



Development of a Clinical Decision Support System for Hospital-Acquired Pressure Injuries

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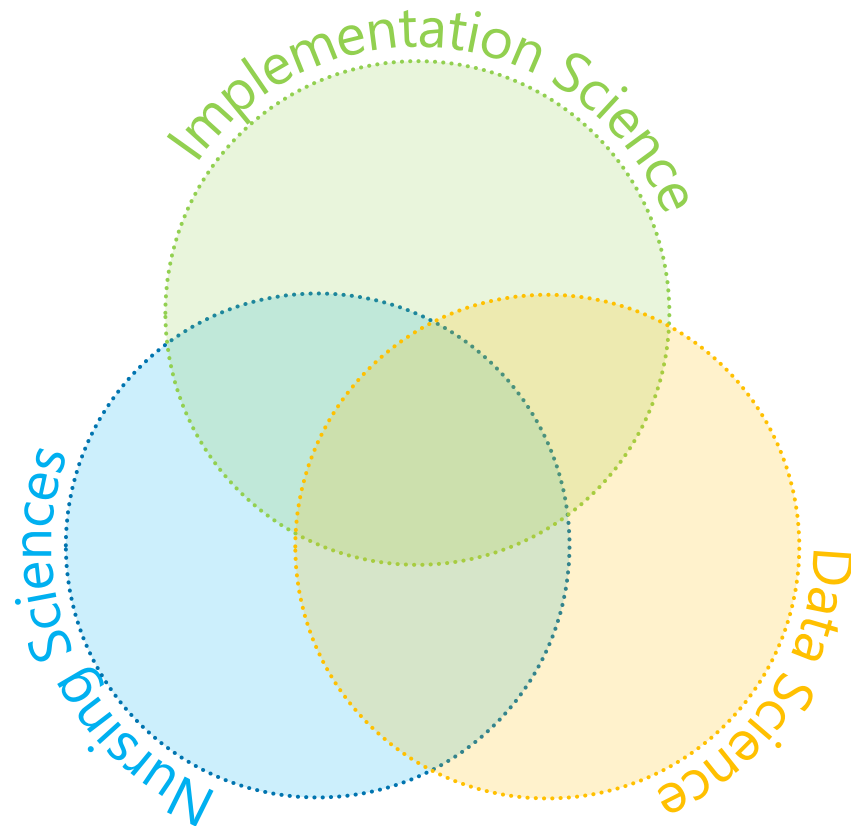
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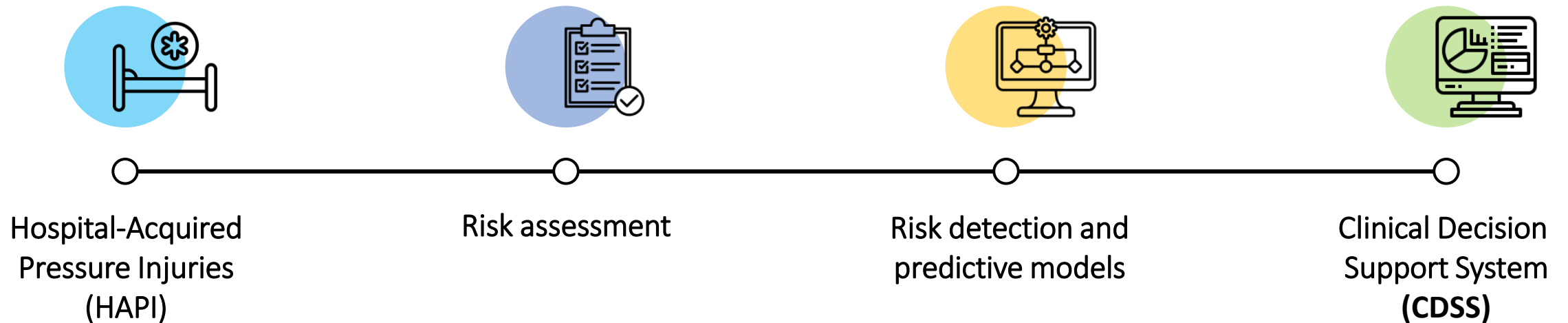


