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ORIGINAL ARTICLE

Beyond technology: Can artificial intelligence support clinical decisions in the prediction of sepsis?

Para além da tecnologia: a inteligência artificial pode apoiar decisões clínicas na predição da sepse?

Más allá de la tecnología: ¿La inteligencia artificial puede apoyar la toma de decisiones clínicas en la predicción de la sepsis?

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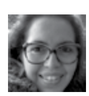

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ABSTRACT

Objective: To analyze the critical alarms predictors of clinical deterioration/sepsis for clinical decision making in patients admitted to a reference hospital complex. **Methods:** An observational retrospective cohort study. The Machine Learning (ML) tool, Robot Laura®, scores changes in vital parameters and lab tests, classifying them by severity. Inpatients and patients over 18 years of age were included. **Results:** A total of 122,703 alarms were extracted from the platform, classified as 2 to 9. The pre-selection of critical alarms (6 to 9) indicated 263 urgent alerts (0.2%), from which, after filtering exclusion criteria, 254 alerts were delimited for 61 inpatients. Patient mortality from sepsis was 75%, of which 52% was due to sepsis related to the new coronavirus. After the alarms were answered, 82% of the patients remained in the sectors. **Conclusions:** Far beyond technology, ML models can speed up assertive clinical decisions by nurses, optimizing time and specialized human resources.
Descriptors: Artificial Intelligence; Machine Learning; Sepsis; Clinical Decision Support; Innovation.

RESUMO

Objetivo: Analisar os alarmes críticos preditores de deterioração clínica/sepse para tomada de decisão clínica nos pacientes internados em complexo hospitalar de referência. **Métodos:** Estudo observacional de coorte retrospectivo. A ferramenta de *Machine Learning* (ML), Robô Laura®, pontua alterações nos parâmetros vitais e exames laboratoriais, classificando-os por gravidade. Incluíram-se pacientes internados e maiores de 18 anos. **Resultados:** Extraíram-se 122.703 alarmes da plataforma, classificados de 2 até 9. A pré-seleção dos alarmes críticos (6 a 9) apontou 263 alertas urgentes (0,2%), dos quais, após o filtro de critérios de exclusão, delimitaram-se 254 alertas para 61 pacientes internados. A mortalidade dos pacientes por sepse foi de 75%, dos quais 52% devido à sepse relacionada ao novo coronavírus. Após os alarmes serem atendidos, 82% dos pacientes permaneceram nos setores. **Conclusões:** Muito além da tecnologia, modelos de ML podem agilizar a decisão clínica assertiva dos enfermeiros, otimizando tempos e recursos humanos especializados.
Descritores: Inteligência Artificial; Aprendizado de Máquina; Sepse; Tomada de Decisão Clínica; Inovação.

RESUMEN

Objetivo: Analizar alarmas críticas predictoras de deterioración clínica/sepsis para toma de decisiones clínicas en pacientes internados en complejo hospitalario de referencia. **Métodos:** Estudio observacional de cohorte retrospectivo. La herramienta *Machine Learning* (ML), Robot Laura®, puntúa alteraciones en parámetros vitales y exámenes laboratoriales, clasificándolos por gravedad. Incluyeron pacientes internados y mayores de 18 años. **Resultados:** Extrajeron 122.703 alarmas de la plataforma, clasificadas de 2 hasta 9. La preselección de alarmas críticas (6 a 9) apuntó 263 alertas urgentes (0,2%), entre ellas, después del filtro de criterios de exclusión, delimitaron 254 alertas para 61 pacientes internados. La mortalidad de pacientes por sepsis fue de 75%, entre ellos 52% debido a sepsis relacionada al nuevo coronavirus. Después de las alarmas ser atendidas, 82% de los pacientes permanecieron en los sectores. **Conclusiones:** Más allá de la tecnología, modelos de ML pueden agilizar la decisión clínica asertiva de enfermeros, optimizando tiempos y recursos humanos especializados.
Descriptores: Inteligencia Artificial; Aprendizaje Automático; Sepsis; Toma de Decisiones Clínicas; Invenciones.

