CSL Behring

The Digital Revolution in Patient Blood Management: The Future is Now!

Moderators: Andrea Steinbicker and Elvira Bisbe

Friday, April 25, 2025

1. PATIENT BLOOD MANAGEMENT IN THE DIGITAL AGE: OPTIMISING OUTCOMES THROUGH INNOVATIVE APPROACHES

Diana Castro Pauperio

There are tech companies that can provide support to digitize hospital processes, such as *patient blood management* (PBM). In Portugal, the Local Health Units in Gaia/Espinho, Matosinhos, and Tamega and Sousa have started the digitization of the journey of patients receiving PBM to achieve value-based care and practices, which has been ongoing since March 2024.

The steps in this process were the following:

1. OPERATIONAL AND INFORMATION MAPPING: WHAT VARIABLES ARE COLLECTED

Operational	Information
• Appointments • Treatments • Tests • Teams • Infrastructure	• CROMs • PROMs • PREMs • Financial information

PROMs, Patient-Reported Outcome Measures; CROMs, Clinician-Reported Outcome Measures; PREMs, Patient-Reported Experience Measures

2. *PATIENT JOURNEY* DIGITIZATION

Subsequently, the tech company may provide different types of data:

Identifiable data	Anonymous data
• At patient level • At patient-group level • Existing platforms in hospital/systems	• Research • Existing platforms in hospital/systems • Decision-making: local administration, pharmacy directors, or clinical directors

The goals set were the following:

- Decreasing the work load
- Efficacy and efficiency of interventions in PBM
- Identifying unmet needs
- Assessing the adherence of patients to digital tools
- Generating data in real-life clinical practice
- Determining standard collection of certain PROMs and CROMs

CROMs are also predetermined and organized in three dimensions, but each site can apply them as they see fit. PROMs have also been predetermined to the convenience of each site, and they are offered in several languages.

Once the patient journey has been generated, processes such as sending educational contents to patients or collecting quality of life measures are automated. The system also determines the assessments that should be performed after surgery and at what time.

The changes experiences since the digitization of the process are the following:

- Exponential increase of data in real-life clinical practice available in one year and dynamic analysis.
- Better monitoring of patients.
- Cost-saving per patient.
- Improved patient adherence
- Operational optimization.
- Increase in clinician motivation.
- Identification of unmet patient needs through the collection of PROMs.
- Obtaining information at individual and global level.
- Decrease in the use of packed red blood cells, platelets, and fresh frozen plasma.

Therefore, PBM in the digital era is possible and achievable, and technology makes customized medicine possible.

KEY MESSAGES:

- **Digitization allows the integration of PBM in clinical flows in a non-intrusive effective way.**
- **Systems must work as active clinical assistants, not just as data repositories.**
- **Hospital system interoperability is critical for PBM continuity.**