Introduction



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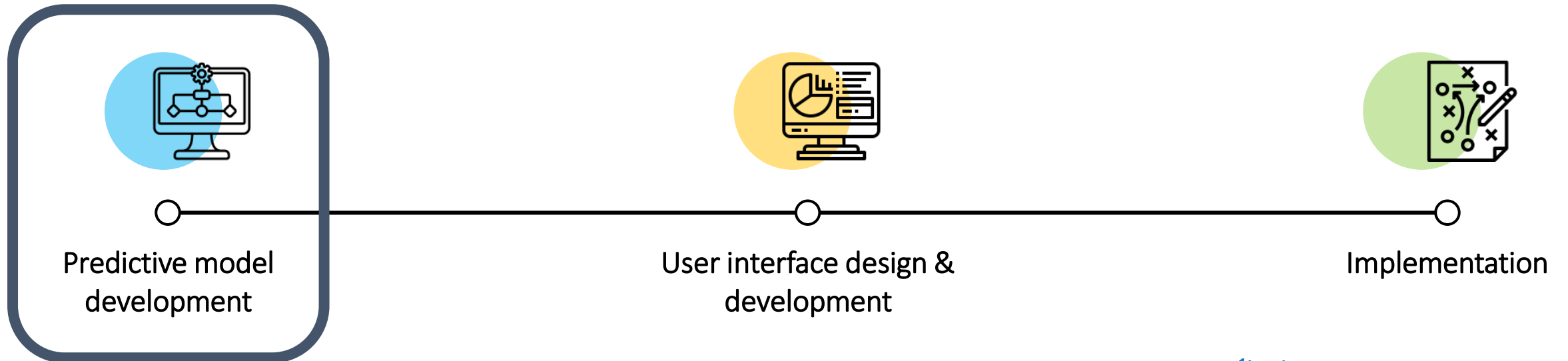
Overview of research topic



(Araujo et al., 2020; Bail et al., 2015; Benda et al., 2020; Coleman et al., 2014; Dweekat et al., 2023; EPUAP, 2019; Gaspar et al., 2022; Huang et al., 2021; Jiang et al., 2021; Long et al., 2013; McRae et al., 2016; Mebrahtu et al., 2021; Moon et al., 2021; Mudge et al., 2019, 2022; Murphy et al., 2021; Qu et al., 2022; Seibert et al., 2021; Shang, 2021; Shi et al., 2019; Tschannen & Anderson, 2020)

General aim

To **develop** and **implement in clinical practice**
a **clinical decision support system** (CDSS)
based on artificial intelligence (AI) for the
early detection of the risk of hospital acquired pressure injury
(HAPI) for people hospitalized at the CHUV



