

WEARABLE PHYSIOLOGICAL SENSOR FUSION FOR PAIN EPISODE DETECTION: A REVIEW

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Article History:

- received 17 April 2026
- accepted 20 August 2026

Abstract. Pain episode detection and forecasting from physiological signals collected by wearable devices is becoming increasingly important. Self-reported pain ratings in daily life are recorded irregularly, leaving episode onset, duration, and dynamics incompletely documented. The reviewed literature shows that physiological changes are driven not only by pain but also by movement, emotional arousal, sleep, and environmental factors. Therefore, real-world reliability and false-episode reduction remain key obstacles. This focused review synthesizes clinical and naturalistic use cases, data acquisition strategies, and modeling approaches. These approaches range from feature engineering and classical machine learning to multimodal fusion with attention mechanisms and transformer architectures. Beyond summarizing established findings from the literature, the paper adds two literature-derived synthesis recommendations. The 2 + 1 rule treats at least two physiological signal families plus one context channel as a practical design heuristic for robust wearable pain detection. The KKS principle uses quality indicators and context information to control fusion weights dynamically. Across the reviewed studies, single-signal solutions are frequently vulnerable to signal-quality fluctuations. By contrast, hybrid strategies with explicit quality and context handling show stronger translational potential. However, these recommendations should be interpreted as conceptual guidance requiring further empirical validation, especially across participants, devices, protocols, and uncontrolled daily-life conditions.

Keywords: pain episode detection, wearable sensors, physiological signals, multimodal fusion, quality control, context-aware modeling, validation.

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1. Introduction

Pain is one of the most salient indicators of a person's state and clinical risk, yet it is fundamentally assessed subjectively. Consequently, reliable detection and forecasting of acute pain episodes in daily life remain challenging. Outside healthcare settings, subjective ratings are recorded irregularly and under varying conditions. Episode onset, duration, and intensity dynamics are therefore incompletely documented and difficult to compare over time. This gap has motivated growing interest in physiological markers and automated models that can complement subjective pain ratings (Camacho-Navas et al., 2026; Gkikas & Tsiknakis, 2023; El-Tallawy et al., 2024). Related wearable studies in clinical and naturalistic settings further support this direction (Abd-Elsayed et al., 2024; Stojancic et al., 2023; Vuong et al., 2023). Additional work likewise examines episode-risk forecasting and related wearable outcomes (Johnson et al., 2019; Patterson et al., 2023; Dudarev et al., 2024). However, physiological signals are not specific to pain. Autonomic and cardiovascular responses also change with

movement, emotional stress, and sleep. Without context and quality assessment, there is a risk of falsely attributing episodes to pain (Moens et al., 2023; Umeda & Okifuji, 2022; Jang et al., 2025). Therefore, the key objective is not to identify a single “best” signal. Instead, synthesis should exploit complementary information across signals, remain robust to signal-quality fluctuations, and be validated beyond the laboratory (Camacho-Navas et al., 2026; Gkikas & Tsiknakis, 2023; Jiang et al., 2024). Multimodal fusion studies further support this framing (Farmani et al., 2025).

The aim of this paper is to provide a concise, structured overview of pain episode detection and forecasting with wearable devices. It covers data accessibility and quality constraints, major physiological signal families, signal quality control and preprocessing, evaluation strategies, and evidence-based recommendations for deploying robust multimodal synthesis in real-world settings.

Although this paper is not a full systematic review or meta-analysis, the reviewed corpus was assembled using a structured focused-review procedure. The aim was to improve transparency and reproducibility, following principles adapted from PRISMA and related literature-search reporting guidance (Rethlefsen et al., 2021). Searches were conducted in bibliographic and publisher sources relevant to biomedical engineering and digital health. These sources included PubMed/MEDLINE, IEEE Xplore, ScienceDirect, SpringerLink, MDPI/Sensors, and Google Scholar. Search strings combined pain-related terms (pain assessment, pain episode, pain forecasting, postoperative pain, chronic pain, migraine) with wearable-sensing terms (wearable device, smartwatch, smart ring, wristband, physiological monitoring). Signal terms (EDA/GSR, PPG, ECG, HRV, IMU, temperature, fNIRS, EEG) and modeling terms (machine learning, deep learning, multimodal fusion, attention, transformer, signal quality, artifact detection) were also included.

