RBFHSS
Revista Brasileira de Farmácia Hospitalar e Serviços de Saúde

Original Paper

Open Access

Artificial intelligence in the clinical pharmacy service in a public hospital in Belo Horizonte/MG

Clara Lemos LEITÃO[1], Amanda Fonseca MEDEIROS[1], Elaine Ferreira DIAS[1], Renan Pedra SOUZA[2], Maria Auxiliadora MARTINS[3]

[1]Hospital Risoleta Tolentino Neves, Minas Gerais, Brasil; [2]Departamento de Genética, Ecologia e Evolução, Instituto de Ciências Biológicas da Universidade Federal de Minas Gerais, Minas Gerais, Brasil; [3]Faculdade de Farmácia, Universidade Federal de Minas Gerais, Minas Gerais, Brasil

Corresponding author: Martins, MA auxiliadorapmartins@hotmail.com

Submitted: 31-03-2023 Resubmitted: 28-05-2023 Accepted: 31-03-2023

Double blind peer review

Abstract

Objective: To evaluate aspects related to the analysis of prescriptions by clinical pharmacists and the rate of medication-related errors after implementing an AI tool for the analysis of medical prescriptions in a large public teaching hospital from the city of Belo Horizonte/MG. **Method:** This is an observational study in which the results of the analysis of medical prescriptions performed in two periods were verified: the first one (denoted as BEFORE), period previously to the use of the AI tool (NoHarm.ai), from March to September 2021; and the second one (named AFTER), comprises the same period in 2022, already in use of the AI tool. **Results:** In the BEFORE period, it was found that the rate of prescriptions evaluated was 0.6%, with an error rate of 13% and an average of 85 pharmaceutical interventions/month, which resulted in average savings of direct medication costs of R$ 1,020.76/month. In the AFTER period, there was a 49% evaluated prescription rate, a 0.3% error rate, and a mean of 239 pharmaceutical interventions/month, with estimated savings of R$ 7,848.39/month. **Conclusion:** Using the AI tool contributed substantially to the pharmaceutical analysis of medical prescriptions, with a mean increase of 50% in the evaluated prescriptions and a 43-fold reduction in the number of errors, in addition to generating almost three times the number of pharmaceutical interventions after implementing the tool, as well as the direct savings obtained with these interventions, which were increased by seven times. The results of this study indicate that the AI tool analyzed likely generated savings in financial resources and increased productivity in the Clinical Pharmacy service and greater safety related to medication use.

Keywords: artificial intelligence, patient safety, pharmacy; medication errors.

Inteligência artificial no serviço farmacêutico de análise de prescrições médicas em um hospital público

Resumo

Objetivo: Avaliar aspectos relacionados a análise das prescrições por farmacêuticos clínicos e a taxa de erros relacionados a medicamentos após a implantação de uma ferramenta IA para análise das prescrições médicas em um hospital público de ensino de grande porte na cidade de Belo Horizonte/MG. **Método:** Trata-se de estudo observacional em que se verificaram os resultados da análise das prescrições médicas realizadas em dois períodos: o primeiro (denotado ANTES), período prévio a utilização da ferramenta de IA (*NoHarm.ai),* nos meses de março a setembro de 2021; o segundo (denotado DEPOIS), compreendeu o mesmo período em 2022, já em uso da ferramenta de IA. **Resultados:** No período ANTES, verificou-se que a taxa de prescrições avaliadas foi de 0,6%, com taxa de erro de 13% e em média 85 intervenções farmacêuticas/mês, que resultaram em economia média dos custos diretos de medicamentos de R$1020,76/mês. No período DEPOIS, verificou-se taxa de prescrições avaliadas igual a 49% e uma taxa de erro de 0,3% e a realização em média de 239 intervenções farmacêuticas/mês com valor médio de economia estimado de R$7848,39/mês. **Conclusão:** O uso da ferramenta IA contribuiu substancialmente na análise farmacêutica das prescrições médicas com aumento médio de 50% nas prescrições avaliadas, redução em 43 vezes o número de erros e gerou quase o triplo de intervenções farmacêuticas após a implantação da ferramenta, além da economia direta obtida com essas intervenções que aumentou em sete vezes. Os resultados desse estudo apontam que a ferramenta IA analisada gerou provável economia de recursos financeiros, aumento na produtividade do serviço de Farmácia Clínica e maior segurança relacionada ao uso de medicamentos.

Palavras-chave: segurança do paciente, inteligência artificial, serviço de farmácia hospitalar, erros de medicação.

Introduction

Adverse events are defined as unintentional injuries or harms that result in death, temporary or permanent disability or impairment, or prolonged hospitalization time as a result of health care[1]. Among adverse events there are medication errors (MEs), which can be understood as "any preventable event that may cause or lead to inappropriate medication use or harms to the patient while the medication is under control of the health professional, the patient or the consumer"[2].

MEs cause at least one death per day in the United States (US) and harms to approximately 1.3 million people a year. An annual cost associated with MEs is estimated at US$ 42 billion, almost 1% of the total global health expenditures[3]. In this context, health services and agencies around the world have been transforming the view of quality in health and have incorporated patient safety as one of its dimensions, highlighting a priority agenda with a view to improving care[4].

MEs encompass prescription errors, which can occur at different care stages, ranging from the therapeutic decision process to writing of the prescription itself, which can result in harms in 70% of the cases[5]. Data from the literature recorded that four out of every 1,000 prescriptions contain errors. In addition to that, other data from the USA showed that such errors generated additional health care expenses estimated at more than $20 billion per year[6].