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2. MACHINE LEARNING AND PBM

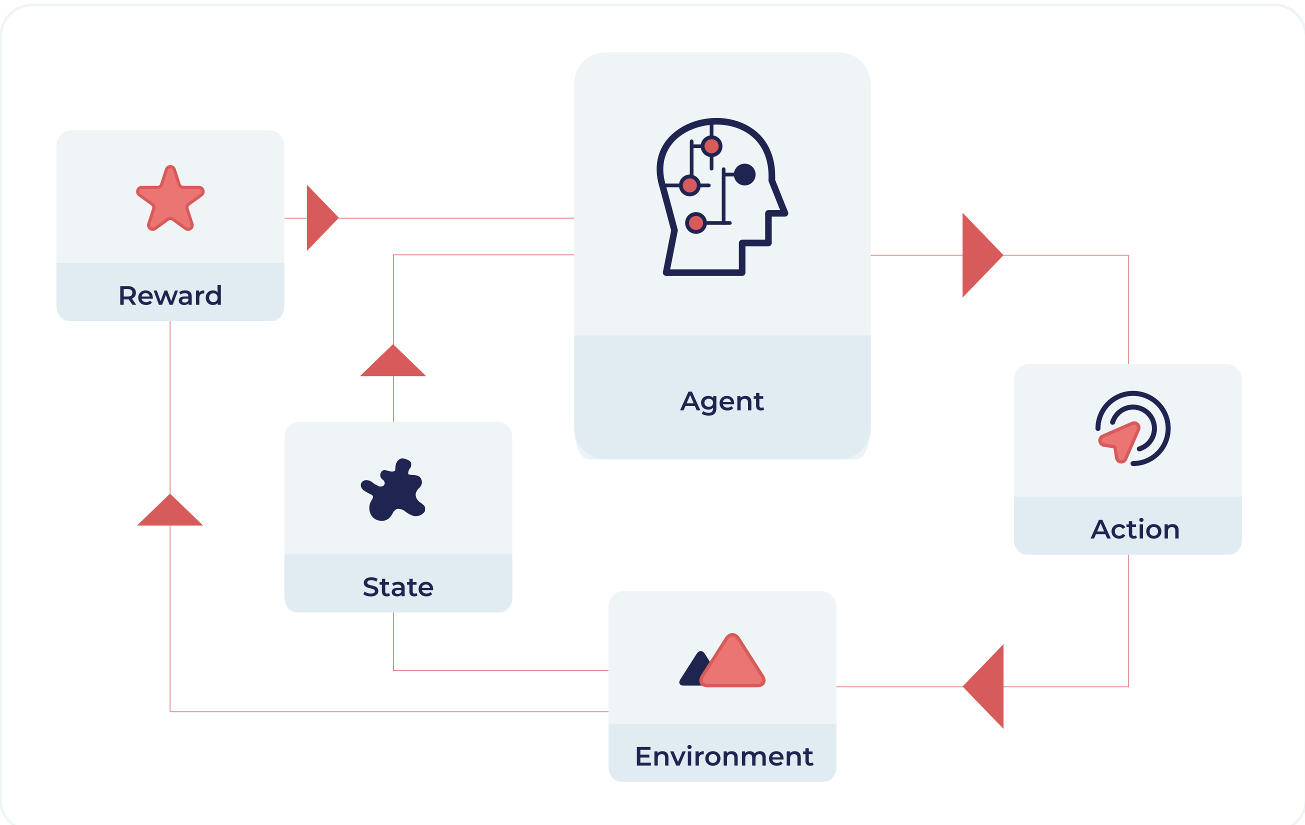
Jens Meier

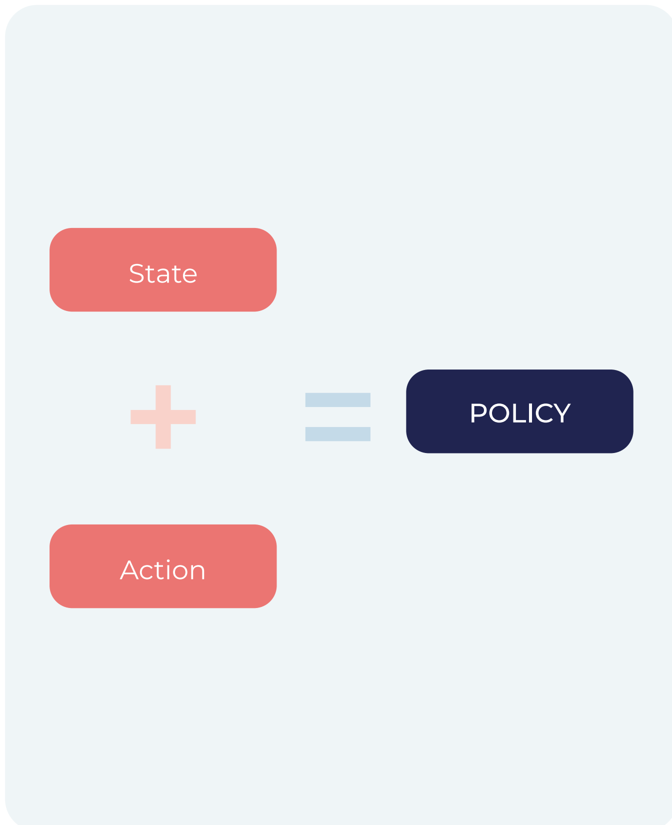
Currently, there are many publications on models predicting whether a patient will be transfused or not. However, in the context of transfusion, the goal would be for artificial intelligence (AI) tools to help decide whether a patient should be transfused or not.

