Quantifying Workplace Stress: A Systematic Review and Meta-Analysis of Wearable Technologies in Organizational Contexts

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Introduction

Recent advances in workplace technologies are transforming how organizations understand and manage employee health and safety (Tirabeni, 2024). Across a wide range of occupational contexts, wearable devices are increasingly deployed to monitor physiological states, anticipate risks, and support wellness initiatives (Howard, 2019). For instance, a construction worker exposed to extreme heat may use a smartwatch to track body temperature and detect heat stress (EU-OSHA, 2025), while an office employee may engage with similar devices through corporate wellness programs that prompt behavioural changes and enable peer comparison (Maltseva, 2020). In logistics settings, smart garments can transmit biometric data to managerial dashboards to monitor physical strain and prevent accidents (Patel et al., 2022).

Despite contextual differences, these applications reflect a broader trajectory: the growing datafication of workers' bodies, whereby health, safety, and well-being are rendered measurable, comparable, and actionable (Pawirosumarto & Kurniawan, 2026). This paradigm promises more preventive and precise approaches to occupational health, supported by continuous data collection and AI-driven analytics (Massaro et al., 2026).

This development is particularly relevant in addressing work-related stress, a pervasive yet complex phenomenon affecting both physical and psychological well-being. Wearable technologies propose to capture stress through standardized physiological indicators such as heart rate variability, skin conductance, and body temperature (Bliese et al., 2017). The relevance of this issue is substantial: nearly half of European workers report experiencing daily stress (ManpowerGroup, 2024), with significant consequences for productivity, including an estimated loss of 12 billion working days annually and a global economic cost of $1 trillion (World Health Organization, 2019). Beyond organizational impacts, stress also affects workers' personal lives and broader social contexts (Hassard et al., 2018; World Health Organization, 2022).

Driven by institutional pressures (EU-OSHA, 2024) and a growing market for preventive health solutions (Patel et al., 2022; Plester et al., 2024), organizations are increasingly adopting wearable technologies to detect and manage stress-related risks. However, despite their rapid diffusion, existing research remains fragmented, often divided between technical validation studies and organizational analyses (Pan & Froese, 2023). Consequently, how stress is defined, measured, and operationalized through wearable technologies, and with what implications for work and employment, remains insufficiently understood.

This gap is particularly critical because organizational research tends to engage with these technologies only after they have been stabilized and widely implemented, rather than during their development (Tirabeni, 2024). As a result, it has limited capacity to examine how design choices embed assumptions about workers' bodies, acceptable forms of monitoring, and the boundaries of organizational control (Pawirosumarto & Kurniawan, 2026). These risks overlooking how wearable technologies actively shape, rather than simply reflect, work practices, managerial control, and worker experiences (Leonardi & Treem, 2020; Mettler, 2024).

To address this limitation, this study examines how stress is operationalized within AI-enabled wearable technologies during a phase of ongoing development and diffusion. Adopting a job design perspective across different work contexts, it analyzes the technical characteristics, capabilities, and limitations of these systems, alongside the tasks, roles, and environments of the workers involved in the studies. The aim is to contribute to both scholarly debate and stakeholder awareness by clarifying how these technologies influence work design and organizational practices.

Drawing on datafication and sociomateriality perspectives (Leonardi & Treem, 2020; Scott & Orlikowski, 2025), the study conceptualizes wearable-generated biometric data as transforming stress from a situated and relational process (Cox & Griffith, 2010) into standardized data objects that can be monitored and acted upon (Alaimo & Kallinikos, 2022; Pawirosumarto & Kurniawan, 2026). While this transformation enables new forms of behavioral visibility, it also introduces risks of reductionism, misinterpretation, and decontextualization for both workers and managers (Boldi & Rapp, 2022). Moreover, it extends organizational monitoring beyond performance to include psychophysiological states, blurring the boundaries between care, control, and surveillance (Mettler, 2024).

The study addresses three research questions:

(1) How do AI-enabled wearables define and classify workplace stress?
(2) Which physiological and behavioral signals are made visible, and which remain excluded?
(3) What managerial assumptions and organizational practices shape the use of biometric stress data for evaluation, ranking, or reporting?

Methodologically, the paper combines a systematic review (Page et al., 2021) with meta-analytic techniques (Card & Little, 2016) and thematic analysis (Terry et al., 2017) of the technical literature.

The paper makes three contributions. First, it provides a systematic mapping of how wearable technologies detect and operationalize stress in work contexts, highlighting their mechanisms, accuracy, and technical limitations, while revealing the algorithmic decomposition of workers embedded in these processes (Alaimo & Kallinikos, 2022; Mettler, 2024). Second, it shows that stress is often inconsistently and ambiguously defined in technical research, increasing the risk of misalignment as data are interpreted across organizational actors (Tirabeni, 2024). This produces a form of informational drift, whereby unclear constructs at the design stage lead to problematic applications in practice (Massaro et al., 2026). Third, the study identifies a *caring paradox*: occupations with lower physical risk or greater autonomy are often subject to more intensive monitoring, resulting in increased exposure to surveillance despite the stated goal of improving well-being (Mettler, 2024; Pawirosumarto & Kurniawan, 2026).

