https://doi.org/10.15360/1813-9779-2025-6-2627

Artificial Intelligence Applications for Automatic Pain Assessment in the ICU (Short Review)

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For citation: *Marco Cascella.* Artificial Intelligence Applications for Automatic Pain Assessment in the ICU (Short Review). *Obshchaya Reanimatologiya=General Reanimatology.* 2025; 21 (6): 86–92. https://doi.org/10.15360/1813-9779-2025-6-2627 [In Engl.]

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Summary

Pain remains a major clinical challenge in the intensive care unit (ICU), especially in sedated, mechanically ventilated, or curarized patients due to their inability to self-report and the limited accuracy of behavioral tools. Therefore, innovative approaches must be developed. In this scenario, objective and observer-independent pain assessment can support and improve personalized analgesic management.

The aim of this review is to analyze the current artificial intelligence (AI) applications for automatic pain assessment (APA) in the ICU, focusing on the integration of biosignals, behavioral indicators, and multimodal data to detect nociceptive responses.

A systematic search was conducted in PubMed, Web of Science, and IEEE Xplore databases (2015–2025) using the terms pain assessment, critical care, artificial intelligence, machine learning, facial expression, pupillometry, heart rate variability, and nociception monitor. The scientific output was grouped into three main domains: behavioral and computer-vision methods, autonomic and electrophysiological indices, and multimodal and AI-driven integrated systems.

Conclusion. Although AI systems for APA in the ICU show promising performance, several challenges limit their clinical translation. Signal variability due to pharmacological, neurological, or hemodynamic factors may compromise model reliability. Moreover, the scarcity of labeled ICU datasets can affect generalizability. Ethical, regulatory, and interoperability issues should be addressed. Therefore, for routine implementation, large-scale validation across diverse ICU populations is required to confirm reliability, ensure fairness, and establish clinical utility.

Keywords: artificial intelligence; automatic pain assessment; nociception; intensive care unit; biosignals; multimodal monitoring; deep learning

Conflict of interest. The author declares no conflict of interest.

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Introduction

Despite advances in critical care, pain is still highly prevalent in the intensive care unit (ICU), with an incidence of up to 70% in medical and surgical patients, at rest and mostly during procedures [1]. Untreated pain can induce cardiac instability, respiratory compromise, and immune suppression. Additionally, pain is often associated with agitation, delirium, and longer ICU stays [2], as well as chronic pain in ICU survivors [3].

Although the underlying reasons for this lack are complex, pain assessment is the main issue. In critically ill patients, proper pain evaluation remains challenging, particularly for those who are sedated, on mechanical ventilation, or unable to communicate, as only a limited number of reliable strategies are currently available [4]. In patients who can communicate, pain is evaluated through self-report. Meanwhile, in non-communicative ICU patients, behavioral observation tools like the Behavioral Pain Scale (BPS) and the Critical-Care Pain Observation Tool (CPOT) are commonly used [5]. They are recommended by clinical practice guidelines [6]. However, these tools tend to lack reliability in deeply sedated or paralyzed patients [7]. Additionally, their accuracy depends on proper training and active participation by the assessor, which increases the nursing workload. Furthermore, intermittent manual scoring cannot provide real-time, dynamic pain assessment, limiting its effectiveness in guiding prompt clinical decisions.

In this complex scenario, developing objective and automated methods to detect nociceptive responses and pain is essential. Recently, there has been increasing interest in using artificial intelligence (AI) and sensor technologies to achieve Automatic Pain Assessment (APA) in critical care [8,9]. This interdisciplinary field of study utilizes various data-driven techniques that can combine information from vital signs, facial expressions, and different biosignals to estimate nociception features and pain levels continuously [10].

On these premises, this review aims to provide a comprehensive, state-of-the-art overview of AI-based approaches for APA in the ICU. Specifically, the objective is to summarize current AI applications, evaluate their validation level and clinical applicability, and discuss future directions for integrating these technologies into routine critical care practice.

Materials and Methods

A literature search in PubMed, Web of Science, and IEEE Xplore (from 2015 to September 2025) was performed using combinations of: «pain assessment», «ICU» OR «critical care», «artificial intelligence», «machine learning», «nociception monitor», «pupillometry», «heart rate variability», «facial expression», «electrodermal activity», «multimodal pain». Peer-reviewed clinical studies in ICU settings and technical studies relevant to pain detection in the ICU were considered. Approximately 80 sources underwent full-text review; key findings are summarized by thematic category. Specifically, clinical applications of AI-based pain assessment are grouped into behavioral pain assessment and computer vision (CV) approaches, autonomic and electrophysiological pain modalities, and multimodal and AI-driven integrated systems.

