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ORIGINAL ARTICLE

Artificial Intelligence:
Vigiexcelence a Strategy Developed During the Covid-19 Pandemic

Eliza Miranda Ramos[1]
Alexandra Maria Almeida Carvalho[2]

Highlights

(1). AI development optimizes epidemiological surveillance and reduces human error.
(2). Implement AI policies urgently at national, state, and municipal levels for SUS.
(3). AI improves healthcare service delivery and enhances decision-making efficiency.

ABSTRACT

Objective: To describe the development process of na AI using Machine Learning for decision making related to Covid-19. *Metodology*: This quantitative, descriptive and exploratory study utilized secondary public domain data from SUS network systems, collected from the OpenDataSUS platform and the municipal health network. The objetctive was to describe the development process of na AI called VIGIEXCELÊNCIA, using machine learning for rapid decision-making in response to COVID-19. *Result*: Through the use of machine learning, the algorithm was able to perform assessments and provide quick responses based on predictive models. *Conclusion*: The use of AI in Epidemiological surveillance improves health servisse delivery.

Palavras-chave: Covid-19; machine learning; surveillance; epidemiology; neural networks.

[1] Universidade Federal de Mato Grosso do Sul – Campo Grande/ MS, Brasil. https://orcid.org/0000-0003-2683-636X
[2] Universidade Federal de Mato Grosso do Sul – Campo Grande/ MS, Brasil. https://orcid.org/0000-0002-7868-3214

INTRODUCTION

The use of Artificial Intelligence (AI) in Epidemiological surveillance for Covid-19 control can be efficiently employed for decision-making in the Unified Health System (SUS)[1]. Resources should be allocated to improve the functioning of organizations responsible for Epidemiological surveillance, promoting eficiente effective and impactful actions[1].

In Brazil, the techmological challenges associated with and social crises, reinforced by territorial and Epidemiological demographic transittion, exacerbate the difficulties in making efficient and effective decision[2]. Nevertheless, the SUS has invested in and reinforced actions for the impemetation of innovative health policies, particularly technological ones, in the use of AI[2].

In this theoretical perspective, the theory of data governance stands out in the development of artificial Intelligence (AI) applied to Epidemiological surveillance [02, 03, 04] aiming to involve different actors and institutions with strategies and procedural actions to manage effectively[3], with inter-federative and shared decission-making that provides a better response to health and economic challenges[3,4].

Governmental strategies using AI in healthcare are capable of offering decisions that encompass informal, non-governmental control mechamisms[4]. Thus, healthcare professionals or managers develop the ability to act and make efficient rapid-reponse decisions based on the serverity of the problem in their territory, whether environmental, viral, bacterial or chemical[1,4]. According to the Federal Constitution of Brazil[5], health services must carry out actions with public relevance and should be used by the Population in a regional and hierarchical manner, ensuring comprehensive care for individuals across the national territory[2,5], especially in decision-making, monitoring, treatment and preventive actions[4].

Descentralized management with a single direction by the government is reinforced, building a system based on the participation of the population in it´s development and implementation process[2,4]. For the most part, SUS carries out actions with decentralized management at the municipal level, maintaining erros in it´s structure and governance methods, and not broadly strengthening equity in the distribution of health services in Brazil[3,4]. In this context of difficulties and challenges in the Brazilian territory, the use of AI has been described with the purpose of supporting a rapid response to Covid-19 and reducing the high pressure on SUS[6,10]. Technological strategies, such as the use of Artificial Intelligence in healthcare, play a fundamental role, especially in increasing the effectiveness of access to the Brazilian public health system[6]. The use of indicators of signs and symptoms in AI, through self-directed risk assessment tools known as chatbots, contributes to improving the quality of life of patients in healthcare[6,7]. Using tools with indicators of signs and symptoms of diseases in AI increases the potential for identifying symptomatic patients or those at risk of deterioration and death[6,8].

The objective of these tools is to perform patient screening in order to enhance clinical assessment and health management in providing specific and safe care [05, 06]. In France, an online application was used for self-screening of suspected Covid-19 cases, helping to reduce calls to the emergency call center and proving to be effective in predicting an increased need for hospital beds[7].