If we use AI tools, such as CHATGPT, then chances are that, in certain clinical settings and when doubts arise, the answers given come from clinical practice guidelines. Nevertheless, we know that guidelines are crude generalist tools not providing bespoke solutions. Additionally, these documents have been drafted from evidence-based medicine and, occasionally, from expert opinions.

In real-life clinical practice, each patient is unique, with specific comorbidities, and so it is each clinical situation. The same clinical decision, made respecting and following the guidelines, may have completely different outcomes in each patient, depending on their path and circumstances.

Taking all of this into account, the new paradigm is reinforcement learning, a field within AI which is about building systems that learn from data to make predictions and decisions. This is a type of automated learning in which an agent learns to make decisions with trial and error, while interacting with the environment to maximize the reward. In this framework, a policy is the strategy applied by an agent to decide what action to adopt in each state of the environment.





Automated learning models are well established in transfusion prediction, but not yet to determine whether a patient should receive a transfusion.

In the future, large language models (LLM) will be able to guide transfusion decisions, and reinforcement learning is the path to achieve that goal.

A model designed with patient data collected in the *Medical Information Mart for Intensive Care IV* (MIMIC-IV) and in the eICU database is presented. It includes different variables (age, gender, *International Classification Diseases*, lab values, etc.), and it assesses the outcome of having used hemoglobin concentration as a policy:

Permite minimizar la transfusión

Sin efecto en la supervivencia

However, reinforcement learning still poses several challenges:

- Environment-state formulation.
- Formulation of actions.
- Reward design.
- Assessment: confidence in simulations and assessment methods.
- Roll-out in the production environment:
  - Shortage of clinical trials
  - Safety guidelines for real-world implementation

KEY MESSAGES:

- **Machine learning can anticipate transfusion-related needs and risks better than isolated clinical assessment.**
- **It is essential to validate models in local populations and to keep them up to date with recent data.**
- **Artificial intelligence cannot replace clinical judgment, but it can amplify it and reinforce it.**

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3. DATA SCIENCE: THE NEXT REVOLUTION IN PATIENT BLOOD MANAGEMENT

Kevin Trentino

The work of data managers is increasingly demanded. AI is increasingly popular in business, and companies feel they need this role to develop AI models[1]. The future of medicine will integrate patient care with constant remote monitoring of patients, both at the hospital and at home. All these data can be integrated and analyzed.

Early medical alert systems that will be implemented in the future are the following[2]:

- Systems based on AI and automated learning
- Electronic clinical history, Real-time hemodynamic monitors
- Real-time hemodynamic data
- Cognitive data
- Surgery and OR video monitoring
- Social-economic and racial/ethnic determinants of health
- Genetic testing and precision medicine

Predictive models in medicine are increasingly more relevant in PBM. However, most transfusion predictive models entail a high risk of bias in their development and validation (participant selection, predictive factors, result, and analysis), and start from poor information and methodological quality. These aspects should be tackled before they can be safely used in clinical practice[3].

Present limitations are the following:

- Data quality
- Overadjustment
- Transparency
- Relevance

In 2008, the Western Australian Department of Health started a holistic PBM program. During the early stages, data were collected and it was observed that feedback was fundamental for the program to succeed. In 2013, an article was published describing the associated PBM data system, and proving its usefulness to monitor transfusions practices and the use of the product in the framework of a PBM pilot program[4]. Models such as this may help effectively guide PBM strategies, as well as continuously monitor its impact. A subsequent publication described the development of totally automated control panel revolving around three key indicators: transfusions of single red blood cell unit, transfusions to patients with hemoglobin >8g/dL, and elective surgery patients admitted with anemia. Further indicators may be added depending on the needs. These panels may allow comparison between clinicians, departments, and even hospitals[5].

Other studies have shown that the need for in-hospital transfusion, unlike the amount of red blood cell units transfused during a hospital stay, may be predicted reliably[6,7].

In summary, AI an automated learning models can improve patient care and the selective use of resources, but their current methodological quality must improve significantly.

KEY MESSAGES:

- **Thanks to data science, PBM performance can be monitored and improved at a population level.**
- **Displaying data transforms clinical behavior better than coercive policies.**
- **Clinical teams should lead the interpretation and application of the generated data.**

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