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INTRODUCTION

Estimates show that sepsis is one of the leading causes of global mortality[1], in Brazil, the mortality rate can exceed 55.7%, according to a multicenter study conducted in intensive care centers, where one third of the beds were occupied by septic patients[2]. Defined by the latest consensus as "life-threatening organ dysfunction caused by an exacerbated host response to infection," sepsis needs early diagnosis for a more favorable prognosis[1,3].

In its prognosis, successful treatment is time-dependent, where recommendations to initiate antibiotic therapy within the first hours of disease presentation and timely monitoring positively interfere with outcomes. Although highly desirable, early diagnosis is challenging given the nonspecific nature of signs and symptoms, as well as their similarity to other pathologies[4-5]. In this scenario of care to the patient with sepsis, the performance of the multidisciplinary team is essential, especially the nursing team, because it is at the bedside, providing assistance, monitoring and evaluating the developments of hospitalization[6].

An alternative to assist nurses' decision making would be a technological screening tool that identifies patients at high risk of sepsis and allows both higher rates of early diagnosis and better utilization of specialized human resources. By collecting and assessing continuous physiological variables, such as vital signs, using sophisticated classification algorithms, artificial intelligence (AI) has the potential to provide timely and accurate detection of sepsis, bypassing current clinical alert scores, which are based on not-so-advanced mathematical models[7–9].

Thus, a decision support system based on Machine Learning (ML) algorithms trained on patient data, usually based on electronic medical records, vital signs and/or laboratory results, could support and encourage early detection of sepsis. Robot Laura® is an expert clinical deterioration assessment system that integrates with data environments to collect, organize and finally perform complex statistical calculations, compare results with probabilistic ranges and accurately conclude on whether conditions are favorable for a risk event to occur[9].

Technologies like ML continue to improve the accuracy of clinical predictions, but even a perfectly calibrated prediction model may not translate into better clinical care. An assertive prediction about a patient does not determine how to change that outcome; in fact, it cannot even be assumed that it is possible to change the predicted outcomes[10-11]. In this context, the dimensions and infrastructure of the institution, its information system and quality of records must be considered. One must consider that the work dynamics of nurses and other members of the health team are intense, in which records are eventually left in the background.

Gaining agility for assertive decision-making, especially at peculiar times like during the COVID-19 pandemic, when healthcare teams are overwhelmed, makes AI a useful tool in an unfavorable and challenging scenario.

However, the use of AI simultaneously introduces a certain distrust of the technology due to a possible negative impact on the nursing staff[12]. This calls into question what advantages and disadvantages nurses find in using AI as a predictor of sepsis in their routine.

For a reliable interpretation of the records, it is not enough to mine/capture the data without correlating them to the underlying pathology and expected evolution for each case, according to institutional clinical protocols. Far beyond technology, the gap in the interface between electronic medical records (vital signs and other simultaneous information) and the real clinical situation of the patient justifies this research, which seeks to elucidate whether the decision making of the care team, in cases of clinical deterioration/sepsis, can be supported by AI.

OBJECTIVE

To analyze the critical alarms predictors of clinical deterioration/sepsis for clinical decision making in patients admitted to a reference hospital complex.

METHODS

Ethical aspects

This research obtained the Certificate of Ethical Appraisal Presentation issued by the Research Ethics Committee of the institutions involved and complied with Resolution Nº466/2012 of the National Health Council in all stages.

Study design, time and place

Observational cohort study guided by STROBE tool[13], conducted from March to September 2020, in a reference hospital complex in the city of Porto Alegre, state of Rio Grande do Sul (RS), Brazil.