AI, through Machine Learning or Deep Learning language and neural networks, is capable of performing self-screening and risk assessment of patients, distributing health information and knowledge, tracking and monitoring Covid-19 signs and symptoms, and identifying the highest exposure risks[8,9,10]. The pandemic prompted health managers and professionals in Brazil to respond quickly to Covid-19 within the healthcare system, following the strategy defined to address the issue at the municipal level[2,9]. Defining a rapid response to the situation involves variations in disease progression, intensity, and duration, typically related to the onset and end of symptoms, with decisions strengthened by the political alignment of SUS[9,13,14].

The purpose of these tools is to screen patients in a way that benefits clinical evaluation and health management by providing specific and safe care[5,6]. In France, an online application was used for self-screening of suspected Covid-19 cases and helped to reduce calls to the emergency call center, proving to be effective in predicting an increased need for hospital beds[7]. AI, through Machine Learning or Deep Learning and neurais networks, is capable of performing self-screening and risk assessment of patients, distributing health information and knowledge, tracking and monitoring Covid-19 signs and symptoms, and identifying the highest exposure risks[8,9,10]. The pandemic has led health managers and professionals to respond quickly to Covid-19 within Brazil's health system, following the strategy defined to address the situation at the municipal level[2,4]. Defining a rapid response to the situation involves variations in disease progression, intensity, and duration, usually related to the onset and end of symptoms, and these decisions are strengthened by the political alignment of SUS[9,13,14].

In Brazil, no studies have been found that assess the impact of implementing Artificial Intelligence in decision-making and providing a rapid response to epidemiological surveillance. With the strategic aim of supporting the execution of health system actions at the municipal level, VIGIEXCELÊNCIA was developed, an artificial intelligence system for monitoring Covid-19 indicators of signs and symptoms, providing a rapid response.

Thus, this study aims to describe the development process of an AI using Machine Learning for decision-making related to Covid-19.

METODOLOGY

For the development of the AI, data modeling was based on patients with Covid-19 attended from June 2020 to June 2021 in the city of Campo Grande, the capital of the State of Mato Grosso do Sul. The study was submitted to the Research Ethics Committee of the Federal University of Mato Grosso do Sul and received approval (CAAE – 4296320.0.0000.0021). Individualized patient data with Covid-19 available on OpenDataSUS were used. OpenDataSUS provides information to support epidemiological analyses according to the sanitary situation, evidence-based decision-making, and the development of health action programs.

Patients with a positive result for Covid-19 by RT-PCR test, classified as mild, moderate, or severe, were included[13]. The RT-PCR test was used as the gold standard in laboratory diagnosis, as it is a biomolecular test that identifies the genetic material (RNA) of the Sars-Cov-2 virus in respiratory secretion samples[13,14]. Patients with signs of deterioration showed oxygen saturation below 95%, dyspnea, changes in X-ray or CT scan, followed by hospitalization[13,14]. The Bloom filter technique was used for case identification, and variables included identification fields such as age range, municipality of residence, date of birth, sex, and patient name, along with the final case classification[13,14] (Figure 1). Approximately 15.526 patient data were registered in OpenDataSUS during this period. Five predictor variables were selected: deaths, oxygen saturation below 95%, dyspnea, image changes using X-ray or CT scan, and hospitalization in intensive care[13,14]. The data underwent an initial preprocessing stage to address missing variables and transform the data for use in constructing different types of machine learning predictive models. As variable selection was performed, it was observed that all variables were fully completed, with no missing values. Variables with more than two categories were classified as dummy variables, with each category generating a set of variables with equivalent values of zero or one[22]. Continuous variables were constructed using z-score[18,22]. Numeric correlation testing revealed a high correlation between the number of inhabitants in the municipality and the average number of cases classified as mild, moderate, and severe (52.86%). Therefore, the variable of the number of inhabitants was dichotomized using the definition of 500.000 inhabitants to identify large cities in the state of Mato Grosso do Sul. For preprocessing and data loading, the MongoDB database management system was used. Data analysis and model construction were carried out using Python on the Google Colab platform. VIGIEXCELÊNCIA was developed in May 2022, using natural language processing to address monitoring and decision-making challenges during the Covid-19 pandemic. Machine learning techniques such as Random Forest and neurais networks were employed[21,22]. To illustrate and visualize the results, tests characterizing a simple experiment were conducted[22].

