IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 10 October 2025, accepted 23 January 2026, date of publication 2 February 2026, date of current version 6 February 2026.

Digital Object Identifier 10.1109/ACCESS.2026.3659998

TOPICAL REVIEW

Electrodermal Activity and Sweat Rate Sensing Technologies for Occupational Health Monitoring: A Systematic Review

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This study was carried out within the MICS (Made in Italy–Circular and Sustainable) Extended Partnership and received funding from Next-Generation EU (Italian PNRR–M4 C2, Invest 1.3–D.D. 1551.11-10-2022, PE00000004) CUP MICS C93C22005280001.

ABSTRACT The human-centered paradigm of Industry 5.0 framework has boosted demand for wearable sensing technologies to monitor operators' health, safety, and well-being. Among physiological signals, Electrodermal Activity (EDA) and Sweat Rate (SR) stand out as suitable candidates for detecting stress, fatigue, and workload in occupational contexts. Despite extensive research into sensing approaches for both EDA and SR, a limited comprehensive classification and analysis of design, characterization protocols, and performances can be highlighted. This systematic review aims to fill this gap by analyzing the last decade of literature concerning EDA and SR as operator monitoring tools. The analysis spans across applications, sensing technologies, testing protocols, signal processing, and multimodal integration. Each of these classes is deeply analyzed to compare commercial devices and custom-built solutions, with particular attention to novel approaches exploiting flexible electronics, advanced materials, and microfluidics. Results show promising adoption in sectors such as construction, agriculture, manufacturing, and office work, despite persistent challenges in heterogeneous testing protocols, lack of standardized metrics for reliability and usability, motion artifacts, comfort, battery life, and user compliance. A major trend is the integration of EDA/SR with other biosignals—such as HRV, EEG, and skin temperature—enabling more robust detection of stress and emotional states through multimodal approaches. The discussion and conclusion outline current advances and identify future directions to guide the development of user-centric, multimodal monitoring systems for occupational health.

INDEX TERMS Electrodermal activity, sweat rate, wearable sensors, occupational health monitoring, multimodal systems, operator monitoring.

I. INTRODUCTION

In the last decade, the introduction of the Industry 5.0 paradigm has accelerated human-centric innovation, personalization, and the integration of advanced technologies to enhance workers' overall well-being. Unlike previous industrial paradigms focused on productivity and automation, Industry 5.0 aims - in fact - at prioritizing holistic health also by managing cognitive load and supporting emotional resilience to foster a sustainable and efficient workforce [1], [2]. In this context, there is growing interest in effective technologies able to seamlessly and non-invasively monitor physiological parameters related to operator health and well-being. Specifically focusing on physiological stress, Electrodermal Activity (EDA) and Sweat Rate (SR) analyses stand out as convenient and effective methodologies used

The associate editor coordinating the review of this manuscript and approving it for publication was Andrea De Marcellis.

to detect critical states in the workers, easily integrable into multimodal systems [3].

Indeed, EDA and SR represent biomarkers of the eccrine sweat gland activity. This activity is regulated by the sympathetic nervous system, which is well-established as one of the key players in emotional arousal and stress responses [4]. More specifically, EDA measures changes in skin conductance proportional to sweat secretion onto the skin surface, providing an indirect but highly sensitive indicator of emotional or physiological arousal [5]. In contrast, sweat rate monitors the volume of surface sweat produced over time, offering a direct measure of glandular activity. The combination of EDA and SR is extremely effective; in fact, EDA provides high temporal resolution for detecting rapid fluctuations in arousal while SR adds valuable information about the intensity and duration of sweating episodes, which is relevant in occupational settings involving physical exertion and/or thermal stress.

Non-invasive surface electrodes based on conductive materials represent the most used solution for facilitating the measurement of both EDA and SR [3]. Indeed, these sensing elements can be effectively integrated within wearable devices, alongside properly designed electronic frontends and microfluidics. Moreover, the miniaturization of these solutions combined with recent advancements in machine learning algorithms to enhanced analyses of EDA/SR outputs, has been enhancing their applications and acceptance, thus enabling adaptive interventions and personalized feedback to improve occupational safety and overall worker well-being [6].

A focus on the current state-of-the-art reveals several examples on occupational monitoring, with a primary interest in EDA and, more rarely, on SR. Furthermore, although many of these works involved real-world applications with specific focus on the overall stress of the workers, a significant lack of standardization and uniformity can be observed in terms of:

- design/implementation of the sensing solutions;
- characteristics and testing protocols;
- integration within multimodal solutions.

Regarding design, a primary distinction exists between studies relying on commercially available solutions and those using custom-built approaches. Commercial devices (e.g., Empatica E4, Shimmer, and Biopac) are mainly employed for EDA assessment, while custom-built solutions are typically used for SR monitoring. Although commercial devices - especially those integrated in simple wearables - present several advantages for long-term on-field monitoring in terms of robustness, ease of use and readiness in data interpretation, they can present several limitations regarding customization, integration with other sensors, or cost [7]. Consequently, custom-built EDA sensors are receiving increasing attention, leveraging novel advanced manufacturing techniques, conformable and biocompatible materials, and flexible and stretchable electronics [8]. These approaches provide greater flexibility in both hardware and software, which can be easily tailored to specific application needs, enabling integrated multimodal and real-time feedback systems.

Moreover, a further relevant aspect to consider is related to all those factors that can affect signal quality, measurement reliability, and overall usability. Indeed, scientific literature did not always analyze and describe these metrics with standardized approaches. Several factors - including sensor placement (e.g., palm, wrist, fingers), electrode material and design, sampling frequency, and skin-electrode contact impedance - can significantly influence the signal-to-noise ratio (SNR) and the reliability of the features extracted from the raw acquired data [9]. Therefore, especially in real-world scenarios where motion artifact and/or external interference are common, suboptimal design and poor robustness can significantly impair the possibility to acquire meaningful data. Other relevant factors, crucial for long-term monitoring but often poorly described in literature, specifically address usability and include device comfort, battery life, data accessibility, and user compliance [10].

The integration of EDA with other sensors in multimodal systems represents a major emerging trend, even in occupational context. In recent years, combining the information provided by EDA with other biosignals, such as heart rate variability (HRV), electroencephalography (EEG), and skin temperature, has proven effective for improving the overall robustness and the capacity of properly discriminating stress and emotional states [11] Advances in miniaturized and flexible electronics, and AI-based signal analyses have further accelerated scientific research into more adaptive, context-aware, and personalized sensing platforms.

Given the occupational context, the specific aim of this review was to systematically categorize the most updated state-of-the-art (>2015) concerning EDA and SR, specifically focusing on design, characterization and testing protocols for the sensing components, approaches proposed for signal processing, and integration solutions to enable multimodal monitoring devices. The main finding of this review will set the basis for defining proper guidelines to inform future research directions and guide the design of more effective and user-centric EDA/SR-based systems for both basic and applied research within the occupational context.

II. BACKGROUND AND SCOPE

Previously published review papers focused on sweat rate and electrodermal activity sensors used in working environments allowed us to perfectly frame the context of this novel work and properly set its background. In fact, [12] reviews several studies performed on physiological signals adopted to detect stress and fatigue reported that EDA was found to be the most used approach in that context. Reference [13] investigating the allostatic load among workers as a source of additional exposure to risk - while underlining the importance of EDA as an effective tool for quantifying the level of stress - focused on the necessity of a holistic approach to reliably predict potential diseases and illnesses that may emerge due to stress. Furthermore, [14] and [15] setting the state-of-the-art of wearable applications in construction safety and health and considering different types of sensors - including skin response measurement sensors - reported that EDA was mainly adopted for assessing physical workload and fatigue and monitoring workers' mental status. Shifting the focus towards the aeronautical fields, [16] analogously reported that biomedical sensors in aviation are vastly adopted to measure the cognitive workload level and stress of operators by exploiting their relationship with EDA-based parameters, which could be measured via wearable solutions.

The work performed by [17] mainly focusing on human factors, sensory principles and a wide range of commercial wearable solutions available for human-centered working operation in Industry 5.0, considered the vast possibilities given by the adoption of different kinds of biosensors. With an approach more focused on the workplace settings and the type of stressors that are present within, [18] investigated different physiological sensors and assessment methods to determine the most affine and precise intervention modes to assess the cognitive overload, thus highlighting that EDA presented the highest accuracy in determining stress level and encouraging further research on this modality.

Previous literature reviews often covered a wide range of commercial solutions or focused on specific application domains. However, they did not adequately address the actual sensing technologies and integration challenges of wearable solutions for assessing stress and mental workload. Indeed, this is a crucial gap, as these technologies are essential in this field. This work aims to dive deeper, focusing specifically on sweat rate and electrodermal activity (EDA) sensors. We will examine their technological features, characterization, integration into broader ecosystems, and adoption in various work environments and covering different application domains. Therefore, this review aimed at covering a specific niche present within the holistic view proposed by [17] specifically addressing the technological issues while focusing on workplace setting as performed by [18] The final scope of this work was, therefore, to summarize existing findings and identify the methodologies and sensor technologies used for quantifying SR and EDA in the different working environments, with specific focus on design solutions and possible integration into wearables.

III. METHODOLOGY

To provide a comprehensive review of the state-of-the-art in EDA/SR measurements, this study followed the PRISMA guidelines [19], so as to evaluate the use of specific sensing technologies specifically used in the occupational contexts. Accordingly, this systematic review was based on defining proper research questions, implementing an effective search strategy including keywords and database selection, and presenting the main findings to offer novel insight to the reader.

In order to cover all the relevant studies and properly guide the assessment and discussion, the primary focus and contribution of this review study was based on the following research questions specifically addressing the sensing technologies that have been implemented within the occupation contexts, the working populations on which these technologies were used, the specific outcomes that were provided, including their overall reliability, and the current trends in multimodal system integration:

RQ1: In which primary populations have sweat rate and/or EDA assessments been applied?

RQ2: What are the primary commercial and custom-made sensing technologies used for sweat rate and/or EDA analysis?

RQ3: How do existing sweat rate and/or EDA sensors compare in terms of signal quality, reliability, and usability?

RQ4: What are the current trends in integrating sweat rate and/or EDA sensors into multimodal systems?

To find relevant articles, we examined 3 different online databases, specifically Scopus, Web of Science and PubMed, since they represent the most popular and well-known research sources in this field. To realize an effective search strategy for the identified databases, we used a combination of different keywords, as reported in Table 1. These keywords were organized in 4 different groups according to the specific topic they covered. In order to refine the search, among the keywords present within the same group we used the OR logical operator, whereas the AND operator was used between the groups.

TABLE 1. Groups of keywords adopted for the proposed systematic literature review.

Group 1	Group 2	Group 3	Group 4
- Electrodermal AND activity - Galvanic AND skin AND response - EDA - GSR - Sweat AND rate	- Sensor* - Electrode* - Device*	- Workforce - Labor - Worker* - Operator*	- Monitor* - Measur*

The search on databases was performed on April, 2025; hence, papers published after this date were not considered in this work. The search results from each identified database were imported into the Rayyan platform (https://www.rayyan.ai/) to support the following phases of screening and selection.

After obtaining the list of the papers, we conducted 2 different rounds of screening, according to specific inclusion criteria. Specifically, within the 1st round we focused on the title, abstract and keywords and considered studies that were: published as peer-reviewed and indexed articles from journals, conferences, and workshops; surveys and review papers were excluded;

- published in English;
- accessible as full text;
- published starting from 2015;
- relevant with respect to the identified research questions.

In the 2nd round of screening, we focused on the full text, specifically considering only studies that:

- specifically investigated the use of SR/EDA sensors on workers/operators within specific working environments;
- adopted SR/EDA sensors to implement use cases in experimental conditions;
- tested SR/EDA sensors on human participants including validation testing.