Study selection followed three complementary steps. First, keyword-guided identification of recent and methodologically relevant studies was performed. Second, backward citation tracking from recent reviews, dataset papers, and methodological anchor papers was used. Third, studies were retained selectively when they provided sufficient methodological detail on wearable or near-wearable physiological sensing for pain detection, pain forecasting, signal-quality handling, multimodal modeling, or validation in clinical or naturalistic settings. Priority was given to peer-reviewed studies and to papers reporting signal types, devices, preprocessing, modeling logic, or validation design. Papers centered only on non-wearable monitoring, non-physiological modalities, purely subjective pain reporting without physiological sensing, or insufficient methodological detail were not retained. Accordingly, the article should be interpreted as a structured focused review aimed at synthesis and methodological positioning rather than as an exhaustive formal systematic review.

2. Overview of pain detection approaches

The reviewed literature clusters around three main application scenarios. First, clinical monitoring of acute pain (particularly postoperative) requires detection of pain levels or episodes from wearable physiology. This must be balanced against data loss, patient comfort, protocol adherence, and interpretability in routine care (Aqajari et al., 2021; Subramanian et al., 2025;

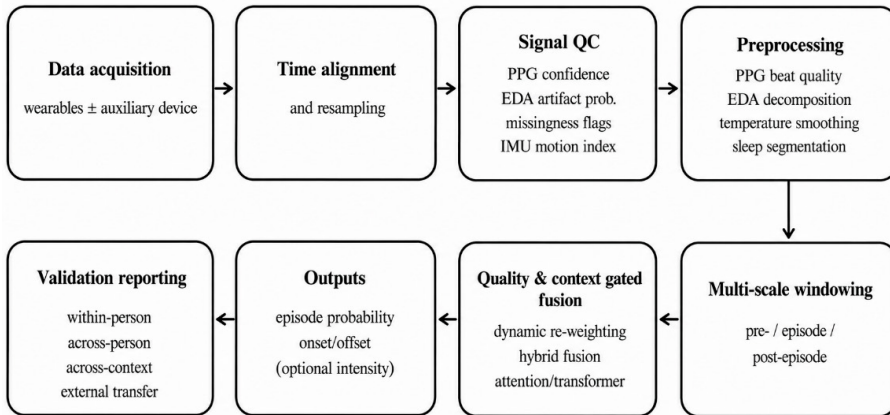


Figure 1. Recommended methodological pipeline for wearable pain episode detection (quality- and context-aware fusion)

Domínguez et al., 2026). Second, long-term monitoring and forecasting in chronic pain predict next-day pain intensity or therapy response from passively collected physiological and behavioral indicators. Such studies often use nighttime or sleep periods (Patterson et al., 2023; Dudarev et al., 2024; Heros et al., 2023). Related chronic-pain contexts also include conditions where pain co-varies with movement and state changes, for example Parkinson's disease (Gungormus et al., 2024; Rukavina et al., 2025). Third, episodic pain such as migraine and headache disorders emphasizes pre-episode changes and forecasting. Night windows are commonly used as a more stable physiological baseline and lower-noise context (Stubberud et al., 2023; Kapustynska et al., 2025; De Brouwer et al., 2022). To harmonize interpretation across scenarios, we propose a three-interval episode structure. The pre-episode interval is supported by forecasting-oriented migraine studies (Stubberud et al., 2023; Kapustynska et al., 2025; De Brouwer et al., 2022). The episode interval is based on short real-time windows (Aqajari et al., 2021; Subramanian et al., 2025; Kong et al., 2021). Complementary continuous-detection work further illustrates this interval (Pinzon-Arenas et al., 2023). The post-episode recovery interval covers return to baseline and next-day forecasting context (Patterson et al., 2023; Dudarev et al., 2024; Heros et al., 2023). Related recovery and forecasting evidence is also reported by Gungormus et al. (2024). This structure is embedded in the recommended methodological pipeline presented in Figure 1.

3. Wearable devices and data accessibility

A key distinction in wearable-sensing studies is data granularity. Researchers may have access to raw physiological signals, such as photoplethysmography (PPG) waveforms and electrodermal activity (EDA) time series. Alternatively, only aggregated metrics may be available, such as heart rate, activity, and sleep summaries. Studies based on widely available commercial wearables show that even aggregated metrics can support pain level estimation or episode-risk forecasting in clinical practice (Stojancic et al., 2023; Vuong et al., 2023; Johnson et al., 2019).

