ORIGINAL ARTICLE

TECHNOLOGICAL PROSPECTION: ARTIFICIAL INTELLIGENCE FOR PREDICTING RISK FACTORS IN PRIMARY HEALTH CARE

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Highlights: No technologies were found for predicting risk factors within the scope of Primary Health Care in this technological prospection, evidencing a gap that needs to be filled to meet the demands of Primary Health Care.

PRE-PROOF
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ABSTRACT

Objective: To identify artificial intelligence technologies for predicting risk factors within the scope of Primary Health Care (PHC). **Method:** Technological prospection, with searches conducted in patent databases. Data collection took place in April 2024. Artificial intelligence (AI) technologies addressing risk prediction in PHC and technologies available in English, Portuguese, and Spanish were included. The analysis was conducted through a qualitative comparative approach using Microsoft Excel spreadsheets extracted directly from patent databases. **Results:** Thirty patents were identified, most of them launched in 2022. The country with the highest number of developments was Brazil (29.03%), followed by the United States (25.8%) and India (25.8%). Regarding developers, most patents were filed by the inventors themselves (40%), followed by healthcare companies (20%) and health technology companies (13.33%). The objectives of the identified technologies were prediction of risks of a specific disease (46.67%), prediction of disease diagnosis (23.33%), prediction in health management (13.33%), and provision of health recommendations (16.67%). **Final consideration:** No technologies were found for predicting and assessing risk factors originating from the territory and thus providing risk stratification of the demand of Basic Health Units. Therefore, a gap was identified that can be filled through the use of AI, transforming PHC into a more predictive and less reactive model, optimizing resources and directing preventive actions more effectively.

Keywords: Risk factors; Primary Health Care; Artificial Intelligence; Information and Communication Technology Projects.

INTRODUCTION

Primary Health Care (PHC) is the main gateway in most countries and is also the level of care responsible for organizing the entire public network, acting in the promotion, prevention, and management of chronic health conditions[1-3]. Assessing its quality in promoting change is a major challenge due to the wide diversity of available methodologies, the need for access to reliable databases, and the importance of considering the perspectives of all stakeholders: healthcare professionals, managers, and users[2,4].

There are many risk factors associated with different types of diseases that are part of PHC assessment and stratification, such as noncommunicable chronic diseases (NCDs), risk factors for preeclampsia and gestational hypertension, cervical cancer, among others, reinforcing the premise that PHC is primarily responsible for assessing the risks of the enrolled population and for implementing intervention actions targeting the appropriate population groups[5-8]. Thus, the implementation of public health actions to combat NCD risk factors is necessary, as protecting the population is an essential mission to be carried out by the Ministry of Health[9].

Therefore, early identification of risk factors is crucial for improving health outcomes of the enrolled population, in addition to reducing costs associated with healthcare[3]. In this sense, technologies enable improvements in the understanding, assessment, and prediction of risk factors within PHC, with the support of advanced data analysis tools such as artificial intelligence (AI) algorithms and machine learning[10], allowing the identification of complex patterns and relationships among multiple variables, including individual, behavioral, social, economic, and environmental characteristics. This enables a more comprehensive and accurate analysis of risk factors, facilitating the identification of patients at higher risk of developing diseases or health conditions.

In summary, assessing the quality and risk factors in PHC is not merely a bureaucratic exercise but rather an essential tool to drive positive changes in the health system, preventing diseases, predicting risk factors, and improving the quality of life of the population in that territory[11-13]. A study conducted in the United States describes the first experiences of healthcare professionals with health risk assessment and concludes that, after 18 months from the start of the project, a minority of professionals believed that the project would lead to behavioral changes to reduce the identified risk factors[11].

Regarding AI, there is still no clear consensus on its definition. Some authors consider it an area aimed at reproducing human intelligence[14], others define it as an area focused on creating systems and data analysis methods[15], and there are also authors who combine both concepts, describing it as a broad and complex system capable of reproducing human intelligence[16]. In healthcare, the idea emerges that AI can solve complex problems at lower

costs, being incorporated with the aim of exploring datasets to diagnose, treat, and predict clinical outcomes, increasing accuracy and efficiency[17-18].