According to the literature, medication error prevention strategy could involve pharmacotherapy review by trained clinical pharmacists[7]. Clinical Pharmacy interventions can contribute to care quality, increasing safety and efficiency by optimizing the pharmacotherapy results, identifying and preventing problems related to medication use[8].

Although reviewing prescriptions is a safety barrier for care already regulated in Brazil, Clinical Pharmacy services face challenges for its implementation in a consolidated and consistent way. Some factors may explain this gap, such as the scarce financial resources in the sector that impact sizing of pharmacy services, as well as the need for trained professionals and the increasing number of hospitalizations combined with the patients' complexity. Thus, there is a need to prioritize those with the potential to present more medication errors, using objective criteria and technological tools to optimize the process[9].

In these circumstances, several tools have emerged, with Artificial Intelligence (AI) among them, which allows decision support on clinical risks based on diverse information from the electronic medical record and assists in prioritizing patients with greater potential for adverse events. The algorithm classifies atypical prescriptions (according to the database standard), allowing optimization and agility in the pharmacotherapy review process performed by clinical pharmacists[10]. In this context, the current study aimed at evaluating aspects related to the analysis of prescriptions by clinical pharmacists and the rate of medication-related errors after implementing an AI tool for the analysis of medical prescriptions in a large public teaching hospital from the city of Belo Horizonte/MG.

Methods

Study design

The current study is observational and addresses the use of an AI tool in the pharmaceutical service to analyze medical prescriptions in a hospital. The results of the analysis of medical prescriptions carried out in two periods were verified: the first one (denoted as BEFORE), prior to using the AI tool (*NoHarm.ai)*, was from March to September 2021; and the second one (denoted as AFTER) comprises the same period in 2022, already in use of the AI tool. Retrospective data collection took place in October 2022, based on reports generated on the *NoHarm.ai* platform and on service indicator spreadsheets using *Microsoft Excel®*, generating an aggregated analysis of all the information. There was no change in the way in which the information was recorded during the study period. To measure the savings, only the direct cost of the medication was considered: its unit price (based on the mean cost of the product) multiplied by the dosage frequency and treatment time. In cases where there was no pre-established treatment period, the unit value was multiplied by the dosage considering seven hospitalization days. This project was approved at the institution by the Commission for the Evaluation of Research and Extension Projects belonging to the Teaching, Research and Extension Center (*Comissão de Avaliação de Projetos de Pesquisa e Extensão/Núcleo de Ensino, Pesquisa e Extensão*, CAPPE/NEPE) under the aegis of opinion No. 12/2022. Informed consent was not required, as there was no individual recruitment of participants.

Study setting

The study setting is a teaching hospital linked to the to the Brazilian Public Health System *(Sistema Único de Saúde)* and a reference for more than 1.5 million residents in the northern region of Belo Horizonte/MG and adjacent municipalities, operating without demand regulation: 24-hour open door service. The institution has 400 beds, assisting a mean of 5,080 urgencies and 1,076 hospitalizations in 2022. It has six operating rooms and a mean production of 445 procedures per month, anticoagulation outpatient clinic and discharge for different clinical conditions: orthopedic, vascular, neurological, palliative care and internal medicine care. The care model is based on four lines: clinical care, surgical care, mother-child care, and intensive care.

The institution's care vision is focused on the integration of multidisciplinary teams. The pharmacy team consisted of 14 pharmacists distributed among the processes that comprise the steps of pharmaceutical assistance cycle (11 non-clinical and three clinical pharmacists, before AI and, as of July 2022, redistributed into nine non-clinical and five clinical pharmacists), four resident pharmacists and two Pharmacy undergraduates, in addition to Pharmacy assistants, storekeeper and administrative clerks. The clinical activities encompasses medication reconciliation, pharmacotherapy monitoring, technical analysis of prescriptions, health education, sequential therapy, and outpatient care.

The tool

NoHarm.ai interfaces with the hospital's operating system (*MVSOUL®*) and the *Matrix®* laboratory management software, seeking to identify patients' risk factors such as age, hospitalization time, altered laboratory tests, prescription alerts for therapeutic duplicity, allergy to medications, cross-reactivity, toxicity, and

warning doses. In addition to that, it identifies prescription risk factors such as presence of antimicrobials, high-alert, controlled and non-standardized medications, drugs to be administered via a tube, and those prescribed with some difference from the previous prescription.

(...) The AI from NoHarm.ai generates a score according to the distance between the dose x the most commonly prescribed frequency points, with a score of 0 for the most common dosages (dense dots - green) and 3 for the most uncommon dosages (less dense dots - red), using data from the hospital itself. This work was validated by the tool's developers through an accuracy assessment, when analyzing precision of the algorithm evaluating overdose and predefined underdose[11].

In this way, *NoHarm.ai* can calculate the patient's global score (Figure 1). The higher the score, the greater the risk. The indication of prescriptions or patients at higher risk helps optimize the evaluation and pharmaceutical interventions.