Duplicated studies were removed before entering the screening and selection process. Then, each identified paper was analyzed by a minimum of two reviewers in parallel, and the final inclusion decision was defined based on the positive remarks of both authors. In case of doubtful outcomes, a third reviewer was involved in the suitability selection process of the papers to determine whether inclusion criteria were all met.

Subsequently, we assessed the outcomes of the performed search focusing on quantitative measures, such as the annual publication count, and on the classification of the studies according to the applications/contexts, the sensing technologies – including electrode design –, the validation protocols, the possibility of integration into wearable solutions, and the signal processing algorithms/processes.

IV. BACKGROUND AND SCOPE

The initial literature search process revealed that a total of 198 studies were identified in the defined databases; specifically, 90 (45.4% of the total) were found in Scopus, 71 (35.9% of the total) in Web of Science, and 37 (18.7% of the total) in PubMed. After duplicate removal (N=92, 46.5% of the total), 106 studies were systematically analyzed. As previously reported, title, abstract and keyword of the identified documents were reviewed to assess relevance, followed by a comprehensive evaluation of the full text to determine their suitability for the purpose of this review. During the evaluation of the studies, we rigorously applied the previously described inclusion criteria into 2 different rounds. First round of screening process through titles, abstracts and keywords examination allowed to exclude 17 papers:

- studies not accessible through academic subscription - 7 papers;
- studies out-of-topic with respect to the identified research questions - 3 papers;
- surveys or review papers - 7 papers.

After the first round of screening, we specifically obtained 88 papers. Second round of screening process through full text examination allowed to exclude 23 papers:

- studies that did not investigate the adoption of sensors on workers (e.g., hospitalized patients, infants, people living in specific urban context) - 16 papers;
- studies that did not adopt sweat rate and/or electrodermal activity sensors to implement use cases in experimental conditions - 4 papers;
- studies that did not test sensors on human participants with specific validation through experimental tests - 3 papers.

At the end of the selection process, the total number of papers that met the inclusion criteria was 66. The overall screening and selection process, according to PRISMA flowchart, is reported in FIGURE 1. All these studies were then carefully analyzed in detail; the synthesis of the information extracted from this final group is reported and discussed in the next sections according to applications, sensor design, wearability, signal processing and integrability within multimodal system. The number of papers suitable for analysis is reported, according to their year of publication, in FIGURE 2.

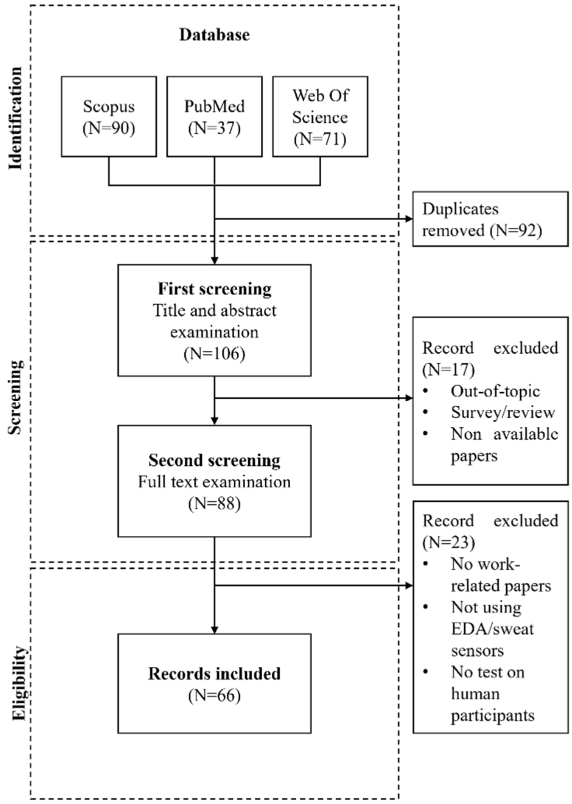

FIGURE 1. PRISMA flowchart describing the review methodology adopted for the current study.

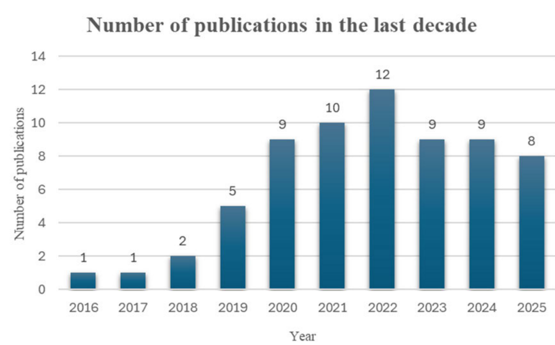

FIGURE 2. Annual publications statistics for the last decade of literature.

V. APPLICATIONS

The adoption of sweat rate and EDA assessment for monitoring workers' health and wellbeing represents a step forward in the prevention of risks related to overall stress, fatigue and mental workload. Smart devices - whether commercial or developed in laboratory – can provide either in real-time or in a post-process analysis information related to the alteration in sweat rate and skin conductivity, thus allowing timely intervention before critical conditions occur. In industrial sectors - such as construction, agriculture, and manufacturing - where workers are exposed to high temperatures and intense physical exertion, the adoption of these sensors enhances safety and supports overall well-being, contributing to healthier and more sustainable work environments.

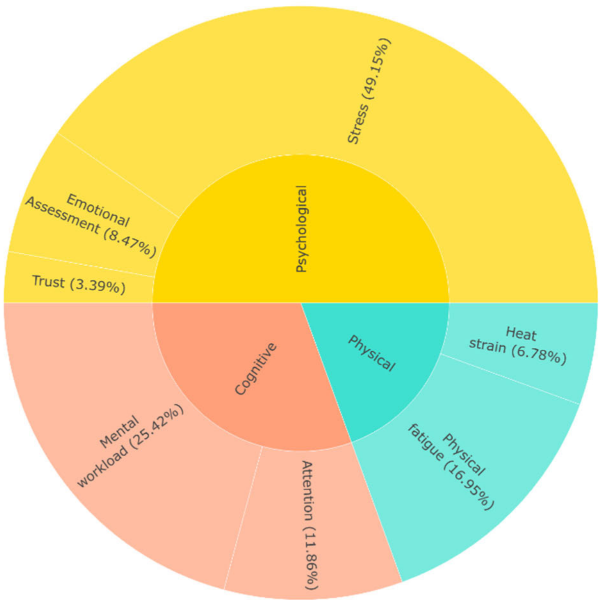

FIGURE 3. Subdivision of papers based on specific work-related application. It is worth noting that the total percentage exceeds 100% because several studies cover multiple aspects within the same research framework.

Therefore, it is fundamental to identify the different possible applications where electrodermal conductivity and sweat rate sensors have been adopted to highlight hazardous scenarios and determine possible critical issues in physical and cognitive load during daily work activity. Following the classification proposed by [17] we specifically investigated the different human factors highlighted in the identified papers to determine which specific application was investigated and which purposes were targeted; thence we specifically identified physical, cognitive and psychological states as the main factors to classify the identified studies. In this concern, FIGURE 3 provides an overview of the application fields individuated during the review process, while Table 2 reports the details corresponding to the different published studies according to main identified categories.

A. PHYSICAL STATES

Among the reviewed papers, the assessment of workers' physical conditions was mainly focused on both their overall well-being and the ability to correctly perceive – and thus handle - external stimuli, such as heat stress. Literature demonstrates how sweat rate and electrodermal activity can support the identification of different working conditions that could determine discomfort and possible harms according to the physical level of exertion that is associated to the completion of specific working tasks. Providing more detail, the adoption of sweat rate and EDA sensors resulted to be widely applied in the study of physical fatigue across various working contexts. In fact, these technologies have been adopted both in office environments (2 out of 14 papers) - involving white-collar workers - and in operational settings such as construction and agricultural applications, which mainly involve blue-collar workers (12 out of 14 papers). In these fields, the assessment of physical fatigue levels through sweat rate sensors allows timely detection of physical overload conditions, enabling real-time interventions to prevent fatigue-related injuries and reduce the overall risk exposure. Indeed, physical fatigue resulted to be the most investigated physical state (10 out of 14 papers), that was assessed within specific experimental sessions and was the target for the development of innovative methodological approaches devoted to detecting early signs of that condition. Moreover, literature showed increasing interest in work environments that were characterized by extreme conditions, such as high-temperature settings in construction domain, where sweat rate and EDA sensors can detect heat-related stress conditions (4 out of 14 papers). In fact, monitoring sweating rate and electrodermal activity enables the assessment of the thermal resistance of personal protective equipment or workers' physical tolerance, identifying the maximum thresholds beyond which significant harm to workers' health may occur.

B. COGNITIVE STATES

The literature highlighted that the analysis of cognitive states mainly included the assessment of mental workload and workers' attention, thus ensuring safety and performance in demanding work settings. Indeed, mental workload refers to the amount of cognitive effort required to carry out a task, while attention – reported also in terms of risk detection – refers to worker's ability to recognize potentially dangerous situations within their workplace [77]. In this regard, the adoption of sweat rate and EDA sensors can help to monitor these aspects by tracking biological changes of the workers' psychophysical conditions, allowing to quantify the task demand in terms of cognitive effort, and how effectively a worker can maintain a high state of alert with respect to possible risks. The analysis of current literature highlighted how the adoption of sweat rate and EDA sensors was not limited to monitoring physical fatigue but largely includes the assessment of mental workload during the execution of tasks and job activities (i.e., almost one third of the total papers). Most of the studies addressed both the cognitive workload and risk detection mainly using EDA and sweat rate sensors. Consideration was specifically given to the construction sector, where the mental workload and the attention may play an extremely critical role for the workers' safety (11 out of

TABLE 2. **Research clustered on a set of work-related conditions and their specific applications (59 out of 66 total papers).**

Human Factors	Main Work-related Factor	Additional Factor(s)	Application Context	Reference
Physical states (14 papers)	Physical fatigue (10 papers)	Stress	Office workers	[20]
		Stress	Maritime	[21]
		-	Construction	[22]
		-	Construction	[23]
		Heat strain	Agriculture	[24]
		Stress	Office workers	[25]
		-	Construction	[26]
		Attention (Risk perception)	Construction	[27]
		-	Construction	[28]
		-	Manufacturing	[29]
	Heat strain (4 papers)	-	Construction	[30]
		Physical fatigue	Agriculture	[24]
		-	General applications	[31]
		-	General applications	[32]
Cognitive states (22 papers)	Mental workload (15 papers)	-	General applications	[33]
		-	General applications	[34]
		-	Agriculture	[35]
		-	Office workers	[11]
		-	Office workers	[36]
		-	Manufacturing	[37]
		Emotional assessment; Stress	General applications	[38]
		-	Office workers	[39]
		-	Construction	[40]
		-	General applications	[41]
		Stress	General applications	[16]
		-	Construction	[42]
		-	General applications	[43]
		Attention (Risk perception)	Construction	[44]
		-	Construction	[45]
	Attention (Risk perception) (7 papers)	-	Construction	[46]
		-	Construction	[47]
		-	Construction	[48]
		-	Construction	[49]
		Emotional assessment	Construction	[50]
		Physical fatigue	Construction	[15]
		Mental workload	Construction	[44]
Psychological states (36 papers)	Stress (29 papers)	Fatigue	Office workers	[20]
		Emotional assessment	Healthcare workers	[51]
		Physical workload	Maritime	[21]
		-	General applications	[52]
		-	Construction	[53]
		-	Construction	[54]
		-	Aviation	[55]
		-	Office workers	[56]
		-	AI-based work	[57]
		-	Education	[58]
		-	Office workers	[59]
		Emotional state; Mental workload	General applications	[38]
		-	Driving task	[60]
		Trust	General applications	[61]
		-	Office workers	[62]
		-	Agriculture	[63]
		-	Manufacturing	[64]
		Physical fatigue	Office workers	[25]
		-	Drones	[65]
		-	Nuclear	[66]
		-	Manufacturing	[67]
		-	Manufacturing	[68]
		-	Agriculture	[69]
		Trust	Construction	[70]
		Mental workload	General applications	[16]
		-	Healthcare workers	[71]
		-	Construction	[72]
		-	Office workers	[73]
		-	Manufacturing	[74]