At a global level, AI has become a focal point of research across all professional fields due to its potential to solve complex problems[19] being used in healthcare for medical diagnoses through X-ray imaging[17] for clinical decision-making[18,20], for identifying patterns for disease diagnosis[17] and also for predicting patient hospitalizations[21].

Thus, the distinguishing feature of this study is the novelty of conducting a technological prospection in national and international patent databases to identify AI technologies for predicting risk factors within PHC, since, as shown in the review by Kueper *et al*. (2020), research on AI and PHC is progressing slowly, and no published studies were found in Brazil or Latin America[22].

Therefore, considering that AI may predict risk factors within PHC, the following research question was formulated: Which AI-based technologies have been developed with the objective of predicting risk factors in PHC?

METHOD

This is a technological prospection study with a qualitative comparative approach, based on the prediction of risk factors in PHC, following the guideline Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews[23]. The study was developed during the first semester of 2024, within the course on technologies and innovations for health and nursing care, which is part of the doctoral program in nursing at *Universidade Federal de Santa Catarina*.

The sample consisted of national and international patent records related to the prediction of risk factors in PHC. The search was conducted in April 2024, and no filters were applied regarding the sampling scope.

The methodology used in technological prospection falls within the field of technology future analysis, which is characterized by a systematic search aimed at producing judgments about emerging technologies[24]. These types of studies are divided into Assessment, Forecasting, and Foresight. Monitoring is carried out systematically and continuously to detect

future technologies and their interaction with society and the environment[25]. This prospection was conducted in nine stages, as follows:

First stage – The following research question was developed: Which AI-based technologies have been produced with the objective of predicting risk factors in PHC? Based on this, the objectives were defined.

Second stage – AI technologies addressing the prediction of risk factors within PHC and technologies available in English, Portuguese, and Spanish were included. Technologies that do not use AI, technologies without descriptions of the addressed topic, duplicate technologies, and technologies focused on the hospital setting were excluded.

Third stage – Data search strategies were defined using patent databases with high global coverage: World Intellectual Property Organization, The Lens (Lens.org), European Patent Office, and, at the national level, the *Instituto Nacional da Propriedade Industrial*.

Fourth stage – Data collection was carried out in patent databases using the following search strings: “Factor Risk”, “Artificial Intelligence”, “Primary Health Care”, combined with the Boolean operators AND and OR. The following combinations were applied: “Factors Risk” AND “Artificial Intelligence”; “Factors Risk” AND “Primary Health Care”; and “Factors Risk” OR “Primary Health Care” AND “Artificial Intelligence”.

Fifth stage – Technologies were selected through reading titles and abstracts, followed by the completion of a Microsoft Excel table with relevant data for discussion. Duplicate technologies were excluded, and inclusion and exclusion criteria were applied by two reviewers who were experts in the field.

Sixth stage – Results were processed, and qualitative data were interpreted in an interrelated manner. Subsequently, categorization was performed based on the objectives of the identified technologies.

Seventh stage – A qualitative comparative analysis of the data was conducted, identifying the objective of each technology and its potential for application within PHC. The critical analysis of the technologies was supported by scientific literature.

Eighth stage – Tables were constructed, and findings were discussed based on data available in the literature.

Ninth stage – The findings and identified gaps are presented in the conclusion of this technological prospection.

This study followed ethical research principles and, as it did not involve human subjects, it was not submitted for review by an institutional ethics committee.

RESULTS

A total of 425 technology records (systems, methods, software, applications, wearable devices) were identified in patent databases. Subsequently, titles and abstracts were reviewed, and 377 records were excluded for not meeting the inclusion criteria. From this, 48 records were included for full-text reading available in the database; eight duplicate records and ten records that did not address risk prediction and/or were related to hospital care or high technological density technologies, thus falling outside the scope of PHC, were excluded (Figure 1).