Clinical Applications of AI-Based Pain Assessment

1. Behavioral pain assessment and computer-vision approaches. Conventional behavioral scales, including CPOT and BPS, remain the gold-standard bedside tools for non-communicative adult ICU patients and are guideline-endorsed [6]. AI-based strategies can be implemented for overcoming their limitations, such as observer dependence, intermittency, and reduced utility under deep sedation. For example, in the field of automated facial expression recognition, CV models can detect pain-related facial expression through facial action unit (AU) analysis. It is a framework originally developed within the Facial Action Coding System (FACS). Specifically, each AU corresponds to a specific muscle (or muscle group) contraction or facial movement (e.g., brow lowering, eye tightening, nose wrinkling), which can be objectively quantified from video data. Deep learning (DL)-based models, typically convolutional or recurrent neural networks, can automatically extract and classify these AUs to identify characteristic facial patterns associated with nociceptive responses [11, 12]. In a prospective ICU study, DL architectures fine-tuned and trained on video clips achieved approximately 80% accuracy for pain vs no-pain classification and generalized to unseen patients, with temporal video models outperforming single-frame models [13]. Nevertheless, ICU constraints such as tubes, masks, lighting, and sedation can limit the efficacy of these methods. Methodological attempts have been conducted to overcome these limitations. For example, a study by X. Yuan et al. [14] proposed a facial AUs-guided pain assessment network specifically designed to address one of the main challenges, which is facial occlusion due to tubes or masks. The DL model integrated an AU-guided module that automatically identified AUs in visible, non-occluded regions with a texture feature extraction module capturing both local and global facial patterns. These multimodal features were then fused in a pain assessment module to estimate pain state and intensity. Importantly, validated on both public (UNBC-McMaster shoulder pain datasets) and proprietary datasets, the approach outperformed conventional models in binary and multi-class pain classification as well as in intensity regression (accuracy > 90%).

Concerning other behaviors, body movement and ventilator synchrony may signal pain (or discomfort), but are less studied for automation in the ICU. Probably, multimodal systems may incorporate pose tracking and audio when applicable [9, 10].

2. Autonomic and electrophysiological pain modalities. Since physiological modalities can capture involuntary responses mediated by the autonomic nervous system (ANS), they can be adopted for developing APA systems [9, 10]. Among the most investigated approaches are pupillometry, heart rate variability (HRV), electrodermal activity (EDA), and multimodal nociception indices that integrate several biosignals through AI-driven algorithms. These methods offer the potential to continuously quantify nociceptive responses, reducing observer bias.

Infrared pupillometry quantifies the pupillary dilation reflex to noxious stimulation. Therefore, pupillometric indices such as the Pupillary Pain Index (PPI) may correlate with analgesic adequacy [15]. A recent prospective study evaluated the utility of videopupillometry for nociception assessment in deeply sedated, non-neurological ICU patients. The authors compared pupillary dilation reflex (PDR) responses to non-noxious versus noxious procedures, such as gentle shoulder touch versus endotracheal suctioning or repositioning. Results demonstrated that PDR significantly increased during noxious procedures, with a mean difference of approximately 32%. After adjusting for confounders, only the noxious procedure remained a significant predictor of pupil change. A PDR threshold of > 12% yielded 65% sensitivity and 94% specificity for nociception detection (AUC = 0.83) [16]. These findings support the approach as a promising and objective indicator of nociceptive responses in deeply sedated ICU patients. Nevertheless, neurologic injury and other limitations, such as lighting, can confound measurements.

Electrocardiogram (ECG)-derived parameters such as HRV were also investigated. It is the variation in time intervals between consecutive

heartbeats (the R–R intervals on an ECG), reflecting the balance and dynamic interaction between the sympathetic and parasympathetic branches of the ANS. This physiological marker of nociception was adopted to develop indices such as the Analgesia Nociception Index (ANI), which quantifies the autonomic response to pain or stress. The ANI index, ranging from 0 to 100, reflects parasympathetic predominance. In ICU patients, ANI showed moderate correlation with behavioral pain and a high negative predictive value for moderate-to-severe pain when ANI was high, although sensitivity/specificity were limited [17]. Importantly, arrhythmias, pacemakers, β-blockers, and non-pain stressors confound HRV-based indices.