TABLE 2. *(Continued.)* **Research clustered on a set of work-related conditions and their specific applications (59 out of 66 total papers).**

Trust (2 papers)	Stress	General applications	[61]
	Stress	Construction	[70]
Emotional Assessment (5 papers)	Stress	Healthcare workers	[51]
	-	Aviation	[75]
	Mental workload; Stress	General applications	[38]
	Attention (Risk perception)	Construction	[50]
	-	General applications	[76]

22 papers). Few studies focused on proposing comprehensive frameworks for the assessment of mental workload [11], [40], while most of the research mainly addressed experimental studies - performed in both laboratory settings and real working environments - to measure cognitive load experienced by workers during their daily tasks. Among the studies investigating cognitive workload, only two presented structured datasets to support further research [34], [41]. Furthermore, research on cognitive workload resulted to be closely related to the analysis of stress development. In fact, exceeding the individual threshold of cognitive workload tolerance may adversely affect individual performance and overall wellbeing. In this regard, several studies, exploring the interaction between the cognitive workload and stress, investigated the identification of possible thresholds beyond which overload conditions occur [16], [38]. Moreover, it is worth noting that cognitive workload was reported to affect not only workers' wellbeing but also their levels of attention (7 out of 22 papers). In fact, the analysis of literature reported several contributions that assess workers' attention states to monitor their concentration in operational contexts, as well as the variations during the whole working day. It is worth underlining that, from the technological point of view, a few studies, conducted both in the field and laboratory settings, also employed extended reality solutions (XR) to simulate complex work environments in order to monitor workers' attention levels [47], [49].

C. PSYCHOLOGICAL STATES

The analysis of psychological states - including stress, trust, and emotional assessment – was reported to help understand workers' mental states in overloading situations. Stress can be defined as the collection of external task demands, such as time pressure, complexity, or workload intensity, that are placed on an individual during task performance. These demands represent one side of the mental workload equation and are often contrasted with strain, which reflects the individual's internal response. Stress interacts with the resources available to the person, such as cognitive capacity, team support, or technological tools and this balance between demands and resources plays a central role in shaping mental workload [77]. In this regard, trust has been reported to be particularly important when workers are operating in collaborative workplaces or in collaboration with technologies (e.g., robots, drones) to fulfil specific targets. Indeed, literature highlighted that being able to quantify how much an operator trusts technology helps determine a level of confidence that supports productivity and contributes to positive work experience. Lastly, emotional assessment allows for the detection of a worker's emotional arousal in response to specific stressors or work-related events. Understanding these emotional responses has been highlighted as a key element to improving both safety and well-being in the workplace. As categorized by [17], among the human factors that can be monitored using sweat and EDA sensors, the development of stress in work-related activities represents, in fact, one of the most extensively studied phenomena, with a total of 36 out of 66 papers. The performed analysis highlighted that research applications covered a wide range of sectors, including construction (5 papers), manufacturing (4), agriculture (2), education (1), healthcare (1), the nuclear industry (1), air traffic control (1), and finally, administrative work environments involving white-collar workers (6). Lastly, only one study focused on monitoring trust levels in the use of collaborative robots in a VR construction environment [70]. While stress turned out to be one of the most investigated psychological factors, emotion recognition has also attracted some attention. Few studies explored emotional changes (e.g., level of arousal) using EDA and sweat rate sensors, with empirical validation obtained in both workplace settings and laboratory environments (5 out of 36 papers). Moreover, skin conductance assessment through EDA or custom-made sensing solutions has been adopted in various applications that consider multiple perspectives rather than focusing on a single aspect, where correlation analyses are often used to detect the co-occurrence of multiple effects on workforce wellbeing. Working situations where physical fatigue and stress can arise together have been often investigated in the literature to determine the impact of physical overload on cognitive load and vice versa. Such analyses are often performed on construction workers due to the high physical workload they need to sustain in their work environment [78] but also white collars in office work environment are frequently evaluated to determine the correlation between physical and cognitive demands [20], [21], [25].

D. GENERAL WELLBEING, SAFETY AND PERFORMANCE PREDICTION

Since not all the identified papers could be classified according to the human factors proposed by [17], our analysis included also detailed indication of general applications where SR and EDA sensors were adopted to monitor and measure wellbeing conditions including safety, and workers' performance level. All these studies are separately collected in Table 3. In fact, the promotion of well-being at work through prevention represents a widely explored topic where sweat rate and electrodermal activity sensors have been widely adopted. Within this context, [78] linked psychological factors to accident rates in construction, while [79] and [80] proposed low-cost sweat rate monitoring devices to prevent chronic disorders. Reference [81] developed a Mixed Reality interface to promote safety and task efficiency through real-time operator monitoring. Finally, [82] demonstrated with EDA sensors that reducing sedentary behavior could positively impact worker health. On the other side, overall productivity was reported to be a core target for companies in every context; in this frame, [83] explored unobtrusive metrics to assess operators' performance during clinical procedures using multiple sensors and psychophysiological measurements. Similarly, [84] applied machine learning to predict office workers' perceived productivity, integrating physiological, behavioral, and psychological data.

TABLE 3. Research clustered based on general wellbeing (safety) and performance (7 out of 66 total papers).

Analyzed Factors	Application Context	Reference
Wellbeing (Safety) (5 papers)	Construction	[78]
	General applications	[79]
	General applications	[85]
	Manufacturing	[81]
	Office workers	[82]
Productivity (2 papers)	Healthcare workers	[83]
	Office workers	[84]

VI. DESIGN SOLUTIONS AND WEARABLE INTEGRATION

A further important classification of the SR and EDA solutions found in the literature concerns electrode design, device maturity, portability and integration level. In this regard, Table 4 provides this information. It is worth highlighting how dry electrodes embedded in portable solutions appear to be the most frequently adopted methodology for monitoring operators in real world scenarios; in fact, 75% of the papers analyzed relied on this specific approach.

A. ELECTRODES DESIGN: WET VS DRY

Dry electrodes (employed, for instance, by Empatica, Shimmer, and Biopac) have been reported to represent the most frequently adopted solution (80% of the papers analyzed), not only in real-world scenarios but also in laboratory settings. This solution was found to be the most comfortable in terms of wearability and ease of positioning, as these electrodes are usually integrated into wearable devices and do not need to be attached to the body at specific locations. On the downside, the absence of an electrolytic interface makes this approach more prone to motion artifacts and temporary signal loss compared to gel-based electrodes, especially when monitoring high-dynamic tasks. In fact, in most of the identified studies, the complementary use of electrolytic gel applied between the skin and the electrodes has been widely suggested to minimize skin–electrode electrical impedance. The use of wet electrodes (employed in about 20% of the papers analyzed and including commercial devices such as PLUX Biosignal, ErgoLAB, and FlexComp Infinity Biofeedback) has been reported to rely mainly on traditional Ag/AgCl electrodes, which need to be firmly attached to the skin to remain in place throughout the acquisition. This approach can ensure an optimal signal-to-noise ratio; however, it presents several limitations, including reduced durability, more complex positioning, and a higher likelihood of causing allergies or cutaneous reactions.

B. LEVEL OF DEVICE MATURITY: COMMERCIAL VS CUSTOM

The analysis of the literature highlights the prevalence of commercial solutions for estimating SR and EDA. This predominance is mainly due to the fact that, from an application perspective, high stability, repeatability, and robustness of both sensing elements and conditioning electronics are essential when monitoring workers in the field and during real-world scenarios. In this context, newly developed custom technologies and devices may still present several challenges. However, given the limitations that persist in EDA acquisition with commercial devices, several noteworthy examples have emerged in the literature, proposing innovative sensing technologies designed to maximize the advantages of both dry and wet electrodes while overcoming their current drawbacks. For instance, printed electronics have been reported as one of the most promising approaches, enabling the fabrication of dry electrodes capable of improving skin adhesion. These technologies, which leverage innovative conductive inks, ultra-thin laser-printed surfaces, and conformable or tattoo-like devices, have demonstrated reliable and effective monitoring performance [24]. Another promising strategy involves the direct integration of conductive materials into fabrics, resulting in electronic textiles (e-textiles) that create miniaturized sensing points easily wearable alongside standard personal protective equipment (PPE) or workwear [31]. In their study, Kim and colleagues proposed integrating a nano-fabric radiative cooler (NFRC) and a miniaturized temperature sensor alongside EDA electrodes to improve signal stability under hot outdoor conditions. Furthermore, customized EDA monitoring solutions have been developed for scenarios in which electrodes must be directly integrated into work instruments or tools—for example, embedding electrodes within a computer mouse, as demonstrated by [87]. Finally, [71] introduced a novel approach in which EDA electrodes, along with multiple other sensing elements, were miniaturized to fit within a ring. This unobtrusive solution allows for continuous, long-term monitoring while enhancing user comfort. Following this trend, electrode miniaturization—although particularly challenging for low-amplitude signals like EDA—represents a highly promising and powerful strategy to reduce motion artifacts and attachment-related issues.

TABLE 4. Classification based on design, portability and integration level.

Electrodes Type	Commercial/Custom	Portability	Integration Level	References
Wet electrodes	Commercial EDA (e.g., Plux biosignal, Biopac)	Portable device	Single wearable with single sensor	[58]
			Single wearable with multiple sensors	[67], [81]
			Multiple wearable with single sensors	[74], [11]
			Multiple wearables with multiple sensors	[75]
		Benchtop instrumentation	No wearable integration	[43], [61], [66]
Dry electrodes	Commercial EDA (e.g., Shimmer, TD203s) (often + gel)	Portable device	Single wearable with single sensor	[39], [42], [46], [50], [57], [69], [79]
			Single wearable with multiple sensors	[28], [30], [31], [32], [48], [53], [63], [64], [71], [73], [78]
			Multiple wearable with single sensors	[21], [27], [33], [34], [40], [41], [44], [45], [47], [51], [52], [55], [59], [68], [70], [72], [82]
			Multiple wearables with multiple sensors	[22], [23], [25], [29], [36], [38], [54], [56], [65], [83], [84]
		Benchtop instrumentation	No wearable integration	[37], [76], [86]
	Custom EDA or SR (printed, copper tape)	Portable device	Single wearable with multiple sensors	[24], [80]
			Single wearable with single sensors	[87]

In contrast to EDA monitoring, sweat collection and quantification rely more frequently on customized solutions than on commercially available devices. Accurate and long-term reliable sweat collection represents an active area of research, with efforts focused on developing low-cost microfluidic sensors that enable rapid sweat sampling, provide an effective interface between microfluidics and multiplexed electrochemical readouts, and ensure accurate detection for continuous sweat biomarker analysis. Despite these advancements, several challenges remain, including the high cost of electrode and microfluidic fabrication, irregular sweat transfer and capture rates, sample evaporation, and inconsistent sweat volumes. For instance, [80] proposed customized copper-based electrodes designed for monitoring operator well-being. Their approach demonstrated how combining copper-based dry electrodes with skin-interfaced microfluidics can enable admittance measurements that correlate with sweat production during various tasks. Similarly, [79] addressed the limitations of traditional collection techniques, such as absorbent patch methods, which are prone to contamination, labor-intensive, and limited in the number of samples that can be collected over time for offline reference analysis. They developed an easy-to-fabricate sweat collection patch that integrates an analysis chamber hosting a conductivity sensor and a sequence of 5 to 10 reservoirs equipped with level indicators to monitor filling speed. This system enables continuous electrochemical monitoring while simultaneously allowing chronological sweat sampling for offline biomarker analysis.

