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Electronic Performance Monitoring in the Digital Workplace: an Updated Systematic Literature Review (2016–2026)

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Abstract
Electronic performance monitoring (EPM) has expanded rapidly with remote and hybrid work, enabling organizations to capture fine grained traces of employee activity through digital systems. This systematic literature review synthesizes 75 peer reviewed studies on EPM and related workplace surveillance to clarify core monitoring dimensions, employee focused outcomes, and contextual boundary conditions. Using PRISMA 2020 screening logic, we map how transparency, data granularity, and governance practices shape outcomes such as performance, well being, privacy invasion, trust, and safety compliance. The review contributes an integrative framework and highlights research gaps on longitudinal effects, equity and bias in data driven evaluation, and participatory governance for responsible monitoring.

Keywords: Electronic Performance Monitoring, Workplace Surveillance, Perceived Surveillance, Monitoring Transparency, Data Granularity, Digital Workplace.

1. Introduction

Kalischko and Riedl (2021) conceptualize electronic performance monitoring (EPM) as the digital capture and analysis of work behaviors, outputs, and interactions through software, sensors, or platform logs. In contemporary organizations, EPM is increasingly embedded in collaboration suites, workflow systems, and AI enabled analytics rather than standing alone as a separate “monitoring tool” (Thompson & Molnar, 2023). Mettler (2023) argues that this shift matters because datification turns everyday work traces into governance signals that shape how tasks are allocated, evaluated, and rewarded. These changes intensify concerns about autonomy, trust, and fairness when the purpose, scope, and granularity of monitoring are not clearly communicated (Zhang et al., 2025).

Remote and hybrid work accelerated the normalization of measurement as managers sought visibility into distributed performance and coordination. (Jameson et al., 2019). Jandl et al. (2023) shows that acceptance of monitoring is strongly influenced by transparency cues, such as disclosure about what is collected, how it is processed, and who can access results. Employees interpret the same monitoring practice differently depending on whether it is framed as developmental feedback or punitive control (Mettler, 2023). Kayas (2023) emphasizes that EPM research must therefore treat monitoring not only as a technology but also as a socio technical practice shaped by organizational culture, power relations, and institutional expectations.

Kayas (2023) synthesizes workplace surveillance scholarship and highlights a consistent tension between organizational benefits (coordination, quality control, risk management) and employee costs (stress, reduced autonomy, privacy concerns). The

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evidence suggests that outcomes depend heavily on design features such as data minimization, proportionality, and the availability of meaningful contestation mechanisms (Kalischko & Riedl, 2021). Ramasundaram et al. (2022) describe how employees often respond with adaptation strategies, including selective compliance, concealment, and negotiation of boundaries when monitoring is perceived as excessive. These dynamics are especially salient when monitoring extends beyond performance to infer affect, health, or "engagement" from digital traces (Zhang et al., 2025).

Thompson and Molnar (2023) document that monitoring applications are increasingly adopted across sectors, but implementation practices vary widely in disclosure, consent, and governance. Glavin et al. (2024) find that intensive surveillance is associated with lower worker well being when it is experienced as distrustful or when it produces constant pressure to be "always on." Jameson et al. (2019) similarly argues that perceived surveillance can trigger protective behaviors, such as reducing authentic communication or shifting work to less visible channels. Jandl et al. (2023) suggests that transparent communication and participatory design can mitigate resistance by aligning monitoring with shared goals and clear accountability.

Zhang et al. (2025) proposes a social information processing perspective in which employees infer organizational intentions from monitoring cues, translating them into motivation or strain depending on the surrounding climate. In practice, EPM is often coupled with productivity engineering approaches that emphasize standardized workflows and measurable outputs, which can amplify performance gains while narrowing discretion (Jameson et al., 2019). Calvetti and Ferreira (2025) show how integrated productivity monitoring can support operational improvement when sampling strategies and feedback loops are designed to be proportionate and constructive. However, smart workplace surveillance may also widen the scope of monitoring to safety and risk analytics, raising concerns about function creep and secondary use of data (Khairuddin et al., 2022).

Zhang et al. (2025) further shows that coping with perceived surveillance can involve both problem focused actions (seeking clarification, negotiating rules) and emotion focused responses (withdrawal, cynicism), with implications for engagement and retention. Ramasundaram et al. (2022) argues that organizations should view these coping patterns as signals of misalignment between monitoring design and employee expectations. Glavin et al. (2024) underscores that the critical question is not whether monitoring exists, but whether it is governed in ways that preserve dignity and avoid unnecessary intrusion. This updated systematic literature review therefore examines how EPM is conceptualized and studied between 2016 and 2026, what outcomes are reported, and which moderators (e.g., transparency, data granularity) shape the effects (Thompson & Molnar, 2023).