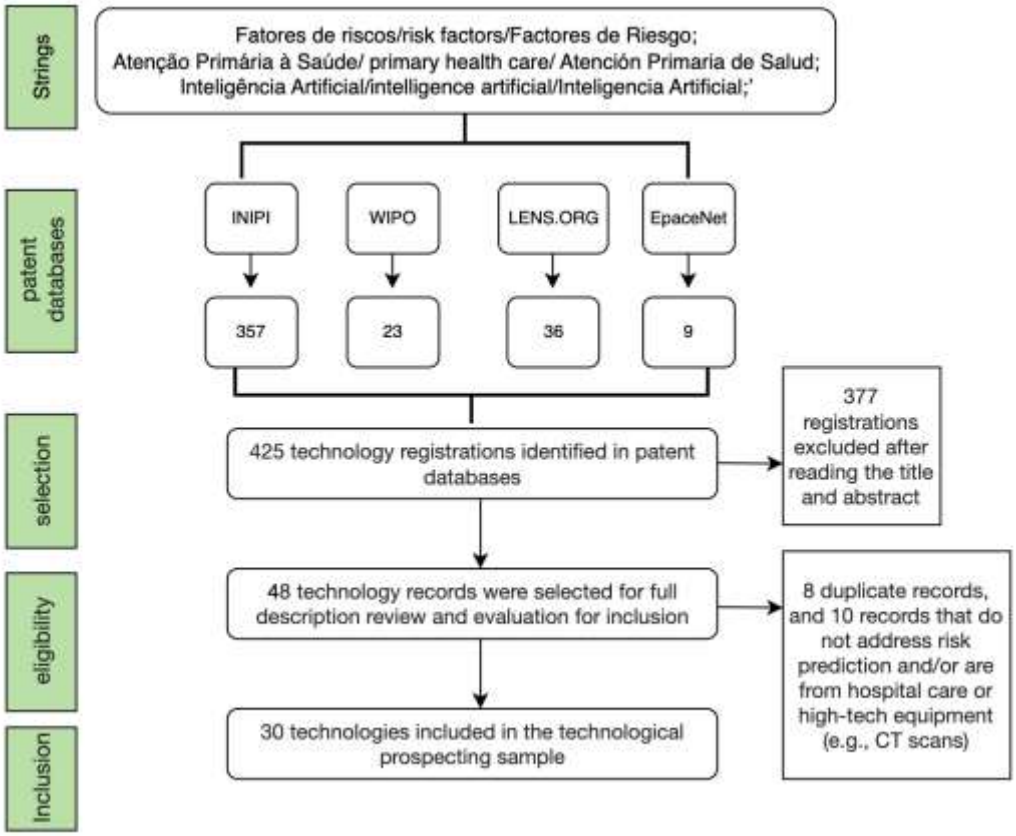

Figure 1: Flowchart of the stages for selecting technology records in patent databases. Florianópolis, SC, Brazil, 2024 (N=30)
Source: Model adapted from the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews[23].

Regarding the year of release, most technologies were launched in 2022 (36.67%), followed by 2019 (26.67%), 2021 (16.67%), 2023 (10.0%), and 2014, 2017, and 2020 with 3.33% each (Table 1). It can be observed in Table 1 that few technologies were patented before 2022, with Brazil being the country with the highest number of developments (29.03%), followed by the United States (25.8%) and India (25.8%). Regarding developers, most patents were filed by the inventors themselves (40%), followed by healthcare companies (20%) and health technology companies (13.33%).

Table 1: Characterization of artificial intelligence technologies included in this technological prospection. Florianópolis, SC, Brazil, 2024 (N=30)

Characteristics	N	%
Year of release		
2014	1	3.33
2017	1	3.33
2019	8	26.67
2020	1	3.33
2021	5	16.67
2022	11	36.67
2023	3	10.0
Country of development		
United States	8*	25.8
South Korea	2	6.46
Brazil	9	29.03
India	8	25.8
Canada	3*	9.68
Australia	1	3.23
Developer		
Healthcare company	6	20.0
Technology company	2	6.67
Healthcare technology company	4	13.33
University	3	10.0
Inventors	12	40.0
Intellectual property company	3	10.0

Legend: *The same company and the same inventors patented the same technology in two countries (United States and Canada).
Source: Developed by the authors (2024).

The technologies identified in patent databases were categorized according to the objective described in the available documents, being divided into four thematic categories: technologies for disease risk prediction, technologies for disease diagnosis prediction, technologies for prediction in health management, and technologies for health recommendations, as presented in Table 2.