C. DEVICE PORTABILITY: WEARABLE VS BENCHTOP INSTRUMENTATION

Focusing on the integration of EDA sensing within more complex wearable systems, the analyzed studies can be broadly classified into two main categories:

- those employing fully wearable devices (e.g., wristbands, smartwatches, patches);
- those relying on attached electrodes interfaced with non-wearable electronics.

In this regard, Table 4 details this classification and further distinguishes between solutions that used single or multiple devices, designed for single- or multi-sensing applications. All these aspects will be discussed in the next sections.

As already reported, most wearable EDA devices typically employ dry electrodes and are commonly integrated into patches—mainly as part of customized solutions [24], [31], [79], [80] —or into wristbands. Among commercial solutions, the Empatica E4 wristband emerges as the most widely adopted, being employed in more than 30 of the analyzed studies, as highlighted in Table 4. This possibility of integration, combined with the absence of adhesive fixation, was reported to offer significant advantages for long-term monitoring and on-site data collection in real-world scenarios, where wireless solutions were preferable to avoid interfering with working activities. To enable seamless integration within compact devices, the conditioning electronics and, when applicable, the processing unit were typically implemented on miniaturized boards. This design ensured optimal portability, with lightweight and compact dimensions. However, such configurations presented limitations when high measurement accuracy was required—for instance, when investigating subtle phenomena such as mental workload or attention-related tasks. In contrast, non-wearable solutions generally employ wet Ag/AgCl electrodes connected to portable or benchtop instrumentation housing the conditioning electronics. These setups were identified to be particularly suitable for monitoring static tasks that do not involve significant movement, where the presence of wires would not interfere with performance and where high measurement accuracy was essential.

For example, they are often preferred for laboratory-based studies assessing mental concentration and cognitive load, benefiting from the precision of certified high-performance instrumentation.

D. LEVEL OF INTEGRATION IN WEARABLES: SINGLE OR MULTI-SENSING APPROACHES

As previously introduced, another relevant classification concerns whether operator monitoring relied solely on EDA devices or combines EDA with additional sensors. Apart from a few studies where EDA was monitored in isolation [88], [89], most of the analyzed literature reports EDA measurements combined with other physiological and/or biomechanical parameters. This multimodal approach has been identified as particularly valuable because conditions such as arousal, workload, and stress involve complex physiological responses across multiple systems and could not be effectively assessed through a single parameter. Among the complementary signals, cardiac activity represented the solution most integrated with EDA. This was reported to be monitored via electrocardiography (ECG), photoplethysmography (PPG), or blood pressure measurements. Both ECG and PPG signals allowed for the extraction of heart rate variability (HRV) metrics, which have been reported to be well-established markers associated with stress and mental workload. Notably, several of the wearable devices reviewed in the literature already incorporated integrated PPG or ECG monitoring. Respiratory activity was another parameter frequently combined with EDA to improve the detection of stress-related events [22], [33]. Like ECG and EDA measurements, respiratory monitoring was performed by unobtrusively using elastic belts worn around the chest, enabling data collection during normal working tasks without interfering with activity. In addition to these standard physiological measures, many studies combined EDA with biomechanical data, such as motion tracking via inertial measurement units (IMUs). This integration was reported to facilitate the correlation of EDA responses with specific body positions and movements, improving the interpretation of psychophysiological patterns during occupational task execution. One of the most recent and challenging trends identified in the literature is the development of dedicated infrastructures capable of managing and synchronizing multimodal data streams from multiple sensors using a software platform or ecosystem [67]. Such integrated frameworks represent a significant advancement, as they enable the extraction of correlated features across diverse physiological and biomechanical signals, thereby improving the robustness and accuracy of psychophysiological state detection.

VII. SENSORS CHARACTERIZATION AND TESTING PROTOCOLS

As discussed in the previous sections, since most of the EDA solutions – including sensing component, such as electrodes - present in the analyzed literature and specifically used for operator monitoring are based on commercially available devices (95% of the studies), limited information was typically provided regarding the metrological characterization of these systems. Standard evaluations of characteristics such as accuracy, resolution, and measurement range are generally carried out by device manufacturers rather than reported in research study. Consequently, performance metrics were usually derived from datasheets provided by suppliers rather than from independent experimental validation. In contrast, some details about characterization procedures were available in studies employing custom sensors, both for EDA and sweat rate quantification (representing approximately 5% of the analyzed literature). Based on these considerations, Table 5 classifies the reviewed works according to four criteria:

- electrodes/sensing components category – commercial or customized;
- testing environment – laboratory-based or field-based;
- test type – standardized or customized;
- specific characterization tests – either methodological or application-driven.

As shown in Table 5, most of the reported standard or customized tests were highly application-specific and were rarely repeated across multiple studies, with the majority appearing in only one or two scientific papers. Among the more commonly employed tests, customized evaluations involving software- or video-based tasks, simulations, or virtual and mixed reality environments accounted for approximately 25% of all tests reported in the analyzed studies. Additionally, manual task-based evaluations represented a significant portion (26%) of the testing protocols. These assessments included both controlled laboratory tasks and work-related routines, as well as modified procedures designed specifically for testing purposes—such as repetitive tasks, activities performed under added mental workload, or workflows restricted to specific subtasks.

A. COMMERCIAL DEVICES TESTING PROTOCOLS

Most of the analyzed studies employing commercial sensors reported characterizations focused primarily on assessing the suitability of the electrodes for detecting the specific psychophysiological aspects targeted in the monitored tasks—such as fatigue, stress, well-being, or concentration. In this regard, Table 5 summarizes all the types of tests identified in the reviewed literature, classified according to three dimensions:

- Sensor type – commercial vs. customized;
- Testing setting – laboratory vs. field;
- Test type – standardized, customized, or preliminary characterization.

As reported in that table, the most frequently recurring customized tests involved software- or video-based tasks, manual tasks (either simple or collaborative with robotic systems), virtual and mixed reality setups, and task-specific simulations. Standardized tests were mainly applied

TABLE 5. **Classification based on protocols for in lab and on field testing.**

Electrodes/Sensing Components Category	Testing Environment	Testing Category	Testing Type	References
Commercial EDA	In lab	Standard tests	Multi-Attribute Task Battery II (MATB-II) Software for Human Performance and Workload Research	[34]
			Corsi test for visuospatial memory	[37]
			Trier Social Stress Test (TSST) (Kirschbaum, 1993)	[67]
			Stroop Color-Word Test (SCWT) (Stroop et al, 1935)	[36], [67], [86]
			Montreal Imaging Stress Task (MIST) (Dedovic, 2005)	[67]
			Continuous performance test (CPT)	[27]
			N-Back (induced visual, auditory, and dual mental workload)	[36], [86]
			Simple reaction test (SRT)	[36]
			Flanker test	[36]
		Custom tests	Software/video-based tasks	[33], [39], [45], [50], [84]
			Manual task (simple or with collaborative robots)	[23], [37], [45], [64], [68], [74]
			Virtual/mixed reality	[43], [44], [47], [49], [56], [65], [71]
			Custom simulations	[11], [20], [22], [55], [66], [70], [71], [75], [83]
			Custom cognitive tests	[11], [37], [67]
			Manual proof reading	[57]
			Approach and touch task	[81]
			Trust game decision	[81]
			Combined cognitive + physical task	[27], [58]
			Dual task (cognitive task + sing-a-song stress test + speaking task + startle movie condition).	[76]
			Drawing with CAD	[59]
			Office-like workstation	[25], [84]
			Noise exposure	[72]
	On field	Standard tests	2-Choice Reaction Time evaluation test	[21]
			N-back task,	[38]
			Doctor Game task	[38]
			Webcall task	[38]
		Custom tests	Standard working routine	[28], [41], [46], [48], [73], [78]
			Standard working routine + specific tasks	[63] , [82]
			Specific working task + cognitive tasks	[35], [36], [42], [69]
			Driving tasks	[60]
			Specific selected working tasks	[30], [53], [54]
			Simulated scenarios	[51], [65]
			Repetitive working tasks	[40]
			Weight lifting task	[29]
			Custom residential spa program (with psychological intervention, physical activity, thermal spa treatment, health education and eating disorder therapy)	[52]
Custom EDA or SR	In lab	Preliminary characterization	Calibration with known target quantity (sweat)	[24], [32], [79], [80]
			Wearability tests and robustness against sweating	[24]
		Standard tests	Stroop Color Word Task Mental Arithmetic Task	[49], [62]
		Custom tests	Reliability of the device comparing with reference data	[24], [31], [79]
	On field	Custom tests	Standard working routine	[24], [31], [79]
			In vivo physical excercise (biking, trademilling)	[32], [80]

in laboratory settings, with the Stroop Color–Word Test (SCWT) and N-Back tasks (visual, auditory, or dual) emerging as the most commonly used paradigms for inducing and assessing mental workload. Only a limited number of studies employed non-wearable reference instrumentation to validate the performance of wearable commercial devices (e.g., [38]).

A wide variety of experimental setups can be identified across the analyzed literature, which can be broadly classified into two main categories:

- Static setups – operators perform tasks with minimal or no movement, such as workstation activities involving computers or bench-top tasks;
- Dynamic setups – operators are required to perform tasks involving significant physical effort, typical of manufacturing, industrial, or construction environments.

The protocols adopted for these tests exhibited considerable heterogeneity, largely due to the diversity of psychophysical aspects under investigation and the specific challenges associated with each testing category. For static tasks targeting cognitive states - such as attention, mental workload, or concentration [11], [34], [35], [37], [39], [40], [41], [42], [44], [45], [46], [47], [48], [49], [50], [87] - the absence of significant movement typically improved the signal quality, as recordings were less affected by motion artifacts. However, in tests where mental effort and concentration were assessed without applying external stressors, protocols often require a higher number of repetitions and/or the integration of self-reported questionnaires to better contextualize the acquired data. In contrast, for dynamic tests targeting physical states - such as fatigue and stress [22], [23], [24], [27], [28], [29], [30], [31], [32], [61], [79], [82] - special attention was given to protocol design. Increasing both the number of repetitions and the number of sensors was often necessary to enable effective post-processing techniques, such as Principal Component Analysis (PCA) or mix source separation (MSS), which helped remove motion artifacts and disentangle physiological responses due to physical exertion caused by those caused by psychological stress.

B. CUSTOMIZED DEVICES CHARACTERIZATION AND TESTING

Experimental validation of customized electrodermal activity (EDA) and sweat rate (SR) sensors mainly involved a wide range of testing settings and calibration strategies. The studies analyzed can be broadly categorized based on:

- Testing environment – laboratory-based vs. real-world scenarios;
- Type of test – standardized vs. customized protocols;
- Objective – preliminary metrological characterization vs. validation for practical use.

For newly fabricated customized devices, preliminary characterization typically involved optical and/or electrical assessments to ensure that the sensor accurately measures the target variables - such as changes in conductance or admittance. Customized SR sensors often undergo additional laboratory-based calibration, where controlled quantities of synthetic or sweat-like fluids are used to characterize sensitivity and stability prior to in vivo validation [79], [80]. An essential aspect of these protocols was calibration against known physiological baselines, particularly sweat secretion rates, which enables the quantification of sensor performance and facilitates cross-study comparisons. Wearability and robustness were also commonly evaluated, particularly for SR electrodes, using physical exercise protocols such as cycling or treadmill trials [32], [80].

