

## REVIEW ARTICLE

Artificial intelligence-assisted  
thermoluminescence and optically stimulated  
luminescence dose analysis in radiological  
protection, medical imaging, nuclear medicine,  
and radiotherapyFaycal Kharfi<sup>1\*</sup>  and Chahra-Zed Benkhelifa<sup>2</sup><sup>1</sup>Laboratory of Dosing, Analysis, and Characterization High Resolution, Department of Physics, Faculty of Sciences, University Sétif1-Ferhat Abbas, Campus El-Bèz, Sétif, Algeria<sup>2</sup>Nuclear Research Center of Algiers, Algiers, Algeria**Abstract**

Thermoluminescence (TL) and optically stimulated luminescence (OSL) dosimetry have long been established as reliable techniques for quantifying ionizing radiation dose in radiation protection, medical imaging, radiotherapy, and nuclear medicine. The main value of TL and OSL dosimetry in medical applications lies in their ability to provide accurate, passive, and small-scale radiation measurements. These systems are essential for patient safety (*in vivo* dosimetry) and regulatory radiation protection for staff. While TL requires heat to release stored energy, OSL uses light stimulation (lasers/light-emitting diodes) and may allow repeated readouts of the same dosimeter, providing a key advantage for data verification. This review examines the emerging role of artificial intelligence (AI) in enhancing dose analysis. It synthesizes current knowledge of luminescent dosimetry principles with recent advances in machine learning and deep learning, highlighting how AI-driven models improve glow-curve and decay-curve processing, reduce uncertainties, and enable high-precision dose estimation across medical applications. The review also explores new trends such as physics-informed neural networks, hybrid TL-OSL data fusion, real-time embedded AI in portable dosimeters, and three-dimensional dose reconstruction using AI-assisted detector arrays. By integrating foundational dosimetry science with state-of-the-art computational methods, the review provides a comprehensive overview of how AI can strengthen accuracy, efficiency, and clinical impact in luminescence-based dosimetry.

**Keywords:** Thermoluminescence; Optically stimulated luminescence; Radiation dosimetry; Artificial intelligence; Dose analysis

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**1. Introduction**

Thermoluminescence (TL) and optically stimulated luminescence (OSL) dosimetry have long been established as reliable techniques for quantifying ionizing radiation dose in radiation protection, medical imaging, radiotherapy, and nuclear medicine. Their

advantages, such as high sensitivity, tissue-equivalent properties, reusability, and broad dose-response ranges, have made them essential tools for patient dose verification, occupational monitoring, and quality assurance in clinical environments.<sup>1-3</sup> Traditional analysis of TL glow curves (GCs) and OSL decay signals, however, is often limited by sources of variability such as reader instability, fading, complex luminescence kinetics, and nonlinear dose response at high doses.<sup>4-6</sup> These limitations can challenge the precision of dose estimation, particularly as modern radiotherapy and nuclear medicine procedures demand increasingly accurate and individualized dosimetry.

Recent progress in artificial intelligence (AI), especially in machine learning (ML) and deep learning (DL), offers a transformative opportunity to enhance the reliability and information content of luminescence-based dosimetry systems. AI methods have demonstrated strong capability in signal processing, noise reduction, pattern recognition, and predictive modeling across many areas of medical physics and ionizing radiation applications.<sup>7,8</sup> When applied to TL and OSL dosimetry, AI can support automated glow-curve deconvolution, peak identification, background subtraction, and robust dose estimation even under challenging conditions such as low-dose exposures or mixed radiation fields.<sup>9-11</sup> Moreover, neural networks trained on large datasets can capture subtle variations in luminescence behavior arising from material defects, trap distributions, and reader electronics, surpassing the predictive power of traditional analytical models. Thus, AI is rapidly transforming radiation dosimetry, particularly TL and OSL techniques, by enhancing accuracy, workflow efficiency, and the reliability of patient-specific dose verification.

In radiotherapy, AI-enhanced TL/OSL dose mapping enables more accurate verification of complex treatment plans, supports adaptive workflows, and improves three-dimensional dose reconstruction using arrays of pellets or fibers.<sup>12-14</sup> In diagnostic radiology and nuclear medicine, AI-driven algorithms facilitate high-precision assessment of low-level doses to patients and staff, contributing to optimization and radiation protection efforts in accordance with “as low as reasonably achievable” (ALARA) principles.<sup>15</sup> Emerging innovations, including physics-informed neural networks (PINNs), hybrid TL–OSL fusion models, and embedded real-time AI processors in portable dosimeters, are shaping the future of luminescent dosimetry toward fully automated, high-throughput, and personalized dose analysis. Together, these developments position AI-assisted TL/OSL dosimetry as a critical component of next-generation precision radiation medicine, offering improved accuracy, reliability, and clinical integration

across a wide range of medical radiation applications such as X-ray radiology, radiotherapy, and nuclear medicine.

This review is timely and valuable for the applied physics community because AI is rapidly reshaping experimental and medical physics, offering new capabilities for analyzing complex luminescence signals in TL and OSL dosimetry. As modern radiotherapy, diagnostic imaging, and nuclear medicine demand ever-greater accuracy, AI-driven approaches provide enhanced sensitivity, reduced uncertainties, and streamlined workflows. The integration of solid-state physics with data-driven modeling, combined with emerging detector materials and large datasets, positions AI-assisted dosimetry as a key technology for future smart, automated, and real-time radiation monitoring systems. Yet, despite this momentum, comprehensive reviews bridging AI and luminescent dosimetry remain scarce, making this synthesis both relevant and urgently needed.

## 2. Literature search strategy

The bibliographic search strategy for this review was designed to comprehensively identify studies addressing the integration of AI, ML, and DL in TL and OSL dosimetry for medical imaging, nuclear medicine, radiation protection, and radiotherapy. A structured literature search was conducted using the major bibliographic databases, including PubMed, Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, with additional screening of reference lists from relevant review articles and key papers to identify further eligible and relevant studies. The search covered publications from January 2000 to February 2026, with particular emphasis on the most recent eight years (2018–2026), during which the majority of AI-assisted TL/OSL dosimetry studies were published, reflecting the recent acceleration of this field.