Finally, the study contributes to debates on behavioral visibility by showing that biometric monitoring captures forms of data that workers can only partially control. This limits their ability to manage visibility and raises concerns about the collection and potential use of sensitive health information (Boldi & Rapp, 2022; Leonardi & Treem, 2020). In this sense, wearable technologies do not merely enhance organizational knowledge but actively reshape the conditions under which workers experience autonomy, control, and participation in increasingly datafied workplaces (Mettler, 2024).

Background

Work-Related Stress: Construct and Operationalization

Work-related stress is a complex and multidimensional construct, widely used as an umbrella term in occupational research (Bliese et al., 2017). A useful distinction separates stressors (external demands), perceived stress (individual appraisal), and strains (physiological, emotional, or behavioral outcomes). Building on this, the European Commission (2000), as systematized by Cox and Griffith (2010), defines stress as a set of responses to adverse work conditions arising from misalignment between individuals and their work environment.

Early models conceptualized stress through linear relationships: stimulus-based approaches framed it as an environmental property, while response-based models focused on physiological reactions. More recent interactional and transactional perspectives instead conceptualize stress as a dynamic process emerging from ongoing interactions between individuals and their work context. While these approaches better capture complexity, they make stress harder to operationalize consistently. This tension is reflected in measurement practices. Traditional reliance on self-reported data captures subjective experience but limits comparability and real-time intervention. In contrast, wearable technologies enable continuous monitoring through physiological proxies such as heart rate variability and skin conductance. However, by translating stress into standardized indicators, these technologies privilege measurable physiological dimensions while potentially overlooking cognitive, emotional, and contextual aspects (Cox and Griffith, 2010; Bliese et al., 2017).

Datafied Workers and Behavioral Visibility

Self-tracking practices have evolved from individual, voluntary use into organizational contexts, contributing to forms of dataveillance (Lupton, 2016). This shift is driven by increasing emphasis on employee well-being and the rise of data-driven management, supported by institutional pressures to demonstrate measurable outcomes.

Wearable technologies play a central role in this transformation by converting workers' experiences into quantifiable data streams (Alaimo & Kallinikos, 2022). This process underpins behavioral visibility (Leonardi & Treem, 2020), where work is understood through digital traces rather than direct observation. While this expands what can be monitored, it also constrains visibility to what is measurable, obscuring context and meaning, and extending managerial control to physiological states (Mettler, 2024).

Although workers may attempt to manage their visibility, biometric data are often continuously collected and only partially controllable, limiting such strategies and raising concerns about privacy and data governance (Boldi & Rapp, 2022). These issues are particularly salient for stress, which is reframed through wearable technologies as a set of physiological signals, potentially detached from its broader context.

This transformation has important implications: it may reduce stress to decontextualized data, privilege data-driven interpretations over subjective experience, and expand monitoring into sensitive domains of workers' lives (Mettler, 2024). These effects vary across contexts, supporting safety in high-risk environments while potentially increasing pressure in knowledge-intensive work (Patel et al., 2022; Plester et al., 2024) highlighting a tension between care and control.

Methodology

This study adopts a systematic literature review combined with meta-analysis to synthesize research on the use of AI-enabled wearable and ambient sensors for detecting and predicting workplace stress (Card & Little, 2016). Following PRISMA guidelines (Page et al., 2021), we developed search queries and collected studies from Scopus, Web of Science, PubMed, PsychInfo, IEEX.

Study Eligibility Criteria

The review includes studies that develop or apply AI algorithms to detect or predict stress among workers using data from wearable or ambient technologies. Eligible studies involve employees across occupational contexts (e.g., office, manufacturing, healthcare) and report model performance using metrics such as accuracy, sensitivity, or specificity. Included studies use non-invasive wearable devices (e.g., smartwatches, smart rings) and/or ambient sensors capturing behavioral data (e.g., facial expressions, device usage). Additional data sources (e.g., surveys, interviews) were accepted when combined with sensor data. The review considers peer-reviewed journal articles and conference papers published in English from 2015 onward, excluding reviews and non-research outputs. For each study, we extracted metadata, device characteristics, AI methods, and performance results. Study quality was assessed using the QUADAS-2 framework (Whiting et al., 2011).

Data Synthesis

We combined narrative and statistical synthesis. The narrative analysis summarizes study characteristics, technologies, and AI approaches. Meta-analyses were conducted when at least two studies provided comparable data, using the meta package in R. Multilevel models were applied to account for dependent effect sizes within studies and reduce bias.