Laboratory validation of customized EDA and SR devices frequently relied on cognitive stress-inducing protocols to elicit controlled sympathetic nervous system responses. Commonly used paradigms include the Stroop Color–Word Test and mental arithmetic tasks [49], [62]. These protocols were considered gold standards because they reliably were able to induce psychological stress under reproducible conditions, enabling researchers to assess the sensitivity, temporal resolution, and responsiveness of the devices without introducing the variability associated with physical stressors.

On the other hand, in contrast to controlled laboratory tests, on-field evaluations focused on real-world working routines and application-specific tasks, such as repetitive industrial activities, to assess device performance in practical scenarios [31], [79]. During these tests, customized EDA sensors are often benchmarked against commercial reference devices to evaluate accuracy and reliability under naturalistic conditions. Quantitative comparison metrics - such as mean values or root-mean-square (RMS) errors - were frequently used to assess agreement between customized and standardized devices. On-field protocols also enabled the evaluation of sensor performance under uncontrolled environmental factors, including motion variability, ambient temperature fluctuations, and emotional responses, which are, in general, challenging to replicate in laboratory conditions. This step is reported to be crucial for assessing the reliability, usability, and robustness of customized devices in real operational contexts.

Overall, the validation strategies reported in the analyzed literature demonstrated a progressive two-step framework:

- Initial laboratory-based characterization in controlled environments to establish sensor performance and signal quality;
- Subsequent on-field testing under realistic conditions to evaluate practical applicability and long-term usability.

This combined approach reflects a broader trend in wearable biosensing research, emphasizing the importance of bridging laboratory validation with real-world performance to ensure the accuracy and robustness of customized EDA and SR sensors.

C. GUIDELINES FOR PROTOCOLS DURING EDA MONITORING

Despite the lack of uniformity in the testing protocols reported in the analyzed literature (as summarized in Table 5), several recurring methodological choices can be identified as good practices specifically for EDA signal acquisition. These best practices relate to five main aspects:

1) ELECTRODE/SENSING POINTS PLACEMENT

Across studies, fingers and the inner wrist emerge as the most used electrode/sensing points locations, provided they did not impair the movements required by the monitored task. In the literature, two-finger acquisition was widely regarded as the gold standard for EDA monitoring. However, alternative locations - such as the wrist, shoulder, or forehead – have been increasingly used when finger activity was central to the monitored task, hand freedom should be preserved or multimodal sensors were co-located on the same patch (e.g., EDA and heart rate). When alternative placements were adopted, equivalence with the gold-standard finger acquisition should be verified by simultaneous recordings from both locations on the same subject [24]. This was crucial due to the high inter- and intra-individual variability in EDA amplitudes across different body sites.

2) INFORMATIVE/BRIEFING SESSIONS

An often overlooked yet critical aspect was reported to be the inclusion of a comprehensive informative session at the start of the testing protocol. Proper participant training or briefing helps ensure that measured stress, fatigue, wellbeing, and concentration levels reflect the task demands rather than the novelty of the task or equipment. This was particularly relevant when subjects were required to use unfamiliar tools, operate complex instrumentation or engage with simulated or virtual environments [37], [62], [66]. Providing participants with clear explanations and, when appropriate, practice trials reduced confounding stress signals unrelated to the monitored task.

3) BASELINE RECORDINGS

Concerning baseline recordings, most studies adopt a three-phase acquisition structure, including initial baseline recording, task recording; and final baseline recording. Baseline recordings were typically performed with participants in a relaxed and motionless state, ideally with eyes closed and no active engagement (e.g., talking or moving). These recordings were critical since they allowed normalization of EDA signals during tasks by accounting for individual physiological variability and enabled the detection of baseline drift occurring over time, which is particularly relevant for long-duration experiments. Baseline durations varied substantially across studies, ranging from 1–2 minutes to several days when participants were acclimating to complex equipment [71].

4) TASK SETTING AND REPETITIONS

During task acquisition, a recurring best practice was the repetition of the same task across multiple trials. This approach offered several methodological advantages including the fact that it enabled the use of robust statistical models, such as mixed-effects models [90], to account for inter-individual variability and within-subject changes over time, it increased the statistical power to detect subtle effects by reducing the influence of background noise and motion artifacts and it helped disentangle stress responses caused by task novelty from those intrinsically linked to the activity itself [40], [81]. Repetition-based protocols also enhanced the reliability of detecting trends in fatigue, stress, or mental workload within and across individuals [66], [74].

5) DEBRIEFING AND QUESTIONNAIRES

Finally, incorporating a closing debriefing session was reported to provide complementary subjective data that enhanced the interpretation of EDA signals. This phase typically involved self-reported questionnaires capturing participants' perceived stress, mental workload, fatigue, or emotional states, gathering feedback about task difficulty and comfort, and collecting insights into individual characteristics potentially influencing EDA responses. These subjective measures were particularly useful when correlating physiological responses with self-perceived states, strengthening the interpretation of EDA-derived metrics.

Therefore, from the literature analyzed, a set of standardized methodological recommendations emerged despite the variability in testing protocols. Ensuring optimal electrode placement, providing clear participant briefings, integrating baseline recordings, adopting task repetitions, and including post-task debriefing sessions represent best practices to improve the quality, interpretability, and comparability of EDA data across studies.

VIII. SIGNAL PROCESSING

Although no standardized framework for EDA signal processing emerged from the analyzed literature, several common steps can be identified across studies. To facilitate comparison,

Table 6 provides a structured summary of the main processing procedures reported. However, as can be observed, there was substantial variability in the processing workflows adopted. Notably, nearly one-third of the studies (about 33%, i.e., 21 out of 65 papers) either did not report any processing details or explicitly stated that the raw EDA signal was used for analysis. This lack of methodological transparency complicated comparisons across studies and highlighted the need for more standardized processing pipelines in future research.

The processing of EDA signals involved several recurring steps across the analyzed literature, although no standardized methodology has yet been established.

The first stage in most studies was *filtering*, which typically addressed two main objectives including artifact removal and signal smoothing. In some cases, these were explicitly described as separate steps, while in others they were merged into a single filtering procedure.

High-frequency noise and low-frequency artifacts were commonly mitigated using median, low-pass, high-pass (often Butterworth or elliptical), or root-mean-square (RMS) filters [11]. This denoising stage was found to be crucial for reducing artifacts introduced by factors such as excessive sweating, abrupt body movements, electrode pressure, or intense cardiovascular activity. Some studies reported that large-magnitude artifacts – mainly caused by motion or electrode displacement – often required manual inspection or rolling filters for correction [22], [85]. While a few papers

TABLE 6. Processing strategies main steps.

Processing step	Methods	References
Artifact removal	Standard Pass Band filtering (usually typical ranges 0.05–5 Hz) or rolling filters (moving average, median filter, or adaptive versions)	[46], [47], [70]
	Noisy signal segments removed manually or automatically	[41]
	Automatic removal through Neurokit2 tool	[76]
	Savitzky-Golay filter	[54]
	Manual visual inspection to exclude poor-quality data with artifacts	[61]
Smoothing	Moving Average Filter	[28], [48], [70], [87]
	Blackman Window Filter	[47]
	Hanning Smoothing	[84]
	Median Smoothing / Filter	[43], [50], [81]
	Savitzky-Golay Filter	[79]
	Adaptive Smoothing	[45]
	Rolling Filter	[42], [46], [53]
Normalization	Ratio between mean SCL during task and mean of resting baseline SCL	[35], [43], [67]
	Min-max rescaling, to fall in a range 0-1	[41]
	based on statistical features of short windows of EDA before and after specific task	[47], [54]
	Using z-score to offset individual variations	[46]
	Using the first-order difference equation	[60]
	square root transformed o correct for positive skew	[61]
	scaled with use of the Python StandardScaler function from scikit-learn	[76]
	not specified, generic normalization per participant to remove interpersonal differences	[70], [71], [74]
Segmentation	Bottom-up segmentation using the *Ruptures* Python package; segments used to detect state changes in EDA.	[47]
	Fixed-length sliding windows: 30s frames with 50% overlap (120 data points with 60 data points overlap).	[28]
	Fixed-length windows: 30s windows with no overlap.	[34], [84]
	Event related segmentation: segments corresponding to rest and different tasks	[35], [60], [76]
	Segmentation only around specific devents: 10s before/after alarm.	[70]
Decomposition	Continuous Decomposition Analysis (CDA)	[27], [36], [55], [59], [64], [73], [76]
	Ledalab (CDA inside)	[27], [47], [55], [59], [75], [76], [84]
	Convex Optimization / cvxEDA (ARMA/IIR)	[35], [46], [86]
	Bateman Function-Based Deconvolution	[73]
	Tonic-Phasic Separation (generic, with customized methods)	[40], [42], [43], [45], [68], [72], [74]
Feature extraction/ Peak detection	find_peaks() (Python)	[81]
	Ledalab (in-built SCR detection)	[27], [47], [75], [84]
	Threshold-based (min amplitude or time)	[35], [69], [73]
	SCR = EDA - SCL formula	[81]
	NS-SCRs per minute	[43]
	Custom Algorithms / Trough-to-peak	[35]
Machine Learning classification	General ML / unspecified	[71], [78]
	StandardScaler (scikit-learn)	[76]
	Supervised Learning / SCR-based classification	[35], [47]
	Feature-based statistical modeling (not always ML)	[47], [67], [84]
	Signal-based segmentation + classification	[47]

described semi-automatic or threshold-based artifact rejection (e.g., excluding values outside physiological limits), fully automated approaches such as Independent Component Analysis (ICA) were rarely applied, likely due to the typical single-channel nature of EDA recordings.

Smoothing was frequently integrated with the filtering step, most commonly through moving averages of varying window sizes. While median filters and Savitzky–Golay smoothing were less common, they were preferred in studies seeking to preserve waveform morphology. Rolling filters were also employed more often than traditionally assumed, especially in scenarios involving high motion variability.

Regarding normalization, no consistently adopted method emerged from the literature. Many studies did not explicitly report whether normalization was applied, suggesting it may have been integrated implicitly within feature extraction pipelines. Among those that described their approach, z-score normalization was commonly used for inter-subject comparisons, while others applied min-max normalization or baseline subtraction to reduce inter-individual variability, resulting in normalized signals typically ranging between 0 and 1.

Following normalization, many studies performed signal segmentation, which served two primary purposes including enabling the extraction of more complex features from the raw signal, and facilitating correlation analyses with other physiological measures (e.g., ECG, HR) or with specific experimental tasks. Fixed-length windows - often around 30 seconds - were widely used for baseline or feature extraction, sometimes with overlapping segments to increase temporal resolution. Alternatively, several studies adopted event-centered segmentation, isolating physiological responses around predefined stimuli such as alarms or specific task events. This could be then synchronized with beat-to-beat segmentation when correlating with cardiac signals [91] or aligned with task-specific time intervals [60]. A smaller subset of studies relied on data-driven segmentation methods - such as the Ruptures algorithm - for detecting spontaneous state transitions, although their adoption remained limited due to methodological complexity and lack of standardization.