Related forecasting and monitoring studies likewise rely on commercial-device summaries (Patterson et al., 2023; Dudarev et al., 2024). However, such settings limit artifact control, standardized preprocessing, and reliable error analysis. In contrast, studies that collect multiple physiological signals typically enable stronger synthesis and comparability (Farmani et al., 2025; Aqajari et al., 2021; Subramanian et al., 2025). They also introduce deployment constraints, including wear comfort, battery limitations, data continuity, and synchronization across modalities (De Brouwer et al., 2022; Khan et al., 2026). Practical reliability is particularly affected by the sensitivity of PPG measurements to motion and perfusion. Quality control and context handling are therefore essential, for example through motion indices, rejection of low-quality segments, or confidence-aware weighting (Charlton et al., 2023; Chow & Yang, 2020; Park et al., 2025). Complementary artifact-detection work further supports this requirement (Maity et al., 2022). Similarly, the EDA channel is constrained by contact, wear location, and motion artifacts. Without quality control, it can become a major source of false episodes (Kong & Chon, 2024; Posada-Quintero & Chon, 2020; Kong et al., 2024). Location-dependent EDA properties are also reported by Gamboa et al. (2025). The most commonly reported sensor types across the reviewed studies are summarized in Table 1.

Table 1. Sensor types in the reviewed reference set

No.	Sensor type	Count	Keywords / typical outputs	Representative examples
1	EDA / skin conductance	25	EDA, GSR, tonic/phasic	Aqajari et al. (2021), Kong et al. (2021), Kong and Chon (2024)
2	PPG / optical pulse	24	PPG waveform, HR, PRV, sometimes SpO ₂	Charlton et al. (2023), Park et al. (2025), Morimoto et al. (2024)
3	ECG / RR intervals & HRV	20	RR intervals, HRV, variability metrics	Moens et al. (2023), Umeda and Okifuji (2022), Kim et al. (2025)
4	IMU / context	22	Motion index, activity, sleep context	De Brouwer et al. (2022), Dudarev et al. (2024), Stubberud et al. (2023)
5	Temperature	13	Skin/peripheral temperature	Kim et al. (2025), Morimoto et al. (2024)
6	fNIRS / oxygenation	3	fNIRS, hemodynamics, StO ₂ (protocol-dependent)	Khan et al. (2026), Shafiei et al. (2025)
7	EEG	3	Wearable EEG features	Teel et al. (2022), Chen et al. (2025)

Note: Counts are non-exclusive: one paper may include multiple sensor types. A paper was counted under a sensor type when the modality was acquired, analyzed, or explicitly used for feature extraction, modeling, quality control, or context interpretation in the reviewed reference set; therefore, row counts do not sum to the number of included studies.

4. Physiological signals

In wearable pain episode detection, the most common physiological signal families include autonomic markers (e.g., electrodermal activity (EDA)). Cardiovascular markers are also common, including photoplethysmography (PPG) and derived heart rate (HR) and heart rate variability (HRV). Contextual markers include inertial measurement unit (IMU) motion/activity

and sleep segmentation. Specialized neurophysiological and hemodynamic measurements are also used in selected studies. These include functional near-infrared spectroscopy (fNIRS), tissue oxygen saturation (StO₂), and electroencephalography (EEG) (Khan et al., 2026; Charlton et al., 2023; Kong & Chon, 2024). Complementary evidence is available for related hemodynamic and autonomic sensing (Posada-Quintero & Chon, 2020; Kim et al., 2025). Neurophysiological wearable studies further illustrate this group of modalities (Shafiei et al., 2025; Teel et al., 2022; Chen et al., 2025). A consolidated overview of these signals and their utility scores for pain episode detection is provided in Table 2.