Electrodermal activity (EDA) reflects changes in skin conductance mediated by sympathetic nervous system activation, which increases during stress, emotional arousal, or nociceptive stimulation [18–20]. When a painful or emotionally salient stimulus occurs, sweat gland activity rises, transiently decreasing skin resistance and generating measurable skin conductance responses (SCRs). In research and experimental settings, EDA has proven to be a reliable measure of pain intensity. Machine learning (ML) models trained on time- and frequency-domain SCR features, such as response amplitude, frequency, rise time, and recovery slope, have demonstrated good predictive performance for differentiating pain levels, as seen in datasets like BioVid or SenseEmotion [19]. However, several factors can affect the reliability of EDA in the ICU environment. Physiological conditions (e. g., hypoperfusion, neuropathies), pharmacological influences (e. g., vasopressors, sedatives, and anticholinergic drugs), and environmental factors (e. g., temperature, humidity, and electrode placement) can introduce artifacts or attenuate the signal.

Based on biosignals, multiparameter nociception monitors have been developed. The Nociception Level (NOL) integrates HR, HRV, pulse wave amplitude, skin conductance, and temperature into a composite 0–100 index using a proprietary (AI-derived) algorithm. In critical care, a randomized trial found NOL-guided analgesia reduced opioid dosing without worsening pain scores, with a trend toward shorter ICU stays [21, 22]. Moreover, in a prospective cohort study, T. S. Shahiri et al. [23] investigated the potential of NOL for pain assessment among mechanically ventilated patients able to self-report pain. Data was collected before, during, and after a non-nociceptive procedure (blood pressure cuff inflation) and a nociceptive procedure (endotracheal suctioning). Pain intensity (0–10 scale), CPOT scores, and NOL values were analyzed using non-parametric statistical tests. The authors found that NOL values significantly increased during endotracheal suctioning compared with pre- and post-procedure values and with cuff inflation ($P < 0.001$). NOL values also correlated with both self-reported pain and CPOT scores ($P < 0.05$). More recently, Bonvecchio et al. [24] conducted a retrospective cohort study to evaluate the same device in deeply sedated and curarized critically ill patients, a population in which traditional pain monitoring is unreliable. The study compared NOL performance with standard neurovegetative indicators (e. g., heart rate, blood pressure) and examined its relationship with sedation depth measured by bispectral index (BIS). Results showed that NOL demonstrated superior accuracy in detecting nociceptive events across the overall cohort compared with conventional physiological indicators. In non-curarized patients, all indices, including NOL, identified nociceptive stimulation, whereas in paralyzed patients, only NOL reliably detected nociceptive responses. Since electroencephalography (EEG)-derived sedation indices are not able to capture nociception, in the curarized group, no correlation was found between BIS values and NOL. On the other hand, sensor complexity, artifact susceptibility (e. g., movements), hemodynamic instability due to shock, and arrhythmias are key limitations.

3. Multimodal and AI-driven integrated systems. Combining different modalities such as facial action units, biosignals, and clinical data can offer more robust pain detection. For example, Othman et al. [25] fused facial analysis with EDA and used three different approaches, including random forest (RF), Long-Short Term Memory Network (LSTM), and LSTM with the sample-weighting method (LSTM-SW). They found that models improved multi-level pain classification over single-modality models, supporting complementary information across channels. Moreover, classical ML, such as support vector machines (SVMs) and RFs, and DL architectures have been applied.

A particularly advanced framework for ICU pain evaluation is represented by the Intelligent Intensive Care Unit (I2CU) system [26]. This architecture integrated multimodal sensing and DL to enable continuous, real-time visual and physiological assessment of patients' states, including pain, acuity, mobility, and delirium risk. The system collected data simultaneously from multiple modalities such as imaging, accelerometry, electromyography (EMG), environmental sensors (light and noise), and vital signs. For pain assessment, the visual module applied an AUs detection pipeline based on the FACS, using a multitask cascaded convolutional network (MTCNN) and a Swin Transformer model trained to recognize twelve AUs that align with established behavioral pain metrics such as CPOT and BPS. Moreover, cameras captured posture and mobility data analyzed with CV-based You Only Like Once (YOLO) models, while physiological time-

Table. AI-based tools and methods for automatic pain assessment in ICU patients.

