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ARTIFICIAL INTELLIGENCE AND DIFFERENTIAL EQUATIONS IN POSTMORTEM INTERVAL ESTIMATION: A CRITICAL REVIEW OF CADAVER COOLING MODELS AND THEIR APPLICATIONS IN CRIMINAL INVESTIGATION

INTELIGENCIA ARTIFICIAL Y ECUACIONES DIFERENCIALES EN LA ESTIMACIÓN DEL INTERVALO POST MORTEM: REVISIÓN CRÍTICA DE LOS MODELOS DE ENFRIAMIENTO CADAVÉRICO Y SUS APLICACIONES EN CRIMINALÍSTICA

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Artificial Intelligence and Differential Equations in Postmortem Interval Estimation: A Critical Review of Cadaver Cooling Models and their Applications in Criminal Investigation

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ABSTRACT

This review examines the relationship between cadaver cooling, differential equations and artificial intelligence in postmortem interval estimation, distinguishing computational plausibility from forensic validation. A critical narrative review of 60 references combined documentary screening, individual bibliographic identity checks and examination of available abstracts or full texts. The synthesis distinguished controlled experiments, human observations and computational foundations. Thermal models make mechanisms explicit, but their inversion depends on partly unknown initial and environmental conditions. Machine learning incorporates metabolomic, molecular and imaging information; heterogeneous performance measures do not establish overall superiority. Surrogate-based optimization provides a documented integration of physical simulation and computation in human cadavers, although validation remains limited. Physics-informed neural networks offer tools for inverse problems; computational effectiveness alone does not establish forensic usefulness. Translation into criminal investigation requires a defined application domain, separation of decedents between training and evaluation, assessment of calibration and uncertainty, and external validation. A model should be judged by the reliability of its inferences under documented conditions as well as its predictive fit.

***Keywords*:** forensic medicine, artificial intelligence, models, theoretical, computer simulation

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Inteligencia Artificial y Ecuaciones Diferenciales en la Estimación del Intervalo Post Mortem: Revisión Crítica de los Modelos de Enfriamiento Cadavérico y sus Aplicaciones en Criminalística

RESUMEN

Esta revisión analiza la articulación entre enfriamiento cadavérico, ecuaciones diferenciales e inteligencia artificial en la estimación del intervalo post mortem, diferenciando plausibilidad computacional y validación forense. Se desarrolló una revisión narrativa crítica de 60 referencias, con depuración documental, comprobación individual de identidad bibliográfica y examen de resúmenes o textos disponibles. La síntesis distinguió experimentación controlada, observaciones humanas y fundamentos computacionales. Los modelos térmicos permiten explicitar mecanismos, pero su inversión depende de condiciones iniciales y ambientales parcialmente desconocidas. El aprendizaje automático incorpora información metabolómica, molecular e imagenológica; sus métricas resultan heterogéneas y no permiten establecer una superioridad general. La optimización mediante modelos sustitutos constituye una integración física-computacional documentada en cadáveres humanos, aunque con validación limitada. Las redes informadas por física ofrecen herramientas para problemas inversos; su eficacia computacional no acredita por sí misma utilidad pericial. El traslado a criminalística requiere identificar el dominio de aplicación, separar cadáveres entre entrenamiento y evaluación, comprobar calibración e incertidumbre y realizar validación externa. La contribución de un modelo debe juzgarse por la confiabilidad de sus inferencias bajo condiciones documentadas, además de su ajuste predictivo.

***Palabras clave*:** medicina legal, inteligencia artificial, modelos teóricos, simulación por computador, modelos de aprendizaje predictivo

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Inteligência Artificial e Equações Diferenciais na Estimativa do Intervalo Post Mortem: Revisão Crítica dos Modelos de Resfriamento Cadavérico e Suas Aplicações na Criminalística

RESUMO

Esta revisão analisa a articulação entre resfriamento cadavérico, equações diferenciais e inteligência artificial na estimativa do intervalo post mortem, distinguindo plausibilidade computacional e validação forense. Foi realizada uma revisão narrativa crítica de 60 referências, com depuração documental, verificação individual da identidade bibliográfica e exame dos resumos ou textos disponíveis. A síntese diferenciou experimentos controlados, observações humanas e fundamentos computacionais. Os modelos térmicos explicitam mecanismos, mas sua inversão depende de condições iniciais e ambientais parcialmente desconhecidas. O aprendizado de máquina incorpora informações metabolômicas, moleculares e de imagens; métricas heterogêneas não permitem estabelecer superioridade geral. A otimização por modelos substitutos constitui uma integração físico-computacional documentada em cadáveres humanos, embora com validação limitada. Redes informadas pela física oferecem ferramentas para problemas inversos; sua eficácia computacional não comprova, por si só, utilidade pericial. A aplicação à criminalística exige delimitar o domínio de uso, separar indivíduos entre treinamento e avaliação, verificar calibração e incerteza e realizar validação externa. A contribuição de um modelo deve ser avaliada pela confiabilidade das inferências sob condições documentadas, além do ajuste preditivo.