A total of three supervised machine learning algorithms were developed: logistic regression, random forest, and neurais networks. In cross-validation, the data were divided into two phases[18,22]. In the first phase, 70% of the data were used for algorithm training, and in the second phase, a 30% sample was used for testing with model hyperparameter adjustments, simulating new data and selecting hyperparameters that optimized the chosen performance metric[18,20,21]. This training phase allowed the algorithm to achieve better predictive performance when encountering new data sets. The cross-validation technique used was k-fold[26,27]. The study modeled the description of two groups of artificial intelligence actions: risk analysis and prediction of Covid-19 signs and symptoms indicators[18,21,26]. Risk analysis was developed to predict death or recovery in Covid-19 patients, while prediction was based on symptom indicators related to epidemiological surveillance, aiming to recommend disease prevention and control measures.

The data modeling for machine learning was developed based on the collected data to predict the number of individuals infected with Covid-19 who progressed to death. Quantitative analysis of these data was conducted using machine learning models developed by VIGIEXCELÊNCIA. The machine learning algorithms were designed to assist in decision-making (prevention, treatment, monitoring, and rapid response) to issues identified in patient monitoring in the municipality. The AI was updated weekly with algorithms developed by the interdisciplinary team, following the guidelines of the International Health Regulations of the CDC (Centers for Disease Control and Prevention) for combating Covid-19[25]. If the algorithm identified signs and symptoms consistent with Covid-19, the AI initiated an action flowchart through specific screenings for a rapid response (Figure 1).

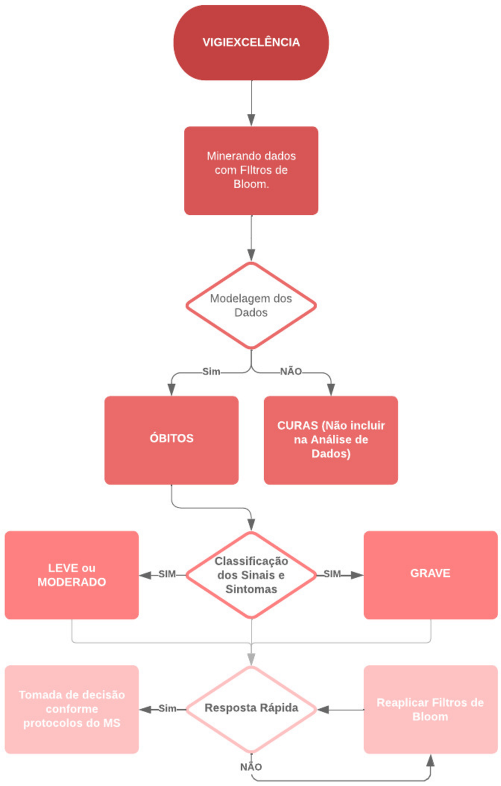

Figure 1 – Flowchart for evaluating worsening symptom indicators in Covid-19, Mato Grosso do Sul, 2023.
Source: Author, 2023.

Thus, a machine learning data model was developed to differentiate between different levels of risk to public health, enabling more specific decision-making by health managers in the municipality. When a patient was diagnosed with symptomatic indicators, they were classified into specific groups, such as mild, moderate, or severe (Figure 1), according to the criteria defined by the Ministry of Health[25].

Patients classified as severe underwent additional screening by the classification algorithm. Every 24 hours, the algorithm interacted with the database to update the patient's clinical information (Figure 1 and Figure 2). Within 72 hours, it provided a rapid response to the manager to assist in decision-making in the territory according to international regulations.