Method	Input	AI technique	Validation level (Internal/External)*	Key limitations	Ref.
Facial expression analysis	Face video	DL (CNN, RNN)	ICU (80% accuracy) (Internal validation)	Occlusion, sedation effects, lighting/ethnic variability	[13]
AU-guided facial pain network	Face video + texture features	DL (CNN + TFE module + fusion)	External validation on public dataset (UNBC-McMaster) and internal ICU dataset (>90% accuracy)	Occlusion handling, need for large annotated datasets	[14]
PPI	Pupil reflex	Algorithmic index	External validation in OR setting; internal discriminative study in the ICU (AUC 0.83)	Drug/neurologic/lighting confounders; stimulus required	[15–16]
HRV (ANI)	ECG/PPG HRV	Proprietary index	ICU diagnostic study; moderate performance, high NPV (Internal validation)	Arrhythmias/pacing/ β-blockers; low specificity	[17]
Skin conductance (EDA)	EDA (SCRs)	Feature engineering + ML (SVM, RF, CNN)	Experimental datasets (e.g., BioVid, SenseEmotion) (External validation)	Motion/temp confounders; peripheral shutdown	[19]
Multiparameter (NOL)	HR/HRV, PPG, EDA, temp	Composite ML index	OR validated (External validation); ICU RCT opioids, similar pain scores (Internal validation)	Artifacts; sensor complexity; hemodynamic instability	[21–24]
Vital-sign ML model	HR, BP, RR, age, sex, RASS	ML (RF model)	Retrospective ICU (>10,000 pts; AUC 0.903) (Internal validation)	Retrospective bias; limited external validation	[29]
Multimodal fusion (EDA + video)	Video + EDA	DL (CNN/LSTM/ transformers)	Internal prototype validation with cross-modal fusion; external validation pending	Data needs; integration and missing-data handling	[25]
I2CU (Intelligent ICU)	Video, depth, EMG, vitals, environment	DL (FACS-based AU + Swin Transformer + YOLO + transformers)	Internal real-ICU pilot validation; external multicenter validation pending	Complex infrastructure; computational load; data privacy issues	[26]

Note. * Internal validation refers to testing within the same dataset or cohort, while external validation refers to independent datasets or different clinical contexts. DL — Deep Learning; CNN — Convolutional Neural Network; RNN — Recurrent Neural Network; AU — Action Unit; TFE — Texture Feature Extraction; HRV — Heart Rate Variability; HR — Heart Rate; PPI — Pupillary Pain Index; BP — Blood Pressure; EMG — Electromyography; ECG — Electrocardiogram; PPG — Photoplethysmography; EDA — Electrodermal Activity; SCR — Skin Conductance Response; OR — Operating Room; ICU — Intensive Care Unit; ANI — Analgesia Nociception Index; NOL — Nociception Level Index; SVM — Support Vector Machine; RF — Random Forest; RASS — Richmond Agitation–Sedation Scale; YOLO — You Only Look Once; LSTM — Long Short-Term Memory network.

series were processed using self-supervised transformers trained on more than 300 clinical variables to estimate acuity and autonomic states. The AI system merged these heterogeneous data streams through a real-time ML engine and displayed them via a clinician dashboard showing inferred pain scores, mobility indices, delirium risk, and environmental parameters. Overall, the I2CU architecture demonstrated how AI-enhanced multimodal sensing and FACS-based facial analysis can operationalize continuous and interpretable pain assessment in real ICU environments, addressing many of the current barriers to observer-independent, real-time nociception monitoring.

Although these approaches are promising, for generalizability, larger and diverse datasets, and standardized evaluation are mandatory [8, 9].

The characteristics of AI-based tools and methods for automatic pain assessment in ICU patients are presented in the table.

Limitations and Challenges

Several critical issues influence the effective implementation of AI strategies for APA in the ICU. First, there is the fundamental distinction between pain and nociception. In particular, current monitoring systems can capture only physiological responses, not the patient's subjective experience of suffering [10]. Second, patient variability and confounding factors, such as arrhythmias, pharmacologic agents, neurologic injury, or vasopressor use, can significantly alter the biosignals on which AI algorithms rely, thereby affecting model reliability [20–24]. A third challenge is the limited availability of labeled ICU datasets suitable for model training. Because pain cannot be objectively measured, most datasets use proxy labels derived from behavioral tools like CPOT or BPS, which introduce noise and variability into AI training [8, 9]. From an operational standpoint, real-time integration into ICU workflows raises additional concerns, such as system interoperability. Moreover, clinician acceptance and training remain essential as AI outputs must be interpretable and easily understood by healthcare professionals to foster trust and effective use at the bedside [8]. Finally, there are important regulatory, ethical, and fairness considerations. These include safeguarding data privacy, ensuring unbiased model performance across diverse patient populations, and maintaining human oversight in decision-making processes through human-in-the-loop designs [8, 9].

