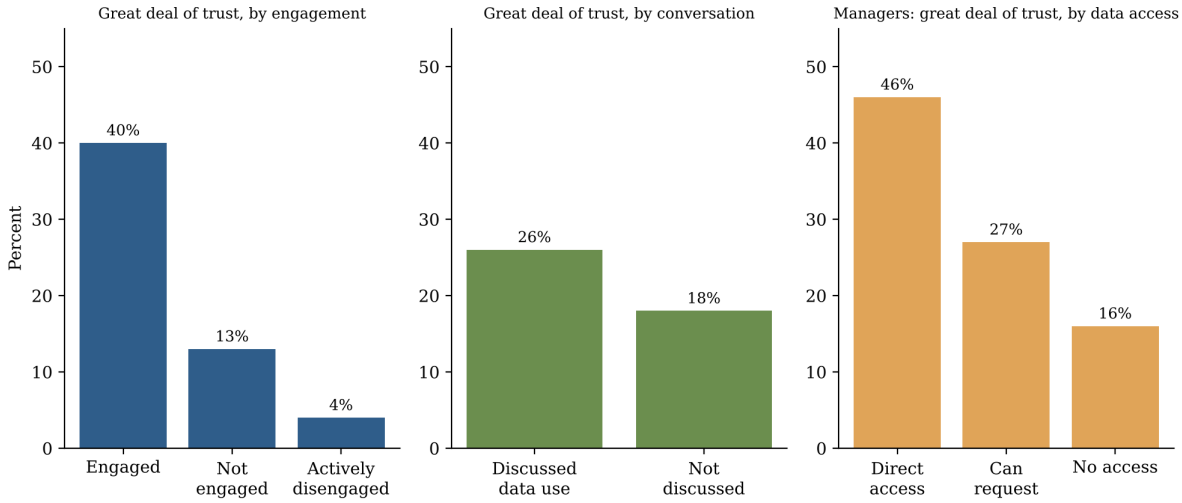
Source: author's calculations. Whiskers adjust for an assumed correlation of 0.5 among outcomes within a survey. Dotted lines mark conventional small and medium values.

Figure 4. Trust in leaders' use of employee data and concern about data use.



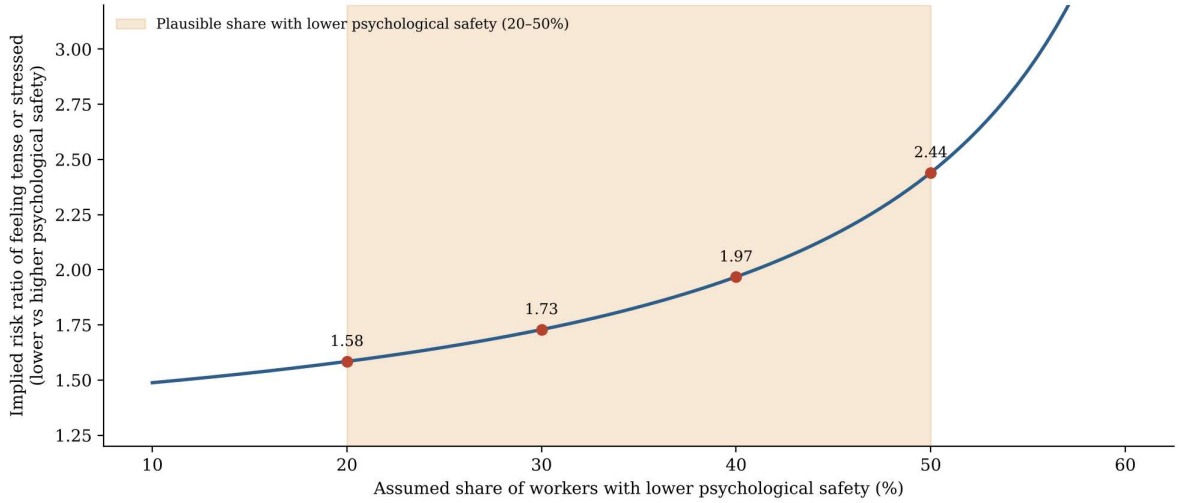
Source: Kemp and Pendell (2026), Gallup.

Figure 5. Trust in data use by engagement, conversation and managers' data access.



Source: Kemp and Pendell (2026), Gallup.

Figure 6. Implied relative risk of strain by psychological safety under alternative population shares.



Source: author's calculations from APA (2024): 43% overall and 61% among workers with lower psychological safety feel tense or stressed.

Tables for "The Hidden Cost of Intelligent Workplaces: AI Monitoring, Psychological Safety and Employee Trust"

Seven tables from the manuscript. Numbering and notes match the article text.