The search terms combined keywords related to luminescent dosimetry and AI using Boolean operators, including “thermoluminescence dosimetry,” “TLD,” “optically stimulated luminescence,” “OSL dosimetry,” “glow curve analysis,” “decay curve analysis,” “radiation dose assessment,” “machine learning,” “artificial intelligence,” “deep learning,” “artificial neural network,” “ANN,” “support vector machine,” “gradient boosting,” “LightGBM,” “physics-informed neural networks,” “PINNs,” “dose reconstruction,” “anomaly detection,” and “radiotherapy quality assurance.” Additional targeted terms such as “TLDetect,” “RadField3D,” “3D dose reconstruction,” and “embedded AI dosimetry” were also included to capture emerging applications and software platforms discussed in the review.

Inclusion criteria comprised original research articles,

review papers, conference proceedings, and technical reports published in English that specifically addressed AI-assisted analysis of TL or OSL signals, dose estimation, glow-curve or decay-curve processing, anomaly detection, dose reconstruction, or clinical/operational applications in radiotherapy, diagnostic imaging, and nuclear medicine. Studies involving AI applications in general radiation dosimetry were included when their methodology was directly relevant to TL/OSL systems. Exclusion criteria included papers unrelated to luminescent dosimetry, studies focused solely on conventional dosimetry without AI integration, purely theoretical AI papers without dosimetric application, duplicate publications, and articles lacking sufficient methodological detail or clinical relevance.

The review also considered foundational references on TL/OSL physics and radiation dosimetry to provide the necessary scientific background. Importantly, the literature search confirmed that published work specifically combining AI with TL and OSL dosimetry remains relatively limited compared with broader medical imaging AI research. As highlighted in the manuscript, comprehensive reviews bridging AI and luminescent dosimetry remain scarce, and publicly available datasets are still very few, with most work remaining experimental, laboratory-based, or institution-specific rather than supported by large shared databases. This relative scarcity of published studies further emphasizes the novelty and importance of the present review.

### 3. Principles of thermoluminescence and optically stimulated luminescence dosimetry

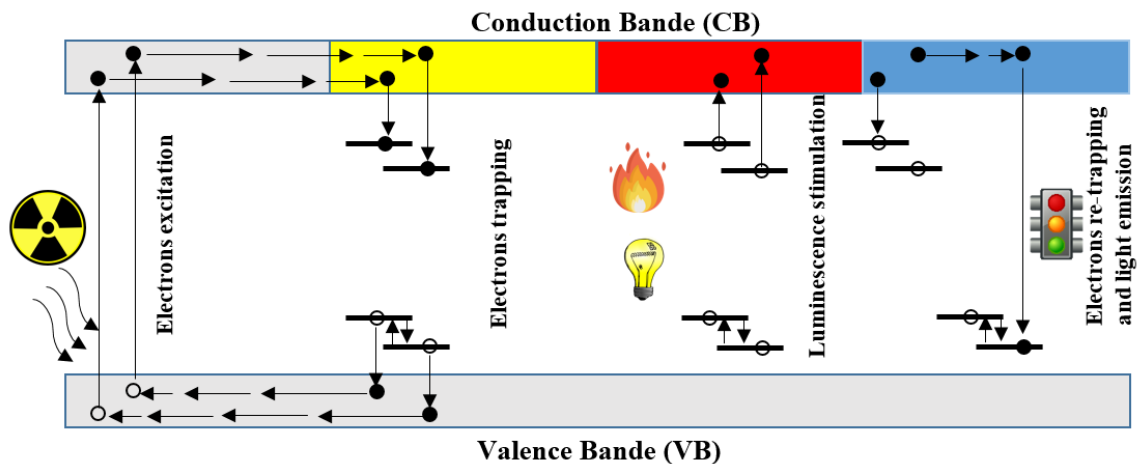
Thermoluminescence and optically stimulated luminescence are radiation dosimetry techniques based on charge trapping in insulating crystals (Figure 1). When a material is exposed to ionizing radiation, electrons are excited from the valence band to the conduction band. Some electrons become trapped in metastable defect levels within the band gap. This stored energy remains in the material until it is externally stimulated. In TL, the material is heated, releasing trapped electrons. These electrons recombine with holes at luminescent centers and emit light proportional to the absorbed dose. In OSL, trapped electrons are released by optical stimulation (lasers or light-emitting diodes [LEDs]) instead of heat. The emitted light intensity is also proportional to the absorbed radiation dose. TL readout is generally destructive, while OSL can allow partial re-reading. Both techniques rely on solid-state physics principles and are widely used in radiation dosimetry and medical physics.

Thermoluminescence and optically stimulated luminescence dosimeters have long been valued for their high sensitivity, tissue-equivalence, and wide dose-response range. Traditionally, these dosimeters rely on manual signal processing and calibration models that can be limited by noise, variability in reader systems, fading effects, and complex dose–response behaviors.

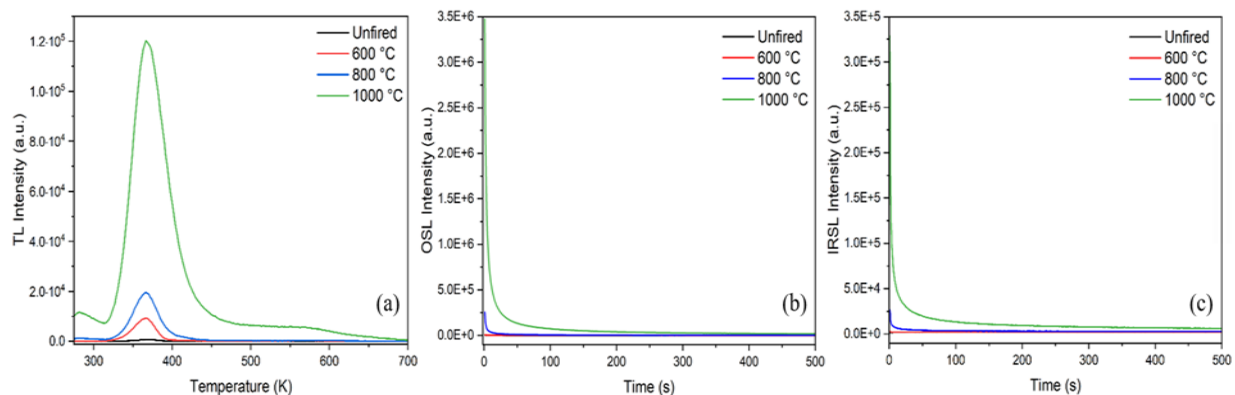
Recent advances in ML and DL make it possible to extract richer information from TL GCs and OSL decay profiles (Figure 2), enabling more precise estimation of absorbed dose in clinical environments.<sup>16–19</sup> AI-assisted analysis improves several key stages of dosimetry: automated glow-curve deconvolution, peak identification, background subtraction, correction for nonlinearity, and prediction of dose in mixed or low-dose fields. Neural networks trained on large datasets can model complex luminescence kinetics and rapidly infer dose even in the presence of reader drift or material imperfections. In radiotherapy, AI-driven pattern recognition supports high-resolution three-dimensional (3D) dose reconstruction using arrays of TL/OSL pellets or fiber-based systems, enhancing treatment-plan verification and adaptive radiotherapy workflows. In diagnostic and nuclear medicine applications, AI improves low-level dose assessment and supports quality assurance in patient and staff monitoring. Emerging trends include PINNs, hybrid TL–OSL data fusion models, real-time predictive algorithms embedded in portable dosimeters, and generative models for synthetic training datasets. These innovations position AI-assisted TL/OSL dosimetry as a cornerstone of next-generation, precision-based medical radiation practices.