Data collection

Selection criteria

18+ y.o. patients

Hospitalized for >48h

Period: 1st April 2019 to 31

March 2020

HAPI >24h after admission

Cohort

~16k patients,

~24k hospitalizations

49% are 65+

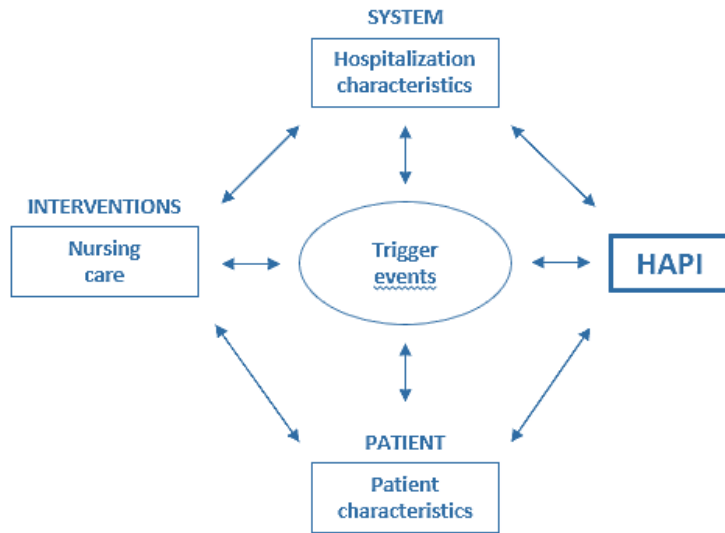
2.4% stays with HAPI

 Routine data extraction = Real-world data



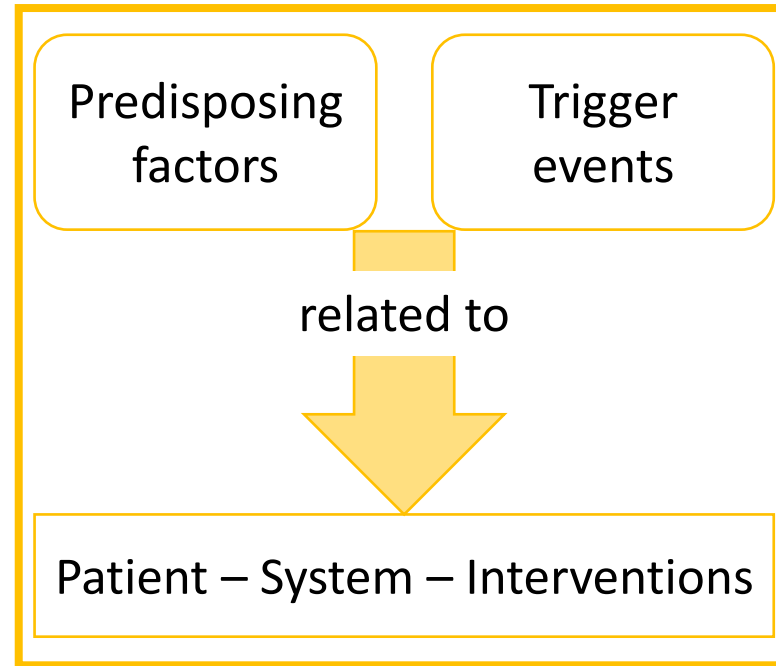
Data preparation

Cascade iatrogenesis



Adaptation of Thornlow's
conceptual model of cascade
iatrogenesis to the development of
HAPI

(Thornlow et al., 2009)



Transformation into
variables



Data availability in EHR



65 variables
into the predictive model



Modelization

*Recurrent neural network
model (LSTM)*

Random forest model (RF)