Once preprocessed, signals were typically decomposed into tonic and phasic components, a crucial step for extracting meaningful physiological features. The tonic component, also referred to as Skin Conductance Level (SCL), represents the slow-varying background activity, generally ranging between 2–20 μS. It is highly sensitive to inter-individual variability and can fluctuate substantially within the same subject under different psychological states. The phasic component, known as the Skin Conductance Response (SCR), captures rapid oscillations typically ranging from 0.05 to 0.1 μS, often triggered by discrete stimuli (e.g., deep breaths or motor actions) or occurring spontaneously. Separation of these components was commonly performed using narrow bandpass filters (cutoff frequencies around 0.1–0.2 Hz and 1–2 Hz) or advanced decomposition algorithms, including wavelet-based decomposition, convex optimization models, or Continuous Decomposition Analysis (CDA). For example, [50] used a 0.3 Hz cutoff to eliminate abnormal baseline interferences related to instrumentation artifacts. Among available tools, *Ledalab* (a MATLAB-based toolbox) and its CDA module were the most widely used, while *cvxEDA*, a convex optimization approach, was often preferred when extracting interpretable phasic components. In some cases, authors mentioned tonic-phasic separation without specifying the method, suggesting reliance on built-in functions or proprietary pipelines.

After decomposition, the focus shifted to feature extraction from both SCL and SCR components. A recurring step was the automatic detection of SCR peaks, frequently implemented using *Ledalab*'s built-in functions, which incorporated constraints on amplitude and latency. When custom methods were used, threshold-based detection was quite common, for example by considering SCR amplitudes greater than 0.01–0.02 μS. In more recent studies, *Python*'s and *MATLAB*'s *find_peaks*() functions (e.g., via *SciPy*) have been increasingly adopted for flexibility and reproducibility. Several authors computed SCRs directly as EDA minus SCL, while others relied on trough-to-peak analysis to isolate responses. For studies lacking explicit normalization, baseline SCL levels were sometimes used to normalize the processed signals before meaningful peak detection [67].

Finally, a growing number of studies leveraged machine learning to analyze extracted EDA features. By integrating EDA-derived measures with other multimodal physiological data, researchers aimed to classify mental workload, stress levels, or other psychophysiological states, as well as to build predictive regression models [11], [67]. This emerging trend underscored the potential of combining advanced sensing, feature engineering, and data-driven modeling to improve the discrimination between stress-related fluctuations and movement-induced artifacts, ultimately enhancing the robustness of EDA-based analyses.

IX. QUANTITATIVE FEATURES

To derive objective and justified conclusions from experimental tests, the studies analyzed consistently relied on quantitative features extracted from EDA signals. As highlighted in this review, the previously presented signal processing procedures primarily served as a preparatory step for extracting reliable features from properly preprocessed signals.

Based on the examined literature, the quantitative features extracted from EDA data can be broadly categorized into several groups (Table 7), including descriptive statistics (41% of the studies), peak analysis–related features (25% of the studies), outputs from statistical tests (20% of the studies), shape-related features (6% of the studies), complex composite indexes (e.g., stress-related indices) (4% of the studies); frequency-domain features (3% of the studies) and machine learning–derived outputs (3% of the studies).

A substantial proportion of studies focused on descriptive and inferential features, computed from both the complete EDA signal and its decomposed components - namely, the tonic Skin Conductance Level (SCL) and the phasic Skin Conductance Response (SCR). Among the most commonly extracted features were central tendency metrics such as the mean, median, and mode, widely used to assess the overall arousal level or baseline skin conductance. Similarly, dispersion measures - including standard deviation, variance, and interquartile range - were frequently employed to characterize the variability in conductance responses.

In the time domain, features related to the phasic component were particularly prevalent, as they provided insights into signal shape and dynamics. Examples included slope, skewness, kurtosis, zero crossings, and cumulative maxima/minima. However, the most widely reported metrics in this context were those associated with peak analysis, given their close relationship to psychophysiological responses. Specifically, peak amplitude, peak count, rise time, and area under the curve (AUC) were among the most significant indicators used to quantify stress levels and to correlate EDA responses with other physiological measures such as heart rate (HR). Conversely, frequency-domain features - such as mean frequency, median frequency, and spectral power - were less frequently reported and appear predominantly in technically oriented studies involving more advanced analysis pipelines.

Regarding statistical analysis, both parametric and non-parametric tests were frequently employed to evaluate the significance of observed differences across experimental conditions. Most studies began by performing normality checks, typically using the Shapiro–Wilk or Kolmogorov–Smirnov tests, to determine the appropriate statistical approach. Among the parametric methods, Analysis of Variance (ANOVA) - including one-way, two-way, and repeated-measures designs - was the most commonly applied technique for comparing group differences. In addition, correlation analyses using Pearson or Spearman coefficients were widely used to relate EDA-derived features to other physiological or psychological measures. When the assumption of normality was violated, studies typically adopted non-parametric tests, with the Mann–Whitney U test, Wilcoxon signed-rank test, and Kruskal–Wallis test being the most frequently employed alternatives.

It is worth noting that, beyond individual feature extraction, some studies proposed composite indexes to provide a holistic quantification of psychophysiological states. For instance, [81] introduced a physiological state index (R), defined as a weighted average of normalized physiological triggers. These triggers were computed as individually calibrated ramps, scaled from each participant's baseline value up to 130% of that baseline. Based on this index, three distinct states were specifically defined: relaxed (0–30%), standard (30–65%), and stressed (65–100%). The weighting factors were determined experimentally, according to the contribution of each

TABLE 7. Classification of quantitative features extracted from EDA/sweat rate signals.

Category	Features	References
Descriptive Statistics (EDA and tonic or SCL)	Mean	[21], [22], [23], [25], [27], [29], [35], [37], [38], [39], [42], [44], [46], [49], [50], [53], [54], [57], [59], [62], [64], [66], [67], [72], [74], [75], [82], [83], [84], [86], [87]
	Standard Deviation	[25], [29], [34], [46], [48], [50], [53], [57], [65], [67], [70], [75], [76], [82], [83], [84], [86]
	Median	[34], [48], [53], [54], [65], [67], [73], [82], [84]
	Mode	[54]
	Minimum/Maximum (local or cumulative)	[34], [46], [47], [48], [50], [53], [54], [65], [73], [83], [84]
	Percentiles/IQR	[58], [82], [84]
	Variance	[53], [54], [65]
Shape Features (Slope, Skewness, Kurtosis)	Slope	[65], [84], [86]
	Skewness	[40], [65], [76]
	Kurtosis	[40], [48], [53], [65], [76]
Entropy Features	Approximate Entropy	[65]
Frequency Domain Features	Mean/Median Frequency	[48], [53], [73]
	Spectral Power Bands	[48], [53]
	Power Spectral Density	[53]
Peaks Analysis features (phasic EDA or SCR)	Amplitude, Rise Time, Recovery	[24], [27], [35], [36], [40], [44], [50], [53], [60], [67], [68], [73], [76], [86]
	Number of Peaks	[43], [46], [53], [57], [63], [67], [68], [73], [81], [86]
	Peak-to-root mean square	[48]
	Peak Energy	[50], [53], [67], [76]
	Peak Timing (latency, location)	[27], [50], [53], [60], [67], [68], [73], [86]
	AUC (Area Under Curve)	[27], [65], [76]
Statistical Tests – Parametric	t-test	[20], [21], [35], [59], [83]
	ANOVA	[22], [23], [25], [38], [44], [47], [50], [56], [70], [74]
	Bonferroni	[47], [83]
	Bartlett's	[56]
	Correlation analysis	[21], [22], [28], [33], [70], [78]
Statistical Tests – Non-parametric	Wilcoxon	[37], [46], [59]
	Mann–Whitney U	[28], [62], [73], [83], [87]
	Kruskal–Wallis	[28]
	Shapiro–Wilk	[56], [59], [82]
	Friedman	[55]
	Kolmogorov–Smirnov	[70]
Machine Learning Outputs	Accuracy	[30], [39], [67]
	Precision/Recall	[11], [67]
	F1 Score	[67]
Other features or indexes	Sweat Rate	[32], [79]
	Sodium Concentration	[32]
	First derivates EDA/Difference (%) of Mean values of EDA in different timepoints	[50], [56], [59]
	Stress Rate / Event Frequency	[69], [81]

physiological parameter to the overall state estimation. Heart rate (HR) received the largest weight (0.6) due to its sensitivity to situational stressors, while respiratory rate (RR) was assigned a weight of 0.3 as it reflects longer-term trends and complements HR in assessing bodily unrest. Finally, EDA contributed a weight of 0.1, given its rapid responsiveness to stress but also its susceptibility to temperature and environmental arousal.

X. RATING QUESTIONNAIRES

As highlighted in Table 8, alongside the extraction of quantitative features from acquired EDA data, many studies integrated the analysis of structured interviews and questionnaires - both standardized and custom - as a complementary approach to enhance data interpretation.

Among the standardized tools, the NASA Task Load Index (NASA-TLX) emerged as the most frequently adopted instrument, appearing in approximately 14% of the studies analyzed. Widely recognized for its ability to evaluate perceived workload, the NASA-TLX measures six distinct dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. Its widespread use highlighted a growing research focus on understanding workload and cognitive demand in EDA studies involving human operators, where electrodermal responses were often influenced by subjective perceptions of task difficulty.

Beyond workload evaluation, other standardized questionnaires reflected a broader interest in exploring how stress, emotion, fatigue, and well-being interact with physiological signals. Tools such as the Borg-20 Scale, the Positive and Negative Affect Schedule (PANAS-10), and the State–Trait Anxiety Inventory (STAI) collectively accounted for around 8% of the reported questionnaires. The Borg-20 Scale, employed in three studies, quantifies perceived exertion and is particularly relevant in contexts involving physical tasks or exercise, where researchers aimed to relate subjective effort to EDA-derived physiological measures. Similarly, the PANAS-10, used in two studies, evaluates emotional states by capturing participants' positive and negative affect, providing a means to relate electrodermal responses to emotional or affective changes.

Other recurring standardized instruments include the NEO Personality Inventory (NEO-PI-R), which profiles personality traits based on the "Big Five" framework, the Perceived Stress Scale (PSS), the iGroup Presence Questionnaire (IPQ), and the General Health Questionnaire (GHQ). Collectively, these tools represent approximately 12% of the questionnaires mentioned in the analyzed literature. Their relevance lied in their capacity to provide complementary psychological insights when combined with EDA data, enabling researchers to distinguish between trait-level characteristics (e.g., stable personality features), state-dependent factors (e.g., transient stress or health conditions), and environmental influences (e.g., perceived immersion in virtual settings). This integrative approach facilitated a more comprehensive psychophysiological profiling of participants and improved the interpretation of individual differences in electrodermal responses.

In addition to standardized questionnaires, several studies employ custom instruments tailored to the specific experimental context. The most common custom questionnaires, reported in 7% of the reviewed works, gathered information on lifestyle, nutritional habits, demographics, medical history, physical activity levels, and task-related experience. By incorporating such contextual variables, researchers could better disentangle inter-individual variability in EDA signals. Moreover, another 13% of the studies reported the use of self-assessment questionnaires designed to quantify stress, fatigue, emotions, or perceived exertion through numerical rating scales (e.g., 0–5 or 0–10). These self-reported measures, when analyzed alongside EDA data, allowed for a more nuanced interpretation of physiological responses, especially in task-specific scenarios where subjective perceptions play a critical role.

Finally, a small number of studies incorporated external markers to improve the temporal alignment between EDA responses and task-specific events. For instance, works by [60], [69], and [78] employed additional contextual information, such as expert annotations, historical task data, telematics messages, and machine logs (e.g., machine speed, RTK-GPS data, or RCA metrics). These complementary data sources enhanced the precision of event labeling and enable a more accurate characterization of the relationship between electrodermal dynamics and operational demands.

XI. SIGNAL TRANSMISSION AND ARCHITECTURES

A. WEARABLE INTEGRATION

Measurement architectures in wearable sensing technologies play a decisive role in shaping the accuracy, reliability, and usability of physiological signal acquisition. The reviewed studies revealed a diverse range of measurement setups, each designed to address specific research objectives, application domains, and practical constraints.