***Palavras-chave*:** medicina legal, inteligência artificial, modelos teóricos, simulação por computador, modelos preditivos de aprendizagem

INTRODUCTION

The postmortem interval (PMI) is the time elapsed between death and an explicitly defined reference point, such as discovery, examination or sampling. The expressions *postmortem interval*, *post-mortem interval* and *time since death* denote this interval in the literature, but they are interchangeable only when they share the same endpoint. Confusing discovery with measurement changes the target variable and may introduce an error independently of the algorithm used (Henssge & Madea, 2007; Wenzlow et al., 2023; Wilk et al., 2022).

Thermal estimation reconstructs a history from the body's current state. This inverse problem requires separating observed information from assumed conditions: initial temperature, previous environmental exposure, insulation and geometry. Henssge's nomogram summarizes empirical relationships that are useful under specified conditions. Numerical models represent heat transfer in greater detail, but require parameters that cannot always be recovered at the scene. Greater physical detail does not remove uncertainty about the body's history (Henssge, 1988; Wilk et al., 2020; Wilk et al., 2022).

Machine learning shifts part of the effort from specifying mechanisms to identifying regularities in thermal, molecular or imaging data. Available reviews report encouraging results alongside small samples, heterogeneous validation and difficulties transferring models across settings. A network identifying time categories in animal tissues and a model predicting days since death from human blood address different questions and support different forensic uses (Bugelli et al., 2026; Sharma et al., 2022; Sirago et al., 2026; Teixeira et al., 2025; Tournois et al., 2024).

This review examines what each model family contributes, what information it requires and what evidence supports its application. Its central argument is that the relationship between physics and artificial intelligence should be evaluated through identifiability, transportability and communication of uncertainty. Hybrid models are useful when they integrate complementary information and enable their assumptions to be tested; the label itself guarantees neither accuracy nor forensic validity (Collins et al., 2024; Karniadakis et al., 2021; Kennedy & O'Hagan, 2001).

METHODS

Review design and thematic axes

A critical narrative review combined bibliographic verification with methodological synthesis. Four thematic axes were defined: cadaver cooling and thermometry; differential equations and inverse problems; machine learning applied to PMI; and physical-computational integration, uncertainty and validation. The final corpus comprises 60 distinct works. Classical contributions were retained when they supported models or criteria still in use, together with relevant recent research. The reference count describes the analytical corpus; it does not estimate the full extent of the literature.

This work is not presented as an exhaustive systematic review or meta-analysis. It had no prospective registration, independent dual-reviewer screening or uniform access to full texts. PRISMA 2020 informed distinctions between identification, selection and reporting transparency, without attributing unperformed procedures to the review. TRIPOD, TRIPOD+AI and PROBAST domains guided critical reading; they did not replace a complete formal assessment of every study (Collins et al., 2015; Collins et al., 2024; Page et al., 2021; Wolff et al., 2019).

Search strategy and study selection

References were consulted one by one through bibliographic records, accessible indexes and publisher pages. Actual relevance was checked against the title and, where available, the abstract or full text. DOI, authorship, title, year and publication details were compared. Crossref was used to verify bibliographic identity, not to establish methodological quality. PubMed/MEDLINE, Europe PMC and publisher pages supported content checks; targeted web searches located specific records. These checks closed on September 25, 2026.

Information was extracted by examining available content to avoid confusing general artificial intelligence or thermal-model literature with research applied to *postmortem interval* and its forensic use. An existing DOI was insufficient to establish an attribution: mismatched titles and DOIs were identified and corrected against the corresponding source. Duplicates were consolidated by DOI and title comparison. Retracted records were excluded as substantive evidence, as were unrelated works appearing in the initial compilation.

The expanded strategy was organized as independent searches by thematic axis followed by combined deduplication. The protocol covers Scopus, PubMed, Web of Science, IEEE Xplore, ScienceDirect, Google Scholar, SciELO and Redalyc. Planned coverage must be distinguished from searches actually performed: auditable exports of complete searches across all these platforms were unavailable, and their execution is not claimed. In particular, including a journal hosted on ScienceDirect or indexed in Scopus does not establish that an independent search of that database was conducted. Section 5.2.1 provides complete search strings prepared for replication; retrieval counts remain undetermined.

Search strings and replication criteria

The following strings constitute a prepared protocol for extending and reproducing the search; no retrieval counts or complete execution across all platforms are claimed. Date filters are initially omitted to retrieve foundational work; recent literature is subsequently prioritized and classical exceptions documented. Results from each axis should be exported separately, combined by union and deduplicated by DOI and title. Requiring intersection of every axis is avoided because it would exclude relevant physical foundations and AI studies that do not mention the other model family.

Scopus — thermal axis

TITLE-ABS-KEY(("postmortem interval" OR "post-mortem interval" OR "time since death" OR "cad aver cooling" OR "postmortem cooling") AND (Henssge OR Newton OR "heat transfer" OR "differen tial equation" OR "differential equations" OR "finite element" OR "finite difference"))

Scopus — artificial intelligence axis

TITLE-ABS-KEY(("postmortem interval" OR "post-mortem interval" OR "time since death") AND (" artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network" OR "neural ne tworks" OR "random forest"))

PubMed — forensic application

("postmortem interval"[Title/Abstract] OR "post-mortem interval"[Title/Abstract] OR "time since deat h"[Title/Abstract]) AND ("Artificial Intelligence"[Mesh] OR "Machine Learning"[Mesh] OR "machin e learning"[Title/Abstract] OR "deep learning"[Title/Abstract] OR Henssge[Title/Abstract] OR "body cooling"[Title/Abstract] OR "heat transfer"[Title/Abstract])