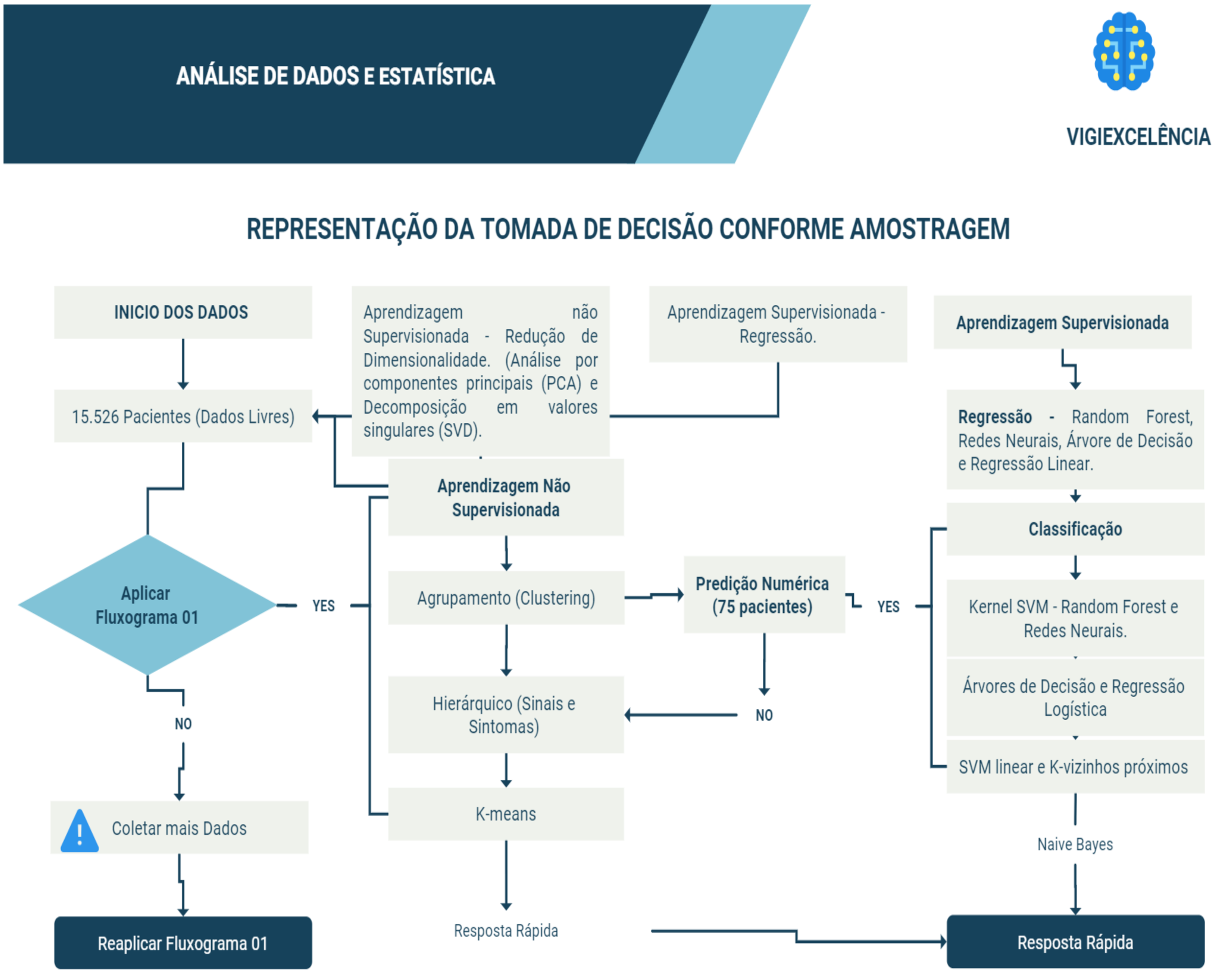

Figure 2 – Flowchart describing decision-making in sampling, Mato Grosso do Sul, 2023.
Source: Author, 2023.