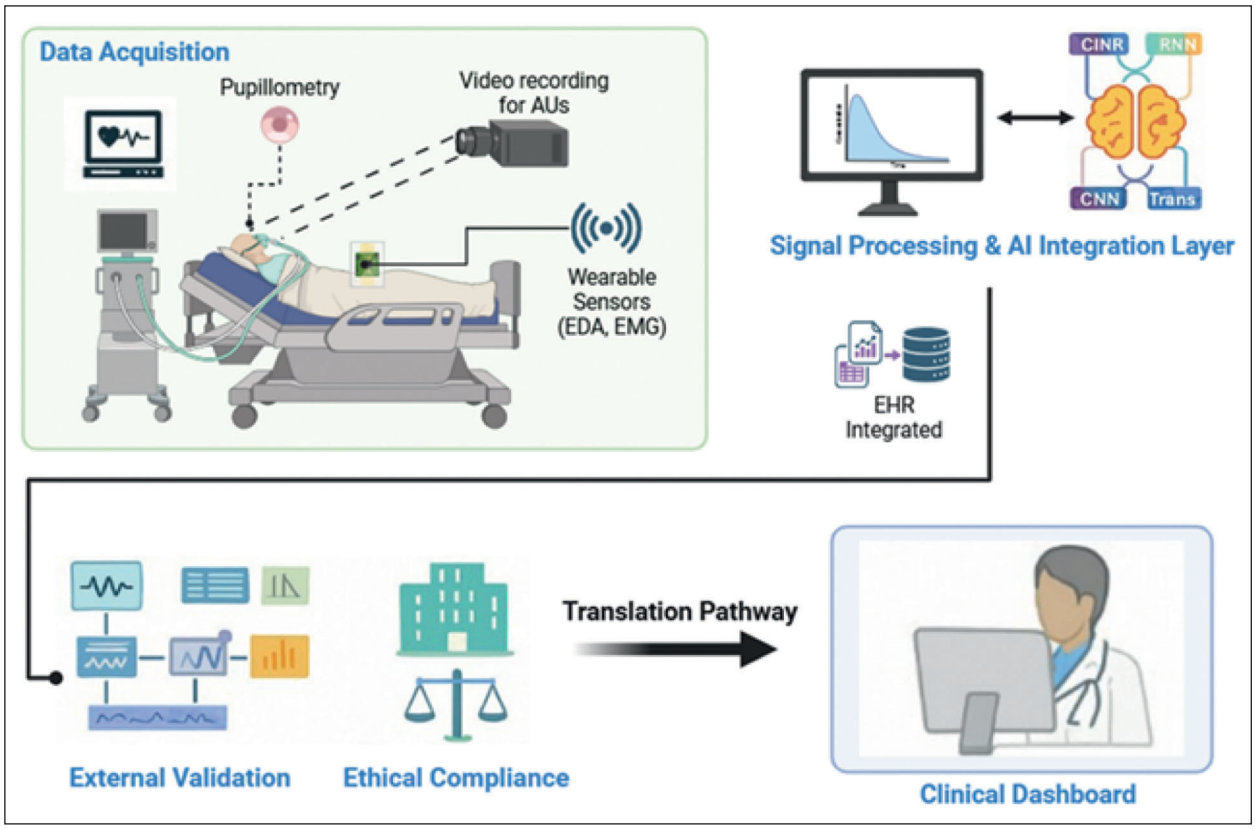

Fig. Schematic overview of AI-driven automatic pain assessment in the ICU (Created by Marco Cascella).
Note. Physiological, behavioral, and multimodal data are collected through bedside sensors and processed by deep learning models to detect nociceptive responses. After external validation and following ethical compliance, model outputs are integrated into clinical dashboards for real-time, observer-independent pain monitoring and personalized analgesic management. AUs — action units; EDA — electrodermal activity; EMG — electromyography; EHR — electronic health record.

Perspectives and Future Directions

Near-term deployment will likely be as decision-support: continuous indices that prompt reassessment or preemptive analgesia, with electronic health record (EHR) integration, trend displays, and smart alarms [21]. Goal-directed analgesia guided by objective indices, for instance, NOL or ANI targets, may reduce drug exposure without compromising comfort [27]. Interestingly, multimodal strategies could integrate brain activity. For example, Chen et al. [28] developed a pain detection framework based on EEG signals and deep convolutional neural networks to distinguish induced pain from resting states.

