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Combining Managerial Innovation and Artificial Intelligence to Predict Unpaid Patient Bills and Reduce Their Incidence,

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Summary:

Managerial Innovation (MI), which involves adopting new management practices or methods essential for enhancing organizational performance, faces limitations, particularly in reducing the number of patients who do not pay their bills. This paper aims to address this issue by developing an Artificial Intelligence (AI) model that predicts early which patients are likely to default on their payments. By doing so, stronger MI strategies can be applied specifically to these patients, thereby avoiding the adverse impact on those expected to fulfill their financial obligations.

In this study, data from two patient groups were used: 683 patients from internal admissions and 753 patients from urgent admissions. The "KNeighborsClassifier" machine learning algorithm was trained and tested 10,000 times on each dataset, each time with 90% of the data randomly selected for training and the remaining 10% for evaluation.

By leveraging these AI predictions, it is possible to implement more focused MI procedures: applied to only 18 out of 100 internal patients, reducing the number of unpaid patients from 10 to 5; and applied to only 10 out of 100 urgent patients, reducing the number of unpaid patients from 6 to 5. Using a larger patient dataset could further enhance these results.

Keywords: Artificial Intelligence - Managerial Innovation - Machine Learning - Payment Prediction - Unpaid Patient Bills.

Combiner l'innovation managériale et l'intelligence artificielle pour prédire les factures patients impayées et réduire leur incidence

Résumé :

L'Innovation Managériale (IM), qui consiste à adopter de nouvelles pratiques ou méthodes de gestion essentielles pour améliorer la performance organisationnelle, présente des limitations, notamment en ce qui concerne la réduction du nombre de patients qui ne paient pas leurs factures. Cet article vise à résoudre ce problème en développant un modèle d'Intelligence Artificielle (IA) capable de prédire de manière précoce quels patients sont susceptibles de ne pas régler leurs paiements. Ce faisant, des stratégies d'IM plus ciblées peuvent être appliquées spécifiquement à ces patients, évitant ainsi les impacts négatifs sur ceux qui sont censés remplir leurs obligations financières.

Dans cette étude, les données de deux groupes de patients ont été utilisées : 683 patients provenant des admissions internes et 753 patients provenant des admissions urgentes. L'algorithme d'apprentissage automatique "KNeighborsClassifier" a été entraîné et testé 10 000 fois sur chaque ensemble de données, à chaque fois avec 90 % des données sélectionnées aléatoirement pour l'entraînement et les 10 % restants pour l'évaluation.

En utilisant ces prédictions d'IA, il est possible de mettre en œuvre des procédures d'IM plus ciblées : appliquées seulement à 18 patients sur 100 dans les admissions internes, réduisant le nombre de patients non réglés de 10 à 5 ; et appliquées seulement à 10 patients sur 100 dans les admissions urgentes, réduisant le nombre de patients non réglés de 6 à 5. L'utilisation d'un ensemble de données plus large pourrait améliorer davantage ces résultats.

Mots-clés : Intelligence Artificielle - Innovation Managériale - Apprentissage Automatique - Prédiction des Paiements - Factures Impayées des Patients.

Introduction:

Managerial Innovation (MI) is defined as the adoption of new management practices or methods crucial for enhancing organizational performance (Birkinshaw, Hamel G, and Mol, 2008). It holds crucial importance in all sectors, especially in the healthcare sector facing increasing financial challenges related to profitability and financial management. This is particularly evident in the inefficient management of unpaid patient bills, which poses a significant challenge to financial stability in this sector. On the other hand, certain significant challenges influence the effectiveness of MI and its implementation. They can delay it, cause it to fail, or more precisely, limit it. A case study conducted within a healthcare facility adopting MI to reduce unpaid patients bills, showed limitations in optimization efforts, with a stable number of unpaid bills reached that couldn't be reduced despite the use of MI.

Recently, Artificial Intelligence (AI) has been widely used in general to find solutions to problems and overcome limitations. AI is a set of theories and techniques implemented to achieve machines capable of simulating human intelligence (Mondal, 2020). Human beings think and act very well, but the problem is that they are limited by their capacity for memory and their speed of reasoning and calculation. The objective of AI is to enable computers, which are characterized by unlimited memory capacity and fast computational abilities, to think and act like human beings. AI can also be defined as “adaptation with insufficient knowledge and resources” (Wang, 2019).