Description of the Machine Learning tool

Robot Laura® is an expert clinical deterioration assessment system that integrates with data environments to collect, organize and finally perform complex statistical calculations, compare results with probabilistic ranges and accurately conclude on whether conditions are favorable for a risk event to occur. The machine learning algorithms used by Robot Laura® are based on vital signs and patient chart information. Two algorithms are used together: Support Vector Machines and Artificial Neural Networks. The output is an average patient deterioration index from both algorithms[14].

In addition, programmers "teach" the system the sepsis protocol adopted in the institution, so that it can classify patients at risk of clinical deterioration/sepsis. The robot mines data from the patient's history and lab tests from the electronic medical record, classifies the severity by adding 1 or 2 points for each altered parameter (increasing values from 2 to 9, illustrated in the "Supplementary Material" section), and warns the assisting team by means of screens deployed in strategic locations in the hospital. This information remains alerting the staff until they intervene or register new corrected data in the system.

Data collection occurred in two stages: in the first, data were manually exported from the platform, tabulated and organized in tables in Microsoft Excel® software; in the second, the patient's electronic medical records were searched for team response time, interventions performed, length of stay and outcomes (discharge, death from sepsis and other causes).

Sample, inclusion and exclusion criteria

The critical alarms (6 to 9) recorded by Robot Laura® in the described period were evaluated, totaling 263 urgent alerts for 61 patients. The eligibility criteria established: patients older than 18 years of age, hospitalized, signaled with an alert for alteration of clinical parameters by the robot (heart and respiratory rates, blood pressure, axillary temperature, capillary glycemia, blood count, platelets, electrolytes, among others), according to the institutional protocol available as supplementary material. As exclusion criteria: minimum length of stay less than 48 hours, patients in palliative care with description of exclusive comfort measures, alarms lower than 6. Patients with RT-PCR test recorded in the medical records were considered positive for COVID-19.

Statistical Analysis

The results of qualitative variables were presented as frequency and percentage; age and percentage of care, as mean and standard deviation; and the other quantitative variables as median and 25th and 75th percentiles. The percentage of care was calculated as the ratio between the number of alarms attended over the number of alarms for each patient times 100. The number of each type of alarm was also calculated. The correlations of the number of alarms and percentage of care with the length of hospitalization were verified by Spearman's correlation coefficient; with death and COVID-19, through the Mann Whitney test; and with the other variables, the Kruskal-Wallis test with Dunn's test for multiple comparisons was used. Results with a p-value less than 0.05 were considered significant, and analyses were performed using the SPSS statistical software (IBM-SPSS-Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp.).

RESULTS

A total of 122,703 alarms were extracted from the platform, classified from a score of 2 to 9. The pre-selection of critical alarms (6 to 9) indicated 263 urgent alerts, from which, after filtering exclusion criteria, 254 alerts (0.2%) were delimited for 61 inpatients.

Table 1 characterizes the attended alarms. The mean age of the patients was 61 years, in a sample of adults and elderly, with a predominance of females (62%). The mortality of patients due to sepsis was 75%, of which 52% due to COVID-19 related sepsis.

The patients monitored by Laura® Robot are followed by a variety of medical specialties, which is justified because it is a reference hospital complex, whose care absorbs the most diverse cases (Table 1). It is noteworthy that onco-hematology patients concentrated the largest number of alarms 33%, followed by patients affected by renal (18%), respiratory (10%) and gastrointestinal (10%) pathologies.

Deaths from sepsis due to COVID-19 exceeded the number of those tested as a result of clinical diagnosis or through imaging examinations.

It is noteworthy that all alarms were answered within the first hour, as recommended by the institutional sepsis protocol, and 82% of patients received some intervention. As for criticality, alarm range 6 had more prevalence of alarms, sometimes for the same patient.

The mortality associated with sepsis due to COVID-19 reached 52% (n = 24) of the study patients (Table 2). For this group, type 6 alarms were more prevalent, whose interquartile ranges illustrate the oscillation of alarm quantities for each group: discharge, sepsis death, and COVID-19 sepsis.