Table 2: Presentation of technologies (software, applications, systems, methods) based on artificial intelligence found in the patent databases of this technological prospecting. Florianópolis, SC, Brazil, 2024 (N=30)

Title	Summary	Database	Area	Description
Technologies for disease prediction and prevention*				
Method for classification of skin lesion images	AI for skin lesion analysis to predict risks.	INPI	Prediction	Prediction of high-risk skin lesions
Artificial intelligence-based blood pressure (BP) drop system to prevent cardiovascular diseases using data mining and machine learning techniques for healthcare management	AI technology for reducing blood pressure to prevent cardiovascular disease through risk prediction.	WIPO	Prediction	Prediction of cardiovascular risks for blood pressure reduction
Artificial intelligence-based systems and methods for predicting cardiac events	AI for predicting the risk of cardiac events using electrocardiogram data from patients. The result is sent to a medical professional or healthcare administrator for risk assessment.	INPI	Prediction	Prediction of cardiac events
Artificial intelligence-based cervical cancer screening service system	AI for predicting cervical cancer. Reads cervical images.	INPI	Prediction	Prediction of cervical cancer risks
Automatic mammography image analysis system and method	AI for predicting breast density and breast positioning quality in mammography images.	INPI	Prediction	Prediction of breast density
Machine learning framework for detecting chronic health conditions	AI for predicting the risk of chronic non-communicable diseases by collecting data from a wearable device (such as an activity tracker or smartwatch). Allows notification of the user or a healthcare professional associated with the user.	Lens.org	Prediction	Prediction of risks for chronic non-communicable diseases

Intelligent healthcare system for automatic prediction and prevention of diabetes and early-stage breast cancer using AI and deep learning	AI for prevention and prediction of diabetes mellitus and early-stage breast cancer in all women (algorithms)*	WIPO	Prediction	Prediction of diabetes mellitus and breast cancer
Cognitive mind-based mobile application and kiosk support for women's mental health issues	AI-based chatbot in English and Tamil to offer friendly mental health support, targeted at women.	WIPO	Prevention	Mobile app for emotional and mental health support
AI-based intelligent healthcare system for automatic prediction and diagnosis of multiple cardiac diseases for early-stage prevention	AI for automatic prediction and diagnosis of multiple heart diseases, for early-stage prevention*.	WIPO	Prevention	Prediction, diagnosis, and prevention of chronic diseases
System and methods using AI algorithms to analyze wearable activity tracker data	AI developed for monitoring health conditions through a wearable device (activity tracker or smartwatch), providing notifications to the user through the wearable device or an associated application or technology, or indirectly, through a primary care provider associated with the user.	Espacenet, Lens.org and WIPO	Prevention (user)	User health monitoring
Method and device for pregnancy health status management using AI	AI developed for monitoring the health status of pregnant women and sending alerts to caregivers. Data is collected by sensors and stored in a database (continuous monitoring).	Espacenet and Lens.org	Obstetrics (user)	Monitoring of gestational health
Continuous operational support method for nurses with a biopsychosocial approach for elderly mental health and quality of life	AI for constant monitoring and identification of patterns that reflect the patient's habits, feelings, and vital signs, indicating suggestions for the best course of action for the patient, whether healthy or ill.	INPI	Monitoring (user)	Monitoring older adults' mental health
AI and machine learning-based detection and prevention of malaria parasites in blood using deep CNN algorithms	AI to detect and prevent malaria parasites.	WIPO	Prevention	Detecting and preventing malaria parasites

AI-based system for prediction and prevention of cardiovascular inflammatory and angiogenic diseases using image processing and deep learning algorithms	AI for the prevention and prediction of inflammatory and angiogenic cardiovascular diseases, using images and AI algorithms.	WIPO	Prediction and prevention	Prediction and prevention of chronic diseases
	Technologies for predictive disease diagnosis*			
Heart failure identification system using voice sound analysis and AI	AI for diagnosing heart failure using the user's voice.	INPI	Diagnosis	Diagnosis of heart failure
Development of a cardiac diagnosis system using AI with an Android application	AI for diagnosing early-stage heart disease using an Android app based on Bluetooth for transmitting acoustic sound captured via mobile phone.	WIPO	Diagnosis	Mobile app for diagnoses of chronic diseases
Multipanel target approach method and use of AI for differential diagnosis and prognosis	AI developed to assist primary care physicians in diagnosing multiple diseases, as well as tracking patients' health status.	Espacenet and Lens.org	Diagnosis	Medical diagnoses
System for diagnosis of cardiac arrhythmias	AI for pre-diagnosing cardiac arrhythmias through autonomous and remote mobile and non-invasive cardiac monitoring.	INPI	Diagnosis	Pre-diagnosis of cardiac arrhythmias
System and method for creating digital therapeutics tailored to specific patient conditions	Computer-based AI system targeted at specific patient care for a disease. Data is entered (conditions and symptoms) and content versions are created in natural language for medical-clinical purposes.	Lens.org	Service	Service for patients specific to a disease
Mobile system and auxiliary process for thermographic breast image evaluation	Mobile device connected with a breast thermographic image capture device for AI analysis to assist healthcare professionals in decision-making.	INPI	Service	Imaging evaluation
Automated melanoma detection process	AI for classifying skin cancer (melanoma) risks through mobile device image capture, image processing, and AI signal classification.	INPI	Risk stratification (diagnosis)	Risk stratification for melanoma