Furthermore, AI represents a major technological revolution in the field of management by offering transformative potential, enabling managers to access precise predictive analyses, optimize operations and decision-making processes, and forecast future trends using advanced algorithms capable of analyzing large quantities of data and delivering tangible benefits for healthcare facilities (Smith and Jones, 2022; Wang et al., 2023).

The article presents the development and validation of an AI model designed to predict unpaid patient bills, aiming to provide a solution to overcome the limitations of MI in reducing the number of unpaid bills. The issue describes the potential of AI to surpass the limitations of MI in reducing the number of unpaid patient bills. To address the issue of this article, research questions will focus on the comparative effectiveness of AI in this context, the challenges associated with its deployment, and the criteria for evaluating its success. Therefore, our research questions are as follows:

- a. **How to develop an Artificial Intelligence model to overcome the limitations of Managerial Innovation in reducing the number of unpaid patient bills?**
- b. **Can Artificial Intelligence be an effective tool to improve the prediction of unpaid patient bills? What are the advantages and challenges of its adoption?**

In the introduction, the objectives and research questions have been addressed. The "Theoretical framework" section examines the concept of MI in general and specifically in the healthcare sector, its challenges and limitations, as well as AI in the healthcare domain and its revolutionary potential

as a solution for predicting unpaid bills. The "Methods" section presents how the AI model was developed and tested based on a study conducted in a hospital. Followed by a "Results" section that presents the findings of this study. Finally, a discussion of the results will synthesize the findings and interpret them in comparison to traditional methods, emphasizing the significance, advantages, and challenges of adopting AI as a potent tool to assist MI in reducing the number of unpaid patient bills.

1. Theoretical framework

1.1. Managerial Innovation

MI is a concept that combines management and innovation, referring to the emergence and adoption of new managerial ideas and practices (Birkinshaw, Hamel G, and Mol, 2008). It is defined as the introduction of new ideas, methods, or technologies that lead to significant improvements in the management and organization of a company. They can be new organizational structures, administrative systems, management practices, processes, and techniques that could create value for the organization (Birkinshaw, Hamel G, and Mol, 2008; Kimberly and Evanisko, 1981). MI is an internal change process within the company, which the organization uses as a means to influence an environment or to cope with a changing internal or external environment (Damanpour, 2018). Recently, Côme and Rouet (2015) defined it as the implementation of new management practices that promote creativity, cross-functionality, flexibility, collective intelligence, and initiative-taking. These practices aim to foster an entrepreneurial culture that values risk-taking, initiative, and accountability, enabling businesses to become more agile and therefore more competitive. MI represents a specific form of organizational change, challenging the practiced management model by evolving it (Mol and Birkinshaw, 2009). It is closely linked to the company's administrative system by introducing novelty in terms of practices, processes, and structures that affect the operational level of management.

1.1.1. Managerial Innovation in the healthcare sector

MI is a crucial element in the healthcare sector to improve the quality of care and patient satisfaction, addressing the growing challenges faced by healthcare facilities such as technological advancements and budget constraints. It aims to enhance healthcare facilities by encompassing initiatives to optimize the quality of care and operational efficiency, and to meet the complex needs of patients and healthcare professionals (Berwick, 2008). The modernization of managerial innovation practices requires leadership that motivates teams to adopt new practices and overcome resistance to change, along with Lean management techniques to eliminate waste and optimize processes in order to improve the quality and safety of care (Nolan et al., 2016). Furthermore, training and developing employees' skills are key elements to promote and strengthen the adaptability of managerial innovation in the healthcare sector (Tushman and O'Reilly, 1997). Therefore, MI in the healthcare sector is seen as a catalyst in transforming clinical and administrative practices, but its adoption faces significant challenges and limitations that can hinder its effectiveness and implementation.