Note in Table 3 that 82% (n = 50) of patients remained in their original units, 15% (n = 9) were transferred to the intensive care unit (ICU). Among the patients who were managed in inpatient or emergency care units were chronic renal patients, whose altered electrolyte alarms were of the risk category in the range 6.

Table 1 – Characterization of the sample and outcomes measured

	All (N = 61)	Death by sepsis (n = 19)	Death by sepsis COVID-19 (n = 24)
Age, years	61.3 ± 14.6	61.2 ± 14.8	62.0 ± 14.8
Sex male, n (%)	23 (38)	12 (63)	17 (71)
Sex female, n (%)	38 (62)	7 (37)	7 (29)
Base Pathologies			
Renal system	11 (18)	5 (26)	4 (17)
Cardiovascular System	5 (8)	1 (5)	3 (12)
Respiratory system	6 (10)	1 (5)	4 (17)
Neurological system	7 (11)	2 (11)	1 (4)
Gastrointestinal system	6 (10)	2 (11)	0 (0)
Oncohematology	20 (33)	7 (37)	8 (33)
Traumatology	2 (3)	1 (5)	0 (0)
No information	4 (7)	0 (0)	4 (17)
Transfer up to 24 h, n (%)			
To the intensive care unit	9 (15)	5 (26)	3 (12)
To inpatient unit	2 (3)	1 (5)	1 (4)
Stayed in the sector	50 (82)	13 (69)	20 (84)
Transfer after 24 h, n (%)			
To the intensive care unit	3 (5)	1 (5)	1 (4)
To inpatient unit	26 (43)	8 (42)	18 (75)
Stayed in the sector	32 (52)	10 (53)	5 (21)
COVID-19 testing			
Positive, n (%)	21 (35)	1 (5)	19 (79)*
Negative, n (%)	7 (11)	2 (11)	3 (12)
No information, n (%)	33 (54)	16 (84)	2 (9)*
Length of stay, days	50 (20-87)	51 (22-85)	39 (17-88)
Outcome, n (%)			
Discharge	15 (25)	-	-
General Death	46 (75)	-	-

*Values presented as mean ± standard deviation or median (interquartile range) and n (%); *P < 0.05.*

Table 2 – Alarms and outcomes in patients monitored by artificial intelligence

	Death by sepsis		
	No (Discharge) (n = 15)	**Yes (n = 22)**	**Sepsis due to COVID-19 (n = 24)**
General alarm quantity	1.0 (1.0-2.0)	1.0 (1.0-2.0)	1.0 (1.0-8.5)
General alarm quantity attended, %	100 (0-100)	100 (100-100)	100 (100-100)
Alarm quantity			
Type 6	1.0 (1.0-2.0)	1.0 (0.0-2.0)	1.0 (0.0-6.5)
Type 7	0.0 (0.0-0.0)	0.0 (0.0-1.0)	1.0 (0.0-1.0)*
Type 8	0.0 (0.0-0.0)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
Type 9	-	-	-

*Values presented as median (interquartile range). *P < 0.05 between the sepsis-related death COVID-19 and non-COVID-19 groups.*

Table 3 – Alarms and transfers up to 24 h in patients monitored by artificial intelligence

		Transfer	
	Stayed in the sector (n = 50)	**ICU (n = 9)**	**IU (n = 2)**
General alarm quantity	1.0 (1.0-3.0)	1.0 (1.0-2.0)	1.0 (1.0-1.0)
General alarm quantity attended, %	100 (70-100)	100 (100-100)	100 (100-100)
Alarm quantity			
Type 6	1.0 (1.0-3.0)	1.0 (0.0-1.0)	0.0 (0.0-0.0)
Type 7	0.0 (0.0-1.0)	0.0 (0.0-1.0)	1.0 (1.0-1.0)
Type 8	0.0 (0.0-0.0)	0.0 (0.0-1.0)	0.0 (0.0-0.0)*
Type 9	-	-	-