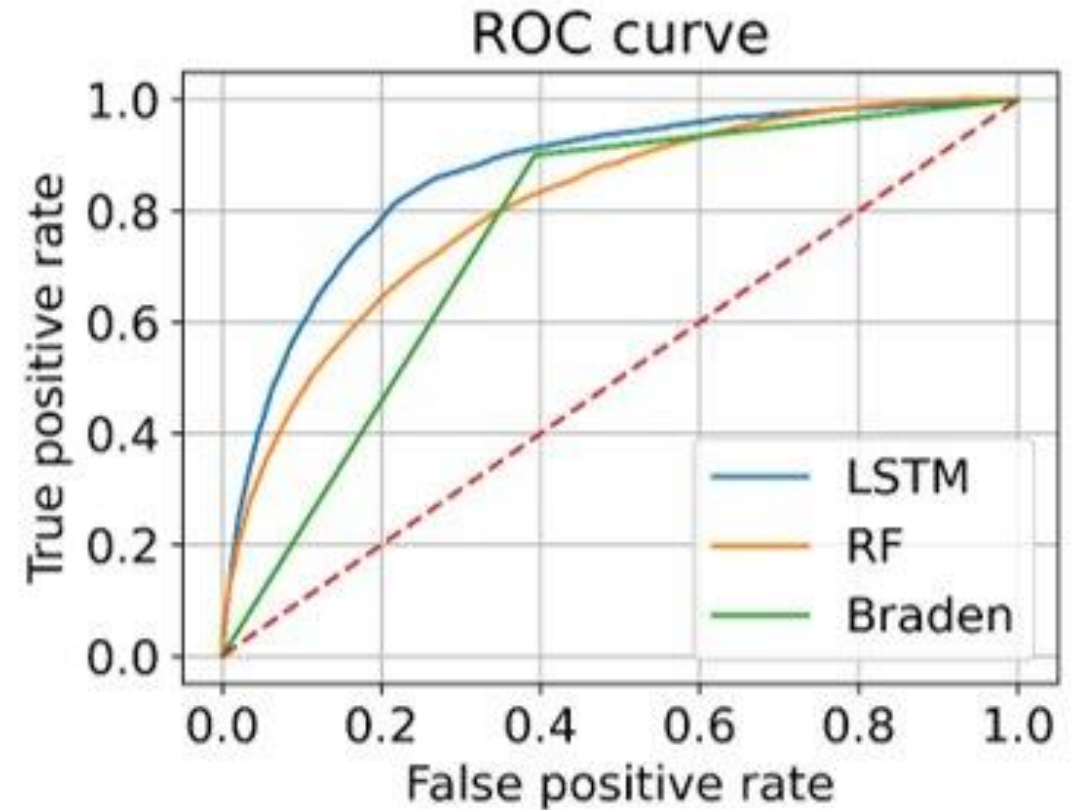


Capture temporality
Structured data
Interpretability



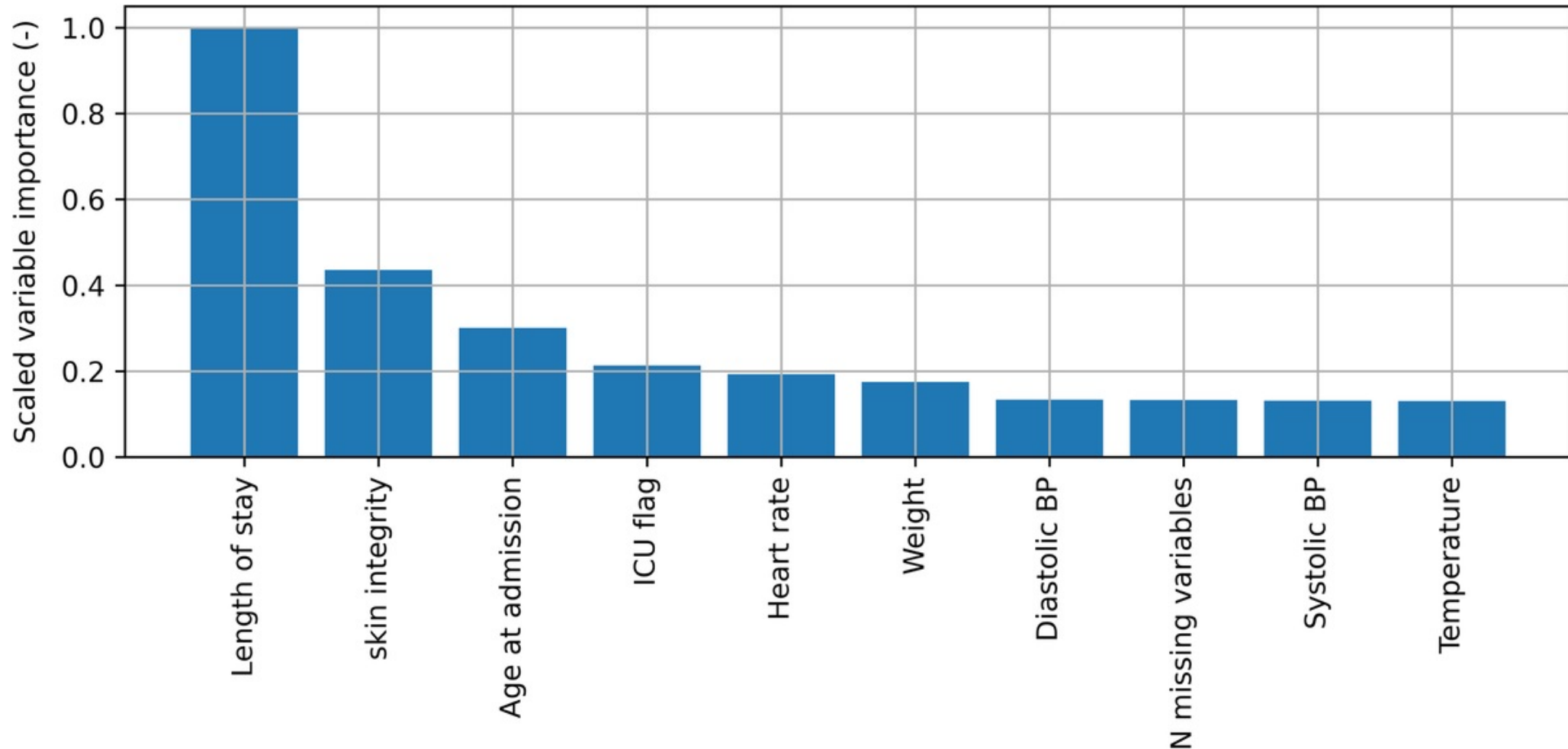
Performances

Model	AUROC	Sensibility	Specificity	Accuracy
Braden		0.88	0.61	0.61
RF	0.80	0.73	0.72	0.72
LSTM	0.87	0.74	0.82	0.82