Web of Science — integration

TS=(("postmortem interval" OR "post-mortem interval" OR "time since death") AND ("heat transfer" OR Henssge OR "differential equation*" OR "machine learning" OR "deep learning" OR "physics-informed" OR "surrogate model*"))

IEEE Xplore — all metadata search

(("All Metadata":"postmortem interval" OR "All Metadata":"time since death") AND ("All Metadata":"machine learning" OR "All Metadata":"neural networks" OR "All Metadata":"heat transfer" OR "All Metadata":"physics-informed"))

ScienceDirect — title, abstract or keywords

("postmortem interval" OR "time since death") AND ("body cooling" OR Henssge OR "machine learning" OR "physics-informed")

Hybrid foundations — independent IEEE Xplore or ScienceDirect search

("physics-informed neural networks" OR "physics-informed machine learning" OR "surrogate model") AND ("heat transfer" OR "inverse problem" OR "uncertainty quantification")

Google Scholar — run the three queries separately

"postmortem interval" "machine learning"

"time since death" "body cooling"

"postmortem interval" "physics-informed"

SciELO and Redalyc — general fields with language variants

("intervalo post mortem" OR "intervalo postmortem" OR "tiempo de muerte" OR "tempo de morte") AND ("inteligencia artificial" OR "inteligência artificial" OR "enfriamiento cadavérico" OR "resfriamento cadavérico" OR "ecuaciones diferenciales" OR "equações diferenciais")

If an interface does not support nested Boolean operators, phrase combinations should be executed and logged as independent queries. Free-text search terms are not presented as controlled descriptors. The article's five DeCS/MeSH descriptors retain conceptual identity across languages; identifiers and links are provided in the traceability supplement.

Inclusion and exclusion criteria

The review included primary studies and reviews on PMI estimation, cooling research with cadaver-related relevance, and physical or statistical foundations needed to interpret hybrid models. Nonforensic methodological literature was explicitly classified as transferable foundational work and was never treated as medicolegal validation. English-language and other publications were considered when their identity and contribution could be established through available abstracts, metadata or text.

Duplicates, retracted records, unresolved bibliographic inconsistencies and studies connected only through generic terms such as temperature or artificial intelligence were excluded. Species identification, cause-of-death diagnosis and injury classification without a relevant temporal outcome were not considered equivalent to PMI estimation. Reviews contextualized the field and informed methodological comparison; their constituent studies were not counted as independent observations in addition to primary studies already included (Bugelli et al., 2026; Sharma et al., 2022; Tournois et al., 2024).

Data extraction and critical appraisal

Extracted information included species, experimental unit, number of individuals when available, time window, environment, input signals, model family, validation strategy, metrics and scope of conclusions. Three evidence levels were distinguished: **A**, laboratory studies, animals or human cadavers under controlled conditions; **B**, human observations related to medicolegal investigations, which do not automatically imply external validation; and **C**, mathematical or computational evidence without direct forensic application. Reviews and guidelines were classified as secondary or methodological evidence.

Critical reading addressed five questions: whether the reference PMI was known or estimated; whether observations from the same individual could cross dataset partitions; whether metrics described regression or classification; whether calibration was assessed; and whether the validation environment represented intended use. Missing information was treated as a limitation of accessible reporting, not proof that a procedure had not been performed. No aggregate quality scores or pooled effects were calculated because outcomes, units and designs were insufficiently homogeneous (Collins et al., 2024; Riley et al., 2019; Wolff et al., 2019).

RESULTS AND CRITICAL DISCUSSION

Overview of postmortem interval estimation

PMI is not directly observable in most retrospective investigations. Estimation links biological and physical transformations to a timescale and depends on documenting modifying factors. The established recommendation to integrate methods remains relevant: thermal signals, supravital muscle responses and molecular markers may provide different constraints. Combining them requires understanding their dependence; accumulating correlated indicators does not amount to assembling independent evidence (Henssge et al., 1988; Henssge & Madea, 2007; Stigter et al., 2024).

Cooling is particularly informative while a thermal contrast with the environment persists. Molecular degradation, microbial succession and postmortem imaging investigate other processes and temporal windows. Reviews by Wenzlow and colleagues and Cianci and colleagues show that species, tissue and storage conditions delimit marker interpretation. Changing modality does not remove environmental effects; it changes how those effects influence the signal (Cianci et al., 2024; Wenzlow et al., 2023; Yuan et al., 2023).

Responsible comparison must hold the prediction problem constant. A study of the first hours after death cannot be ranked against a study of weeks by its raw error value; classification accuracy cannot be translated into minutes either. Henssge and Madea emphasized that methods should be compared over the same interval while accounting for variation in influential factors. This requirement becomes especially important when technologies differ in capabilities and costs (Bugelli et al., 2026; Henssge & Madea, 2007; Sirago et al., 2026).