Two literature-driven observations directly inform synthesis design. First, HRV is not a universal surrogate for pain intensity, particularly in chronic pain populations (Moens et al., 2023). Observed associations depend on protocol, participant characteristics, medication,

Table 2. Wearable physiological signals for pain episode detection: utility and example devices

Signal family	Common wearable sources	Data	Utility	Main value	Main limitations
EDA	Empatica E4/ EmbracePlus; Fitbit Sense	Raw/derived	4	Sympathetic arousal; onset-like changes	Motion/contact artifacts; nonspecific arousal
PPG waveform	Watches/rings (Apple, Samsung, Garmin, Oura); Empatica	Raw or HR/PRV/SpO ₂	3	Continuous monitoring; HR/PRV features	Motion/perfusion sensitivity; needs QC/context
HR / HRV / PRV	Oura; Polar H10; watch-derived HR/HRV apps	Derived	3	Autonomic balance information; useful in stable segments	Not a universal pain surrogate; artifact/protocol dependent
IMU / context	Apple/Samsung/Oura/Empatica; consumer headbands	Raw + derived	4	QC/context gating; reduces false episodes	Not pain-specific; must be fused with physiology
Skin/peripheral temperature	Oura, Empatica, selected smartwatches	Raw/derived	2–3	Sleep/context support; autonomic signal context	Environment-sensitive; low specificity
Sleep/night features	Oura; Apple/Samsung watches (model-dependent)	Derived	4	Stable context window for forecasting	Algorithm, label, and device variability
fNIRS / StO ₂	Wearable fNIRS/NIRS systems	Raw/derived	3–4	Hemodynamic data; autonomic complement	Setup burden; motion artifacts
EEG	Consumer/research EEG headbands	Raw	3	Perceptual-state information	Higher burden; limited consumer deployment

Note: Utility scores are qualitative synthesis ratings, not effect sizes or meta-analytic weights. They were assigned from five criteria: physiological relevance, wearable availability/data granularity, robustness under artifacts, complementarity in multimodal fusion, and breadth of supporting evidence. Scores: 1 = low or indirect utility, 3 = moderate utility, 5 = high practical utility.

sleep, stress, activity level, and recording quality (Umeda & Okifuji, 2022). In some acute or protocol-controlled settings, cardiovascular dynamics can contribute useful information. However, conflicting findings indicate that HRV should not be treated as a standalone pain marker. Consequently, cardiovascular metrics are most defensible as one component of multimodal synthesis rather than as a single-channel decision basis (Jiang et al., 2024; Farmani et al., 2025; Kim et al., 2025). Second, context is essential for reducing false episodes. Physiological changes may be driven by movement, sleep transitions, heat, emotional arousal, or other non-pain states (Dudarev et al., 2024; Jang et al., 2025; Rukavina et al., 2025). Related movement-linked nociceptive responses are also reported by Hamilton et al. (2024).

On this basis, the proposed 2 + 1 rule should be read as a literature-derived design heuristic rather than a universally validated requirement. For commercially available wearables, robust episode detection will often require at least two complementary physiological signal families plus at least one context channel. Typical context channels include IMU-derived activity or sleep segmentation (Jiang et al., 2024; Farmani et al., 2025; Stubberud et al., 2023). Forecasting-oriented migraine studies similarly support the value of contextual windows (Kapustynska et al., 2025; De Brouwer et al., 2022). This recommendation is consistent with existing adaptive multimodal-fusion approaches. Complementary modalities, attention mechanisms, confidence-aware weighting, and context-aware gating are used to reduce dependence on any single noisy signal. Its practical value is therefore greatest as a framework

Table 3. Processing and modeling approach types

#	Approach	n	Typical idea	Examples
1	Review / roadmap context	7	Scope, limitations, deployment barriers	Gkikas and Tsiknakis (2023), Camacho-Navas et al. (2026)
2	Classical feature-based ML / statistical modeling	31	Handcrafted features + RF/SVM/LR models	Aqajari et al. (2021), Johnson et al. (2019), Pouromran et al. (2021)
3	Deep learning (non-transformer)	4	CNN/LSTM/sequence DL; QC DL	Pinzon-Arenas et al. (2023), Wang et al. (2025)
4	Attention / transformer-based modeling	4	Temporal and cross-channel attention	Jiang et al. (2024), Lu et al. (2023), Khan et al. (2026)
5	Explicit multimodal fusion (adaptive)	10	Early/late/hybrid fusion; dynamic re-weighting	Farmani et al. (2025), Jiang et al. (2024), Wang et al. (2025)
6	Explainable AI (XAI)	1	Attribution of physiological contributions	Gouverneur et al. (2023)
7	Signal QC / artifact handling	4	Artifact detection, confidence scoring, gating	Maity et al. (2022), Kong et al. (2024), Park et al. (2025)
8	Dataset / benchmark anchoring	5	Reproducibility and comparability datasets	Gouverneur et al. (2024), Toktay et al. (2025), Park et al. (2025)