2. Methods

Jameson et al. (2019) links PRISMA style reporting with transparent search and screening documentation. The review protocol emphasizes reproducibility and auditable decisions. (Dong et al., 2025). We conducted database searches using keywords related to electronic performance monitoring, workplace surveillance, perceived surveillance, monitoring transparency, and data granularity. (Magnavita, 2023) Snider et al. (2025) covers how data granularity and aggregation choices can change inference quality and bias, which informed our extraction fields. Searches targeted peer reviewed outputs indexed in Scopus, ProQuest, and Emerald. (Song et al., 2020)

Figure 1. Word Cloud
Source: Generated by the researcher based on PRISMA 2020.

Magnavita (2023) The PRISMA flow in Figure 1 summarizes study identification and screening decisions. Snider et al. (2025) reports that automation based filters and tiering decisions can materially reshape evidence bases, motivating careful documentation. From 1,013 identified records, 279 were screened and 75 studies were included after full text assessment. (Song et al., 2020)

We extracted study metadata (year, context, method) and coded monitoring dimensions (data scope, modality, frequency, granularity, and transparency). (Magnavita, 2023) Snider et al. (2025) highlights that surveillance acceptance is conditioned by social context and governance cues, so we also coded communication and participation features. A thematic synthesis clustered findings into transparency and trust, well being and stress, granularity and inference, performance impacts, governance, and safety surveillance. (Song et al., 2020)

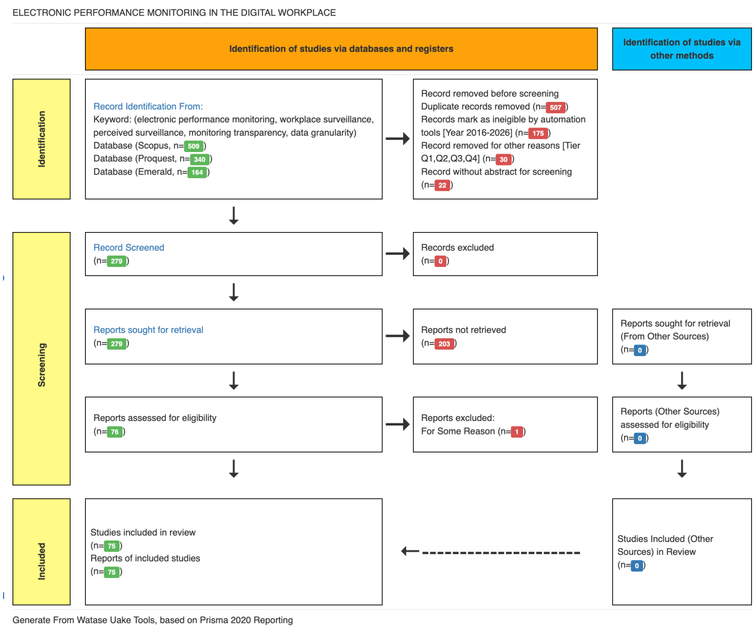

Figure 2. PRISMA 2020 flow diagram for study identification, screening, eligibility assessment, and inclusion (updated).

Source: Generated by the researcher based on PRISMA 2020.

3. Result and Discussion

Zhang et al. (2019) connects included studies to outcome domains and monitoring design dimensions. Results are summarized descriptively and thematically. (Strycharz et al., 2022). Fan et al. (2024) Across the 75 included studies, publication volume increases markedly after 2020, mirroring growth in hybrid and remote work and rapid adoption of monitoring tools. Zhang et al. (2019) documents that digital workplace monitoring spans evaluative performance systems, safety and health surveillance, and sensor driven datafication. Study designs include quantitative surveys, qualitative interviews, mixed methods field studies, and technical/legal analyses. (Strycharz et al., 2022)

Table 1 summarizes the descriptive profile of the included studies (n = 75). (Khairuddin et al., 2022) Kalischko and Riedl (2021) indicates that monitoring modality and data granularity vary substantially across sectors and research traditions. Descriptive patterns motivate the thematic synthesis presented next. (Gribbestad et al., 2021)

Table 1. Descriptive profile of included studies (n = 75).