Cadaver cooling and heat-transfer models

Classical approaches: Newton, Henssge and variants

A lumped Newtonian cooling representation assumes an effectively uniform body temperature, a constant cooling coefficient and constant ambient temperature. As an idealization of heat exchange, it is written as:

$$\frac{dT}{dt} = -k(T - T_a), \qquad T(0) = T_0, \quad k > 0. \quad (1)$$

Its solution and temporal inversion are:

$$T(t) = T_a + (T_0 - T_a)e^{-kt}, \qquad t = \frac{1}{k}\ln\left(\frac{T_0 - T_a}{T - T_a}\right). \quad (2)$$

Here, T denotes modeled temperature, T_a ambient temperature, T_0 initial temperature and k an effective rate with inverse-time units. The equation explains the inverse reasoning but does not itself validate a cadaver estimate. Core-to-surface gradients and the initial cooling phase motivate more complex representations. Rectal temperature should not be equated without justification to the uniform temperature of a lumped body (Henssge, 1988; Henssge & Madea, 2007; Wilk et al., 2020).

In Henssge's approach, the dimensionless ratio $Q = (T_r - T_a)/(T_0 - T_a)$ is related to time through a calibrated biexponential function. A classical branch for lower ambient temperatures uses:

$$Q(t) = 1.25e^{-kt} - 0.25e^{-5kt}. \quad (3)$$

This expression illustrates an initially zero slope; it does not represent every branch or correction of the method. Application requires rectal and ambient temperatures, body mass and correction factors for cooling conditions; an initial temperature of 37.2 °C is commonly assumed. The appropriate parameterization and application limits must be used rather than freely fitting k while retaining the designation of a validated method (Henssge, 1988; Otatsume et al., 2024).

Otatsume and colleagues implemented numerical solution using Solver and tabulated searches in Excel. Nedugov proposed improvements in equation solving and error handling. These contributions reduce reading, discretization or calculation problems, but a more accurate numerical root does not correct an incorrect initial temperature or an unknown environmental history. The accuracy of the equation-solving algorithm must be separated from the validity of the model represented by that equation (G. V. Nedugov, 2021b; Otatsume et al., 2024).

6.2.2. Differential-equation models and physical assumptions

When ambient temperature varies, the lumped equation becomes $dT/dt = -k[T - T_a(t)]$. With constant k, its solution is:

$$T(t) = T_0 e^{-kt} + k\int_0^t e^{-k(t-s)}\, T_a(s)\, ds. \quad (4)$$

This identity, derived with an integrating factor, shows that present temperature depends on the environmental trajectory rather than only its current value. Models with linearly varying ambient temperature and dual-thermometry strategies attempt to represent part of that dependence. The linear assumption must be checked against actual exposure; transfer into refrigeration introduces a regime change that need not follow a single trend (G. V. Nedugov, 2021a; V. G. Nedugov & Nedugov, 2024, 2025).

Distributed conduction represents position **x**, heterogeneity and boundary conditions:

$$\rho c \frac{\partial T}{\partial t} = \nabla \cdot (\lambda \nabla T) + q, \qquad \mathbf{x} \in \Omega. \quad (5)$$

Density ρ, specific heat c and conductivity λ may differ between tissues. The term q collects volumetric sources requiring justification. One possible balance on an exposed surface is:

$$-\lambda \nabla T \cdot \mathbf{n} = h(T - T_a) + \varepsilon\sigma\left(T^4 - T_{\text{rad}}^4\right) - q_{\text{solar}}. \quad (6)$$

Radiative temperatures are absolute, in kelvin; h is the convective coefficient, ε emissivity, σ the Stefan–Boltzmann constant and q_{solar} absorbed solar radiation. Ground or surface contact requires an additional conduction or thermal-resistance condition. Equations (5)–(6) summarize modeling principles; the terms retained depend on the scenario (Belykh & Vavilov, 2025; Wilk et al., 2020; Wilk et al., 2022).

Pennes' bioheat model was developed for living tissue and includes perfusion-related exchange. After death, steady physiological perfusion should not be retained as though circulation continued. A cadaver adaptation must justify which terms vanish, which persist transiently and how the initial temperature distribution is described. Citing a bioheat equation does not establish that its parameterization is valid in postmortem tissue (Pennes, 1948; Wilk et al., 2020).

Numerical models and limits to generalization

Finite differences and finite elements accommodate geometry, layers and boundaries omitted by lumped models. Wilk and colleagues combined surface thermometry with finite-difference simulation in human cadavers. This evidence supports experimental feasibility, but generalization requires scrutiny of anatomical representation and the properties assigned to tissues, clothing and surroundings. More

detailed geometry may also introduce poorly identifiable parameters (Wilk et al., 2020; Wilk et al., 2022).

The history of changing environmental conditions provides an instructive comparison. Althaus and Henssge investigated abrupt changes using objects with body-like cooling. Bovenschen and colleagues evaluated back-calculation in 25 deceased individuals moved into refrigerated storage and found substantial differences between reconstructed and observed temperatures. Transfer from experimental objects to human cadavers therefore requires its own testing. The availability of a mathematical solution does not justify assuming that it reproduces an actual thermal transition (Althaus & Henssge, 1999; Bovenschen et al., 2021).

Solar exposure likewise cannot always be represented as a simple increase in air temperature. Belykh and Vavilov studied substitute objects and cadavers exposed to radiation, incorporating a solar factor dependent on material and environmental conditions. Their contribution identifies a boundary effect that can alter the balance; reported errors should not be interpreted as guarantees for every climate, fabric or surface. Evaluations must distinguish the data used to fit that factor from those used to test it (Belykh & Vavilov, 2025; Kennedy & O'Hagan, 2001).