1.1.2. General limits of Managerial Innovation

Despite the numerous benefits it can bring, MI has limitations and can sometimes hinder company performance (Christensen, 2013). Some innovative practices may be ill-suited and lead to inefficiencies and dysfunctions. This is represented by the adoption of certain costly management practices focused on collaboration and employee autonomy, which can be misunderstood or poorly implemented, resulting in internal conflicts and impacting performance (Teece, 2007). Furthermore, the limitations of MI can also reside in the skills and capabilities of managers and leaders to effectively implement them. If they are not adequately trained and supported in the adoption of new managerial practices, these practices may fail to produce the desired results. Hence, it is essential for companies to consider the limitations of MI in their continuous improvement efforts. It is therefore important to strategically reflect on the managerial practices to be implemented in order to truly enhance the company's performance (Tidd, Bessant, and Pavitt, 2020).

1.1.3. Limitations of Managerial Innovation in the healthcare sector and in reducing the number of unpaid patient bills

Despite the potential benefits of MI in the healthcare sector, numerous challenges and limitations may arise. The complexity of the healthcare system and the diversity of stakeholders involved can make the implementation of organizational changes difficult (Cutler, Davis, and Stremikis, 2010). Furthermore, resistance to change from healthcare professionals and patients alike poses a major obstacle to adopting new practices (Shortell, Marsteller, and Lin, 2004). When adopting MI procedures in hospitals to reduce the number of unpaid patient bills, stability of improvement and limitations in achieving reductions emerge due to the following reasons:

- a. The significant economic challenges faced by patients upon discharge from the hospital affect their ability to pay their bills and can contribute to either the accumulation or stabilization of unpaid bills (Bazzoli et al., 2016). These personal difficulties will not be resolved by the changes implemented in the procedures.
- b. The complexity of the healthcare system, characterized by a multitude of stakeholders, diverse organizational structures, and challenging financial management, makes it difficult to navigate. This complexity leads to delays in payment processing and ineffective management of patient accounts, limiting the implementation of effective new managerial practices (Borgonovi and Compagni, 2013).
- c. The conservative organizational culture resistant to change and innovation can hinder the adoption of new management methods, even if they are beneficial in the long term (Dixon-Woods, McNicol, and Martin, 2012).
- d. The limited financial resources in healthcare facilities facing severe budget constraints restrict their ability to invest, as implementing advanced technologies to reduce unpaid bills requires significant initial investments (Suter et al., 2009).

Therefore, while MI offers potential solutions to improve the reduction of unpaid patient bills, limitations hinder its adoption and may halt its progress before reaching the desired goal. One solution to surpass these limitations in unpaid patient bills case, is to implement and enforce stricter procedures for all patients. However, this tightening disrupts the daily operations of the healthcare facility, leading to increased friction in patient relationships, especially if they result in less personalized interactions perceived as unfair or excessively punitive (Dew, Cumming, and McLeod, 2017), and leads to an increase in the workload of healthcare personnel, requiring additional efforts to maintain operational efficiency (Wu et al., 2016).

1.2. Artificial Intelligence

AI is defined as a set of computer techniques aimed at enabling machines to perform tasks that, if done by humans, would require cognitive abilities such as learning, reasoning, and adaptation to new and unforeseen situations (Russell and Norvig, 2016). This field encompasses several subdomains, including machine learning, natural language processing, computer vision, and robotics. AI is a science with a dual purpose: simulating human reasoning behavior and replacing humans in certain automatic and repetitive tasks (Cassou-Noguès, Degoutin, and Wagon, 2019). According to Russell and Norvig (2016), AI can be defined along four dimensions: acting humanly, thinking humanly, acting rationally, and thinking rationally.

1.2.1. Artificial Intelligence as a transformative potential in management

In the field of management, AI automates processes, optimizes operations, and facilitates managers in making more informed, data-driven decisions to enhance organizational efficiency (Bughin et al., 2018). AI systems can detect and predict potential risks by analyzing extensive historical datasets and identifying predictive patterns, thereby enhancing risk management effectiveness (KORCH and ERRAOUI, 2024). Additionally, they transform human resource management by automating processes such as initial recruitment and skill development, facilitating more efficient human resource management (Marr, 2019).

In conclusion, AI represents a significant advancement in the field of management, offering opportunities to enhance operational efficiency and strategic decision-making. However, its adoption requires thoughtful management of ethical, social, and organizational implications, as well as proactive management of organizational change (Bughin et al., 2018).