### 4. Artificial intelligence databases for thermoluminescence and optically stimulated luminescence dosimetry

The literature on TL/OSL dosimetry developments indicates that far fewer public datasets are available for TL/OSL than for medical imaging or other radiotherapy data. Most TL/OSL work remains experimental, lab-based, or institutional. In this field, GCs, detector readouts, and dosimeter responses tend to be stored internally (in lab databases). At present, the only explicitly AI-oriented, publicly described TL/OSL database is that behind TLDetect.<sup>9</sup> Other resources in radiation dosimetry AI (e.g., RadField3D or ML-based validation of electronic dosimeters) are more general or synthetic, but they show a path forward.<sup>20</sup> Unlike imaging (computed tomography, magnetic resonance imaging) or large-scale medical data, there is no central repository or community-shared database for TL/OSL detector outputs, making data collection and sharing more fragmented.



**Figure 1.** Principles of thermoluminescence and optically stimulated luminescence processes. Figure created by the authors using Microsoft Paint.



**Figure 2.** Typical thermoluminescence (TL), continuous wave blue-light-emitting diode optically stimulated luminescence (OSL) (CW-OSL), and infrared OSL (IRSL) signals of natural and thermally treated quartz irradiated at 100 Gy  $\beta$  dose with a maximum energy of 2.27 MeV. Figure created by the authors.

TLDetect is an AI-based application for automating quality control in TL dosimetry by detecting and classifying anomalous GCs from thermoluminescent dosimeters (TLDs).<sup>8</sup> It uses an artificial neural network (ANN) to screen large GC datasets, distinguish normal from anomalous curves, and flag anomalies such as noise, shifted peaks, and unusual curve widths for human review. This approach improves throughput, reduces human bias, and decreases the workload for laboratory technicians by pre-filtering nonstandard GCs, enabling robust quality control across extensive TL reader databases. The database (SQL-based) stores tens of thousands of curves measured over years (data collected from 2020–2023: ~ 97,512 GCs). This framework provides a useful model for developing ML-ready TL/OSL datasets.

RadField3D, by contrast, is not a database of real TL/OSL measurements but an open-source Geant4-based Monte Carlo data generator and data format for producing

3D radiation-field datasets for DL research.<sup>20</sup> While not a “real measurements” database, RadField3D is used to simulate many radiation scenarios (phantoms, fields, geometries) and generate synthetic data for training/validation of ML models. This resource may be relevant for studies involving physical or 3D-printed phantoms used in TL and OSL dosimetry.<sup>20</sup>

## 5. Review of artificial intelligence applications in thermoluminescence and optically stimulated luminescence dosimetry in radiotherapy, diagnostic imaging, and nuclear medicine

In radiotherapy and diagnostic radiation imaging, including nuclear medicine, AI-assisted TL/OSL dosimetry has several potential applications, including:

- Patient dose verification: AI can automate and

refine phantom dosimetry checks, linking phantom luminescence signals to clinically relevant dose estimates.

- Real-time monitoring: AI processing of TL and OSL signals could enable more accurate and near-real-time dosimetry, improving adaptive radiotherapy.
- Quality assurance: Rapid automatic anomaly detection improves quality assurance workflows in radiology departments.

Artificial intelligence and machine learning offer tools to:

- Automate and improve dosimetric readouts: ML can detect anomalous signals, correct noise, and classify GCs with higher speed and accuracy than manual analysis.
- Enhance dose reconstruction: AI models can learn complex relationships between raw luminescent signals and radiation dose, particularly for multi-parameter or mixed signals.
- Integrate big data analysis: By training on large datasets (e.g., thousands of GCs), AI can refine models of dose response, fading, and energy dependencies.

## 5.1. Machine learning-based dose assessment algorithms

Recent work has compared ANN models and light gradient boosting machine (LightGBM) algorithms against traditional decision-tree (DT)-based TL dose assessments. These ML models showed superior accuracy and reduced bias in classifying radiation fields and predicting shallow and deep dose equivalents. In their study, Lee *et al.*<sup>21</sup> investigated the application of modern ML algorithms to improve TL dosimetry, a key technique for assessing personal radiation exposure. Historically, TL dose assessment in personnel monitoring systems has relied on DT-based approaches to interpret multi-element TL detector responses. While DT methods are simple to implement, they often struggle to accurately classify complex radiation fields and mixed radiation exposures, leading to increased uncertainty in dose estimation. To address these limitations, the authors developed and compared two ML-based approaches, ANN and LightGBM, against the conventional DT algorithm. They constructed a comprehensive dataset by normalizing measured TL element responses to a 1 mSv dose from Cs-137 and augmenting the data within  $\pm 3\%$  to model measurement variability. The dataset covered a range of radiation types, including low- and high-energy photons, beta radiation, and mixed fields, with specially designed hierarchical models to distinguish radiation categories and mixing ratios. Performance evaluation focused on

radiation field classification, mixing ratio determination, and dose equivalent assessment (both deep dose,  $H_p(10)$ , and shallow dose,  $H_p(0.07)$ ). Across these metrics, the LightGBM-based algorithm consistently demonstrated superior classification accuracy and lower performance quotients ( $|\text{Bias}| + \text{Standard deviation}$ ) than both ANN and DT. The LightGBM achieved nearly 99% accuracy in categorizing radiation fields and significantly reduced dose estimation errors compared to DT, particularly for complex mixed exposures where DT exhibited notable misclassification. All tested algorithms met ANSI N13.11 performance criteria under the study's controlled conditions, but the ML models, especially LightGBM, offered marked improvements in precision and reliability. Lee *et al.*<sup>21</sup> noted that real-world conditions might influence performance and highlight the increased complexity of ML models as a trade-off against enhanced accuracy. They suggest future work incorporating advanced learning strategies and experimental validation to further refine these methods. This work provides compelling evidence that ML-based dose assessment algorithms, particularly gradient-boosting approaches like LightGBM, can outperform traditional DTs in TL dosimetry by enhancing accuracy and robustness in radiation field classification and dose estimation.