Technologies for prediction in healthcare management				
Community-oriented primary healthcare data management system	AI developed for management and data analysis in healthcare, sourced from healthcare institutions, through permissions, to prepare for unexpected conditions.	Espacenet	Data analysis (professionals)	Management and data analysis in healthcare
Integrated health platform using AI for data processing and organization	AI for handling health data on a single platform. The AI handles all patient record data to generate easily understandable information for patients. The system provides tools for creating reports, graphs, and clinical evolution of the patient, and also includes resources to guarantee the security and privacy of information.	INPI	Data analysis (user)	Prevention of prescription errors
Telehealth cabin implementation process and derived product	"Live" telehealth consultation booth by healthcare professionals with AI for prediction and control of health services.	INPI	Service (professionals)	Teleservice
Method for providing AI-based primary healthcare services	AI to provide primary healthcare AI medical service according to the user's health database.	Espacenet and Lens.org	Service (professionals)	AI-powered primary healthcare teleservices
Technologies for health recommendations				
Intelligent system for cancer analysis and staging	AI-based software for complex, individualized cancer staging analyses. This will provide an intelligent patient interaction interface to explain and monitor the cancer and the prescribed treatments.	INPI	Oncology	Cancer staging
Personalized health platforms	AI-based system to generate health recommendations for acute and/or chronic conditions (or diseases) through data analysis supported by peer-reviewed clinical literature.	Lens.org	Prediction	Individualized health recommendations

Health and wellness management systems and methods	AI for generating recommendations based on consultations and data analysis.	Lens.org	Service	Health and wellness recommendations
AI-based system for real-time recommendations during telemedicine sessions	AI assisting healthcare professionals with recommendations during consultations.	INPI	Service	Health recommendations
System architecture for digital therapeutics with personalized treatment pathways	AI providing recommendations based on patient profiles, medical assessments, and test results.	Espacenet and WIPO	Service	Health recommendations

Legend: AI – artificial intelligence; INPI - *Instituto Nacional da Propriedade Industrial*; WIPO - World Intellectual Property Organization; *Technology that falls into two categories because it has the option to aid in the diagnosis of a disease, as well as predict the risk of developing a specific disease.
Source: Developed by the authors (2024).

It can be observed in Table 3 that the objectives of the identified technologies are distributed as follows: 46.67% for prediction of risks of a specific disease, 23.33% for prediction of disease diagnosis, 13.33% for prediction in health management, and 16.67% for providing health recommendations.

Table 3: Presentation of AI-mediated technologies within Primary Health Care. Florianópolis, SC, Brazil, 2024, 2024 (N=30)

Characteristics	N	%
Objective		
Technologies for disease prediction and prevention		
Prediction of specific diseases*	10	71.42
User care	3	21.43
Disease prevention	1	7.15
Total	**14**	**46.67**
Technologies for predictive disease diagnosis		
Assisting professionals in medical diagnosis*	5	71.43
Assisting healthcare professionals in providing services	2	28.57
Total	**7**	**23.33**
Technologies for prediction in healthcare management		
Data analysis by healthcare professionals	1	25.0
Care management by users	1	25.0
Teleservice powered by artificial intelligence for professional assistance	2	50.0
Total	**4**	**13.33**
Technologies for health recommendations		
Technologies to assist professionals in making the best recommendations for health and well-being	5	100
Total	**5**	**16.67**

Source: Developed by the authors (2024). **Legend:** * A technology that falls into two categories because it has the option to aid in the diagnosis of a disease, as well as predict the risk of developing a specific disease.