The multimodal integration may also include clinical data derived from validated assessment tools (Fig.).

A recent large-scale study explored the use of ML applied to vital sign data for automatic pain visualization in ICU patients. The authors investigated whether incorporating individual baseline deviations in physiological parameters could enhance model accuracy. Using data from over 10,000 adult ICU patients and more than 117,000 CPOT assessments, a random forest model was trained with arterial pressure, heart rate, respiratory rate, age, gender, and sedation score as predictors. Pain probability was defined as the likelihood of a CPOT $\geqslant 3$, adjusted for each patient's baseline. The model achieved excellent discriminative performance (AUC = 0.903), demonstrating that the use of different clinical and instrumental inputs can enhance the sensitivity of the AI-based automatic pain detection and, ultimately, develop reliable and scalable systems [29].

Nevertheless, another aspect that needs to be clarified is the definition of integration pathways among the different study components, such as between various biosignals and between biosignals and behavioral approaches. For example, a recent observational study compared pupillary response and skin conductance for nociception assessment in unconscious or deeply sedated ICU patients. Fifty-one adults with acute brain injury or under deep sedation underwent tetanic stimulation while both parameters were recorded simultaneously. Pupillary dilation was quantified using the PPI, whereas skin conductance was expressed as the number of peaks per second. Results showed that more than half of the patients (55%) had insufficient analgesia according to the PPI, whereas only 29% displayed measurable SC activity. Importantly, no significant correlation was found between EDA-derived indices and pupillary responses [30]. Therefore, careful integration of differ-

ent modalities is warranted to improve model robustness and reduce false interpretations.

Other challenges need careful attention. Advances in sensing technology (wearables, non-contact vitals) and AI (federated learning, explainable models, multimodal fusion) will enhance the robustness and acceptance of the developed technology [8]. Due to the varied methods used in AI research, interdisciplinary standards for datasets, benchmarks, and reporting are essential [8]. Ethics must also be considered. For instance, adoption requires staff training and transparent communication with patients, as well as ensuring data privacy, reducing algorithmic bias, and maintaining human oversight in decision-making to preserve clinical accountability and patient trust [31]. Ultimately, APA could turn pain into a real «continuous vital sign,» particularly for patients unable to speak for themselves.

Conclusion

To date, research suggests that AI-enabled APA can augment bedside care by continuously detecting nociceptive responses when traditional behavioral scales are infeasible. Evidence supports the utility of pupillometry, HRV-based indices, and multiparameter monitors such as NOL. Furthermore, while facial analysis and multimodal AI systems are promising, these approaches require larger, diverse validation. Further high-quality investigations are needed for the thoughtful integration of APA methods in ICU care pathways.