Lee *et al.*<sup>22</sup> examined the potential of ANNs to analyze the intricate responses of multi-element TLDs when faced with mixed radiation fields. Their research tackled the shortcomings of traditional algorithmic approaches in distinguishing photon energy and components from mixed fields. By utilizing both simulated and real datasets, they trained the ANN to correlate signal patterns from various elements to their respective dose components. The findings indicated a notable enhancement in differentiating between types of radiation and achieving more consistent dose reconstructions than what conventional analytical methods could offer. This work is considered one of the pioneering efforts to incorporate neural networks into personal thermoluminescent dosimetry. In a later study in 2001, the research team also investigated the use of ANNs for personal dose assessment via a multi-area OSL dosimetry system.<sup>23</sup> They created an ANN model designed to analyze complex distributions of OSL signals under different irradiation geometries and energy levels. When compared to standard calibration-based algorithms, this ANN significantly increased the accuracy of dose estimations, especially in environments with mixed or low-energy photon fields. The study underscored the flexibility of neural models in responding to nonlinear detector outputs, offering initial insights that AI-driven methods could improve the reliability of operational dosimetry.

Artificial neural networks were also used to enhance radiation dose estimation in personal dosimetry. In their research, Amit and Datz<sup>24</sup> improved dose reconstruction based on readings from multi-element dosimeters in various irradiation scenarios. By training ANN models with relevant exposure datasets, they were able to decrease bias and uncertainty when compared to traditional dose algorithms. The findings highlighted the ability of ANNs to manage complex nonlinear relationships between detector components and radiation energy levels. In summary, the study illustrated that machine learning has the potential to substantially improve precision in standard and routine radiation protection monitoring.

In a separate study, Mentzel *et al.*<sup>25</sup> explored the potential of DL methods to enhance the estimation of exposure dates in thermoluminescence dosimetry. Rather than relying on traditional regression techniques, the authors utilized deep neural networks to examine the characteristics of TL GCs for retrospective dosimetry. The model was able to identify subtle temporal patterns in the signals that are linked to fading and storage effects. Their findings indicated a notable increase in accuracy when determining the time elapsed since irradiation, a factor that is vital in both accident dosimetry and forensic investigations. This study highlighted the applicability of deep learning not only in dose quantification but also in addressing challenges related to temporal reconstruction.

In their 2024 study, Pathan and colleagues<sup>26</sup> introduced a multi-stage machine learning algorithm aimed at estimating the personal dose equivalent Hp(10) through the use of thermoluminescent dosimeters. This framework integrated the classification of radiation fields with a regression-based approach for dose prediction in a series of stages. By utilizing supervised learning models that were trained on calibrated irradiation datasets, the method enhanced the accuracy of dose estimations across different photon energies and mixed radiation fields. The evaluation of performance indicated that the approach met international dosimetry standards while also minimizing estimation bias when compared to conventional techniques. This research underscores the increasing sophistication of structured machine learning pipelines in the field of operational thermoluminescent dosimetry.

Finally, Rindhatayathon *et al.*<sup>27</sup> used ML techniques to improve dosimeter reading accuracy in relation to the new operational quantities recommended in the International Commission on Radiological Protection within the ICRU 95 framework. They created calibration and correction models based on machine learning that are specifically designed to accommodate the updated definitions of dose quantities. Their comparative analysis revealed a marked

improvement in the consistency between the measured doses and the reference doses, especially when considering different irradiation geometries and energy spectra. This research highlights how artificial intelligence can aid in transitioning from traditional operational quantities to the newly established standards, emphasizing the significance of machine learning in ensuring the future reliability of radiation protection dosimetry systems.

## 5.2. Glow and decay curves processing, classification, and anomaly detection

Recent advances in AI and ML have introduced data-driven alternatives capable of automating anomaly detection, improving dose reconstruction, and extracting latent physical information embedded in GCs. The body of work published in international journals reflects a rapid evolution from proof-of-concept classification models to operational AI tools.

The first major contribution in this domain was made by Amit and Datz<sup>28,29</sup>, who demonstrated that supervised ML models can automatically detect and categorize anomalous TLD GCs. Their 2018 study introduced binary classification for distinguishing normal versus anomalous curves, significantly reducing reliance on manual quality control.<sup>28</sup> The 2019 extension implemented multi-class support vector machines (SVMs) capable of categorizing anomaly types (e.g., shifted peaks, noise-dominated curves, distorted intensities).<sup>29</sup> The strength of their studies lies in the clear operational relevance for large-scale personnel monitoring systems. However, the main limitation is related to feature engineering, which remained partly manual; models depended on predefined descriptors rather than fully raw data learning.

Machine learning regression methods were used by Kröninger *et al.*<sup>30</sup> to shift the focus from anomaly detection to direct GC modeling and dose estimation. Their research illustrated that machine learning can effectively approximate intricate peak patterns without the need for explicit kinetic deconvolution. This method allowed for the estimation of parameters related to dose directly from unprocessed GC data. The study underscored the benefits of data-driven models in managing complex overlapping peaks. The results indicate that ML could serve as either an alternative or an adjunct to traditional GC deconvolution techniques, particularly when dealing with extensive datasets.

Dogan<sup>31</sup> further benchmarked multiple AI methods (ANNs, support vector regression, etc.) for GC estimation, showing that deep neural networks outperform shallow models in reconstruction accuracy, particularly under noisy conditions. The comparative analysis revealed that

deep neural networks generally provided superior curve reconstruction performance. The study emphasized the importance of model selection depending on dataset size and complexity. Overall, the work provides a benchmarking framework for selecting AI tools in TL GC modeling. The main limitations of the study are the limited discussion of the physical interpretability of the learned representations and the lack of uncertainty quantification for predicted dose values.