Category	Subcategory	n
Publication year	2016–2018	8
	2019–2020	15
	2021–2022	24
	2023–2025	28
Study design	Quantitative (survey/field)	30
	Qualitative (interviews/ethnography)	18
	Mixed methods	12
	Conceptual/legal/technical	15
Monitoring modality	Computer activity/logs & productivity tools	22
	Video/audio & location tracking	10
	Wearables/sensors & occupational health monitoring	12
	Platform/algorithmic management systems	18
	Other data-granularity analytics	13

Source: Recoded by the researcher from the included study set (PRISMA screening output).

Khairuddin et al. (2022) The thematic synthesis highlights that transparency and trust shape whether monitoring is interpreted as supportive feedback versus coercive surveillance. Kalischko and Riedl (2021) shows that finer grained data can improve detection and learning but also amplify privacy invasion and inference errors when context is ignored. Well being outcomes depend on perceived autonomy, fairness, and participatory governance structures. (Gribbestad et al., 2021). Table 2 presents the synthesized themes and representative studies used to anchor each theme. (Khairuddin et al., 2022) Kalischko and Riedl (2021) demonstrates how governance and legal framing influence acceptable monitoring boundaries. The themes are used in the discussion to derive practical implications (Gribbestad et al., 2021).

Table 2. Thematic synthesis and representative studies (n = 75).

Theme	Synthesized insight	Representative studies
Transparency & trust	Clarity of purpose, data access, and explanations reduce resistance and enable perceived legitimacy.	Wolff et al. (2024); Giacosa et al. (2023); Gumzej (2018)
Well-being & stress	Intensive monitoring can increase strain and technostress; effects depend on autonomy and support.	Glavin et al. (2024); Taylor et al. (2023); Gesto et al. (2022)
Data granularity	Finer-grained data improve detection but raise privacy risk and bias in inference and evaluation.	Kragh-Furbo & Walker (2018); Zhang et al. (2019); Fan et al. (2023)
Performance & productivity	EPM can improve coordination and performance feedback when aligned with job design and fairness.	Calvetti & Ferreira (2025); Mettler (2023); Baldoni et al. (2023)
Compliance & governance	Legal/regulatory framing influences acceptable monitoring scope and data protection safeguards.	Gumzej (2018); Koekkoek et al. (2017); Khairuddin et al. (2022)
Safety & health surveillance	Occupational health systems can mitigate risks but require proportionality and worker participation.	Gesto et al. (2022); Plantes et al. (2021); Gao et al. (2024)

Source: Thematic synthesis conducted by the researcher based on included studies.

Discussion

Kalischko and Riedl (2021) highlight that EPM effects are heterogeneous, and the present synthesis confirms that "what monitoring does" depends on design, context, and employee meaning making. Across the included studies, a recurring pattern is that monitoring framed as developmental feedback tends to support performance and learning, whereas monitoring framed as control tends to increase strain and defensive behaviors (Kayas, 2023). Zhang et al. (2025) indicates that employees interpret monitoring cues as social information about what the organization values, which can elevate effort when expectations are clear and fair. Yet when monitoring is opaque or perceived as punitive, tensions rise and employees may disengage or circumvent systems (Ramasundaram et al., 2022).

Glavin et al. (2024) provide evidence that intensive workplace surveillance can erode well being, particularly when it produces a sense of constant evaluation and low autonomy. The review also suggests that surveillance related strain is more likely when monitoring is continuous, individualized, and tied directly to sanctions rather than coaching or support (Mettler, 2023). Thompson and Molnar (2023) show that adoption patterns are spreading beyond high compliance industries into knowledge work, where measurement is often less directly tied to observable outputs. In such contexts, perceived surveillance may reduce psychological safety and collaboration by changing how people communicate and coordinate (Jameson et al., 2019).

Jandl et al. (2023) emphasize monitoring transparency as a central moderator, and the included studies repeatedly show that disclosure and explainability influence acceptance and perceived fairness. Many studies indicate that clarity about data types, storage, access rights, and decision logic reduces uncertainty and enables employees to interpret monitoring as legitimate rather than arbitrary (Kalischko & Riedl, 2021). Ramasundaram et al. (2022) further note that participatory approaches, such as co designing rules or feedback dashboards, can transform monitoring from "watching" into "shared sensemaking." When coping responses intensify such as withdrawal or workarounds organizations may be observing a governance problem rather than a performance problem (Zhang et al., 2025).