As previously highlighted, in recent years, considerable efforts have been devoted to exploring different sensor modalities integrated into wearable electronic systems, enabling the continuous, non-invasive monitoring of physiological parameters. Among the most employed biosensing technologies were EDA, PPG, ECG, and IMUs. These sensing modalities were frequently embedded within compact wearable devices, which were deployed both in controlled laboratory environments and in real-world contexts to capture ecologically valid data.

A key distinction observed across the studies related to the number of wearable devices incorporated into the experimental setups. Among the 66 works analyzed, a slightly larger proportion (36 studies) employed multiple wearable devices compared to those relying on a single device (25 studies), while a minority of studies (5 works) did not involve wearable technologies at all. The decision to adopt multiple wearables was often driven by the need to compare

TABLE 8. Classification of questionnaires exploited for completing data analysis.

Category	Features	References
Standard referenced questionnaire	NASA TLX (workload)	[11], [34], [35], [37], [40], [42], [43], [51], [62], [68], [75], [81]
	Dundee Stress State	[11]
	Borg-20 scale	[27], [34], [45]
	PANAS10 (positive and negative affect scale)	[50], [66]
	Chalder Fatigue Scale (CFS)	[41]
	Moral Injury Outcome Scale (MIOS)	[71]
	Subjective Units of Distress Scale (SUDS)	[71]
	Virtual Reality Sickness Questionnaire	[71]
	Likert-type scale	[51]
	10-question Connor-Davidson Resilience Scale	[76]
	Negative Attitude toward Robots Scale (NARS),	[64]
	Self-Assessment Manikin (SAM)	[64]
	Maslach Burnout Inventory (MBI)	[52], [82]
	Hospital Anxiety and Depression Scale (HADS)	[52]
	State–Trait Anxiety Inventory (STAI-Y)	[52]
	7-item Hamilton Anxiety Rating Scale	[52]
	Freiburg Mindfulness Inventory (FMI)	[52]
	Brief COPE Questionnaire	[52]
	Emotion Regulation Questionnaire	[52]
	Karasek's Job Content Questionnaire	[52], [82]
	Perceived Self-efficacy Scale	[52]
	Work Addiction Risk test	[52]
	Brief Illness Perception	[52]
	20-item Toronto Alexithymia Scale	[52]
	Subject Matter Expert (SME) evaluation	[55], [75]
	Evaluation fatigue questionnaire (FAS, fatigue assessment scale)	[39], [52]
	Interpersonal Reactivity Index (empathy)	[61]
	World Values Survey (trust in others)	[61]
	Social Values Orientation survey (prosocial and individualistic preferences)	[61]
	Risk tolerance validated instrument	[61]
	NEO ("big five") personality inventory (personality traits) (NEO-PI-R)	[45], [61], [76]
	Perceived stress scale	[73], [76]
	iGroup Presence Questionnaire (IPQ)	[43], [71]
	General Health Questionnaire (GHQ)	[52], [56], [73]
	Recent Physical Activity Questionnaire (RPAQ)	[82]
	Effort-Reward Imbalance Questionnaire (ERI)	[82]
	11-point annoyance scale questionnaire	[72]
	Heat Strain Score Index (HSSI) questionnaire	[30]
Customized questionnaires	Near-miss recognition questionnaire	[45]
	Generic custom questionnaire (lifestyle, nutritional intake, demographic information, medical history, physical activity,experience on the task…)	[23], [37], [62], [73], [81], [82]
	Self-assessment stress evaluation (scale)	[51], [67]
	Custom questionnaire for interaction quality	[64]
	Self-assessment of valence and arousal (scale)	[76]
	Subjective questionnaires for stress and mood values;	[84]
	Self-ratings of fear, surprise, comfort, safety, and predictability	[74]
	Subjective ratings of stress, fatigue and of perceived exertion	[28], [52]
	Custom qualitative survey related to occupational stress	[59]
	Customquestionnaire to quantify cognitive alteration;	[86]
	Self-evaluation of emotions (scale)	[50]
Other quantities	External markers; Correlation with hystorical accident data; Telematics messages or machine logs (including machine speed, RTK-GPS, and RCA metrics)	[60], [69], [78]

hardware performance across manufacturers, ensure redundancy for improved data reliability, or capture a broader spectrum of physiological signals beyond the capability of a single device. By combining different wearables, researchers were able to collect richer and more diverse datasets, which not only enhanced the robustness of their findings but also enabled more comprehensive and multifaceted analyses.

An equally important distinction emerged when examining single-sensing versus multi-sensing wearable devices. Of the 61 studies that employed wearable sensors, nearly half (31 works) relied on multi-sensing devices capable of capturing multiple physiological signals simultaneously, whereas 30 studies used single-sensing devices restricted to one biosignal. Interestingly, only nine studies adopted an entirely minimalistic setup based on a single, single-sensing wearable, reflecting a relatively conservative approach to measurement. In contrast, most of the literature favored more complex configurations. In fact, 16 studies used a single multi-sensing device, 21 combined multiple single-sensing wearables, and 15 integrated multiple multi-sensing devices. This widespread adoption of heterogeneous sensor architectures underscored a prevailing trend in the field toward multi-modal physiological monitoring, where combining diverse sensing modalities was seen as best practice. Such integration not only improved the accuracy of the acquired data but also supported sensor fusion techniques and ground-truth validation, as complementary data streams provided cross-verification of physiological states.

Another relevant insight concerns the use of real-time data streaming. Despite the growing interest in real-time applications - such as biofeedback, closed-loop adaptive systems, and early intervention frameworks - only six out of the 66 reviewed studies explicitly reported implementing real-time data processing pipelines. This surprisingly low adoption rate appeared to stem from two primary factors. First of all, in many research designs, real-time analysis was not mandatory/necessary, particularly in studies focused on retrospective evaluations or algorithm development, where data were processed offline. Secondly, and perhaps more critically, the limited uptake may reflect technological constraints; in fact, academic setups often relied on software and hardware infrastructures that were not optimized to handle high-fidelity biosignal processing with the speed and robustness required for real-time deployment.

Nevertheless, recent advances in efficient signal processing algorithms, embedded systems, real-time operating systems, and edge computing have been rapidly reducing these technological barriers. While some degree of latency was unavoidable due to filtering and other preprocessing techniques, modern hardware and optimized pipelines has made it possible to achieve near-negligible delays, opening new opportunities for interactive and adaptive applications. This presents significant implications for domains such as neurofeedback, personalized user interfaces, and early-warning systems for fatigue, stress, or health deterioration. Future research should therefore place greater emphasis on developing and validating real-time processing frameworks, carefully balancing latency, computational efficiency, and signal accuracy. Addressing these challenges will be critical to advancing the practical applicability, responsiveness, and ecological validity of wearable physiological monitoring systems.

TABLE 9. Classification of wearable/sensing solutions.

Category	References
Single wearable single-sensing	[39], [42], [46], [50], [57], [58], [69], [79], [80]
Single wearable multi-sensing	[24], [28], [31], [32], [37], [48], [53], [62], [63], [64], [67], [71], [73], [78], [81]
Multiple wearables single-sensing	[40], [11], [21], [27], [33], [34], [41], [44], [45], [47], [49], [51], [52], [55], [59], [60], [68], [70], [72], [74], [82]
Multiple wearables multi-sensing	[20], [22], [23], [25], [29], [35], [36], [38], [54], [56], [65], [75], [83], [84]
No wearables	[43], [61], [66], [76], [86]
Real-time	[40], [24], [31], [32], [79], [81]

As summarized in Table 9, focusing on publication timeline, it is worth underlining that almost all of the studies published prior to 2021 employed multiple wearable devices. This consistent preference likely reflects the limited availability of commercially viable multi-sensing wearables during that period, which often necessitated the use of multiple single-function devices to capture diverse physiological signals. Starting in 2020, a notable shift becomes apparent. There is a marked increase in the use of single wearable devices, with a peak observed in 2022. This trend coincides with a parallel rise in the adoption of multi-sensing technologies, suggesting a growing preference for compact, all-in-one devices that can capture multiple physiological parameters simultaneously. This change is likely driven by the increasing availability of user-friendly, accurate, and commercially accessible multi-sensing wearables, which reduce setup complexity and enhance usability in both clinical and real-world research settings.

Interestingly, the most recent studies showed a renewed interest in multiple wearable setups, accompanied by a relative increase in the use of single-sensing devices. While at first glance this may seem like a regression in terms of technological integration, it more plausibly reflects a methodological shift toward specialized experimentation. In particular, this resurgence might be likely associated with the development and validation of custom or novel wearable sensors that target specific signal types, such as new fatigue, hydration, or stress markers, not yet supported by commercial multi-sensing devices. In such cases, multiple single-sensing wearables may be used concurrently to provide a reliable ground truth, validate new sensing methodologies, or allow flexible and modular configurations. Additionally, employing heterogeneous sensors in parallel can facilitate more sophisticated multimodal data fusion techniques, which are critical for developing novel algorithms aimed at estimating complex physiological and psychological states.

These evolving trends underline the dynamic nature of the wearable sensing landscape and suggest that hardware selection is increasingly driven not only by convenience or technological maturity, but also by the specific goals and methodological demands of each study.

B. MEASUREMENT ARCHITECTURES

Measurement architectures exhibited significant variability across sensor types, primarily dictated by the physiological phenomena being measured and the temporal characteristics of the signals involved. Despite this diversity, certain best practices emerged when aligning sampling frequencies with the intrinsic dynamics of biosignals (Table 10).

High-frequency electrophysiological signals, such as ECG and electromyography (EMG), capture rapidly changing waveforms associated with cardiac and skeletal muscle activity and thus required high temporal resolution. This need was reflected in their mean sampling rates, which reach approximately 511 Hz for ECG and 1024 Hz for EMG, ensuring sufficient detail to resolve subtle waveform features and avoid aliasing.

Similarly, metrics such as heart rate (HR) and EDA were often acquired at relatively high median sampling frequencies - approximately 511 $\pm$ 536 Hz for HR and 57 $\pm$ 208 Hz for EDA. However, the large standard deviations observed in these cases suggest that some studies employed exceptionally high-resolution acquisition setups, often tailored to highly specialized analyses requiring fine-grained temporal detail. In contrast, slowly varying physiological parameters, such as skin temperature and pulse oximetry (SpO2), were typically sampled at much lower frequencies, around 3 Hz. Since these processes evolve gradually over time, they can be accurately captured with lower temporal resolution without compromising data fidelity. It is worth noting that intermediate frequency biosignals, such as EDA, presented a more nuanced picture. While they were generally acquired at moderate sampling rates, considerable variability was observed across studies. This heterogeneity reflects both the diverse methodological approaches adopted and the broad application scope of these sensors, ranging from affective computing to fatigue detection and workload assessment.

Optical sensors such as photoplethysmography (PPG) and blood volume pulse (BVP) typically employed sampling rates around 64 Hz, which effectively balance the need to resolve pulsatile cardiovascular dynamics while minimizing unnecessary data load. Conversely, behavioral and movement-related signals, such as those obtained from IMUs and eye-tracking systems, required higher temporal precision to accurately capture rapid motor actions or gaze shifts. IMUs data were commonly sampled at 32 Hz, whereas eye-tracking systems often operated around 95 Hz, reflecting the demands of precise motion tracking and behavioral analysis.