In addition to dose estimation, Mentzel *et al.*<sup>32</sup> introduced a paradigm shift by using ANNs for the extraction of additional exposure information, such as radiation quality and irradiation conditions. Their model was trained on labeled irradiation scenarios, allowing improved discrimination between photon energies and exposure patterns. Results showed enhanced information retrieval compared with standard single-peak integration techniques. They emphasized that GCs contain latent multidimensional information that can be unlocked using AI tools. This work broadened the application of ML in personal dosimetry beyond anomaly detection toward exposure characterization.

To address the practical limitation of anomalous GCs in operational dosimetry, Pathan *et al.*<sup>33</sup> and Amit *et al.*<sup>9</sup> used AI-based approaches to correct distorted curves rather than reject them. Indeed, they applied ML regression to reconstruct distorted  $\text{CaSO}_4:\text{Dy}$  GCs and recover reliable dose values. Their method addressed practical issues such as peak suppression and abnormal thermal responses. Their results demonstrated improved dose accuracy after ML correction compared with conventional rejection strategies. Instead of discarding anomalous curves, the proposed approach restores usable dosimetric data.<sup>33</sup> These achievements contribute to minimizing data loss and enhancing efficiency in routine monitoring laboratories. Moreover, Amit *et al.*<sup>9</sup> developed TLDetect, an integrated AI software platform for detection and correction. Their study validated the application on experimental and operational dosimetry datasets. Thus, TLDetect demonstrated high accuracy in both identifying anomalies and restoring corrected curves suitable for dose calculation. Through this development, the integration of the proposed solution into a practical software platform marks a transition from methodological research to operational deployment. This work consolidates earlier developments by the group and represents a mature AI-driven quality-control solution for TL dosimetry systems.<sup>9</sup> All these studies demonstrated a strong operational maturity and a direct integration into monitoring workflows by moving beyond classification to active data recovery. However, the generalizability across different TLD materials (LiF,  $\text{CaSO}_4:\text{Dy}$ , etc.) requires

further validation.

Across the above-reviewed studies, several methodological patterns emerge:

- Transition from SVM and shallow models to deep neural networks.
- Shift from detection to reconstruction and information extraction.
- Movement from academic demonstrations to deployable software tools.
- Increasing dataset sizes and supervised learning frameworks.

However, common methodological limitations persist:

- Limited cross-laboratory validation.
- Scarcity of open TL datasets.
- Lack of standardized performance metrics.
- Minimal uncertainty propagation analysis.

### 5.3. Deep learning for irradiation time and environment effects

Studies have used deep networks to predict subtle temporal or environmental effects such as irradiation timing from GCs, showing significantly improved prediction precision compared to conventional methods.

Beyond direct dose estimation, DL methods have shown strong potential for extracting temporal and environmental information from TL GCs and OSL decay signals. One of the major challenges in retrospective dosimetry is the determination of the time elapsed since irradiation, because fading, trap redistribution, and environmental storage conditions progressively modify the luminescence signal after exposure. Conventional analytical approaches often rely on empirical fading corrections or simplified regression models, which may not fully capture the nonlinear relationship between signal evolution and storage history.

Mentzel *et al.*<sup>25</sup> demonstrated that deep neural networks can significantly improve exposure date estimation by learning complex temporal patterns embedded in thermoluminescent GCs. Their model analyzed subtle variations in peak shape, intensity redistribution, and trap population dynamics that are difficult to resolve using traditional peak-integration methods. The study showed that DL achieved higher precision in estimating post-irradiation elapsed time, which is particularly important for accident dosimetry, retrospective exposure reconstruction, and forensic radiation investigations.

Similarly, environmental factors such as temperature, humidity, optical exposure, and storage duration can strongly influence both TL and OSL responses by

accelerating signal fading or modifying trap occupancy distributions. These effects introduce significant uncertainties in dose reconstruction, especially for low-dose measurements and long-term monitoring applications. ANNs offer an effective solution by learning correction models directly from large calibration datasets generated under different environmental conditions. Such models can compensate for nonlinearity and variable fading behavior more robustly than conventional correction factors.

In OSL dosimetry, Lee *et al.*<sup>23</sup> showed that ANN-based models improved personal dose assessment under mixed irradiation geometries and varying photon energies by adapting to complex detector responses. Similar approaches can be extended to account for environmental perturbations affecting OSL signal stability, particularly in personnel monitoring and occupational dosimetry, where storage and transport conditions are often uncontrolled.

Recent work also suggests that recurrent neural networks, long short-term memory architectures, and transformer-based temporal models may provide further improvements by explicitly modeling time-dependent signal evolution rather than relying solely on static curve descriptors. These architectures are particularly promising for predicting long-term fading behavior, reconstructing incomplete historical exposure data, and improving uncertainty quantification in delayed readout conditions.

Overall, DL for irradiation timing and environmental effect correction extends AI applications beyond conventional dose quantification toward full temporal reconstruction of radiation exposure history. This capability is highly relevant for emergency dosimetry, epidemiological studies, forensic investigations, and long-term personnel monitoring, where accurate interpretation of delayed luminescence signals is essential for reliable dose assessment.

## 6. Advantages, limitations, and constraints

The integration of AI into TL/OSL signal analysis and dosimetry offers several potential advantages:

- Automated quality control in national monitoring programs.
- Scalable analysis of large luminescence datasets, reducing the time required for manual review.
- Reduced data rejection rates.
- Adaptive modeling for different luminescent phenomena, glow peaks, fading behavior, and mixed radiation fields.
- Enhanced sensitivity to exposure conditions.
- Enhanced accuracy outperforming traditional

heuristic dosimetry models.

- Potential for real-time GC interpretation.
- Acceleration of kinetic parameter research.

For laboratories in developing countries, or for laboratories expanding national dose-monitoring systems, AI-driven TL and OSL analysis can significantly reduce manual workload while improving reproducibility.

Despite promising progress, important scientific challenges remain:

- Data quality and standardization: High-quality, well-annotated datasets are essential. Noise, detector variance, and reader system differences complicate model training.
- Interpretability: Most models operate as black-box systems. Future work should integrate explainable AI methods to identify which GC regions drive predictions.
- Physics integration: Hybrid models combining kinetic equations with neural networks (PINNs) are largely unexplored in TL.
- Generalization: Models trained on one material or reader system may not generalize to others.
- Regulatory acceptance: In dosimetry for clinical use, rigorous validation against standards is required before AI outputs can be used for patient safety decisions.
- Uncertainty quantification: Dose reconstruction should include confidence intervals to comply with radiological protection standards.