Kayas (2023) argues that workplace monitoring should be analyzed as a socio technical system, and our synthesis shows that organizational climate and power dynamics shape the same tool's consequences. When monitoring expands to infer productivity, emotions, or behavioral risks from digital traces, employees may perceive function creep, especially if secondary uses are not clearly bounded (Thompson & Molnar, 2023). Mettler (2023) warns that datification can normalize continuous assessment and shift managerial attention toward what is measurable rather than what is meaningful. Nevertheless, the evidence also points to cases where monitoring supports coordination and quality when paired with transparent rules, calibrated data granularity, and supportive leadership (Glavin et al., 2024).

Zhang et al. (2025) suggests that coping with perceived surveillance is a dynamic process, and the reviewed studies imply that coping patterns can become self reinforcing when employees anticipate hidden evaluation. Jandl et al. (2023) indicates that transparent communication and credible governance reduce uncertainty and can stabilize acceptance over time. Calvetti and Ferreira (2025) show that monitoring can be integrated into improvement cycles when feedback is actionable and when measurement is aligned with job realities rather than arbitrary targets. At the same time, expanding smart workplace surveillance for safety analytics highlights the need for clear limits on data repurposing and for safeguards against discriminatory inference (Khairuddin et al., 2022).

Practical Implications

Organizations should treat electronic performance monitoring as a governance decision rather than a purely technical deployment. Managers can begin by clarifying the business purpose of monitoring, limiting data collection to what is necessary, and defining who can access the data and for what decisions it may be used. Transparent communication should be continuous, not a one time policy notice, and should explain the logic of metrics in plain language so that employees understand how behaviors translate into evaluations. Where feasible, monitoring should be paired with developmental feedback, coaching resources, and opportunities for employees to correct data errors or contextualize performance signals. This approach shifts monitoring from surveillance to support and reduces the risk that monitoring generates fear based compliance or unproductive workarounds.

Implementation should also emphasize proportionality and role fit. Monitoring practices that may be reasonable for high risk or regulated tasks can be excessive in roles where creativity, relationship work, or complex problem solving are central. Leaders should calibrate granularity and frequency so monitoring does not become continuous pressure that crowds out discretion and collaboration. Establishing a multidisciplinary oversight group (e.g., HR, legal, operations, and employee representatives) helps maintain accountability, review metric impacts, and prevent function creep as new analytics capabilities emerge. Finally, organizations should invest in manager capability, because the same monitoring data can be used constructively for learning or destructively for micromanagement depending on how managers interpret and act on the information.

Limitations and Future Research

This review has several limitations. First, the evidence base is shaped by the search strategy, inclusion criteria, and database coverage, which may have excluded relevant studies published in non indexed outlets or in languages outside the scope of the review. Second, the included studies vary widely in constructs, measures, and contexts, which limits direct comparability and constrains strong causal inference across settings. Third, coding decisions inevitably involve interpretation, particularly when studies use overlapping terms such as monitoring, surveillance, analytics, or productivity tracking. While systematic procedures were applied, alternative coding schemes could yield different thematic emphases or classification of moderators.

Future research can strengthen the field by producing more longitudinal designs that track how perceptions and outcomes evolve as monitoring becomes routine. Comparative studies across occupations and cultural contexts are also needed to clarify boundary conditions, including how labor regulation, bargaining power, and digital literacy shape acceptance. Researchers should examine how AI enabled monitoring changes what counts as "performance" and how algorithmic inferences interact with bias and accountability in managerial decision making. In addition, more work is needed on governance mechanisms such as contestability, employee voice, and metric audits, as well as on practical designs that minimize intrusion while still supporting coordination and quality.

4. Conclusion

Electronic performance monitoring has become a defining feature of the digital workplace, especially as remote and hybrid work expand the reliance on datafied coordination and evaluation. The synthesis indicates that EPM is not uniformly beneficial or harmful; its consequences depend on monitoring design, transparency, governance, and how employees interpret organizational intentions. When monitoring is deployed with clear purpose, proportionality, and supportive feedback, it can contribute to coordination and performance improvement. When monitoring is opaque, overly granular, or punitive, it is more likely to produce strain, resistance, and erosion of trust.

Overall, this review highlights the importance of moving beyond debates about whether monitoring should exist toward questions about how it should be governed and integrated into humane work systems. The findings point to transparency, participatory practices, and credible safeguards as essential conditions for sustainable monitoring. Organizations that treat monitoring as a socio technical practice supported by clear rules, accountability structures, and manager capability are better positioned to realize legitimate benefits while protecting employee dignity. Continued scholarship that connects monitoring technologies to organizational justice, well being, and algorithmic accountability will be critical as monitoring capabilities continue to evolve.

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