Short Editorial

Forty Years of Silent Revolutions in ICUs: From Clinical Records to Intelligent and Predictive Surveillance

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"Measure what is measurable and make measurable what is not so."
Galileo Galilei

Introduction

In the mid-1980s, as modern intensive care medicine was still consolidating as a specialty, a conceptual challenge emerged that would redefine critical care: how to objectively and comparably quantify the severity of illness across different patients and units. In 1985, William A. Knaus *et al*.[1] published the Acute Physiology and Chronic Health Evaluation II (APACHE II). This landmark model translated clinical observations into a mathematical framework capable of estimating hospital mortality based on 12 physiological and chronic health variables collected during the first 24 hours of ICU admission.

At that time, computing power was limited, and data were collected manually, the technological ceiling of that era.

Yet APACHE II inaugurated a more quantitative approach to medicine, providing a universal language for ICUs and enabling comparisons of outcomes and resource planning. Two decades later, Moreno *et al*.[2] introduced the Simplified Acute Physiology Score 3 (SAPS 3), which brought the concept of regional customization, recognizing that mortality risk depends on structural, epidemiological, and healthcare context.

In Latin America, this evolution culminated in the development of the SAPS 3-BR, calibrated by Zampieri *et al*.[3] using the Epimed Monitor ICU Database® — a national repository containing more than 2.5 million ICU admissions and storing terabytes of clinical data in the cloud. Under the coordination of the Brazilian Intensive Care Medicine Association (AMIB), in partnership with Epimed Solutions, this registry has become one of the largest and most comprehensive databases of intensive care in the world. As an outcome of the UTIs Brasileiras project [Brazilian ICUs], the SAPS 3-BR established an autonomous scientific identity for Brazilian intensive care, built on high-quality local data, multicenter validation, and contextual calibration, reflecting both the analytical maturity and the scientific capacity of intensive care in Brazil.[4]

The Paradox of the Digital Era

Nearly forty years after Knaus,[1] intensive care medicine has evolved into a digital ecosystem of high informational density. As Leo Anthony Celi *et al*.[5] aptly summarized, "the ICU is the most data-rich, yet most underutilized, environment in medicine." Every minute of monitoring generates thousands of physiological data points, yet only a fraction of them are integrated and interpreted in real time.

It is estimated that a single critically ill patient may generate tens to hundreds of gigabytes of data per day in highly monitored ICUs, and that in digital hospitals with multiple beds and interconnected devices, total daily volumes can reach the terabyte scale. Intensive care medicine is expanding exponentially — from the bytes of handwritten notes to the terabytes of diagnostic data and even zettabytes of global digital records — ushering in the era of continuous data and real-time learning, in which prognostic models must evolve from static equations to adaptive and intelligent systems (Figure 1).

Historical evolution of prognostic models in intensive care, from APACHE II (1985) to the emerging concept of adaptive and intelligent models (2025+).

The diagram illustrates the transition from static systems based on fixed equations and manual data collection to models continuously recalibrated through big data and AI. These models incorporate physiological and contextual variables tailored to local realities. This trajectory — echoing the principle of particularization proposed by Petri Pinheiro *et al*. for cardiac intensive care units — reflecting the analytical maturity and scientific capacity of Brazilian intensive care medicine.[6]

New Windows for Clinical Prediction

The study by Petri Pinheiro *et al*.,[6] published in this issue of the IJCS, reflects the ongoing transition toward a data-driven intensive care practice calibrated to the Brazilian context. Beyond comparing scoring systems, the authors emphasize the importance of adapting general prognostic models to the specific context of cardiac ICUs—a domain in which the SAPS 3-BR already demonstrates superiority over APACHE II in terms of mortality discrimination and calibration.

Keywords

Critical Care; Prognosis; Simplified Acute Physiology Score; APACHE; Artificial Intelligence.