## 7. Future directions for artificial intelligence in thermoluminescence/optically stimulated luminescence dosimetry

Based on this review, promising future directions include:

- Development of physics-constrained neural networks for TL and OSL kinetics.
- Creation of open, standardized glow and decay curve databases.
- Bayesian neural networks for uncertainty estimation.
- Transfer learning between TLD materials.
- Integration of AI with Monte Carlo-based radiation field simulations.
- Real-time embedded AI in TL reader systems.

Four major future research directions are described below.

### 7.1. Physics-informed neural networks

Thermoluminescence and optically stimulated

luminescence dosimetry rely on charge trapping, thermal or optical detrapping, and radiative recombination processes that are traditionally modeled using nonlinear kinetic equations. Conventional GC and OSL decay analysis involves peak deconvolution or empirical fitting, which can be unstable in the presence of noise, overlapping peaks, or incomplete signals. PINNs<sup>34</sup> represent one of the most promising innovations in AI-assisted TL and OSL dosimetry because they combine data-driven learning with the fundamental physical laws governing luminescence processes. Unlike conventional neural networks that learn only from experimental datasets, PINNs incorporate the governing kinetic equations of charge trapping, detrapping, recombination, and dose-response behavior directly into the model training process through the loss function. This allows the network to respect physical constraints such as charge conservation, trap occupancy limits, and thermally activated transition probabilities while fitting TL GCs or OSL decay signals. The major advantage of this approach is improved robustness when dealing with noisy, incomplete, or limited datasets, which is a common challenge in TL/OSL dosimetry due to the scarcity of large public databases. PINNs also reduce overfitting, enhance model interpretability, and provide physically consistent predictions compared with purely black-box DL models. In addition, they enable simultaneous estimation of absorbed dose and kinetic parameters such as trap depth, frequency factors, and recombination coefficients, which are often difficult to extract accurately using traditional deconvolution methods. This makes PINNs particularly valuable for personalized radiotherapy dosimetry, real-time dose reconstruction, and intelligent detector systems where both precision and physical reliability are essential. Indeed, PINNs can provide a promising alternative by embedding the governing rate equations of trapping and recombination directly into the loss function of DL models (Figure 3). In this framework, the neural network simultaneously fits experimental TL GCs or OSL decay curves while enforcing physical constraints such as charge conservation, trap occupancy limits, and thermally activated transition probabilities. This hybrid approach enables robust estimation of kinetic parameters (trap depth, frequency factor, recombination coefficients) without relying solely on numerical least-squares optimization.<sup>35,36</sup> Moreover, PINNs can incorporate temperature ramp profiles, stimulation power, and dose-dependent initial conditions, improving generalization across irradiation scenarios. By coupling data-driven learning with first- or general-order kinetic equations, PINNs enhance interpretability, reduce overfitting, and allow uncertainty-aware dose reconstruction. The integration of physics-based constraints with neural networks thus represents a

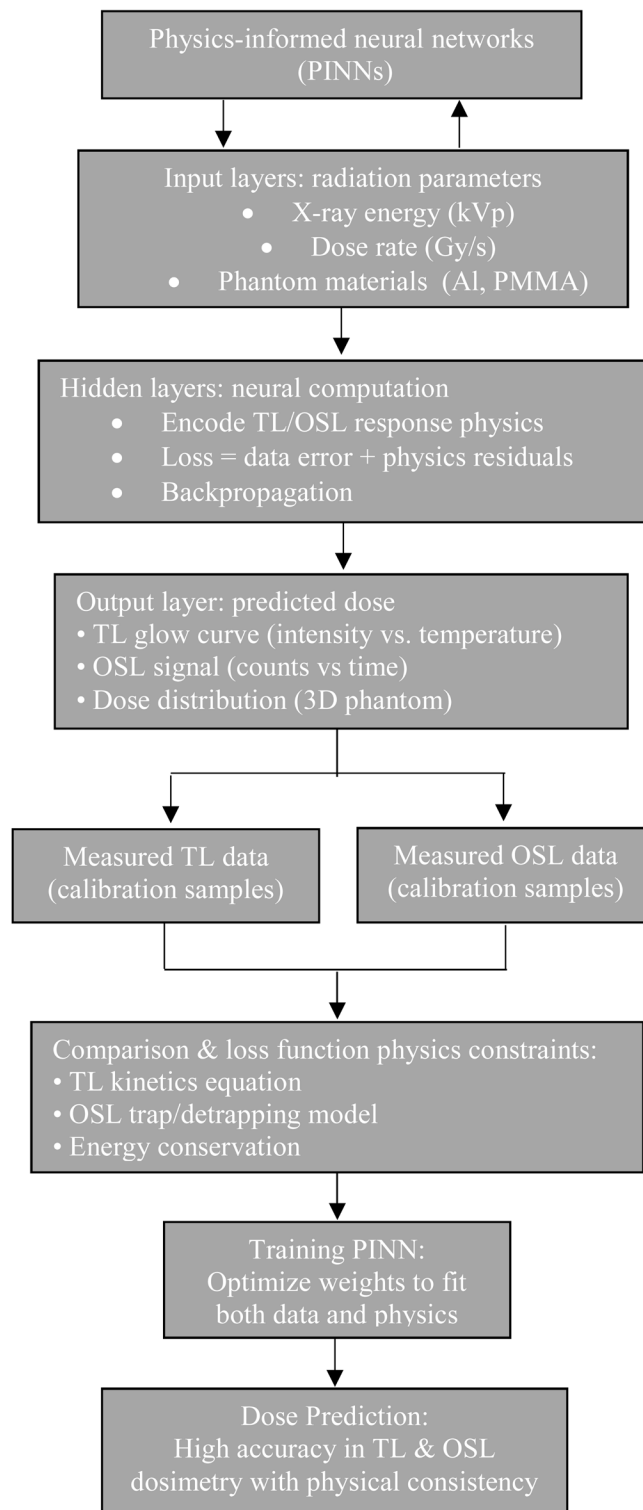
paradigm shift toward more accurate, stable, and physically consistent modeling in TL and OSL dosimetry, with strong potential for next-generation intelligent radiation monitoring systems.