Note: Counts are non-exclusive because one paper may contribute to several categories. Classification reflects each paper's main methodological role. Feature-based ML denotes handcrafted features with conventional models. Deep learning denotes neural representation learning. Transformer/attention denotes a central attention mechanism. Fusion denotes explicit modality combination or re-weighting. Dataset/validation denotes a reproducibility, transfer, deployment, or reliability focus.

for study design and reporting. Prospective validation is still needed to determine when the rule can be relaxed or must be strengthened.

Specialized modalities (fNIRS, StO₂, EEG) can improve specificity in protocol-controlled scenarios. Synthesis studies demonstrate their added value when the use case justifies the additional burden (Khan et al., 2026; Kim et al., 2025; Shafiei et al., 2025). Complementary wearable EEG studies further support this point (Teel et al., 2022; Chen et al., 2025). Nevertheless, these modalities usually require more complex instrumentation and stricter artifact handling. They are also less compatible with typical watch- or ring-based deployments. The main processing and modeling approach families synthesized in this review are summarized in Table 3.

5. Signal quality control and preprocessing

Signal quality control is the key link between theoretical model performance and real-world applicability. PPG signals are frequently distorted by motion during daily activities, which directly degrades the reliability of derived metrics (e.g., HR, HRV, and pulse rate variability (PRV)) (Charlton et al., 2023; Park et al., 2025; Maity et al., 2022). The EDA channel is constrained by contact, motion artifacts, and wear location, so signal properties can differ substantially across locations (Kong et al., 2024; Gamboa et al., 2025). Therefore, filtering at the end of the processing chain is typically insufficient; quality indicators must be incorporated into decision-making and modality weighting (Park et al., 2025; Maity et al., 2022; Kong et al., 2024).

Based on the reviewed evidence, we formulate the KKS principle (quality- and context-aware synthesis) as a heuristic for robust wearable pain-monitoring pipelines. Quality indicators, such as PPG confidence measures and EDA artifact probability estimates, should be treated as synthesis-control inputs. Context signals, such as IMU-derived motion indices and sleep segmentation, should likewise guide modality weighting. Together, these inputs can dynamically re-weight modalities and reduce false episode detections (Jiang et al., 2024; Farmani et al., 2025; Khan et al., 2026). Related quality-control and artifact studies support the same principle (Park et al., 2025; Maity et al., 2022; Kong et al., 2024). This formulation does not claim that one fixed architecture has been universally validated. Rather, it generalizes a recurring principle across adaptive fusion, confidence-aware weighting, and context-aware physiological monitoring: the reliability of each signal should influence its contribution to the final decision. A practical implementation is captured in Figure 1. In that pipeline, time alignment precedes quality control, which in turn precedes multi-scale windowing and synthesis.

The principle also highlights a translational limitation of many high-performing laboratory models. A model may learn cross-channel associations under clean protocol conditions. However, if quality indicators, missingness, device state, and behavioral context are not represented explicitly, the same model may produce false pain episodes during exercise, poor sensor contact, sleep transitions, or emotional arousal. For this reason, quality-aware fusion should be evaluated not only by aggregate accuracy. Failure modes, rejected-window rates, calibration, and performance under realistic sensor degradation should also be reported.

When preparing data for episode analysis, multi-scale windowing is critical. In migraine forecasting, it is often beneficial to analyze a pre-episode interval such as the night before an attack. This provides a more stable physiological baseline with reduced motion noise

(Stubberud et al., 2023; Kapustynska et al., 2025; De Brouwer et al., 2022). In clinical tasks, such as postoperative pain, short real-time windows are required to capture onset and dynamics (Aqajari et al., 2021; Subramanian et al., 2025; Kong et al., 2021). Continuous acute-pain detection studies further illustrate this requirement (Pinzon-Arenas et al., 2023).