Thus, the algorithm-based flowchart adapted the priority of care in the municipality during the pandemic (Figure 2). Two healthcare professionals validated the quality of the rapid response provided by VIGIEXCELÊNCIA, which potentially enabled more effective and efficient decision-making by managers during the pandemic period in the municipality.

RESULTS

The initial step involved a descriptive analysis of the training and test data for the period from 2020 to 2021. The training data includes 7,945 records of patients with Covid-19 in the municipality. An initial descriptive analysis was conducted on the training and testing data from 2020 to 2021. The training data included 7.945 records of Covid-19 patients in the municipality, with 8.208 positive cases diagnosed by the RT-PCR method and classified as symptomatic. The classification was based on worsening symptom indicators, following the protocols established by the Ministry of Health[13,14]. The results revealed the presence of 8.208 symptomatic pairs and 7.318 asymptomatic cases, as detailed in Table 1 and Table 2.

Table 1 – Study population and classification of Covid-19 cases with descriptive data analysis, Campo Grande – MS, June 2020 to June 2021

Variables		**n**	**%**
Population			
General population in the municipality *		916.001	100,00
Population for the AI (VIGIEXCELÊNCIA)		15.526	1,69
Covid-19 Classification			
Mild		3597	23,16
Moderate		4550	29,30
Severe		61	0,40
Asymptomatic		7318	47,14
Symptomatic		**Training**	**Testing**
Variable	**Categoria**	**n (%)**	**n (%)**
Sex	1 – Male	612.10 (21,40)	556.97 (22,63)
	0 - Female	5367.40 (65,44)	4156.20 (77,38)
Covid-19 Classification	0 – Mild	3364.23 (93,54)	3307.37(91,93)
	1 – Moderate	258.14 (5,68)	288.01 (6,33)
	2 - Severe	19 (0,02)	19 (0,02)
Death	0 – No	7945.36 (96,85)	7544.73 (91,96)
	1 - Yes	57 (94,40)	59 (97,15)

Source: OpenDataSUS, 2023.
Note: *Total population of the municipality reported by: https://www.ibge.gov.br/cidades-e-estados/ms/campo-grande.html.

The category with the highest percentage of cases was described in those with moderate signs and symptoms (29,30%). The sociodemographic characterization of Covid-19 cases can be observed in Table 2. Regarding symptomatic patients, the differentiation between the training and test sets stands out. In the gender variable, it is observed that in the training set, 21,40% are male, whereas 65.44% are female. In the test set, these proportions change to 22,63% and 77,38%, respectively. As for the Covid-19 classification, in the training set, most patients (93,54%) present mild forms of the disease, followed by 5,68% with moderate forms, and a minority (0,02%) with severe forms. In the test set, the proportions are 91,93%, 6,33%, and 0,02%, respectively. The mortality variable shows that in the training set, 96,85% of patients did not progress to death, while in the test set, this proportion is 91,96%. However, among female patients in the test set, the mortality rate is higher, reaching 97,15%.

Table 2 – Distribution of symptomatic and asymptomatic Covid-19 cases by sex and age group, Campo Grande – MS, June 2020 to June 2021

Variables	**Symptomatic (8208)**		**Asymptomatic (7318)**	
	n	**%**	**n**	**%**
Sex				
Male	2837	34,56	3586	49,00
Female	5335	65,44	3732	51,00

Age Group				
18 - 24 years	517	6,30	3952	7,99
25 - 34 years	919	11,20	1609	54,00
35 - 44 years	1017	12,39	439	21,99
45 - 54 years	4711	57,40	608	6,00
55 - 64 years	855	10,42	125	8,31
65 years or older	189	2,30	3586	1,71

Source: OpenDataSUS, 2023.

In terms of patient population, most cases were diagnosed in patients aged 25 to 34 years (54%) among asymptomatic individuals. In contrast, among symptomatic individuals, the predominant age group was 45 to 54 years (57.4%). The characterization of Covid-19 cases according to symptoms indicative of worsening can be seen in Table 3.