Ultimately, the choice of sampling frequency was tightly coupled to the spectral content of the target physiological signal. Faster-changing signals require higher sampling rates to ensure waveform fidelity and avoid aliasing, whereas slower-varying processes can be reliably captured at lower frequencies without introducing significant information loss. While the optimal measurement architecture must always be tailored to the specific experimental context and application requirements, the median sampling rates identified across the literature provide valuable benchmarks for guiding sensor configuration. Establishing more structured, domain-specific guidelines based on these empirical insights would facilitate greater standardization and comparability across studies. This becomes particularly relevant for emerging applications, such as biological fatigue estimation and multimodal biosensor integration, where coherent data acquisition practices are essential to ensure both data quality and cross-study reproducibility.

TABLE 10. Classification of sampling frequencies (values with no standard deviations are for data available in a single work).

Signal	Acquisition Frequency (Mean ± Standard Deviation)
Electrocardiogram (ECG)	511 ± 363 Hz
Electromyography (EMG)	1024 Hz
Heart Rate (HR)	511 ± 536 Hz
Electrodermal activity (EDA)	57 ± 208 Hz
Skin temperature (ST)	3.1 ± 1.5 Hz
Pulse oximetry (SpO_2)	3.0 ± 2.8 Hz
Photoplethysmography (PPG)	64 Hz
Blood volume pulse (BVP)	64 Hz
Inertial measurement unit (IMU)	32 Hz
Eye tracking (ET)	95 ± 7 Hz

C. DATA TRANSMISSION

Data transmission methods in the analyzed studies exhibited significant variability, largely shaped by application-specific requirements, including mobility constraints, energy efficiency, integration needs, and the desired level of real-time processing (Table 11). Among the 66 studies reviewed, Bluetooth emerged as the most commonly adopted wireless communication protocol, reported in 16 papers. Its popularity can be attributed to its low power consumption, reliable short-range connectivity, and seamless integration with wearable devices and mobile platforms, making it particularly suitable for continuous physiological monitoring in real-world contexts. In contrast, Wi-Fi was mentioned in only a single study, reflecting its comparatively higher energy demands and the greater complexity involved in maintaining stable, low-latency data streaming—especially in battery-powered or resource-constrained wearable systems. A minority of studies, specifically 5, relied on wired connections, primarily in controlled laboratory environments where high-throughput and minimal-latency transmission are prioritized over mobility. These setups were particularly advantageous when large volumes of high-fidelity biosignals must be streamed continuously without data loss, such as in high-resolution electrophysiological studies or multimodal sensor fusion experiments conducted under highly controlled conditions. Table 11 details the works that employed the different data transmission protocols.

When examining data acquisition and processing software, a clear preference emerged for proprietary platforms, which were used in 16 studies. These software solutions were often bundled with commercial biosensing hardware and provide turnkey pipelines for data acquisition, visualization, and basic processing, thereby reducing the technical burden on researchers. Among the proprietary tools, *Ledalab* (cited in 3 studies) and *MATLAB*-based environments (used in 4 studies) were the most frequently reported. In contrast, custom-built software appeared in only 2 studies, underscoring the technical challenges and development overhead associated with creating tailored acquisition frameworks from scratch. Nonetheless, custom solutions offered distinct advantages in terms of flexibility and control, qualities that have been becoming increasingly valuable in emerging applications requiring real-time operator feedback, adaptive system responses, or dynamic task allocation based on physiological states such as fatigue or cognitive load.

Traditionally, off-the-shelf software was preferred in contexts where real-time performance was not critical and the primary focus lied in *post hoc* analyses. However, the field is now undergoing a paradigm shift toward interactive, adaptive, and context-aware systems that demand low-latency, continuous access to biosignal data streams. Applications such as online fatigue monitoring, closed-loop biofeedback, neuroergonomics, and dynamic human-machine interaction increasingly require real-time data acquisition and processing pipelines. This trend highlights the rising importance of robust developer tools, including high-performance APIs, real-time SDKs, and support for standard networking protocols such as UDP and TCP/IP. Such interfaces enable direct access to raw or minimally processed signals, facilitating integration with custom analytics engines, edge-computing architectures, and embedded real-time systems.

As wearable sensing technologies continue to evolve, the ability to flexibly route, process, and synchronize biosignal data streams across local, edge, and cloud-based infrastructures will become a defining requirement for next-generation applications. To support this shift, vendors and developers must move beyond closed, GUI-centric ecosystems and adopt transparent, well-documented, and performance-oriented APIs. Ideally, these interfaces should ensure cross-platform compatibility and provide guarantees on latency and data integrity, enabling researchers and engineers to design scalable, responsive, and highly integrated biosensing systems capable of meeting the demands of real-time, adaptive, and multimodal monitoring environments.

TABLE 11. **Classification of data transmission methods.**

Transmission Method	References
Bluetooth	[24], [25], [27], [29], [31], [32], [35], [36], [40], [41], [54], [67], [69], [81], [82], [83]
Wi-Fi	[62]
Wired	[26], [50], [66], [83], [86]

XII. DISCUSSION

The literature review conducted in this work demonstrates that electrodermal activity (EDA) and sweat rate (SR) monitoring have been extensively explored across various application domains, with particular emphasis on demanding work environments characterized by high physical intensity, environmental exposure, and inherent safety risks. Many studies focus on hazard prevention, accident mitigation, and monitoring stress levels, as excessive stress in such contexts can endanger both workers and surrounding personnel. Office environments have also been investigated, particularly in relation to cognitive stress and real-time monitoring of cognitive load. Research highlights the importance of identifying and mitigating situations of overload, which can adversely impact both mental and physical health, reduce productivity, and contribute to high staff turnover. Cognitive stress emerges as one of the most frequently monitored factors, reflecting its relevance in high-risk environments where excessive cognitive load can compromise performance and safety. This is particularly critical in occupations where human error can have severe consequences, such as nuclear facilities or air traffic control, where continuous monitoring can help prevent critical incidents.

Sweat rate sensors are primarily employed to assess physical workload, yet they also provide valuable insights into overall psychophysiological well-being, supporting safer and more productive working conditions. The landscape of EDA and SR sensing technologies is defined by a fundamental distinction between commercially available devices and custom-built, purpose-driven designs, reflecting a trade-off between accessibility and flexibility. Commercial devices, such as Empatica E4, Shimmer, and Biopac, are favored for their stability, repeatability, and robustness in long-term, on-field monitoring. These devices are often integrated into simple wearables, like wristbands, offering immediate readiness and streamlined user experience. The Empatica E4 wristband, for example, was employed in over 30 of the analyzed studies, underscoring its popularity. Despite these advantages, commercial solutions are often "black-box" systems with limited hardware and software customization, restricted integration with other sensors, and higher costs, making them less suitable for research that demands fine-grained control or integration into complex systems.

Custom-built solutions, particularly for SR monitoring, are gaining traction as they overcome these limitations. Leveraging advanced manufacturing, flexible electronics, and biocompatible materials, these sensors can be tailored to specific applications. A key innovation focuses on the electrode-skin interface, where conventional electrodes can be disrupted by heavy sweating. Custom electrodes employing breathable, water-permeable materials—such as micro-lace, spiral metal wire, or carbon fiber fabric—maintain reliable signal acquisition even during intense physical activity. Custom designs also facilitate wearable integration, including e-textiles embedded in workwear or protective equipment and miniaturized electrodes in ring form factors, enhancing comfort and compliance for continuous monitoring.

Ensuring signal quality, reliability, and usability remains a critical yet underreported aspect of EDA and SR research. Factors such as sensor placement, electrode design, sampling frequency, and skin-electrode contact significantly influence data fidelity, particularly in on-field scenarios where motion artifacts are prevalent. Sensor placement is a key determinant of signal quality: the fingers are the gold standard due to high eccrine sweat gland density, but alternative locations, such as the wrist, have been explored to balance usability and measurement quality, though findings remain inconsistent.

Despite rapid growth, the field still lacks standardization, particularly regarding signal processing and performance validation. Typical EDA processing pipelines, though not uniform, include filtering to remove high- and low-frequency noise, smoothing, normalization to account for inter-subject variability, and decomposition into tonic (SCL) and phasic (SCR) components. Algorithms such as Continuous Decomposition Analysis (CDA) and convex optimization are widely used. Quantitative features extracted from these signals include descriptive statistics, shape-related measures, and peak-related metrics, with SCR amplitude and count being particularly significant indicators of psychophysiological responses. Statistical analyses, including parametric and non-parametric tests, as well as correlation analyses, are applied to assess feature significance across experimental conditions.

Usability has been reported to be fundamental element for data quality in real-world settings. Device comfort, battery life, and ease of use are critical for user compliance; even highly accurate sensors are ineffective if they are uncomfortable or intrusive. Studies highlight the importance of unobtrusive, miniaturized form factors, such as ring-based sensors, to enhance long-term monitoring compliance.

Furthermore, a major emerging trend is the integration of EDA and SR sensors into multi-sensor, multimodal systems, moving from single-parameter monitoring to comprehensive, context-aware analysis. This approach allows for more precise detection of physical and cognitive overload, recognizing that complex psychophysiological states cannot be fully captured by a single metric. Multi-sensor integration, however, introduces greater complexity in data collection, synchronization, and interpretation, as well as challenges in maintaining data quality suitable for machine learning and predictive modeling.

The combination of multimodal sensing with AI is enabling a shift from reactive monitoring to predictive, proactive health management. Machine learning models can identify subtle correlations across physiological metrics, flagging early signs of health events before symptoms appear. In this context, the Human Digital Twin concept [92] has gained prominence, creating virtual representations of an individual's health status using real-time data from interconnected sensors. While this approach allows advanced insights into human performance and well-being, it also introduces challenges related to data privacy, anonymity, and management, which must comply with regulatory standards. Despite these challenges, multi-sensor integration represents a significant step forward in monitoring complex psychophysiological states and optimizing safety and productivity in diverse work environments.

XIII. CONCLUSION

The systematic review highlights a clear progression in wearable sensing technologies, evolving from simple, single-purpose EDA and SR sensors to complex, multimodal, AI-driven systems capable of providing comprehensive and proactive insights into human health. The analysis confirms that EDA and SR represent powerful biomarkers for assessing both physiological and psychological states across a wide range of populations, with particular relevance in occupational health. One of the primary technological challenges—developing sensors that are simultaneously robust, accurate, and usable in dynamic, real-world environments—is being addressed through innovative, custom-built solutions that emphasize fundamental aspects of the sensor-skin interface. These advancements are setting new standards for data quality, reliability, and usability.

Despite these achievements, several critical challenges remain. Foremost among these is the pervasive lack of standardization in methodologies, testing protocols, and the reporting of signal processing steps. This absence of uniformity complicates cross-study comparisons and limits the ability of the field to build a cumulative, evidence-based knowledge base.

To advance the discipline, methodological standardization must be promoted, with the scientific community establishing clear guidelines for EDA and SR signal processing and reporting. This includes comprehensive documentation of filtering methods, normalization procedures, and feature extraction algorithms to ensure reproducibility and comparability across studies. At the same time, continued research on hardware innovations and sensor placement is essential. Flexible, biocompatible electrodes and miniaturized form factors are promising approaches to overcoming the limitations of conventional sensors, while the exploration of alternative body sites, such as the foot, may expand the practicality of EDA monitoring in ambulatory and real-world contexts.

Equally important is the exploitation of artificial intelligence for data fusion. Developing advanced, privacy-preserving AI models will be essential to fully realize the potential of multimodal sensing systems. Future efforts should focus on creating explainable, federated learning frameworks capable of securely integrating heterogeneous physiological data, thereby providing predictive, personalized, and actionable insights into human states.

Addressing these challenges will enable the field to move from a collection of isolated findings toward a coherent, unified body of knowledge. Such progress will support the development of truly intelligent, human-centric systems that can proactively enhance well-being, optimize performance, and ensure safety across diverse environments, ultimately fulfilling the central vision of Industry 5.0.

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