Artificial intelligence applied to PMI

Supervised learning and neural networks

Supervised learning fits a relationship between predictors and a reference PMI or temporal category. Random forests combine trees to model nonlinear relationships, while deep networks can extract representations from images or high-dimensional profiles. Architectural complexity does not correct imprecise temporal labels or increase the number of independent individuals. Reviews should therefore be read with attention to the biological unit and dataset separation protocol (Breiman, 2001; Sharma et al., 2022; Sirago et al., 2026).

Løber and colleagues developed metabolomic models in rat tissues and tested them in an independent animal dataset. An and colleagues used 12 pigs and added four for external validation of a multiorgan pathomics strategy. Their reported 87.5% external accuracy concerns classification in that design; it does not mean that time of death is estimated with a 12.5% error. Testing new individuals is an advance, although transfer to humans remains unresolved (An et al., 2025; Løber et al., 2025).

Human evidence involves other timescales. Magnusson and colleagues analyzed femoral blood from 4,876 individuals with intervals of 1–67 days. They reported mean and median absolute errors of 1.45 and 1.03 days in testing and 1.78 and 1.29 days in 512 individuals from another year and analytical platform. Temporal and platform validation informs transportability, but does not make the model a tool for resolving differences of a few hours in early PMI (Magnusson et al., 2026).

In imaging, Klontzas and colleagues included 97 human CT examinations and classified intervals on either side of a 12-hour threshold, reporting an AUC of 0.75 for the combined model. Ivanov and colleagues analyzed 544 examinations from 123 decedents. Distinguishing scans from individuals is essential: repeated observations extend the measured trajectory, but are not independent human replicates. Results depend on how these trajectories are separated during training and evaluation (Collins et al., 2024; Ivanov et al., 2025; Klontzas et al., 2023).

Input variables: temperature, environmental context and uncertainty

Temperature acts both as a physical observation and as a modifier of degradation. Fan and colleagues integrated multiorgan metabolomics and ambient temperature in rats; Ren and colleagues investigated microbial succession in bromadiolone-exposed rats. These studies show that tissue, environment and toxicants can alter the relationship between signal and time. Including temperature as a statistical predictor may be useful, but is not equivalent to imposing conservation of energy (Fan et al., 2025; Ren et al., 2026).

Gravesoil microbiota reflect interactions between the body and its ecosystem. Work by Cui and by Metcalf supports investigating succession as a temporal signal; it does not establish microbial composition as a universal clock. Substrate, sampling and decomposition conditions define the inference domain. A model trained in one site–season combination may recognize environmental characteristics rather than a transportable temporal relationship (Cui et al., 2023; Metcalf et al., 2016; Yuan et al., 2023).

RNA profiles add variation associated with sample integrity, normalization and reference-gene stability. Wang and colleagues investigated endogenous and exogenous signals in a mouse model. Cianci and colleagues examined nine refrigerated porcine hearts using leave-one-heart-out validation and found

that data representation affected prediction. Analytical reproducibility and biological validation must be assessed separately (Cianci et al., 2024; Cianci et al., 2026; Y. Wang et al., 2026).

Performance metrics and calibration

For regression, mean absolute error and root mean squared error are:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\hat{t}_i - t_i|, \qquad \mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{t}_i - t_i)^2}. \quad (7)$$

Both require reporting units and the distribution of PMI. Mean signed error may approach zero because overestimates and underestimates cancel. Correlation does not measure agreement either; residuals and limits of agreement should therefore be examined while respecting repeated-measure dependence and statistical assumptions (Bland & Altman, 1986; Sullivan, 2015).

AUC describes discrimination between classes, not the temporal distance of a prediction. Shen and colleagues reported accuracy and AUC for animal CT models; Liang and colleagues distinguished image-patch and slide-level results. Li and colleagues combined semi-supervised learning with classifier selection. Their metrics must retain the analytical level and task for which they were obtained (Li et al., 2026; Liang et al., 2025; Shen et al., 2024).

The review by Cuba-Gutierrez and colleagues reports a pooled AUC of 0.94 with an interval of 0.81–1.08. Its upper bound exceeds the domain of AUC. This requires checking the interval-estimation method and study compatibility rather than interpreting 1.08 as an attainable discrimination capacity. The example shows why meta-analysis does not remove scale problems or replace assessment of its assumptions (Cuba-Gutierrez et al., 2026; Gneiting & Raftery, 2007).

Calibration examines correspondence between predictions and observed frequencies or magnitudes. Classification probabilities require calibration curves; temporal estimates benefit from examination of intercepts, slopes and residuals, alongside prediction intervals. For a nominal 95% interval, coverage should be assessed in new individuals together with interval width. Very wide intervals may achieve coverage but offer limited usefulness; narrow intervals without adequate coverage communicate unjustified certainty (Collins et al., 2024; Gneiting & Raftery, 2007; Van Calster et al., 2019).

Hybrid approaches: artificial intelligence and physics

Effective integration versus parallel learning

A hybrid model explicitly integrates a physical mechanism with learned components or coupled computational inference. It may learn equation parameters, construct a surrogate to accelerate solution or penalize physical violations during training. Simply including temperature among dataset columns does not qualify. Sparse identification of dynamical systems offers another route by selecting equation terms from data, although recovering a parsimonious structure does not itself establish causality or cadaver validity (Brunton et al., 2016; Karniadakis et al., 2021).