Table 3 – Distribution of signs and symptoms indicative of worsening for Covid-19, Campo Grande – MS, June 2020 to June 2021

Symptoms Indicative of Worsening	**n (8208)**	**%**
General Mortality	517	6,30
Oxygen saturation below 95%	4266	52,00
Dyspnea	1313	16,00
Changes in X-ray or CT scan imaging	1560	19,01
Hospitalization	931	11,35
	Training	**Testing**
Death	362	155
Oxygen saturation below 95%	2982	1284
Dyspnea	918	395
Change in X-ray or CT scan imaging Hospitalization	1093	497
Hospitalization	654	277

Source: OpenDataSUS, 2023.

Table describes an analysis of signs and symptoms that proved to be significant indicators for worsening in Covid-19 patients. The initial dataset consisted of 8.208 observed patients, with each symptom expressed in absolute frequency and percentage relative to the total. General mortality identified 571 cases, constituting 6,30% of the dataset, and demands special attention due to the development of worsening signs and symptoms. Oxygen saturation below 95% is notably high, with 4.266 cases (52,00%), making it an important variable in determining patient worsening. Dyspnea was observed in 1.313 cases (16%), frequently associated with clinical deterioration and indicating interventions such as hospitalization. Changes in X-ray or CT scan imaging were observed in 1,560 cases (19,01%), developing in patients who progressed to death with a period of hospitalization. Hospitalization, with 931 cases (11,35%), highlights that severity requires intensive care during hospitalization. The data were divided into training (70%) and test (30%) sets, maintaining proportions of symptomatic cases. This approach preserves representativeness and provides statistical robustness. In Table 3, by dividing the data into training and test sets while maintaining symptom proportions, and based on the need to preserve representativeness, it maintains the specific proportion of worsening symptoms and is supported by the need to preserve statistical integrity with the original dataset of 8.208 observations. This approach effectively generalizes the model to new data and provides an accurate assessment of its performance. By maintaining the proportion of variables that indicate worsening, the risk of selection bias is minimized, ensuring that the analysis was conducted on a sample with a distribution similar to that found in the original dataset. This practice, confirmed by the data in Table 03, specific to training and test proportions, acts as a preventive measure against result distortions and ensures a precise interpretation of the model's performance.

To assess the performance of the AI, an LSTM (Long Short-Term Memory) neural network was used, as an LSTM can use data analysis from scratch, and each new data analysis is verified with loops, allowing information to persist in the data modeling process, especially in predictions. O desempenho do modelo para os cinco temas considerados no estudo pode ser descrito na Tabela 4.

Table 4 – Model Performance for the Five Variables Evaluated with Signs of Worsening, Campo Grande- MS, 2023

Variables	***Simple Testing***	***Symptomatic***	***Asymptomatic***	***Recall***	***Precision***	***F1 Score***
Death	75	20	03	0,97	0,94	0,97
Oxygen Saturation	854	171	32	0,94	0,88	0,96
Dyspnea	263	53	10	0,91	0,93	0,51
Changes in X-ray and CT Scan Imaging	312	63	13	0,87	0,83	0,95
Hospitalization	110	22	05	0,95	0,93	0,57

Source: Author, 2023.

The classification using the LSTM (Long Short-Term Memory) neural network, a long-term memory neural network, was performed for the analysis of five relevant themes. However, due to the low number of samples in the death class, only 75 deaths were identified among symptomatic cases. This limitation in the number of classified death data resulted in challenges during the analysis process. The proportion of the symptomatic class was significantly reduced, ranging from 0,2% to 3,9% across all considered variables. This disproportion affects the classification of asymptomatic cases and, at times, may lead to an overestimation of this class. Consequently, this may result in erroneously high predictions, with correct classification of symptomatic cases being predominant. To correct this bias and evaluate performance accurately, metrics such as recall, precision, and F1 score were used.

Table 04 provides a summary of the performance metrics for the five analyzed themes. It was observed that the best precision and F1 score analyses were achieved for predicting death, oxygen saturation below 95%, and changes detected in X-ray or CT scan images. Specifically, the 97% correct analysis rate for deaths indicates that the model misclassified only 3% of samples labeled as asymptomatic. The 94% precision means that in only 6% of cases, the model incorrectly classified a sample as symptomatic, i.e., related to the symptomatic class. This result is favorable, considering the excellent performance of the model on such an imbalanced dataset, as present in the Ministry of Health databases.