The pharmaceutical evaluation

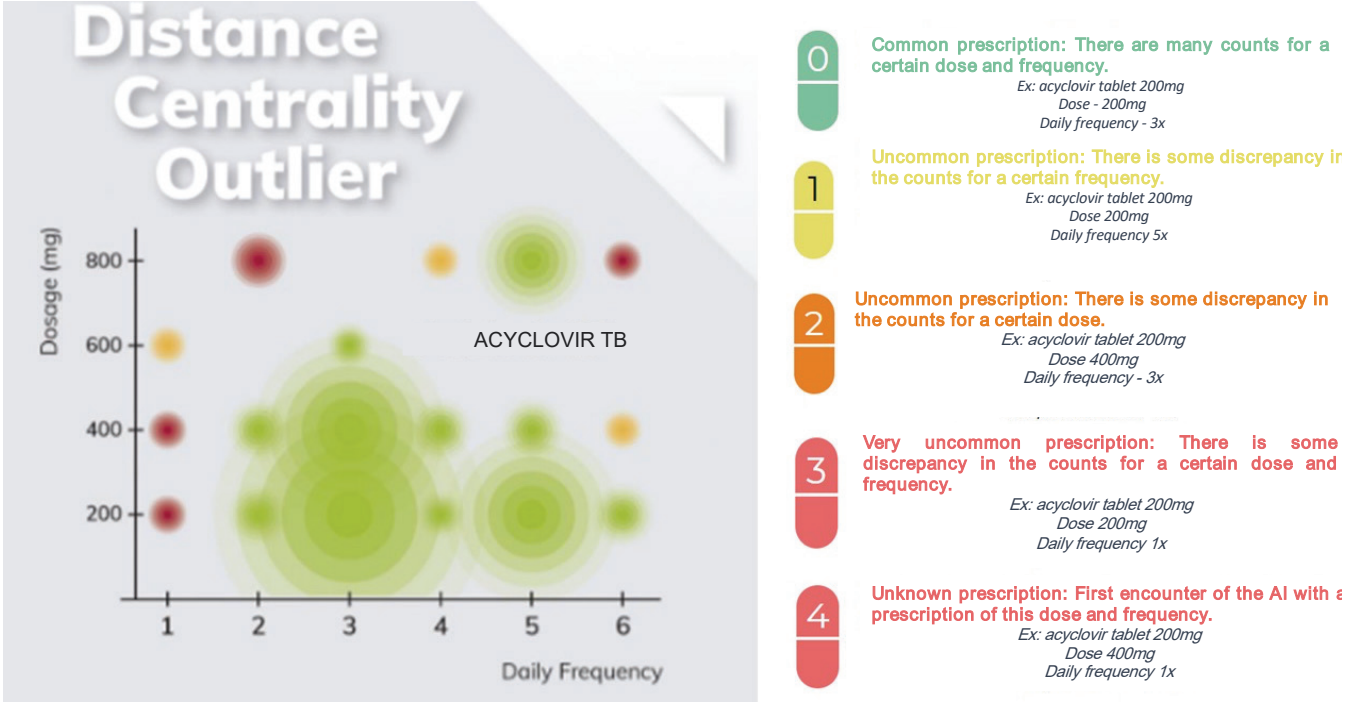
The analysis of all prescriptions was always performed by the clinical pharmacist and allowed detecting safety incidents (also called "near misses"). The tool made the process faster by concatenating all the necessary screens: laboratory tests, prescriptions, information related to medical records and technical information about medications collected from secure databases. The work methodology used to detect and record prescription errors adopted by the institution is in line with Ordinance 2,095 of September 24th, 2013[12].

For greater speed on the evaluation of prescriptions, the pharmacist could choose three different prioritizations: by prescriptions - it allows isolated view of the prescription; by patients - through aggregated prescriptions, a broad view of the individual's clinical status; and reconciliations, such as a new functionality for viewing the patient's continuous or sporadic medication use, as well as pharmaceutical presentation, dose and frequency. In this study, prioritization by prescription was mostly used.

The prescriptions of the internal medicine (IM), surgical clinic (SC), emergency care (ER), intensive and semi-intensive care (ICC/SICC) departments were analyzed. All pharmacists (5), pharmacy residents (4) and pharmacy students (2) who participated in the analysis of prescriptions were previously trained to use the tool. The total number of professionals varied during the study due to absences for vacations or leave. The evaluations occurred from Monday to Friday between 10:00 am and 5:00 pm, and each professional had a computer with Internet access. There was no pharmaceutical evaluation at night, during weekends or on holidays. The completed evaluation generated a check of the prescription in the tool, in order to show that it has already passed the technical scrutiny by a professional. This verification was not linked to medication dispensing. Faced with the need for a technical basis for assessing potential problems related to medication use, databases such as *Micromedex®, Up to date®* and *Sanford®* were employed.

Interventions related to errors were carried out immediately with the prescriber or when he/she was unavailable, along with the assistant physician. Interventions to optimize pharmacotherapy were carried out on the next shift with the reference prescriber. The interventions were carried out in person or by telephone. Interventions that generated changes in the prescription were carried out by the prescriber, except for the prescription of laboratory tests for therapeutic monitoring that were in charge of the pharmacist himself, as provided for in item XII of Art. 7 from CFF Resolution No. 585/2013[13]. The outcome of the interventions was recorded on the prescription analysis platform itself.

Figure 1 Example illustrating the method to calculate the scores corresponding to the medications



Adapted figure. Original version provided by NoHarm.ai in their knowledge database; TB: Tablet

RBFHSS
Revista Brasileira de Farmácia Hospitalar e Serviços de Saúde

Definition of the variables

From the data of interest, aspects related to the structure were described, such as the physical area of the clinical pharmacy, number of computers available, software used and sizing and assignment of the hospital pharmacy team. The data referring to the process were concatenated into working and non-working (Saturday, Sunday, and holidays) days. The variables of interest were the following: (i) total number and percentage of prescriptions issued; (ii) total number and percentage of prescriptions evaluated; (iii) rate of validated prescriptions (rate obtained by dividing the total number of prescriptions evaluated by the total number of prescriptions issued x 100); (iv) total number and percentage of items prescribed; (v) total number and percentage of validated items; and (vi) prescription error rate (rate obtained by dividing the total number of items with errors by the total number of items evaluated x 100[12]); the six previous parameters were compiled globally (Figure 2) and by sector (Figure 3). All interventions carried out by the Clinical Pharmacy service were considered, not only those arising from the prescription analysis, with the other variables being as follows: (vii) total number and percentage of interventions; (viii) total number and percentage of acceptability of interventions per month; (ix) source; (x) types of interventions carried out; and (xi) measurable direct savings.