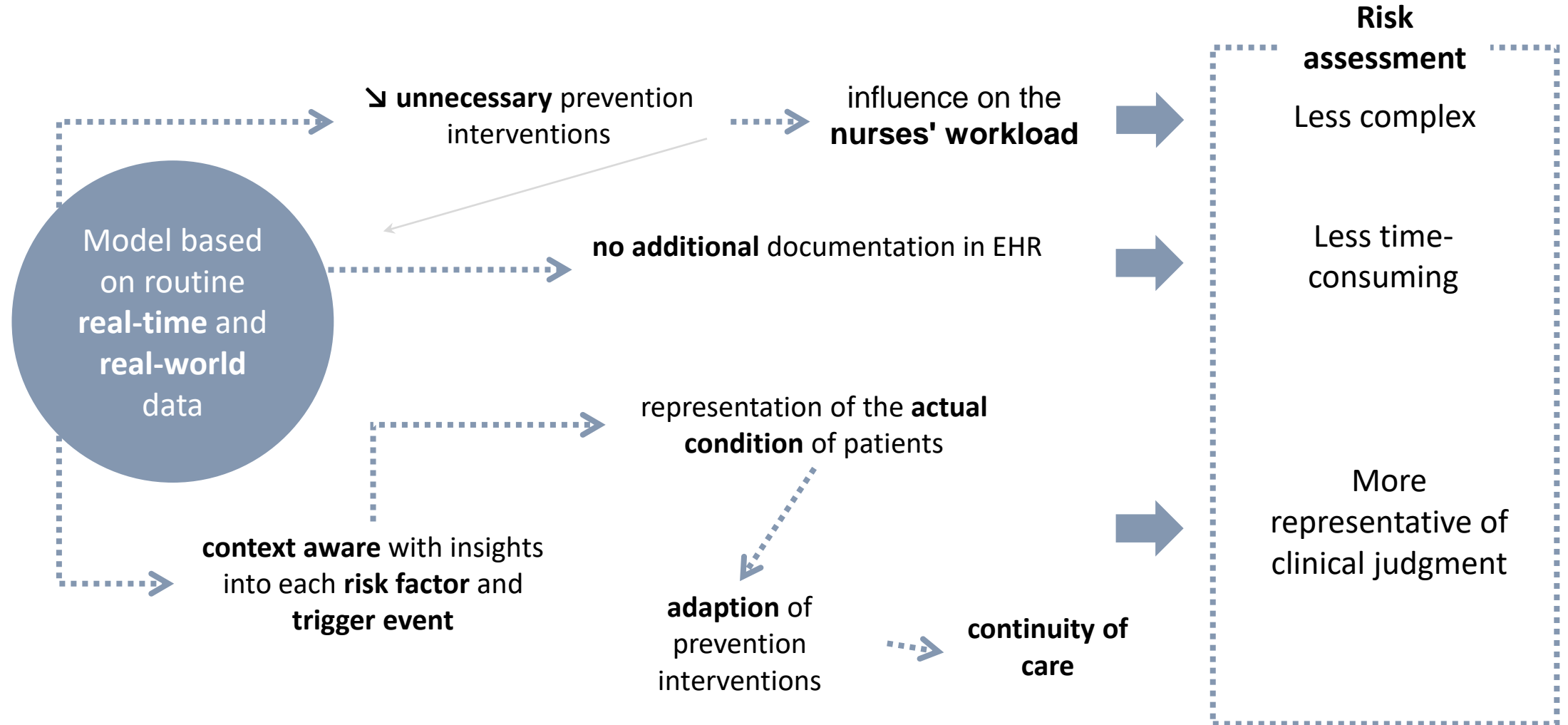


Sensitive analysis

Measuring the effect of LSTM model input parameters on HAPI risk



Relevance to nursing



Potential for significant improvement in nursing work



Conclusion



HAPI and other complications

- Use of **LSTM model** in this domain
- Risk assessment **only with EHR** documentation
- Operational deployment of an automated intelligent system into the hospital information system