DISCUSSION

The development of this technology represents the first description of an Artificial Intelligence with the capability and effectiveness in rapidly responding to worsening conditions and analyzing patients' clinical conditions[4]. In this study, the 8.208 patients who tested positive for Covid-19 via RT-PCR were classified as symptomatic [14] and could be monitored remotely without requiring in-person visits from healthcare professionals or evaluation in emergency rooms. This monitoring could be conducted through direct remote communication, such as through a patient assessment app. These monitoring patterns can be developed as outlined in the Covid-19 monitoring and care management guidelines by the Ministry of Health and the World Health Organization[14,15].

The development of this AI in Brazil strengthens the assertion of the sustainability of implementing and developing Artificial Intelligence as an innovative technology, which requires adaptive standards to the current public health system, specifically the SUS[17]. The distinctive feature of LSTM networks lies in their ability to process temporal sequences[4]. In epidemiological surveillance contexts, where we observe a continuous progression of events and conditions over time, this capability captures complex temporal patterns and allows for a deeper analysis of how evolving events or conditions contribute to the sustainability of findings[17]. Another factor is the LSTM networks' ability to retain long-term Information[17].

In health situations with chronic progressions or when analyzing long-term patterns that contribute to health outcomes, long-term memory becomes essential. LSTM networks overcome the gradient vanishing problem, allowing relevant information to be maintained over extended periods, thus providing a solid foundation for sustainable analyses[17]. Accurate prediction is another feature that enhances the sustainability of findings obtained through LSTM networks[17]. The ability of these networks to learn complex dependencies in data allows for anticipating future trends, providing insights for preventive decision-making. This capability is particularly valuable in epidemiological surveillance contexts, where the ability to predict future scenarios can positively impact health outcomes. Additionally, LSTM networks' adaptability to changes in data conditions contributes to the robustness and sustainability of findings. In dynamic health environments, where patient health patterns may evolve, the flexibility of LSTM networks to adjust to these changes is an important attribute.

The ability to handle heterogeneous data is another characteristic that highlights LSTM networks in health data analysis. The effective integration of different types of data, such as clinical, biomedical, demographic, and epidemiological data, contributes to a more comprehensive analysis and, consequently, to more sustainable findings. In conclusion, the algorithm developed for use in VIGIEXCELÊNCIA and applied in LSTM neurais networks for temporal health data analysis represents a significant advancement due to its easy adaptation to epidemiological surveillance. Its distinctive characteristics, such as effective processing of temporal sequences, long-term memory, accurate prediction, adaptability, and handling of heterogeneous data, converge to provide sustainable and valuable findings, thus enriching understanding and impact on health practices. Therefore, the algorithm developed for data analysis for VIGIEXCELÊNCIA has been standardized for use in the Unified Health System (SUS), leveraging the financial resources available in the chosen data modeling region. Brazil, being a continental country[17], with its complexities and challenges, needs innovative technological actions and efficient health solutions to overcome various obstacles in Brazilian public health[17]. The municipality described in this study belongs to the economically highest cluster in Brazilian territory according to IBGE data[19]. The use of technology by the health management system can improve accessibility to technological solutions using Artificial Intelligence. However, the technological resource and the financial structure for innovation projects in Brazil are major limiting factors for the development of Artificial Intelligence.