Statistical analysis

Descriptive statistical analyses were performed, presenting absolute numbers, means and trend graphs, considering the independent variables. All statistical analyses were performed using the R software (version 4.0; *R Foundation for Statistical Computing, Vienna, Austria*). The study was conducted and reported in accordance with the DEPICT (*Descriptive Elements of Pharmacist Intervention: Characterization Tool*)[14] scientific writing script, version 2.

Results

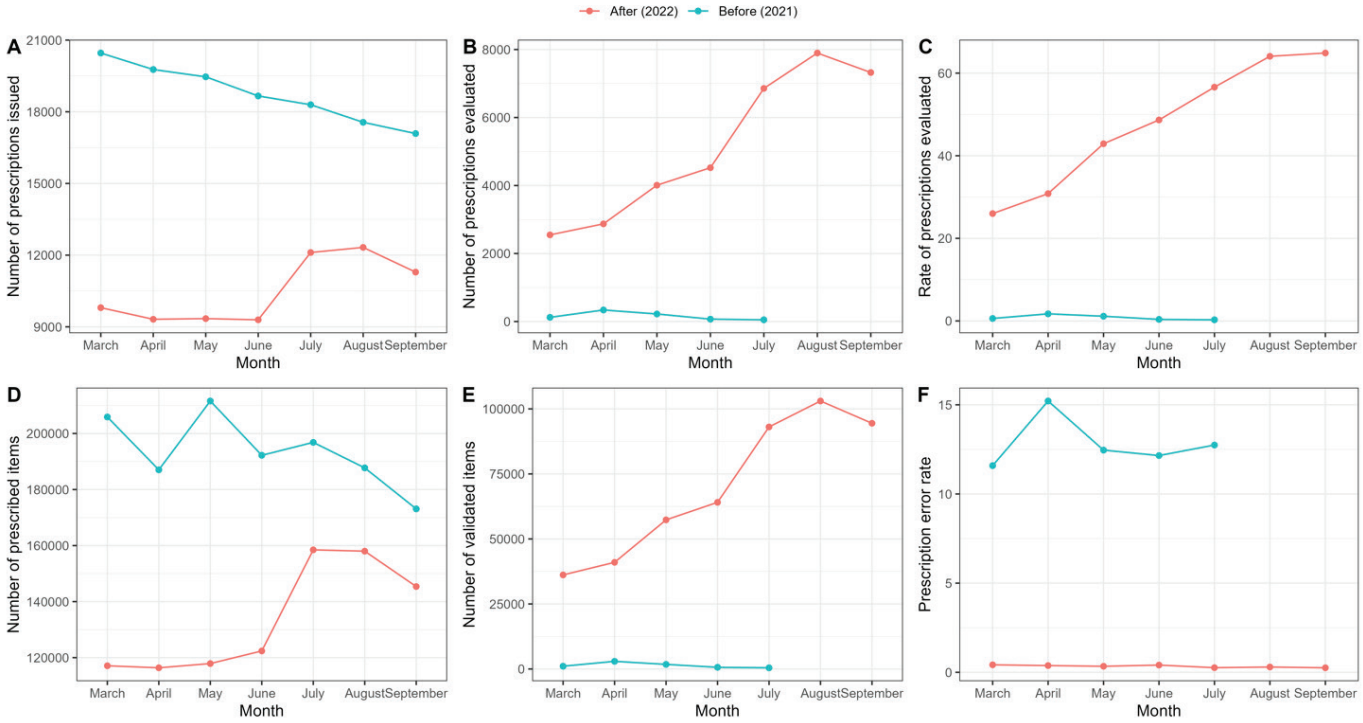
In the BEFORE period, the mean rate of evaluated prescriptions was close to 0.6% and that it represented 0.8% on working days. In the second period, denoted as AFTER, there was a mean rate of evaluated prescriptions equal to 49.0% and 67.0% on working days **(Figure 2C).**

BEFORE implementing the tool, the prescription error rate was 13%. In the AFTER period, a prescription error rate of 0.3% was verified **(Figure 2F)**.

In the first BEFORE period, the rate of medical prescriptions evaluated in the IM sector was 2%. AFTER, in the same sector, the rate of prescriptions evaluated was 54% **(Figure 3C)**. The error rate in the IM corresponds to 13.5% and, in the AFTER period, the error rate was 0.3% **(Figure 3F)**. The other parameters related to the analysis of prescriptions were detailed in the supplementary material.

As for the pharmaceutical interventions, 618 pharmaceutical interventions were carried out (mean of 85 interventions/month) in the BEFORE period. 1,731 interventions were carried out (mean of 239 interventions/month) in the AFTER period.