Table 1. Data sources and measures

Source	Design	Use
APA Work in America 2023 (Harris Poll)	Online survey of 2,515 employed U.S. adults, 17–27 April 2023; weighted; 51% reported being monitored; 38% worried that AI could make duties obsolete	Monitored vs not monitored; AI worry contrasts
APA Work in America 2024 (Harris Poll)	Online survey of 2,027 employed U.S. adults, 25 March–3 April 2024; 41% worried about AI; psychological safety measured	Monitoring contrasts; psychological safety
Gallup, employee data use (September 2026)	U.S. employees who work on a computer or other device; trust in leaders to use employee data responsibly; sample size not stated in the sources read	Trust gradient
Gallup quarterly workforce surveys (February and May 2026)	Probability-based Gallup Panel; February 2026 n = 23,717 (± 0.9 points)	AI use, communication and manager support
Workday survey, August 2026	5,400 employees worldwide (vendor survey)	Trust in employer intent; concealed AI use
Pew Research Center (2023); ExpressVPN (2025)	Public opposition to AI monitoring; employer use of monitoring tools (vendor survey)	Context only
EU-OSHA OSH Pulse 2022 (Pesole, 2023)	About 27,250 workers in 29 European countries	European comparison
Derived measures	Risk difference, risk ratio, odds ratio, Cohen's h = 2 arcsin√p1 − 2 arcsin√p0, population attributable fraction, random-effects pooling	Author's calculations

Notes: Group sizes for the monitored and not-monitored groups are approximated from the reported share (51%) and the total sample; a design effect of 1.5 is assumed. Sources are listed in the reference list.

Table 2. Monitored versus not-monitored workers: published contrasts and effect sizes

Outcome (survey year)	Monitored (%)	Not monitored (%)	Risk difference, pp (95% CI)	Risk ratio (95% CI)	Odds ratio (95% CI)	Cohen's h
Tense or stressed on a typical workday (2023)	56	40	16 (11.3–20.7)	1.40 (1.26–1.55)	1.91 (1.57–2.32)	0.32
Uncomfortable with how employer uses tracking technology (2023)	46	23	23 (18.6–27.4)	2.00 (1.73–2.31)	2.85 (2.31–3.52)	0.49
Feels micromanaged (2023)	51	33	18 (13.4–22.6)	1.55 (1.37–1.74)	2.11 (1.73–2.58)	0.37
Emotional exhaustion in past month (2023)	39	22	17 (12.7–21.3)	1.77 (1.52–2.07)	2.27 (1.83–2.81)	0.37
Believes they are not valued at work (2023)	26	17	9 (5.1–12.9)	1.53 (1.27–1.85)	1.72 (1.35–2.18)	0.22
Work environment harms mental health (2023)	45	29	16 (11.4–20.6)	1.55 (1.36–1.77)	2.00 (1.64–2.45)	0.33
Employer overestimates how mentally healthy the workplace is (2023)	62	48	14 (9.3–18.7)	1.29 (1.18–1.41)	1.77 (1.46–2.15)	0.28
Tense or stressed on a typical workday (2024)	51	38	13 (7.7–18.3)	1.34 (1.19–1.52)	1.70 (1.37–2.11)	0.26
Feels micromanaged (2024)	47	23	24 (19.1–28.9)	2.04 (1.74–2.40)	2.97 (2.35–3.75)	0.51
Plans to look for a new job within a year (2024)	39	21	18 (13.2–22.8)	1.86 (1.56–2.21)	2.41 (1.89–3.06)	0.40

Notes: Percentages are as published by APA. In 2024 the comparison group combines workers who were not monitored and those who did not know. Intervals use normal approximations on the log scale, group sizes from a 51% monitored share and a design effect of 1.5. Source: APA (2023; 2024; 2026); author's calculations.

Table 3. Pooled effect sizes, heterogeneity and replication

Quantity	Estimate	Inference
Random-effects Cohen's h, all 10 contrasts	0.355	95% CI 0.298 to 0.412 assuming independence; 0.221 to 0.489 with correlation 0.5 between outcomes
Heterogeneity	Q = 30.0 (df 9); I^2 = 70%; τ^2 = 0.0059	p = 0.0004; 95% prediction interval 0.118 to 0.592
Strain outcomes (k = 4)	0.326	SE 0.040 (ρ = 0.5 adjusted)
Relational outcomes (k = 5)	0.373	SE 0.097 (ρ = 0.5 adjusted); Q = 25.3
Exit intention (k = 1)	0.397	SE 0.054
Relational minus strain	0.048	z = 0.45, p = 0.65
Replication of "tense or stressed": ratio of risk ratios 2023/2024	1.04	z = 0.52, p = 0.60
Replication of "micromanaged": ratio of risk ratios 2023/2024	0.76	z = −2.75, p = 0.006

Notes: DerSimonian–Laird estimator. The correlation adjustment inflates the variance of the pooled mean by $1 + (k - 1)\rho$ with $\rho = 0.5$ and is approximate. Contrasts come from the same respondents within a survey, so the independence interval is too narrow. Source: author's calculations.