The development of VIGIEXCELÊNCIA was a collaborative effort involving educational institutions, public health, and private sector education. In Brazil, it is important to develop accessibility in projects for implementing new innovative tools in public health in partnership with private institutions to support and protect the development of innovative health Technologies[18,19]. The Unified Health System (SUS) covers most of the population as a health plan, and developing a sustainable and agile technological innovation to offer broader access and enhance equity in health requires coordinated efforts between public and private institutions[17,18], especially research universities[19]. SUS needs to automate a well-developed implementation plan through its public management[19], with rigorous metrics and protocols to assess performance, safety, and efficacy over time[18,19], which encourages the development of innovative technologies for SUS. However, there may be difficulties due to the applicability of Brazilian databases being ununified[19,20]. VIGIEXCELÊNCIA is an effective Artificial Intelligence in evaluating information related to patient worsening with Covid-19 and formulating rapid responses, with the purpose of integrating the data environment, connecting and organizing it, and thus executing data modeling with complex statistical calculations, comparing results with probabilistic ranges, and precisely defining favorable or unfavorable conditions for the occurrence of worsening and a rapid response. The algorithm was developed according to Ministry of Health protocols, with training in a real environment, and indicated which patients might be at risk of worsening or death and how the municipality defined strategies for worsening. It is important to highlight that VIGIEXCELÊNCIA indicates the risk of a particular territory based on data and clinical information of patients (identification of changes in signs and symptoms and changes in imaging exams), recorded by the health team in the standardized public health system [19]. Thus, considering this analysis of VIGIEXCELÊNCIA, it is important that epidemiological and clinical data of patients be available promptly, ideally at the same time they are collected by the healthcare professional[22]. Similarly, laboratory analysis data and other support services should be made available quickly[22,23]. The development of decision-making algorithms[21,29] in epidemiological surveillance optimizes the process of diagnosis, treatment, and monitoring, bringing healthcare professionals closer to their mission of saving lives[21,23,28,29].

The use of Artificial Intelligence, such as VIGIEXCELÊNCIA, in decision-making results in improved performance of care teams and the evolution of AI practice in epidemiology. The main benefits of using Artificial Intelligence are evident despite technological challenges, particularly regarding infrastructure issues such as computer terminals, data recording equipment in the municipality, institutional tablets, smartphones, and Wi-Fi networks, as well as the use of hardware and software by healthcare professionals[21,24,27,28,29], and skepticism about technology accuracy, among others, which diminish the success of implementing Artificial Intelligence projects in epidemiological surveillance[23,27,29]. Notably, this initial descriptive study presents several strengths. Although there are limitations in the development of this Artificial Intelligence, its implementation, supported by recurring supervised testing with data to assess Covid-19-related risks and offer optimal use in diagnosis, monitoring, and treatment with a flexible structure in the SUS territory built under accessible demands, is significant. This study is similar to the results of Hautz et al., (2021)[24] regarding the development of innovative technologies to assist healthcare teams in their actions, thus reducing the burden on the public health system and increasing the likelihood of efficient access to the health system in Brazil. All actions summarized in the development of this Artificial Intelligence were validated with health authorities in Brazil, specifically in the municipality and universities. Therefore, safety was ensured based on rigorous evaluation by the responsible institutions in each territory where the algorithm was implemented. Thus, we offer in the first phase of the study an algorithm aimed at enhancing decision-making, diagnosis, monitoring, and treatment amid the Covid-19 pandemic[29,30]. This descriptive study developed a new context in the use of AI associated with the innovation of well-structured public and private institutions, allied with sustainable incentives, which can generate value in the health field, particularly in low or middle-income countries. In summary, the use of Artificial Intelligence in epidemiological surveillance and health management can improve accessibility through effective and efficient solutions for SUS.

CONCLUSION

The development and implementation of Artificial Intelligence aim to enhance access and optimize decision-making in epidemiological surveillance, potentially reducing human workload and errors. The use of AI in epidemiological surveillance improves healthcare service delivery.

Furthermore, the development of a national, state, and municipal policy for the use of Artificial Intelligence within the SUS should be urgently implemented to make epidemiological surveillance services more effective and efficient throughout Brazil.

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Authors' contributions

Eliza Miranda Ramos: Data collection, modeling, and data analysis to build the Artificial Intelligence used in the study. The process included building the model and writing the explanatory text about its applications and results.

Alexandra Maria Almeida Carvalho: Guidance and writing of the explanatory text.

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Corresponding author
Eliza Miranda Ramos
Universidade Federal de Mato Grosso do Sul
Campo Grande/MS, Brasil
elizamirandaramos@gmail.com

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