References

1. *Chanques G., Pohlman A., Kress J. P., Molinari N., de Jong A., Jaber S., Hall J. B.* Psychometric comparison of three behavioural scales for the assessment of pain in critically ill patients unable to self-report. *Crit Care.* 2014; 18 (5): R160. DOI: 10.1186/cc14000. PMID: 25063269.
2. *Nordness M. F, Hayhurst C. J., Pandharipande P.* Current perspectives on the assessment and management of pain in the intensive care unit. *J Pain Res.* 2021; 14: 1733–1744. DOI: 10.2147/JPR.S256406. PMID: 34163231.
3. *Bourdiol A., Legros V., Vardon-Bounes F., Rimmele T., Abraham P., Hoffmann C., Dahyot-Fizelier C., et al; ALGO-RÉA study group; Atlanréa Group; Société Française d'Anesthésie-Réanimation–SFAR Research Network.* Prevalence and risk factors of significant persistent pain symptoms after critical care illness: a prospective multicentric study. *Crit Care.* 2023; 27 (1): 199. DOI: 10.1186/s13054-023-04491-w. PMID: 37226261.
4. *Sandvik R. K. N. M., Mujakic M., Haarklau I., Emilie G., Moi A. L.* Improving pain management in the intensive care unit by assessment. *Pain Manag Nurs.* 2024; 25 (6): 606–614. DOI: 10.1016/j.pmn.2024.06.013. PMID: 39244399.
5. *Gomarverdi S., Sedighie L., Seifrabiei M. A., Nikooseresht M.* Comparison of two pain scales: behavioral pain scale and critical-care pain observation tool during invasive and noninvasive procedures in intensive care unit-admitted patients. *Iran J Nurs Midwifery Res.* 2019; 24 (2): 151–155. DOI: 10.4103/ijnmr.IJNMR_47_18. PMID: 30820228.
6. *Devlin J. W., Skrobik Y., Gélinas C., Needham D. M., Slooter A. J. C., Pandharipande P. P., Watson P. L., et al.* Clinical practice guidelines for the prevention and management of pain, agitation/sedation, delirium, immobility, and sleep disruption in adult patients in the ICU. *Crit Care Med.* 2018; 46 (9): e825-e873. DOI: 10.1097/CCM.0000000000003299. PMID: 30113379.
7. *Pota V., Coppolino F., Barbarisi A., Passavanti M. B., Aurilio C., Sansone P., Pace M. C.* Pain in intensive care: a narrative review. *Pain Ther.* 2022; 11 (2): 359–367. DOI: 10.1007/s40122-022-00366-0. PMID: 35220551.
8. *Cascella M., Ponsiglione A. M., Santoriello V., Romano M., Cerrone V., Esposito D., Montedoro M., et al.* Expert consensus on feasibility and application of automatic pain assessment in routine clinical use. *J Anesth Analg Crit Care.* 2025; 5 (1): 29. DOI: 10.1186/s44158-025-00249-8. PMID: 40457422.
9. *Cascella M., Schiavo D., Cuomo A., Ottaiano A., Perri F., Patrone R., Migliarelli S., et al.* Artificial intelligence for automatic pain assessment: research methods and perspectives. *Pain Res Manag.* 2023; 2023: 6018736. DOI: 10.1155/2023/6018736. PMID: 37416623.
10. *El-Tallawy S. N., Pergolizzi J. V., Vasiliu-Feltes I., Ahmed R. S., LeQuang J.K., El-Tallawy H. N., Varrassi G., et al.* Incorporation of «artificial intelligence» for objective pain assessment: a comprehensive review. *Pain Ther.* 2024; 13 (3): 293–317. DOI: 10.1007/s40122-024-00584-8. PMID: 38430433.
11. *Cascella M., Shariff M. N., Lo Bianco G., Monaco F., Gargano F., Simonini A., Ponsiglione A. M., et al.* Employing the artificial intelligence object detection tool YOLOv8 for real-time pain detection: a feasibility study. *J Pain Res.* 2024; 17: 3681–3696. DOI: 10.2147/JPR.S491574. PMID: 39540033.
12. *Szczapa B., Daoudi M., Berretti S., Pala P., Bimbo A. D., Hammal Z.* Automatic estimation of self-reported pain by trajectory analysis in the manifold of fixed rank positive semi-definite matrices. *IEEE Trans Affect Comput.* 2022; 13 (4): 1813–1826. DOI: . PMID: 36452255.
13. *Wu C.-L., Liu S.-F., Yu T.-L., Shih S.-J., Chang C.-H., Yang Mao S.-F., Li Y.-S., et al.* Deep learning-based pain classifier based on the facial expression in critically ill patients. *Front Med (Lausanne).* 2022; 9: 851690. DOI: 10.3389/fmed.2022.851690. PMID: 35372435.
14. *Yuan X., Cui Z., Xu D., Zhang S., Zhao C., Wu X., Jia T., et al.* Occluded facial pain assessment in the ICU using Action Units Guided Network. *IEEE J Biomed Health Inform.* 2023; PP. DOI: 10.1109/JBHI.2023.3336157. PMID: 37995171.
15. *Packiasabapathy S., Rangasamy V., Sadhasivam S.* Pupillometry in perioperative medicine: a narrative review. *Can J Anaesth.* 2021; 68 (4): 566–578. DOI: 10.1007/s12630-020-01905-z. PMID: 33432497.
16. *Favre E., Rahmaty Z., Ben-Hamouda N., Miroz J. P., Abed-Maillard S., Rusca M., Oddo M., et al.* Nociception assessment with videopupillometry in deeply sedated intensive care patients: discriminative and criterion validations. *Aust Crit Care.* 2024; 37 (1): 84–90. DOI: 10.1016/j.aucc.2023.07.038. PMID: 37684156.
17. *Chanques G., Tarri T., Ride A., Prades A., De Jong A., Carr J., Molinari N., et al.* Analgesia nociception index for the assessment of pain in critically ill patients: a diagnostic accuracy study. *Br J Anaesth.* 2017; 119 (4): 812–820. DOI: 10.1093/bja/aex210. PMID: 29121287.
18. *Cascella M., Vitale V. N., D'Antò M., Cuomo A., Amato F., Romano M., Ponsiglione A. M.* Exploring biosignals for quantitative pain assessment in cancer patients: a proof of concept. *Electronics.* 2023; 12 (17): 3716. DOI: 10.3390/electronics12173716.
19. *Pouromran F.,, Radhakrishnan S.,, Kamarthi S.* Exploration of physiological sensors, features, and machine learning models for pain intensity estimation. *PLoS One.* 2021; 16 (7): e0254108. DOI: 10.1371/journal.pone.0254108. PMID: 34242325.
20. *Cascella M., Di Gennaro P., Crispo A., Vittori A., Petrucci E., Sciorio F., Marinangeli F., et al.* Advancing the integration of biosignal-based automated pain assessment methods into a comprehensive model for addressing cancer pain. *BMC Palliat Care.* 2024; 23 (1): 198. DOI: 10.1186/s12904-024-01526-z. PMID: 39097739.
21. *Çalýþkan B., Besir Z., Sen O.* Pain monitoring in intensive care: how does the nociception level index affect treatment and prognosis? A randomized, controlled, double-blind trial. *Ulus Travma Acil Cerrahi Derg.* 2024; 30 (6): 415–422. DOI: 10.14744/tjtes.2024.95533. PMID: 38863294.
22. *Gélinas C., Shahiri T. S., Richard-Lalonde M., Laporta D., Morin J. F., Boitor M., Ferland C. E., et al.* Exploration of a multi-parameter technology for pain assessment in postoperative patients after cardiac surgery in the intensive care unit: the nociception level index (NOL) TM. *J Pain Res.* 2021; 14: 3723–3731. DOI: 10.2147/JPR.S332845. PMID: 34908872.
23. *Shahiri T. S., Richard-Lalonde M., Richebé P., Gélinas C.* Exploration of the nociception level (NOL™) index for pain assessment during endotracheal suctioning in mechanically ventilated patients in the intensive care unit: an observational and feasibility study. *Pain Manag Nurs.* 2020; 21 (5): 428–434. DOI: 10.1016/j.pmn.2020.02.067. PMID: 32354616.