Wilk and colleagues coupled a thermodynamic simulation to optimization using a surrogate of the cost function. The surrogate was constructed with radial-basis interpolation to explore perimortem and ambient temperatures. This integration was documented in four human cadavers and should not be described as a PINN. Mean signed error was 0.18 hours, with a standard deviation of 0.77 hours; experimental sample size and dependence between measurement locations limit inference about population performance (Wilk et al., 2022).

In a physics-informed neural network (PINN), an approximation $T_\theta(\mathbf{x}, t)$ can be trained using:

$$\mathcal{L} = \lambda_d \mathcal{L}_{\text{data}} + \lambda_f \mathcal{L}_{\text{PDE}} + \lambda_b \mathcal{L}_{\text{boundary}} + \lambda_0 \mathcal{L}_{\text{initial}}. \quad (8)$$

A physical residual can be defined as $r_\theta = \rho c \ \partial_t T_\theta - \nabla \cdot (\lambda \nabla T_\theta) - q$. Raissi and colleagues established this formulation for forward and inverse problems. Cai and colleagues investigated heat-transfer applications, while Lu and colleagues developed tools for solving differential equations with networks. These are level-C computational contributions, not trials of PMI estimation in criminal investigations (Cai et al., 2021; Lu et al., 2021; Raissi et al., 2019).

Interpretability, physical guarantees and bias

A soft physical penalty does not guarantee exact satisfaction of the equation, its boundaries or integral conservation. Wang and colleagues demonstrated gradient pathologies during PINN training. Before interpreting estimated parameters, scaling, units, collocation-point distribution, residual errors and initialization sensitivity should be assessed. A low aggregate loss may conceal an inadequately fitted physical component (Karniadakis et al., 2021; S. Wang et al., 2021).

Bayesian and adversarial formulations can represent uncertainty in solutions or parameters under explicit assumptions. That uncertainty remains conditional on the chosen model, noise distribution and available observations. If a model omits relocation of the body or a heat source, its posterior may be narrow around an incorrect explanation. Discrepancy between simulator and reality must be considered separately rather than automatically absorbed into parameters interpreted physiologically (Kennedy & O'Hagan, 2001; L. Yang et al., 2021; Y. Yang & Perdikaris, 2019).

Explanations of tree-based models may identify variables contributing to a prediction. Their diagnostic usefulness does not imply that those variables cause the process or that a local explanation validates extrapolation. Rudin's discussion of interpretable models is relevant to high-stakes decisions: understandable alternatives should be compared with complex models under the same evaluation. The burden of justification increases when additional predictive benefit is small and reconstruction of the reasoning is difficult (Lundberg et al., 2020; Rudin, 2019).

Forensic validation and translation into criminal investigation

Laboratory studies and real-world settings

Validation should be described by the change it tests. A new animal dataset examines experimental reproducibility; controlled human cadavers approximate relevant species-specific properties; retrospective human cases evaluate aspects of practice; and an independent prospective evaluation examines the entire procedure. No level automatically replaces the next. Reviews by Sharma and Sirago demonstrate why preclinical and human evidence should remain distinct (Sharma et al., 2022; Sirago et al., 2026).

Knowledge of time of death creates an additional difficulty. A label derived from witness accounts, clinical records or a last-seen-alive window may carry uncertainty. Training against a previous Henssge estimate and then presenting agreement with Henssge as independent validation would be circular. The origin of every label should be documented; interval-valued labels should retain that structure in evaluation instead of being replaced by apparently exact points (Collins et al., 2024; Henssge & Madea, 2007; Wolff et al., 2019).

Partitioning must occur by individual before any operation capable of transferring information between datasets. Feature selection, imputation, normalization and hyperparameter tuning belong within

training. Problems identified by Roberts and colleagues in clinical imaging provide a transferable methodological warning about bias and deficient validation; that review is not evidence of PMI performance. Its inclusion is justified exclusively by this analytical contribution (Collins et al., 2024; Roberts et al., 2021).

Robustness to climate, clothing, body position and substrate

Temperature measured at discovery does not necessarily represent prior exposure. Refrigeration, solar radiation, wet clothing and substrate contact alter heat exchange. Robustness tests should vary these conditions in documented ways and assess both bias and coverage. Back-calculation and surface-modeling results show that environmental history forms part of the inference problem (Belykh & Vavilov, 2025; Bovenschen et al., 2021; Wilk et al., 2020).

Transfer to tropical environments, including Amazonian settings, requires local data; this corpus does not establish operational validation in Caquetá. Thermal cycles, radiation, wet surfaces and indoor–outdoor transitions should be evaluated through controlled protocols followed by independent human cases. This proposal follows from boundary mechanisms and transportability limitations, not from demonstrated regional superiority. Adding “climate” as a predictor without recording exposure does not remedy missing information (Belykh & Vavilov, 2025; Fan et al., 2025; Kennedy & O’Hagan, 2001).