## 7.2. Hybrid thermoluminescence–optically stimulated luminescence data fusion

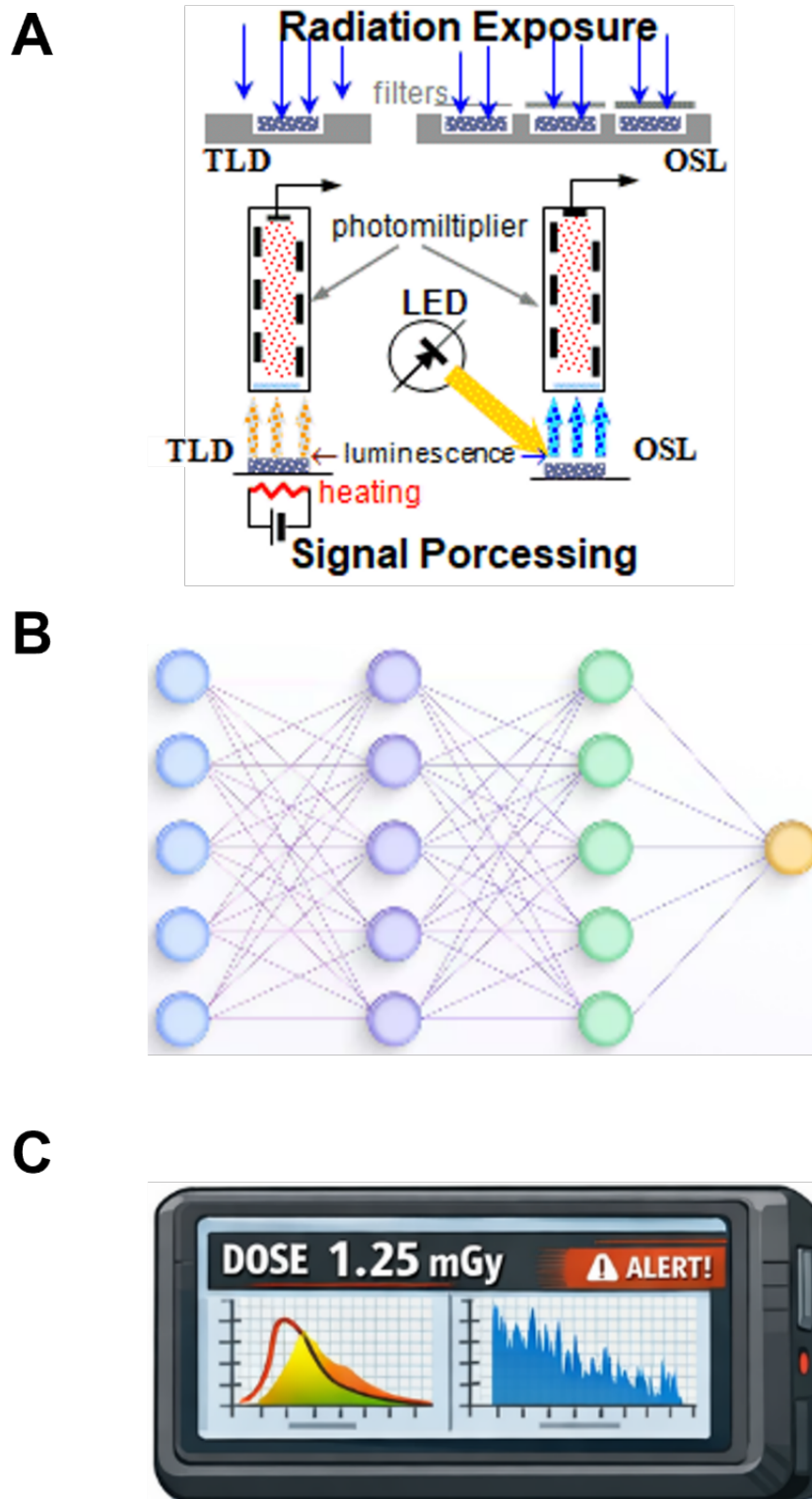
Hybrid TL–OSL data fusion represents an emerging strategy for enhancing radiation dose reconstruction and trap characterization by jointly exploiting TL GCs and OSL decay signals from the same dosimetric material. While TL and OSL are governed by similar charge trapping and recombination mechanisms, they probe complementary aspects of trap populations through thermal and optical detrapping pathways, respectively. Conventional analyses treat these modalities independently, potentially overlooking shared physical information. In a hybrid data fusion framework<sup>37,38</sup>, multimodal neural networks or physics-informed architectures integrate TL temperature-resolved signals and OSL time-resolved decays within a unified model. This approach enables simultaneous estimation of kinetic parameters, trap distributions, and absorbed dose by leveraging cross-correlated features between modalities. By constraining the learning process with coupled rate equations and shared trap occupancy conditions, the model ensures physical consistency across both readout techniques. Hybrid fusion improves robustness against noise, enhances sensitivity to complex irradiation histories, and reduces parameter degeneracy inherent in single-modality fitting. Furthermore, multimodal uncertainty quantification becomes possible through joint likelihood modeling. The integration of TL and OSL via advanced data fusion techniques thus provides a more comprehensive and physically consistent framework for luminescence dosimetry, paving the way for intelligent, high-accuracy radiation monitoring systems capable of multidimensional exposure assessment.<sup>39</sup>

## 7.3. Real-time embedded artificial intelligence in portable thermoluminescence/optically stimulated luminescence dosimeters

Real-time embedded AI in portable TL and OSL dosimeters represents an emerging paradigm in intelligent radiation monitoring (Figure 4). Conventional TL and OSL systems typically rely on post-processing of GCs or decay signals using external computers, limiting immediate dose interpretation and anomaly detection.<sup>40,41</sup> The integration of embedded AI, implemented on microcontrollers, field-programmable gate arrays, or low-power edge processors, enables on-device analysis of luminescence signals in real time. Such systems can perform instant dose estimation, GC anomaly detection, kinetic parameter extraction,



**Figure 3.** Typical architecture of PINNs for thermoluminescence (TL) and optically stimulated luminescence (OSL) dosimetry. Figure created by the authors using Microsoft-Word.