24. *Bonvecchio E., Vailati D., Mura F. D., Marino G.* Nociception level index variations in ICU: curarized vs non-curarized patients — a pilot study. *J Anesth Analg Crit Care.* 2024; 4 (1): 57. DOI: 10.1186/s44158-024-00193-z. PMID: 39164731.
25. *Othman E., Werner P., Saxen F., Al-Hamadi A., Gruss S., Walter S.* Automated electrodermal activity and facial expression analysis for continuous pain intensity monitoring on the X-ITE pain database. *Life (Basel).* 2023; 13 (9): 1828. DOI: 10.3390/life13091828. PMID: 37763232.
26. *Nerella S., Guan Z., Siegel S., Zhang J., Zhu R., Khezeli K., Bihorac A., et al.* AI-enhanced intensive care unit: revolutionizing patient care with pervasive censing. *arXiv:* 2303.06252. DOI: 10.48550/arXiv.2303.06252.
27. *Ledowski T.* Objective monitoring of nociception: a review of current commercial solutions. *Br J Anaesth.* 2019; 123 (2): e312–e321. DOI: 10.1016/j.bja.2019.03.024. PMID: 31047645.
28. *Chen D., Zhang H., Kavitha P. T., Loy F. L., Ng S. H., Wang C., Phua K. S., et al.* Scalp EEG-based pain detection using a convolutional neural network. *IEEE Trans Neural Syst Rehabil Eng.* 2022; 30: 274–285. DOI: . PMID: 35089860.
29. *Kobayashi N., Watanabe K., Murakami H., Yamauchi M.* Continuous visualization and validation of pain in critically ill patients using artificial intelligence: a retrospective observational study. *Sci Rep.* 2023; 13 (1): 17479. DOI: 10.1038/s41598-023-44970-2. PMID: 37838818.
30. *Fratino S., Peluso L., Talamonti M., Menozzi M., Costa Hirai L. A., Lobo F. A., Prezioso C., et al.* Evaluation of nociception using quantitative pupillometry and skin conductance in critically ill unconscious patients: a pilot study. *Brain Sci.* 2021; 11 (1): 109. DOI: 10.3390/brainsci11010109. PMID: 33467451.
31. *Cascella M., Laudani A., Scarpati G., Piazza O.* Ethical issues in pain and palliation. *Curr Opin Anaesthesiol.* 2024; 37 (2): 199–204. DOI: 10.1097/ACO.0000000000001345. PMID: 38288778.

Received 10.10.2025
Accepted 20.11.2025