CDSS implementation

- Data-science **and** implementation science
- Implementation **methodology**



Our hospital

- First AI project in the hospital aiming at using EHR data in real-time for clinical decision support
- **Proof of concept** for next projects
- **Collaboration** between nurses and data-scientists

Financial support



Thank you for your attention



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Development of a Predictive Model for Hospital-Acquired Pressure Injuries

Sophie Pouzols, MScNS, RN, Jérémie Despraz, MSc, Cédric Mabire, PhD, MScNS, RN, Jean-Louis Raisano, PhD

Hospital-acquired pressure injuries are a challenge for healthcare systems, and the nurse's role is essential in their prevention. The first step is risk assessment. The development of advanced data-driven methods based on machine learning techniques can improve risk assessment through the use of routinely collected data. We studied 24 227 records from 15 937 distinct patients admitted to medical and surgical units between April 1, 2019, and March 31, 2020. Two predictive models were developed: random forest and long short-term memory neural network. Model performance was then evaluated and compared with the Braden score. The areas under the receiver operating characteristic curve, the specificity, and the accuracy of the long short-term memory neural network model (0.87, 0.82, and 0.82, respectively) were higher than those of the random forest model (0.80, 0.72, and 0.72, respectively) and the Braden score (0.72, 0.61, and 0.61, respectively). The sensitivity of the Braden score (0.88) was higher than that of long short-term memory neural network model (0.74) and the random forest model (0.73). The long short-term memory neural network model has the potential to support nurses in clinical decision-making. Implementation of this model in the electronic health record could improve assessment and allow nurses to focus on higher-priority interventions.

KEY WORDS: Artificial intelligence, Decision support techniques, Machine learning, Pressure ulcer, Risk assessment

Hospital-acquired pressure injuries (HAPIs) are a challenge for healthcare systems and among the most common nursing-sensitive outcomes.¹⁻³ Hospital-acquired

pressure injuries have many consequences for patients such as a longer length of stay (LOS), higher costs, greater risk of readmission, increased risk of in-hospital mortality, and increased likelihood of developing other hospital-acquired complications.³⁻⁶

The nurse's role is essential in HAPI prevention. The first step in preventing HAPIs is a structured risk assessment based on the Braden Scale to identify required interventions,² which is today the gold standard in clinical practice. The European Pressure Ulcer Advisory Panel recommends using the Braden Scale every 2 days if the score is less than or equal to 18 and every 4 days if the score is more than 18. The predictive performance of the Braden Scale is moderate, with a sensitivity of 0.78 (95% confidence interval [CI], 0.74-0.82), a specificity of 0.72 (95% CI, 0.66-0.78), and an area under the receiver operating characteristic curve of 0.82 (95% CI, 0.79-0.85).⁷ With the Braden Scale, nurses evaluate six risk factors: sensory perception, moisture, activity, mobility, nutrition, and friction and shear.⁸ However, the development of HAPIs may depend on many other factors, such as the patient's characteristics, the hospital environment, interventions, and other health-related factors.⁹⁻¹³ Most of these additional risk factors are routinely captured in the electronic health record (EHR) and need to be taken into account when a structured HAPI risk assessment is performed. This process is complex and time-consuming, and it requires expert clinical judgment. Nonetheless, nurses perceive such a structured risk assessment as a routine task without fully understanding its real meaning.¹⁴

The development of advanced data-driven methods based on machine learning techniques can improve HAPI risk assessment through the use of routinely collected EHR data, supporting nurses in this complex clinical evaluation task and thus strengthening their role in preventing HAPIs. Predictive models can improve nurses' assessment and reasoning and more efficiently identify patients at risk. Early detection of patients at risk of developing HAPIs during their hospital stay would go beyond the single assessment based on the Braden Scale and would be tailored to each individual patient. Many HAPI prediction models have been developed in the past few years with moderate to good predictive performance. Reported sensitivity for predicting HAPI occurrences ranges between 0.48 and 0.87, specificity between 0.66 and 0.93, and area under the receiver operating

CIN: Computers, Informatics, Nursing (Iww.com)

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S.P. and J.L. should be considered joint first authors.

The Cantonal Commission (CC) for Ethics in Human Research (CCR-HD/project ID: 2021-02136) approved this study.

The authors have disclosed that they have no significant relationships with, or financial interest in, any commercial companies pertaining to this article.

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DOI: 10.1097/CIN.00000000000001029

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