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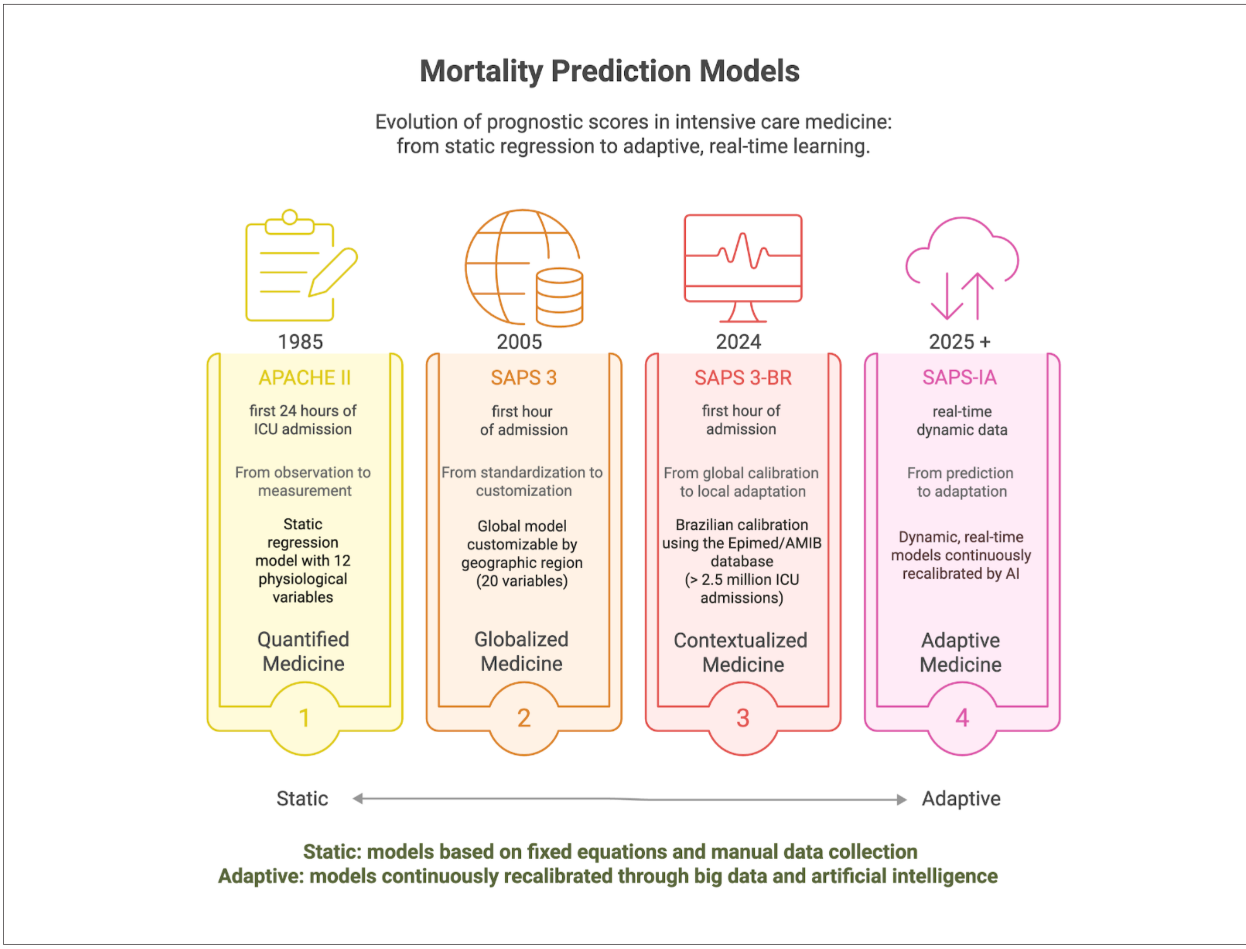

Figure 1 – *Historical evolution of prognostic models in intensive care, from APACHE II (1985) to the contemporary concept of adaptive and intelligent models (2025 +). The diagram illustrates the transition from static systems based on fixed equations and manual data collection to models recalibrated through big data and Artificial Intelligence, capable of integrating physiological and contextual variables adapted to local realities. This trajectory, reflecting the principle of contextualization proposed by Petri Pinheiro et al.[6] for cardiac intensive care units, embodies the scientific and technological maturity now achieved by modern intensive care medicine.*

Although based exclusively on classical clinical and physiological variables, the study opens a window of opportunity for integrating cardiac biomarkers and parameters — such as troponin, ejection fraction, echocardiographic findings, and mechanical circulatory support — that could enhance model sensitivity and improve AUROC performance. This desired integration would render prognostic scores more responsive to the hemodynamic complexity of cardiac patients, bringing statistical prediction closer to real-time clinical reasoning.

In a high-complexity cardiac ICU, such as that analyzed by Petri Pinheiro *et al.*,[6] clinical and physiological data are still extracted from electronic records and systematically organized retrospectively, allowing for a precise assessment of mortality risk and quality of care. However, this same data flow may soon achieve greater predictive capacity through continuous feedback mechanisms that can transform static records into dynamic learning. While still in development, such integration appears increasingly close to becoming part of daily practice in digital ICUs—a decisive step toward turning the growing wealth of data into actionable bedside knowledge.

Over recent decades, the integration of continuous measurement and automated prediction has progressed rapidly. The work of Michael R. Pinsky *et al.*[7] was seminal, proposing the fusion of physiological variables into a single instability index (Vital Signs Index), which gave rise to the Hemodynamic Stability Index (HSI). This model was later validated by Joo Heung Yoon *et al.*,[8] who demonstrated the ability to predict hypotensive episodes up to one hour in advance (AUROC ≈ 0.93), and externally confirmed by Dung-Hung Chiang *et al.*[9] (AUROC ≈ 0.76). More recently, Chiang *et al.*[9] developed the Time-varying Hemodynamic Early Warning Score (TvHEWS), capable of identifying 95% of hemodynamically unstable patients more than five hours before intervention. Together, these advances mark a shift from multiparametric monitoring to predictive surveillance, where clinical data are processed in real-time and converted into dynamic probabilities of deterioration.

Perspectives

These advances define a new frontier in intensive care, the translation and practical application of an expanding volume of information into meaningful clinical decisions. At this stage, data science moves beyond being merely an analytical tool and becomes an integral component of clinical intelligence. With terabytes of information generated daily, the analytical capacity of modern ICUs can no longer remain underutilized. As large language models and neural networks integrate heterogeneous data streams, dimensions of medical decision-making once regarded as intuitive become measurable. Perceptions that previously resided solely within the individual clinician's experience may now be examined and validated at a population level.

Data science thus feeds back into clinical science, providing an analytical and evidence-based foundation that strengthens medical judgment and refines its precision. Just as Forrester et al.[10] established the foundations of hemodynamic stratification by integrating physiological measurements into the clinical management of acute myocardial infarction, intensive care medicine now undergoes a comparable transformation. Prognostic scoring systems continue to evolve, incorporating new variables, technologies, and contextual refinements, while clinical insight becomes more precise and increasingly supported by advanced analytics. This convergence between clinical experience and data science reflects the transition from observation to understanding, a continuous progression in which each advance reshapes critical care into a more sophisticated form of intelligent clinical practice.

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