6. Evaluation and validation strategies

Reviews consistently highlight a generalization gap. Models may perform well in a single protocol or cohort, but they often degrade when participants, conditions, devices, or acquisition regimes change (Camacho-Navas et al., 2026; Gkikas & Tsiknakis, 2023). Inter-subject variability is particularly important. Pain sensitivity, autonomic reactivity, medication use, comorbidities, sleep, stress, and baseline fitness can all alter physiological responses. Consequently, a single aggregate accuracy metric does not answer the key question: whether a solution will remain reliable beyond the specific study setting. We therefore recommend reporting validation across four levels. Within-person evaluation concerns the same individual across days or episodes. Across-person evaluation concerns unseen individuals (Jiang et al., 2024; Farmani et al., 2025). Across-context evaluation concerns contrasts such as sleep versus day-time activity (Dudarev et al., 2024; Stubberud et al., 2023; Kapustynska et al., 2025). Related naturalistic headache monitoring further supports this level (De Brouwer et al., 2022). External transfer to another dataset, protocol, pain condition, or device type should be reported where feasible (Gouverneur et al., 2024; Toktay et al., 2025; Pittara et al., 2025). Complementary benchmarking evidence is also provided by Pouromran et al. (2021).

Device-to-device variability should also be treated as a validation problem rather than a minor technical detail. Commercial wearables differ in sensor placement, sampling rates, proprietary preprocessing, access to raw data, firmware updates, and missing-data handling. These differences can affect HR/HRV estimates, EDA features, sleep staging, and motion-derived context labels. Under uncontrolled daily-life conditions, practical reliability therefore depends on data continuity, adherence, skin contact, charging behavior, and environmental conditions. Transparent reporting of excluded or low-quality windows is likewise required (Stojancic et al., 2023; Vuong et al., 2023; Johnson et al., 2019). Clinical wearable deployments further illustrate these constraints (Aqajari et al., 2021; Subramanian et al., 2025; Domínguez et al., 2026).

Deep learning and transformer-based approaches are promising because they can model nonlinear temporal and cross-modal relationships. Their limitations must nevertheless be stated explicitly. Biomedical pain datasets are often small, imbalanced, participant-specific, and protocol-dependent. Consequently, complex architectures are vulnerable to overfitting, data leakage, weak external validity, and high computational cost for embedded or wearable deployment. Attention weights can support inspection of temporal or modality contributions. However, they are not sufficient for clinical explanation. Interpretable reporting should include feature or modality attribution, calibration, uncertainty or confidence estimates, and error analysis for clinically relevant false positives and false negatives. In migraine forecasting and other episodic conditions, the personalization strategy should be stated explicitly. Pre-episode physiological patterns are often individual-specific (Stubberud et al., 2023; Kapustynska et al., 2025; De Brouwer et al., 2022).

7. Conclusions and future perspectives

Real-world pain episode detection is primarily a reliability-management problem. Physiological signals such as PPG and EDA often degrade under motion or poor contact. Relationships between cardiovascular variability metrics and pain intensity are also context- and population-dependent. As a result, single-signal approaches are fragile. More reliable solutions combine complementary modalities and make quality control an explicit part of the decision process. Two synthesis contributions emerge from this focused review. First, the KKS principle frames quality indicators and context information (e.g., motion and sleep segmentation) as first-class inputs. These inputs should guide fusion weighting rather than being used only for late filtering. Second, the 2 + 1 rule is proposed as a practical design heuristic. For many commercially available wearable settings, at least two physiological signal families plus one context channel may be needed to separate pain episodes from non-pain arousal and to compensate for modality dropouts. These concepts should not be interpreted as universally validated rules. They are literature-derived recommendations that require prospective testing across participants, devices, pain conditions, and daily-life protocols. The most defensible direction is quality-controlled hybrid fusion with dynamic re-weighting, transparent uncertainty handling, and multi-scale windows aligned to the episode structure. Future work should prioritize comparable protocols, external validation, interpretable reporting, and reliability assessment under realistic commercial-device constraints.

Disclosure statement

The authors declare no competing financial, professional, or personal interests.

Author contributions

Anastasija Grubinskienė and Andrius Katkevičius contributed to the conceptualization, literature analysis, interpretation, manuscript preparation, and revision of the manuscript. Both authors approved the submitted version.

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