Subgroup analyses explored how performance varies across factors such as AI algorithms, validation methods, input data types, stress-inducing tasks, and occupational contexts. Statistical significance was set at $p < 0.05$. Heterogeneity was assessed using Cochrane's Q test and the I^2 statistic.

Thematic Analysis

To complement the quantitative analysis, we conducted a thematic analysis (Terry et al., 2017). Drawing on a sociomaterial perspective, we identified recurring themes related to technology and stress meanings, behavioral visibility aspects, and proposed implications for management and monitoring. These insights, combined with the meta-analytic results, inform the discussion and research agenda.

Preliminary Findings and Discussion

Following the screening and eligibility phases, the review identified a final sample of 54 studies, from which observations for the meta-analysis were extracted. The unit of analysis is algorithmic performance (primarily measured through accuracy), and the coding process, currently nearing completion, has produced approximately 500 observations across a total sample of 18,900 subjects. Of the included studies, 37 are peer-reviewed journal articles, 10 are conference papers, and 7 are book chapters.

The dataset shows geographical diversity, with the United States (11 studies) and Italy (8 studies) as the most represented contexts. Notably, the Italian case reflects strong inter-institutional collaboration networks, where a limited number of research groups contribute to multiple studies, often involving international partnerships. Additional contributions come from European countries (e.g., Portugal, Greece, Slovenia, Romania), as well as Asian contexts (e.g., China, Japan, South Korea), although with lower frequency.

A key finding concerns the distribution of occupational contexts. Despite the frequent framing of wearable technologies as tools for occupational health and safety in high-risk environments (EU-OSHA, 2024), the largest share of studies focuses on office workers (21/54) and knowledge workers (12/54). In contrast, traditionally high-risk sectors such as construction (9/54) and manufacturing (6/54) are less represented, while service roles (e.g., healthcare, drivers) account for only a marginal portion of the sample. This imbalance raises questions about the alignment between the stated purpose of these technologies and their actual application contexts.

Preliminary findings highlight a persistent ambiguity in how stress is conceptualized and operationalized. When based primarily on physiological inputs, stress tends to be treated as a measurable biological condition, simplifying its interpretation. However, when framed as a multidimensional and processual construct, significant challenges emerge (Cox & Griffith, 2010). First, it becomes difficult to align physiological measurements with the broader theoretical construct of stress. Second, achieving reliable performance requires controlled environments and the integration of multiple data streams (physiological, behavioral, and environmental).

This results in what can be described as construct opacity, where the relationship between measured signals and the underlying phenomenon remains unclear (Alaimo & Kallinikos, 2022).. At the same time, wearable systems contribute to an algorithmic decomposition of workers' experience, reducing complex, situated realities into discrete and quantifiable features (Lupton, 2015). While this enables computational analysis, it risks detaching stress from its contextual and relational dimensions (Tirabeni, 2024). The findings also point to a growing tendency toward *oversensorization* as a strategy to improve model performance. In real-world ("in-the-wild") settings, algorithmic accuracy tends to be lower than in controlled experimental conditions. To compensate, studies increasingly rely on combining multiple sensors and data sources. This intensification of data collection expands behavioural visibility, placing workers in conditions of near-continuous monitoring

(Lupton, 2015; Mettler, 2024). While such monitoring is often framed as beneficial, it reduces workers' ability to manage and control their own visibility, particularly when data capture extends to physiological signals that are not fully controllable or strictly work-related. The result is a context in which there is effectively "nowhere to hide," as increasingly granular aspects of workers' bodies and behaviours become observable and analysable (Leonardi & Treem, 2020).

These dynamics reflect underlying managerial assumptions about the role of data in improving well-being and performance. Wearable technologies are often introduced with the intention of enhancing worker health; however, their application appears uneven across occupational contexts. In particular, the stronger focus on knowledge and office workers, who typically benefit from autonomy (Bliese et al., 2017), suggests a potential misalignment between technological intervention and actual need.

This leads to what can be conceptualized as a *caring paradox*. While organizations adopt these technologies to promote well-being, their implementation may simultaneously intensify surveillance and reduce autonomy (Mettler, 2024). This tension is further exacerbated by the technical complexity of the data involved. Many systems rely on advanced physiological measures (e.g., ECG, PPG), which are not easily interpretable by workers or managers without specialized expertise. As a result, decision-making may rely on opaque outputs, limiting meaningful engagement with the data.

Overall, preliminary findings suggest that the adoption of AI-enabled wearable technologies does not simply predict workplace stress. Instead, it introduces new forms of monitoring that may outpace their actual benefits, raising important questions about the balance between care, control, and the meaningful use of data in organizational contexts.

References available upon request