*Values presented as median (interquartile range); IU - inpatient unit; ICU - intensive care unit ; *P < 0.05 between groups Stayed in sector and Transfer to ICU*

DISCUSSION

More than 122,000 alerts were analyzed, of which 0.2% belonged to the critical range (from 6 to 9), requiring urgent intervention. The platform "cancels" the alert when it identifies that there was resolution. For example, a change in axillary temperature will be automatically corrected when a new record, within the protocol parameters, is made. The critical range is reached when the patient has several altered parameters or there has been no up-to-date record of physiological correction or adjustment. It is understood that patients are heterogeneous and vulnerable when at risk of sepsis, associated with underlying diseases[15]. Thus, therapy must necessarily be personalized and adapted to meet the requirements of each individual. In this case, reliable and up-to-date registration is fundamental, as well as being a legal prerogative[9]. On the other hand, the work dynamics of health professionals are intense, in which records are eventually left in the background.

As for the sensitivity and refinement of the protocol, the critical alarms of our study pointed to clinical deterioration for various underlying pathologies, in patients of different specialties, but monitored by the same protocol. Deaths from sepsis in renal transplanted patients affected 82% of the cases, but this population is immunosuppressed and more susceptible to infections, as well as tolerate different electrolyte levels. Along this line of reasoning, onco-hematology concentrated 75% of mortality in hospitalized patients[16]. Such a multifaceted scenario allows deep discussions about the refinement of the information introduced in the ML model.

One can understand the resistance of the nursing staff in an inpatient unit for chronic renal patients, with numerous warnings going off. However, serum electrolyte and creatinine levels in these cases are tolerated at a different level than in other patients. For such adjustments, respecting the peculiarities of the specialties, the participation and expertise of specialist nurses is required. In this context, the dimensions and infrastructure of the institution, its information system, and the quality of the records must be considered[17-18]. Pruinelli argues that "AI models need to be built in a safe, ethical and human-centered way"[19]. In this way, the models would follow the progression of diseases, respecting their temporal trajectory and assisting in the provision of care[12,19]. The refinement of the parameters informed to the ML tool is crucial for its performance while respecting the peculiarities of the public served.

Our findings of more prevalent critical alarms in patients with confirmed diagnosis of sepsis reinforce a review conducted in Spain, which states that ML and related techniques can improve overall team performance by combining indicators already in use with other clinical variables, all of which are routinely measured in clinical practice[20]. Although promising, the use of AI cannot replace the staff's clinical management of sepsis. Thus, the selection of the most appropriate treatment strategies still requires the clinical judgment of the care team, the physical examination of the patient, and a thorough knowledge of the patient's history[21]. AI models can help us identify which patients require more attention in order to focus time and resources (human and logistical) on an individual basis. They can also be used to manage specialized human resources, which were scarce and exhausted during the confrontation with the pandemic of COVID-19.

Nurses have the skills and competencies to identify sepsis early, besides the fact that they are continuously at the patient's side. AI tools contribute to direct the team's attention to the most unstable cases, to help nurses and care staff to make assertive judgments, get correct information in order to support the best clinical decision making[18]. Consequently, they collaborate in providing timely and accurate care, which can significantly affect nurses' evidence-based practice, improve the quality of clinical care and outcomes, decrease costs, and ensure patient safety.

In this study, most patients remained in their sectors of origin (Table 2), either emergency care or inpatient units, where the length of stay is prolonged (20 to 87 days). Because of the critical alarms triggered in these locations, it is the inpatient units that require attention regarding the risk of sepsis. The findings of this research confirm a multicenter retrospective study, which relied on a database of more than 50,000 patients and tested a sepsis predictor model in the 24 hours prior to the clinical diagnosis received: these results confirmed the ability of ML models compared to sepsis-related gold standard scores[7]. Sepsis screening should be integrated as part of routine patient assessments and inpatient care rounds.