Sources of error and uncertainty quantification

Measurement error, parameter uncertainty, structural discrepancy and between-individual variation should be distinguished. In Newtonian inversion, holding k, T_0 and T_a constant, sensitivity to T is:

$$\frac{\partial t}{\partial T} = -\frac{1}{k(T - T_a)}. \quad (9)$$

This derivation shows that near thermal equilibrium a small temperature perturbation may cause a large change in inferred time. More thermometer decimal places do not remove this information limitation. When several initial or environmental conditions are unknown, different histories may explain similar observations; identifiability should therefore be examined before parameters are assigned unique interpretations (Henssge & Madea, 2007; Sullivan, 2015; Wilk et al., 2022).

A useful formulation is $y_j = \mathcal{H}\left[T(\mathbf{x}, t_j; \phi)\right] + \delta_j + \epsilon_j$, where $\mathcal{H}$ represents the measuring device and location, ϕ the parameters, δ_j model discrepancy and ϵ_j observation error. This proposed inferential organization draws on simulator calibration. Separating these terms prevents all disagreement from being attributed to instrument noise or compensated for through physically implausible parameter values (Kennedy & O'Hagan, 2001; Sullivan, 2015).

A forensic report should retain raw data, measurement locations and times, instrument calibration, model version, environmental assumptions, point estimate and uncertainty range. An abstention rule is proposed for cases outside the validated domain. Reporting should allow another professional to reproduce the calculation and understand the assumptions supporting the interval. These recommendations derive from predictive transparency; they are not presented as a universal legal standard (Collins et al., 2015; Collins et al., 2024; Rudin, 2019).