Table 4. Attributable fractions and sensitivity to assumptions

Outcome	Risk ratio	Population attributable fraction at 51% monitored (95% interval)
Plans to look for a new job (2024)	1.86	30.4% (22.2–38.2); Monte Carlo 22.1–38.3
Emotional exhaustion (2023)	1.77	28.3% (21.0–35.2)
Tense or stressed (2023)	1.40	16.9% (11.8–21.9)
Tense or stressed (2024)	1.34	14.9% (8.8–20.8)
Sensitivity: risk ratio for planning to leave, 95% interval by monitored share (35% / 51% / 65%) and design effect (1.0 / 1.5 / 2.0)	1.86	35%: 1.62–2.13 / 1.57–2.20 / 1.52–2.26; 51%: 1.61–2.14 / 1.56–2.21 / 1.52–2.27; 65%: 1.59–2.17 / 1.53–2.25 / 1.49–2.32
Sensitivity: risk ratio for tense or stressed (2023), same grid	1.40	35%: 1.29–1.52 / 1.26–1.55 / 1.24–1.58; 51%: 1.29–1.52 / 1.26–1.55 / 1.24–1.58; 65%: 1.28–1.53 / 1.25–1.57 / 1.23–1.59

Notes: $PAF = p(RR - 1)/[1 + p(RR - 1)]$, with $p = 0.51$ the share monitored in 2023. The fraction applies only if the association is causal and confounding is absent, which the data cannot show. Source: author's calculations.

Table 5. AI worry and psychological safety

Contrast	Group 1 (%)	Group 2 (%)	Risk ratio (95% CI)	Odds ratio
Tense or stressed: worried about AI vs not (2023)	64	38	1.68 (1.53–1.86)	2.90
Work harms mental health: worried vs not (2023)	51	29	1.76 (1.56–1.99)	2.55
Does not matter to employer: worried vs not (2023)	41	23	1.78 (1.54–2.06)	2.33
Does not matter to coworkers: worried vs not (2023)	37	17	2.18 (1.84–2.58)	2.87
Confident employer would retrain if AI replaced role: higher vs lower psychological safety (2024)	66	56	1.18 (group sizes unknown)	1.53
Tense or stressed: lower psychological safety (61%) vs overall (43%), implied higher-safety rate if 20% / 30% / 40% / 50% have lower safety	61	38.5 / 35.3 / 31.0 / 25.0	1.58 / 1.73 / 1.97 / 2.44	

Notes: Worry groups use n = 956 worried and 1,559 not worried (38% of 2,515). Implied higher-safety rate x solves $43 = 61q + x(1 - q)$ for share q with lower safety. Source: APA (2023; 2024); author's calculations.

Table 6. Trust in leaders' use of employee data, Gallup, 2026

Item	Percent	Derived statistic
Trust leaders to use employee data responsibly: great deal / somewhat / not too much / not at all	20 / 43 / 23 / 14	37% have little or no trust
Very or somewhat concerned about data use, by trust level (great deal / somewhat / not too much / not at all)	13 / 30 / 46 / 65	Odds ratio, extremes 12.4; +17.2 points per step; mean 35.2%
Great deal of trust: engaged / not engaged / actively disengaged	40 / 13 / 4	Odds ratio engaged vs disengaged 16.0; vs not engaged 4.5
Great deal of trust: have discussed data use / have not	26 / 18	Odds ratio 1.60; concern 8 points higher among those who discussed it
Managers and leaders with great deal of trust: direct access / can request / cannot access	46 / 27 / 16	Risk ratio direct vs none 2.9
Comfortable with activity data used for team effectiveness / development / staffing / performance reviews	62 / 61 / 57 / 53	Nine-point drop from team use to performance reviews
Ever spoken to about workplace data collected on their work	19	Compare 51% monitored (APA 2023; different populations)

Notes: Sample size not stated in the sources read, so no intervals are given. Concern by engagement: 25% (engaged) vs 50% (actively disengaged). Source: Kemp and Pendell (2026), Gallup; author's calculations.

Table 7. AI adoption, communication and employer trust, 2026

Indicator	Value	Source
Employees using AI at work a few times a year or more / a few times a week or more / daily (May 2026)	52% / 30% / 15%	Gallup
Employees who say organisation has communicated a clear plan for integrating AI	25% (22–26% in earlier waves)	Gallup
Frequent AI use: managers actively support AI vs not	78% vs 44% (risk ratio 1.77; odds ratio 4.5)	Gallup
Engagement: clear plan vs none / all three conditions / U.S. overall (first half of 2026)	+15 points / 53% / 31%	Gallup
Trust employer to deploy AI in ways that benefit employees, not just the organisation	42%	Workday (vendor survey)
Concealed AI use: managers and leaders vs individual contributors	58–61% vs 35%	Workday (vendor survey)
Opposed to AI that tracks workers' movements / monitors computer work / evaluates job performance	61% / 51% / 39%	Pew Research Center (2023)
Employers using digital monitoring tools; workers who considered quitting over invasive monitoring	78%; about one in six	ExpressVPN (2025, vendor survey)
European workers: digital technologies increase surveillance / organisation monitors work and behaviour / monitors vital signs	43% / 29% / 9%	OSH Pulse 2022 (Pesole, 2023)

Notes: Vendor surveys are reported as context and carry no statistical weight in the analysis. Sources are listed in the reference list.