Since nurses play a significant role in identifying patients with sepsis through their unique position of having constant interaction with the patient, they should be included in the development of both bedside protocols and AI models[12,22]. Even, according to the Nursing and Artificial Intelligence Leadership Collaborative (NAIL), there is a need on the part of nursing leadership to take ownership of AI models in order to optimize nursing care delivery and free up time for nurses to spend on direct (versus indirect) patient care. Another benefit of AI technologies would be the potential to boost skills and encourage nurses to provide more evidence-based and personalized care to their patients.

In addition, AI can help healthcare professionals make correct judgments, obtain accurate information, at the right time, to support better clinical decision making and provide timely care to patients. Such a dynamic would take place "through the dissemination of cognitive knowledge and decision support"[19], by visualizing patient trends, which can provide input for both immediate patient care and long-term planning and management[12,18].

As advantages, within an unequal health context, AI applications for sepsis can offer many opportunities where resources and expertise are lacking, becoming a "lever for providing access to universal, high-quality, affordable health care for all." However, if the implementation of this technology is not framed as part of an overall sustainable development strategy, AI may exacerbate public health issues in countries already dealing with substantial problems and urgencies[23]. To balance this balance, alternatives must be found within the institutions themselves, including and training the teams, seeking innovation in the care processes, in the sense of rethinking, rediscovering, inventing themselves within each reality.

Study limitations

The pandemic of COVID-19 affected health services in numerous ways, with repercussions to a greater or lesser degree in several areas. As we conducted our research in this period, it changed the care and management processes and flows of the institution that hosted the study.

This fact influenced and limited our sample. If the intention of the research is to generalize its findings, during the pandemic our sample may have revealed the most severely ill patients, since elective care was suspended. Another factor to be considered is the reference position occupied by the institution, to which the most severe cases converge.

Moreover, there was mischaracterization suffered by the sectors, as COVID-19 cases were received where there were beds. As a consequence, the teams were relocated and exhausted. If, with a favorable scenario, there is already a lack of records and a delay in the information in the medical records, one can imagine a chaotic scenario when there is a need for records to trigger a risk alert.

Contributions to Health Care and Nursing

This research values the debate about AI and ML related to sepsis in a reference hospital complex, where the refinement of care processes associated with technology can result in long-term improvements. Also, it highlights the relevance of inclusion and active participation of nurses in the development, implementation and alignment of AI models related to their area of insertion.

To do so, these professionals must overcome their natural resistance to innovation, their mistrust of technology due to the fear of being replaced. It is necessary to "know the possibilities of action in technological innovation scenarios[9]", since Robot Laura® warns of the risk of sepsis, but the interpretation of that risk is a key step in the process that can contribute to safer, more effective, technology-based, patient-centered care.

CONCLUSIONS

Far beyond technology, ML models can speed up assertive clinical decisions by nurses, through critical alarms, optimizing time and specialized human resources.

After analyzing the critical alerts that predict clinical deterioration/sepsis, our results suggest that the AI can support assertive clinical decisions, as long as some prerequisites are respected: adaptation of protocols based on the target patients' profiles and involvement of the multi-professional team, especially the nurses, due to their uninterrupted presence next to the patients.

It is suggested that AI development teams in healthcare be interdisciplinary, including nurses, to ensure that contributions from informatics and engineering team members are aligned with clinical realities and adjusted to patients. Such tools are and will be increasingly embedded in the healthcare environment, supporting and streamlining care and enabling more assertive decisions. However, the ethical and moral issues related to patient outcomes will always be the responsibility of the teams, who know and are involved with people, beyond the technology.

SUPPLEMENTARY MATERIAL

Robot Laura®'s Alert Protocol. https://doi.org/10.48331/scielodata.PHGO2Q

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