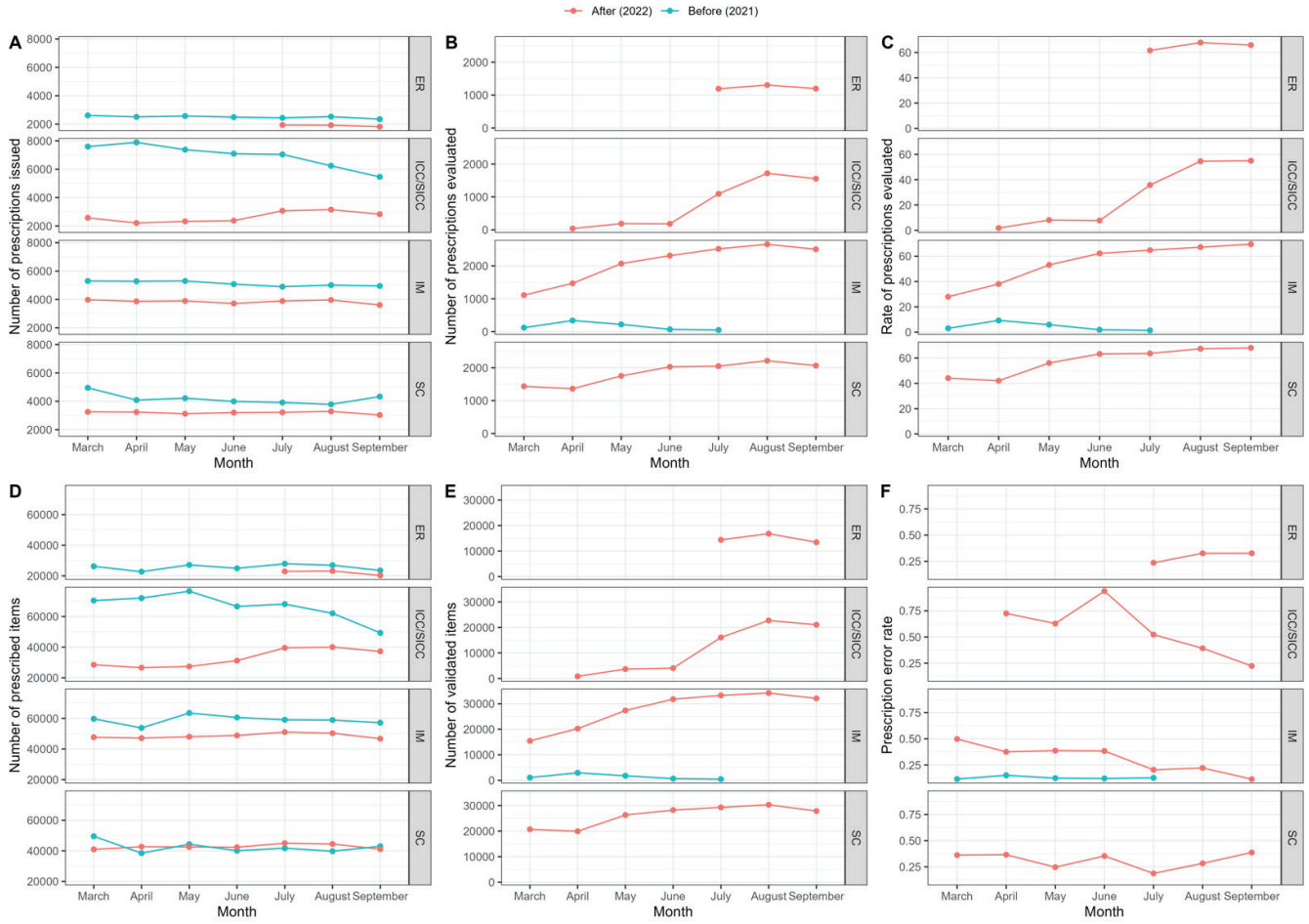
Figure 2. Variables related to the analysis of the medical prescriptions BEFORE AND AFTER



Of the interventions performed BEFORE, 554 were accepted (89%). In the AFTER period, 1,674 interventions were accepted (78%). It was possible to verify that BEFORE, the prescription analysis was the source of 27 pharmaceutical interventions (mean of four interventions resulting from the prescription analysis per month). AFTER, it was the source of 1,342 interventions (mean of 192 interventions resulting from the prescription analysis per month).

BEFORE, the main type of intervention carried out corresponded to health education, with a mean of 25/month. AFTER, dose adjustment was the most common type of intervention, with a mean of 80/month. The complete data regarding the pharmaceutical interventions performed are described in the supplementary material.

Figure 3 Variables related to the analysis of the medical prescriptions by sector BEFORE AND AFTER



In the BEFORE period, the mean savings in direct medication costs was R$ 1,020.76/month. In the AFTER period, the estimated mean value was R$ 7,848.39/month (Table 1).

Table 1 Direct savings with the interventions BEFORE and AFTER, Belo Horizonte, 2022

Months analyzed	Interventions Performed		Reduction of Direct Costs (R$)	
	2021	2022	2021	2022
March	66	119	1,894.19	6,139.60
April	102	150	1,114.76	5,145.63
May	88	221	631.36	3,319.50
June	102	280	1,718.39	15,270.64
July	75	303	765.85	8,245.64
August	70	372	-	11,555.44
September	116	286	-	5,262.29
Total	**619**	**1,445**	**6,124.55**	**54,938.74**

No analyses of prescriptions were carried out in the months of August and September.

Discussion

In this study, it was observed that using AI optimized the prescription analysis process, which represents an important stage in promoting the safety of patients in medication use. There was a mean growth of 50% in the number of prescriptions analyzed, after the changes implemented in the service. The rate of prescription errors was reduced by 43 times and the number of interventions performed by pharmacists after implementing the tool almost tripled (2.8), with dose adjustment as the main reason for intervention. The direct savings obtained from these interventions increased by seven times.