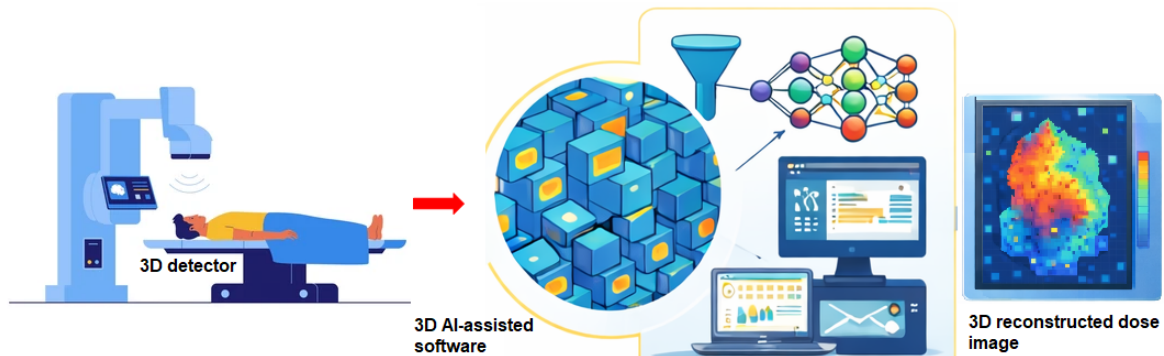
**Figure 4.** Typical real-time embedded artificial intelligence (AI) in portable thermoluminescence (TL) and optically stimulated luminescence (OSL) dosimeters for intelligent radiation monitoring. (A) Radiation exposure and detection signal processing. (B) AI processing. (C) Real-time dose monitoring, data storage, data communication, and data display. Figure created by the authors using Microsoft-Paint.

and signal denoising directly within portable readers. By combining compact neural networks or physics-informed models with optimized hardware architectures, embedded AI enhances operational autonomy, reduces latency, and minimizes data transmission requirements. In OSL systems, real-time AI can dynamically adapt stimulation protocols based on signal evolution, improving dose precision at low exposures. In TL readers, intelligent algorithms could classify peak distortions, compensate for heating-rate variations, and predict absorbed dose before full curve acquisition is completed. These developments pave the way toward next-generation smart dosimeters capable of adaptive measurement, uncertainty-aware reporting, and integration into wireless radiation monitoring networks. Real-time embedded AI thus constitutes a transformative step toward fully autonomous, portable, and high-reliability TL and OSL dosimetry systems.

### 7.4. 3D dose reconstruction using artificial intelligence-assisted detector arrays

Three-dimensional detection<sup>42</sup> and dose reconstruction using TL and OSL detector arrays enhanced with AI

represents a transformative approach in advanced radiation dosimetry. Traditional 3D dosimetry techniques often rely on point measurements or gel dosimeters, limiting spatial resolution and requiring labor-intensive readout. By embedding dense arrays of TL/OSL detectors within phantoms or wearable matrices, high-resolution spatial information about dose distributions can be acquired. AI algorithms, including deep convolutional neural networks, PINNs, and hybrid ML models, can be trained to interpret the multidimensional signal patterns produced by these arrays, compensating for non-uniform detector responses, energy dependence, and geometrical artifacts. This AI-assisted framework will enable rapid reconstruction of complex dose distributions from partial or noisy TL/OSL data by improving accuracy, robustness to noise, and computational efficiency compared to conventional analytical methods. Applications will span radiotherapy quality assurance (Figure 5), environmental radiation mapping, and retrospective accident dosimetry. By coupling intelligent reconstruction with 3D-printed phantom geometries and flexible detector arrays, this integrated approach will advance the field toward real-



**Figure 5.** Three-dimensional (3D) dose reconstruction using thermoluminescence and/or optically stimulated luminescence detector arrays for radiotherapy quality assurance

time, high-resolution volumetric dosimetry capable of adaptive treatment verification and personalized radiation assessment.

## 8. Conclusion

This review demonstrates that AI is rapidly transforming TL and OSL dosimetry from conventional peak-based analytical methods into data-driven, multidimensional modeling frameworks. Over the past decade, and particularly within the last eight years, AI applications have evolved from preliminary anomaly detection tools to advanced systems capable of glow-curve reconstruction, dose estimation in mixed radiation fields, kinetic

parameter extraction, and operational deployment in clinical workflows.

Machine learning models, including ANNs, gradient-boosting algorithms, and DL architectures, consistently demonstrate improved accuracy, robustness, and bias reduction compared with traditional DT or heuristic calibration methods. Beyond simple dose quantification, AI approaches unlock latent information embedded within TL GCs and OSL decay signals, enabling radiation field classification, exposure condition identification, irradiation time estimation, and multidimensional dose reconstruction. The progression from classification to reconstruction, and ultimately to integrated software

platforms such as TLDetect, reflects clear technological maturation and growing operational readiness.

Importantly, the integration of PINNs, hybrid TL–OSL data fusion strategies, and AI-assisted 3D detector array reconstruction marks a paradigm shift toward physically constrained, high-resolution, and potentially real-time intelligent dosimetry systems. These developments align strongly with the increasing demands of precision radiotherapy, optimized diagnostic imaging, adaptive treatment verification, and modern radiation protection standards.

However, several scientific and regulatory challenges must be addressed before AI-assisted luminescence dosimetry achieves full clinical integration. These include the scarcity of open standardized datasets, cross-laboratory validation, model generalization across materials and reader systems, explainability of predictions, and rigorous uncertainty quantification compliant with radiological protection frameworks. Addressing these limitations through physics-constrained modeling, Bayesian uncertainty estimation, standardized benchmarking protocols, and regulatory validation pathways will be essential.

In conclusion, AI-assisted TL and OSL dosimetry represents more than a methodological enhancement; it constitutes a fundamental conceptual transition in radiation measurement science. By coupling solid-state luminescence physics with advanced computational intelligence, the field is moving toward autonomous, scalable, and high-precision radiation monitoring systems capable of supporting next-generation medical imaging, radiotherapy quality assurance, nuclear medicine, and radiation protection programs. With continued interdisciplinary collaboration and rigorous validation, AI-driven luminescence dosimetry is poised to become a cornerstone technology in precision radiation medicine.

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## Conflict of interest

The authors declare they have no competing interests.

## Author contributions

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## Ethics approval and consent to participate

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## Consent for publication

Not applicable.

## Availability of data

Not applicable.

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