DISCUSSION

The technological prospection made it possible to identify patented technologies that use AI for predicting risk factors to be applied in PHC. It was observed that few technologies are focused on NCDs, with most being directed toward cardiovascular diseases, which is concerning given that NCDs are not limited to cardiovascular diseases but also include cancers, diabetes, and respiratory diseases[26].

Currently, known risk factors for NCDs include male sex, age over 60 years, smoking, alcohol consumption, obesity, physical inactivity, and impaired mental health, as identified in different studies[6,26-27]. The main action guidelines include surveillance, information, assessment, and health monitoring, as well as health promotion and comprehensive care[26].

It is known that PHC faces numerous demands, and monitoring individuals throughout the entire life cycle does not appear to be a simple task[3]. Therefore, health technologies play an essential role in transforming PHC, enabling a more proactive and patient-centered approach for identifying, predicting, and managing risk factors, with the ultimate goal of improving population health outcomes[10, 28].

In addition, health technologies such as AI provide support to both professionals and patients by enabling continuous collection of large datasets related to lifestyle, medical conditions, and environmental factors. These data can be integrated into health information systems and used to develop personalized predictive models tailored to each patient's specific needs[28-29]. This allows for more targeted and efficient interventions, where healthcare professionals can implement personalized prevention and disease management strategies aligned with individual patient characteristics[28-29].

On the other hand, AI in PHC is still in its early stages, with most studies focusing on the development or adaptation of methods to support diagnosis or treatment[22]. This finding is consistent with the results of this prospection, in which 16 technologies are aimed at disease diagnosis and/or treatment.

It is important to highlight that Brazil (29.03%), the United States (25.8%), and India (25.8%) were the countries with the highest number of AI patents for predicting risk factors in PHC. This partially aligns with the Global Innovation Index Report, which identified North America as the region with the highest number of innovative technologies worldwide. The same

report indicates that the countries with the highest number of patent applications in 2020 were China, Korea, and the United States[30]. Concerning the year with the highest production of AI technologies, 2022 had the highest percentage (36.67%), which may be associated with the response to COVID-19[9]. As for developers, 40% of patents were filed by the inventors themselves.

It is important to note that among the four technologies aimed at users for risk prediction/prevention (pregnant women, older adults, and adults), all employed some type of wearable device for health data collection, such as smartwatches and mobile phones, providing notifications and/or chatbot support via mobile applications. This finding is consistent with Schestatsky (2020), who emphasizes the individual as the center of their own healthcare, with health monitoring performed through devices such as smartwatches and smartphones to track heart rate, glucose levels, sleep quality, stress levels, among others[31]. Thus, decision-making can be carried out jointly with healthcare professionals, which may reduce human error[18, 31].

Study limitations

A limitation of this study is its restricted scope, as other databases could be explored to obtain a broader and more diverse view of relevant technologies for predicting risk factors within PHC.

Contributions to nursing, health, or public policy

This technological prospection provides essential information on AI-based technologies for predicting risk factors in PHC. These technologies can be used for early identification of risks within the enrolled population and to support proactive interventions. Additionally, they may contribute to improved public resource management, personalized care, and the generation of valuable data for policymakers.

Final considerations

It was possible to identify that AI is still continuously evolving and that few technologies available in patent databases use AI for predicting risk factors within PHC. It is worth noting that the identified technologies are mainly directed toward predicting specific

diseases (cardiovascular diseases, skin diseases, cervical cancer, diabetes mellitus, breast cancer, among others), supporting medical diagnosis, predicting and analyzing health management, and providing health recommendations.

No technologies were found for predicting and assessing risk factors originating from the territory and for providing risk stratification of the demand in Basic Health Units. Therefore, a gap was identified that can be addressed through the use of AI, transforming PHC into a more predictive and less reactive model, optimizing resources and directing preventive actions more effectively.

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PROSPECÇÃO TECNOLÓGICA: INTELIGÊNCIA ARTIFICIAL PARA PREDICTION DOS FATORES DE RISCO NO ÂMBITO DA ATENÇÃO PRIMÁRIA À SAÚDE

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