Table 2 Parameters related to structure, process and result BEFORE and AFTER

Parameters evaluated	Before	After
Structure		
Physical area	20 m²	32 m²
Computers available	3	9
Software used	MV 2000i®	MV Soul® and NoHarm.ai
Pharmacists/Sector		
Coordination	1 pharmacist	1 pharmacist
On-duty professionals	4 pharmacists	4 pharmacists
HICS	1 pharmacist	-
Pharmaceutical Assistance	7 pharmacists	5 pharmacists
Clinical Pharmacy	2 pharmacists, 4 resident pharmacists, 2 students	5 pharmacists, 4 resident pharmacists, 2 students
Process		
Prescription analysis	2 resident pharmacists carried out analyses only in the MC sector and other clinical activities	5 pharmacists, 4 resident pharmacists and 1 pharmacy student carried out the analyzes of the IM, SC, ER, ICC/SICC sectors and other clinical activities
Result		
Indicators corresponding to prescription analysis, Pharmacoeconomics, pharmaceutical interventions	Recording in the indicator worksheet of the institution	Recording in the indicator worksheet of the institution

HICS: Hospital Infection Control Service; IM: Internal Medicine; SC: Surgical Clinic; ER: Emergency Service; ICC/SICC: Intensive/Semi-Intensive Care Center

Donabedian proposed the "structure", "process" and "result" triad to assess quality of health services. From this perspective, it is assumed that a good structure increases the chance of establishing processes and obtaining good results[15]. The historical series shows that the rate of evaluated prescriptions grew gradually after implementing the tool, reaching 65% in the last month of analysis. This result was influenced by aspects inherent to the structure, such as the increase in the physical area, hardware, software, and redistribution of professionals, in addition to aspects related to organization of the process, such as remodeling of the Clinical Pharmacy operation with inversion of processes between the morning and afternoon shifts, in addition to concentrating prescription analysis activities in the afternoon shift. The AI tool interface with the programs for hospital management, laboratory management and knowledge databases also speed up analysis of prescriptions by the pharmacist. Such facts also result from the algorithm learning curve and from the team that is now more familiar with handling the tool.

As for the pharmaceutical professional's performance in different departments of the service, the focus was exclusively on the IM with beds for elderly, patients that receive pharmacotherapy monitoring and analysis by pharmacy residents. As of July, the Hospital Pharmacy Service was restructured, and another three pharmacists were transferred from general pharmaceutical care activities to exclusive tasks in Clinical Pharmacy. At the end of the period evaluated, the prescription analysis rate increased 75 times when compared to the same period in 2021. The constant presence of pharmacists by ward sectors results in a greater number of interventions, a significant reduction in the incidence of prescription errors and preventable adverse events, and higher acceptance percentages[16,17].

Patients admitted to the intensive care unit are at an increased risk of medication errors and preventable adverse events due to the critical nature of their diseases, polypharmacy, prevalent use of high-alert medications, and high frequency of changes in pharmacotherapy[18]. In 2021, the prescriptions from this unit represented 37% of the total (n=131,296) medical prescriptions evaluated across the four departments studied, evidencing the results of the actions adopted to comply with the national regulatory agenda[12, 13,19].

Using an AI tool to prioritize prescriptions based on their risk of containing at least one medication-related problem allows for a more accurate and faster approach to review by clinical pharmacists, significantly improving patient safety[20]. The prescription error rate dropped from 13 to 0.3%. AI optimized the process, and with a greater volume of medications evaluated by pharmacists, there was also an increase in the accuracy of the prescription error indicator, as the denominator became closer to the total number of medications prescribed. Another proposal is that with more capillarized pharmaceutical care, doubts were discussed with the multiprofessional team before issuing the prescription, which may have prevented errors in the decision or writing of the prescription. In addition to that, more interventions were carried out, protocols were reviewed and *in loco* discussions were disseminated, leading to greater attention from the professional in issuing future prescriptions.

During the study period, there was an increase in the monthly mean of interventions related to medication use: from 85 to 239. Reorganization of the Clinical Pharmacy workflow based on the introduction of AI made it possible to maintain the interventions previously carried out in the service, such as health education actions, in addition to expanding to other types of interventions targeted at patient safety during hospitalization, such as dose adjustment. Incorrect dosage regimen is one of the most common prescription errors[21,22,23]. Previous studies have shown that the main reason for pharmaceutical interventions was dose-related and that the pharmacists' participation can prevent problems related to medication use and reduce the overall occurrence rate of medication errors, with potential savings of up to US$ 2,657,820[21,24,25,].

As for acceptability of the interventions, the mean rate dropped from 88% to 75%, results also in line with data sourced from literature which showed that the acceptability rate of pharmaceutical interventions was greater than 70% in more than 60% of the studies reviewed[21,26,27,28]. With critical and in-depth clinical reasoning, it is up to the pharmacist to seek to add the prescription data as well as data from the electronic medical record to present the diverse evidence of the intervention proposal and the risk/benefit ratio, so that together with the prescriber they can decide on the therapeutic plan that will bring about direct and indirect benefits for the patient's health and care safety, contributing to the promotion of more satisfactory clinical results through systematic routines for analyzing prescriptions and encouraging safe prescription. However, the time employed for the analysis is scarce and does not allow bedside collection of other individual and subjective aspects about the patient that may interfere with the rational and safe medication use. Therefore, when approaching the attending physician, some of the interventions proposed may not have been accepted.