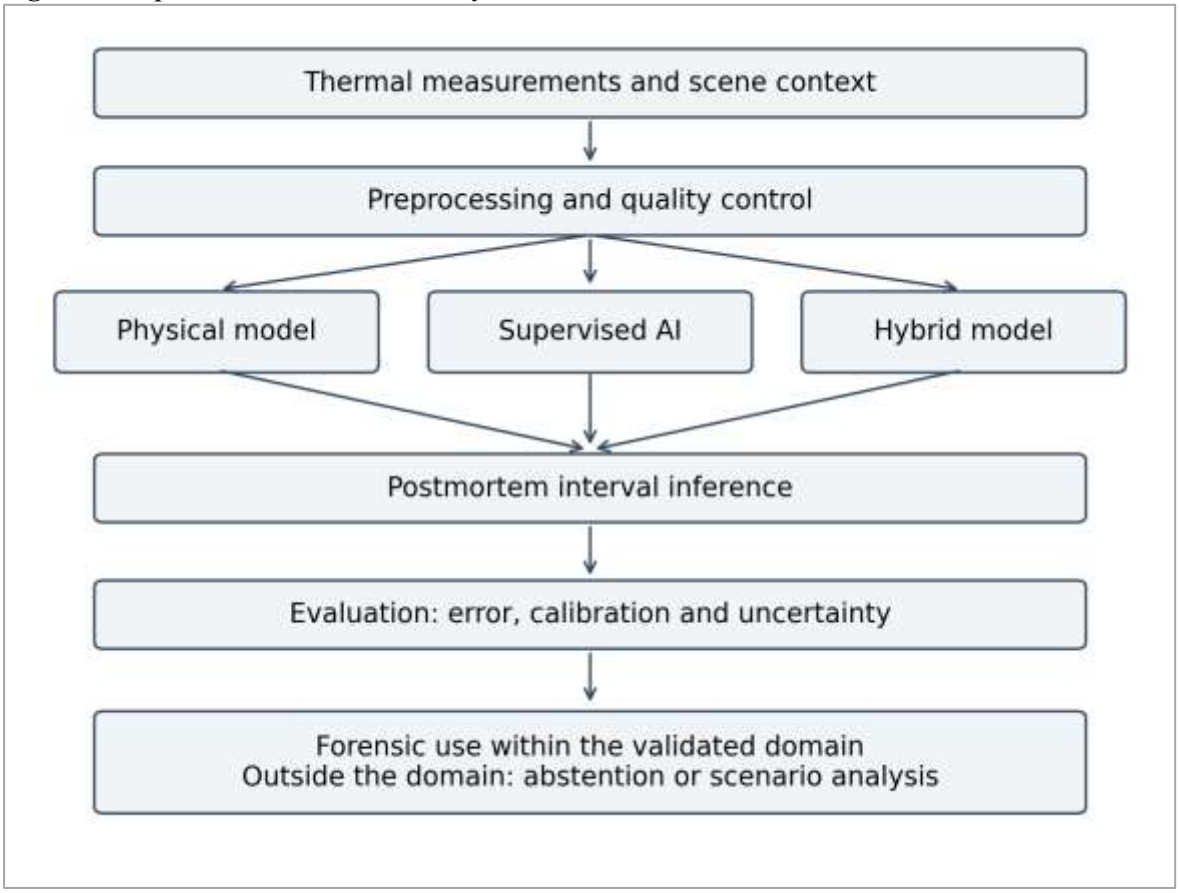
Comparative synthesis and model map

Table 1 Conceptual comparison of models and scope of evidence

Model or approach	Equations or architecture	Required inputs	Relevant validation	Main limitations	Metrics and interpretation
Newton	Lumped ODE, exponential	Initial, body and ambient temperatures; k	Physical idealization; no universal cadaver validation	Thermal uniformity, constant environment, initial phase	Time error conditional on assumptions
Henssge	Biexponential relation and empirical corrections	Rectal and ambient temperatures, mass, insulation	Experiments and human application within a restricted domain	Environmental history, initial temperature, corrections	Method-specific intervals; resolution is not accuracy
Numerical PDEs	Distributed conduction; finite differences or elements	Geometry, properties, boundaries, serial temperatures	Controlled human cadavers; specific designs	Unknown parameters, mesh, anatomical discrepancy	Both thermal residuals and PMI errors are needed
ML/DL	Trees, regression, networks and ensembles	Metabolomics, RNA, images, context	Animal and human evidence distinguished by study	Leakage, labels, transportability	MAE/RMSE for regression; AUC/accuracy for classes
PINN	Network with PDE residual and auxiliary conditions	Thermal data, equation, boundaries and parameters	Computation and engineering; no direct forensic validation in this selection	Identifiability and training; imposed physics may be wrong	Solution error and residual are not forensic error
Surrogate hybrid	Physical simulator and cost-function approximation	Serial temperatures, geometry, parameter bounds	Four human cadavers in Wilk et al.	Small sample; dependence between locations	Signed error 0.18 h; SD 0.77 h; not MAE

Note. Synthesis based on Henssge, Otatsume, Wilk, Raissi, Cai and the AI reviews (Bugelli et al., 2026; Cai et al., 2021; Henssge, 1988; Otatsume et al., 2024; Raissi et al., 2019; Sirago et al., 2026; Wilk et al., 2020; Wilk et al., 2022). ML: machine learning; DL: deep learning; ODE: ordinary differential equation; PDE: partial differential equation; SD: standard deviation. Metrics retain their original meanings.

Figure 1 Proposed inference and validity-assessment workflow



Data and context acquisition, preprocessing by individual, physical, AI or hybrid models, temporal inference, uncertainty assessment and conditional forensic use.

Note. Conceptual design based on thermal modeling and predictive reporting recommendations (Collins et al., 2024; Wilk et al., 2022). The workflow is a methodological proposal, not an already validated clinical or forensic system. When evaluation identifies insufficient data or a case outside the domain, the appropriate response is to widen the interval, request additional information or abstain from an automated estimate.

The conceptual map separates two questions: what structure the model uses and where it has been tested. "Physical," "statistical" and "hybrid" describe construction; "animal," "controlled human" and "external forensic" describe evidence. Confusing these axes assigns an architecture a maturity level that only validation can establish. Comparison must retain both axes alongside the temporal window and the resolution required by the investigation (Karniadakis et al., 2021; Sirago et al., 2026; Wolff et al., 2019).

CONCLUSIONS

Differential equations and artificial intelligence offer complementary approaches to PMI estimation: the former make mechanisms and constraints explicit, while the latter relate high-dimensional signals to temporal information.

Their integration is scientifically defensible when learned structure, parameters and boundary conditions are tested. The reviewed evidence does not establish general superiority of one family or equivalence between experimental performance and forensic validity. Advances in cadaver simulation, human metabolomics and surrogate-based optimization must be interpreted within their populations, time windows and designs. Meaningful progress consists of reproducible, calibrated and transportable inferences with uncertainty made sufficiently explicit to prevent an apparently precise prediction from becoming an unjustified temporal claim.

Review limitations

The corpus was assembled through critical selection and targeted supplementation, not exhaustive reproducible retrieval across every planned database. Individual verification of bibliographic identity does not amount to full-text reading of every publication. Some extraction relied on available abstracts; sample size, partitioning or methodological safeguards may therefore be described more fully in inaccessible texts. The absence of independent review and a prospective protocol permits selection and interpretation bias.

The 60 references include primary studies, reviews and methodological foundations; they are not 60 forensic trials. Heterogeneity prevents a single quantitative ranking or valid meta-analysis of temporal errors. Regulations governing evidential admissibility were not exhaustively assessed across jurisdictions. The absence of forensic PINN validation in this selection limits the corpus; it is not a claim of universal nonexistence. Proposed tropical validation and algorithmic abstention require empirical evaluation before recommendation as operational procedures.

Implications for future research

A staged research program should compare Henssge, distributed models, parsimonious statistical predictors and hybrid systems on the same individuals and time windows. Before analysis, the design should define decision-relevant errors, reference standards, partitioning units and procedures for uncertain intervals. Sample-size planning must be based on independent individuals and effective complexity; formulas developed for regression cannot be mechanically transferred to deep networks (Collins et al., 2024; Riley et al., 2019).

Prospective acquisition of thermal series and documented environments would better separate parameters from discrepancy. External evaluation should include different institutions, instruments, seasons and storage conditions. Hybrid models require ablation studies comparing data alone, physics alone and their coupling with equal access to information. Improvements should persist outside the dataset used to choose architecture, losses or hyperparameters (Karniadakis et al., 2021; S. Wang et al., 2021; Wilk et al., 2022).

Research must also define when information cannot support a useful estimate. A method acknowledging its application limits is preferable to a narrow interval without demonstrated coverage. The goal should be to reduce relevant uncertainty and verify that reduction in new cases, rather than increase algorithmic complexity or present as exact a chronology that the data do not identify (Gneiting & Raftery, 2007; Kennedy & O'Hagan, 2001; Rudin, 2019; Sullivan, 2015).

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