Discussing problems related to medication use mainly involves aspects inherent to patient safety. However, as far as inputs are concerned, their inappropriate use is also related to a substantial increase in care costs and to the institutions' financial sustainability. In this study, medication-related savings from R$ 6,124.00 to R$ 54,938.74 were evidenced by using AI. However, the comparison with the data identified in the literature is complex due to the different study designs and the patients' profiles at the institutions[29].

As strengths of this study, the notoriety of the topic is highlighted, reporting results in a public teaching hospital. As a limitation, the fact that the research was carried out in a single center stands out, with potential information bias, as the data sheets are entered by each professional, who may forget or incompletely make such records. In addition to that, the AI tool detects prescription patterns, which in itself can be a limitation in identifying prescription errors, as AI would not detect a practice based on an outdated guideline. However, no tool captures the completeness and uniqueness of each patient and their needs, which can only be seen at the bedside with other care processes, with prescription analysis as a stage in a broader process, which is pharmacotherapy monitoring. Another confounding factor was the change in the physical and technological structure, in the sizing of human resources and in work processes, concomitant with implementation of the AI tool.

Conclusion

Along with structure improvements and process optimization, using an AI tool substantially interfered in the pharmaceutical analysis of medical prescriptions in a teaching hospital with a mean increase of 50% in the volume of evaluated prescriptions. The rate of prescription errors was reduced by 43 times (0.3%) and the number of interventions performed by pharmacists after implementing the tool almost tripled (239/month), with dose adjustment as the main reason for intervention. The direct savings obtained from these interventions were increased by seven times. The results of this study suggest that AI tools can add quality to the prescription analysis process in Hospital Pharmacy. The interrelationship between structure, processes and results in Hospital Pharmacy as an essential unit is fundamental for promoting care quality and patient safety.

Funding sources

The authors declare that the research did not receive funding for its conduction.

Conflict of interests

The authors declare having no conflict of interests.

Collaborators

Upon concluding the study, the collaborations were highlighted as per established ICMJE standards, available in https://www.icmje.org/. CLL, AFM and MAM designed the project; CLL collected the data; CLL and AFM analyzed and interpreted the data and wrote the article; RPS performed the statistics; and MAM and EFD critically reviewed the article. All the authors read and agreed with the final version and are responsible for any and all aspects of the paper in terms of ensuring accuracy and integrity of any of its parts.

Acknowledgments

We would like to thank the Hospital where the study was conducted for promoting safe care of our patients and supporting the implementation of the Artificial Intelligence tool, as well as the Ministry of Education for funding the Multiprofessional Residency in Health program.

References

1. Mendes W, Martins M, Rozenfeld S, Travassos C. The assessment of adverse events in hospitals in Brazil. Int J Qual Health Care. 2009 Aug;21(4):279-84. DOI: 10.1093/intqhc/mzp022.
2. National Coordinating Council for Medication Error Reporting and Prevention. What is a Medication Error? Available in: https://www.nccmerp.org/about-medication-errors. Accessed on 16th January 2023.
3. World Health Organization. Medication Without Harm. Available in: https://www.who.int/initiatives/medication-without-harm. Accessed on 13th May 2022.
4. Luxford K. 'First, do no harm': shifting the paradigm towards a culture of health. Patient Exp J 2016;3:5–8. DOI: https://doi.org/10.35680/2372-0247.1189.
5. Instituto para práticas seguras no uso de medicamentos. Prevenção de erros de prescrição. Boletim ISMP 2021;10. Available in: https://www.ismp-brasil.org/site/wp-content/uploads/2021/03/Boletim-ISMP-Prevencao-Erros-Prescricao.pdf. Accessed on 14th January 2023.
6. Schiff GD, Volk LA, Volodarskaya M, *et al*. Screening for medication errors using an outlier detection system. Journal of the American Medical Informatics Association: JAMIA. 2017 Mar;24(2):281-287. DOI: 10.1093/jamia/ocw171.
7. Corny J, Rajkumar A, Martin O, Dode X, Lajonchère JP, Billuart O, Bézie Y, Buronfosse A. A machine learning-based clinical decision support system to identify prescriptions with a high risk of medication error. J Am Med Inform Assoc. 2020 Nov 1;27(11):1688-1694. DOI: 10.1093/jamia/ocaa154.

8. Botelho SF, Neiva Pantuzza LL, Marinho CP, Moreira Reis AM. Prognostic prediction models and clinical tools based on consensus to support patient prioritization for clinical pharmacy services in hospitals: A scoping review. Res Social Adm Pharm. 2021 Apr;17(4):653-663. DOI: 10.1016/j.sapharm.2020.08.002.

9. Alshakrah MA, Steinke DT, Lewis PJ. Patient prioritization for pharmaceutical care in hospital: A systematic review of assessment tools. Res Social Adm Pharm. 2019 Jun;15(6):767-779. DOI: 10.1016/j.sapharm.2018.09.009.

10. Santos HDP. Applying machine learning to electronic health records: a study on two adverse events. Programa de Pós-Graduação em Ciência da Computação - Doutorado em Ciência da Computação. Pontifícia Universidade Católica do Rio Grande do Sul, 2021.Available in: https://repositorio.pucrs.br/dspace/handle/10923/17324. Accessed on 14th January 2023.

11. NoHarm.ai. Como a IA da NoHarm calcula os escores dos medicamentos? n.d. https://noharm.octadesk.com/kb/article/escore-e-tags-clicaveis. Accessed on 16th January 2023.

12. Ministério da Saúde. Portaria nº 2.095. Aprova os Protocolos Básicos de Segurança do Paciente; 2013. Available in https://bvsms.saude.gov.br/bvs/saudelegis/gm/2013/prt2095_24_09_2013.html. Accessed on 13th May 2022.

13. Conselho Federal de Farmácia. Resolução nº 585 de 29 de agosto de 2013. Regulamenta as atribuições clínicas do farmacêutico e dá outras providências. Available in https://www.cff.org.br/userfiles/file/resolucoes/585.pdf. Accessed on 13h May 2022.

14. Rotta I, Salgado TM, Felix DC, Souza TT, Correr CJ, Fernandez-Llimos F. Ensuring consistent reporting of clinical pharmacy services to enhance reproducibility in practice: an improved version of DEPICT. J Eval Clin Pract. 2015 Aug;21(4):584-90. DOI: 10.1111/jep.12339.

15. 15 Donabedian A. Evaluating the quality of medical care. 1966. Milbank Q. 2005;83(4):691-729. DOI: 10.1111/j.1468-0009.2005.00397.x.

16. Ooi PL, Zainal H, Lean QY, Ming LC, Ibrahim B. Pharmacists' Interventions on Electronic Prescriptions from Various Specialty Wards in a Malaysian Public Hospital: A Cross-Sectional Study. Pharmacy (Basel). 2021 Oct 1;9(4):161. DOI: 10.3390/pharmacy9040161.

17. Klopotowska JE, Kuiper R, van Kan HJ, de Pont AC, Dijkgraaf MG, Lie-A-Huen L, Vroom MB, Smorenburg SM. On-ward participation of a hospital pharmacist in a Dutch intensive care unit reduces prescribing errors and related patient harm: an intervention study. Crit Care. 2010;14(5):R174. DOI: 10.1186/cc9278.

18. 18 Moyen E, Camiré E, Stelfox HT. Clinical review: medication errors in critical care. Crit Care. 2008;12(2):208. DOI: 10.1186/cc6813.

19. 19 Conselho Federal de Farmácia. Resolução nº 675, de 31 de outubro de 2019. Regulamenta as atribuições do farmacêutico clínico em unidades de terapia intensiva, e dá outras providências; 2019. Available in: https://pesquisa.in.gov.br/imprensa/jsp/visualiza/index.jsp?data=21/11/2019&jornal=515&pagina=128&totalArquivos=133https://pesquisa.in.gov.br/imprensa/jsp/visualiza/index.jsp?data=21/11/2019&jornal=515&pagina=128&totalArquivos=133. Accessed on 22th January 2023.

20. Levivien C, Cavagna P, Grah A, Buronfosse A, Courseau R, Bézie Y, Corny J. Assessment of a hybrid decision support system using machine learning with artificial intelligence to safely rule out prescriptions from medication review in daily practice. Int J Clin Pharm. 2022 Apr;44(2):459-465. DOI: 10.1007/s11096-021-01366-4.

21. Reis WC, Scopel CT, Correr CJ, Andrzejevski VM. Analysis of clinical pharmacist interventions in a tertiary teaching hospital in Brazil. Einstein (Sao Paulo). 2013 Apr-Jun;11(2):190-6. DOI: 10.1590/s1679-45082013000200010.

22. Lewis PJ, Dornan T, Taylor D, Tully MP, Wass V, Ashcroft DM. Prevalence, incidence and nature of prescribing errors in hospital inpatients: a systematic review. Drug Saf. 2009;32(5):379-89. DOI: 10.2165/00002018-200932050-00002.

23. Korb-Savoldelli V, Boussadi A, Durieux P, Sabatier B. Prevalence of computerized physician order entry systems-related medication prescription errors: A systematic review. Int J Med Inform. 2018 Mar;111:112-122. DOI: 10.1016/j.ijmedinf.2017.12.022.

24. Naseralallah LM, Hussain TA, Jaam M, Pawluk SA. Impact of pharmacist interventions on medication errors in hospitalized pediatric patients: a systematic review and meta-analysis. Int J Clin Pharm. 2020 Aug;42(4):979-994. DOI: 10.1007/s11096-020-01034-z.

25. Tasaka Y, Tanaka A, Yasunaga D, Asakawa T, Araki H, Tanaka M. Potential drug-related problems detected by routine pharmaceutical interventions: safety and economic contributions made by hospital pharmacists in Japan. J Pharm Health Care Sci. 2018 Dec 13;4:33. DOI: 10.1186/s40780-018-0125-z.

26. Barros ME, Araújo IG. Evaluation of pharmaceutical interventions in an intensive care unit of a teaching hospital. Rev Bras Farm Hosp Serv Saude. 2021;12(3):0561. DOI: 10.30968/rbfhss.2021.123.0561.

27. Blum MR, Sallevelt BTGM, Spinewine A, O'Mahony D, Moutzouri E, Feller M, *et al.* Optimizing Therapy to Prevent Avoidable Hospital Admissions in Multimorbid Older Adults (OPERAM): Cluster randomised controlled trial. BMJ 2021;374. DOI: https://doi.org/10.1136/bmj.n1585.

28. Dias D, Wiese LPL, Pereira EM, Fernandes FM. Evaluation of pharmaceutical clinical interventions in the icu of a public hospital of Santa Catarina. Rev Bras Farm Hosp Serv Saude, 9(3): 1-5, 2019. DOI: https://doi.org/10.30968/rbfhss.2018.093.005.

29. Arantes T, Durval C, Pinto V. Avaliação da economia gerada por meio das intervenções farmacêuticas realizadas em um hospital universitário terciário de grande porte. Clin Biomed Res 2020;40:96–104. DOI: https://doi.org/10.22491/2357-9730.95646.