1.2.2. Artificial Intelligence in the healthcare sector

AI is revolutionizing healthcare through various innovative applications (Al Kuwaiti et al., 2023): medical imaging and diagnostics, virtual patient care, medical research and drug discovery, patient engagement and compliance, rehabilitation, and other administrative applications. AI revolutionary potential promotes innovation, enhances efficiency, and increases patient engagement (Wang et al., 2023). To successfully implement it, it is essential to promote knowledge and adoption of AI among healthcare professionals (Brynjolfsson and McAfee, 2017). Its implementation provides innovative solutions that were not possible with traditional methods. By creating new AI-based healthcare solutions, organizations can enhance patient experience,

improve clinical decision-making, and differentiate themselves in the market, leading to a competitive advantage and greater value-added (Chen and Decary, 2020). Additionally, AI has the potential to transform healthcare operations by streamlining processes, enhancing efficiency, and reducing costs (Wang et al., 2023), not only enabling cost savings but also improving overall quality of patient care, resulting in better patient outcomes and increased value for healthcare organizations (Davenport et Mittal, 2023). Finally, the human aspect of implementing AI is crucial to its success, involving visionary leadership and developing AI talent.

1.2.3. Artificial Intelligence as a solution for predicting unpaid patient bills

Few studies address the prediction of payments and problems of unpaid bills in the healthcare sector. Zollinger et al. (1991) used a multiple regression AI model to determine the effect of patient and hospital characteristics on the variation in unpaid hospital charges. They found that insurance coverage, total hospital charges, pregnancy, marital and employment status, urban residence, and hospital total income were significant factors in predicting unpaid hospital bills, while length of stay, gender, age, and diagnoses unrelated to pregnancy and childbirth were not significant. Zurada and Lonial (2005), compared the effectiveness of five data mining techniques to understand and predict payment behaviors without having access to a patient's financial information. Recently, four studies have examined the effectiveness of computational intelligence methods for predicting patients' ability to pay their bills in imbalanced datasets, demonstrating the role of cost-sensitive learning methods in classifying unknown cases. Other studies have demonstrated that using AI for predicting payment behaviors can significantly reduce financial losses in the healthcare sector (Smith et al., 2020). Furthermore, a study developed and tested by Davis et al. (2021), leveraging machine learning models and employing advanced predictive modelling techniques and statistical evaluation, aimed to predict patient payment behaviors. This research demonstrates that such approaches can yield robust and reliable predictive results. The potential limitation of this study was that all patient data were aggregated and de-identified, and thus lacked potentially important information such as zip-code, visit frequency, and payment history. In conclusion, the implementation and integration of an AI program for predicting unpaid patient bills in healthcare sectors are crucial for enhancing operational and financial efficiency while maintaining economic viability (Jones and Despotou, 2019).

2. Methods

The structure and writing of the article were inspired by the guidelines of the “Checklist for Artificial Intelligence in Medical Imaging (CLAIM): A Guide for Authors and Reviewers” (Mongan, Moy, and Kahn, 2020). The elements described in this guide should be viewed as “best practices” to help authors present their research effectively.

2.1. Study design, data inclusion, ground truth and aim of the study

In the financial department of a hospital, MI project was implemented to minimize the number of patients who leave the hospital without paying their bills, thereby reducing financial losses. Therefore, in the present article, a retrospective cross-sectional study was conducted using data

from the MI project database during its final optimization phase, when the number of unpaid bills had stabilized and could no longer be reduced. Patients with a guarantor party who have a contract for 100% repayment to the hospital were excluded from this study. The MI project was divided into two parts: the first for patients requiring internal admission and the second for patients requiring urgent admission. Therefore, the data in the present article was divided into two groups: "Internal Patients" and "Urgent Patients". 683 "Internal Patients" and 753 "Urgent Patients" were included in this study. Out of this data, 9.8% (67 patients) of "Internal Patients" and 5.4% (41 patients) of "Urgent Patients" did not complete the payment of their bills within one month after discharge from the hospital.

The data for "Internal Patients" includes information on the following "Features" and "Label": estimated length of hospital stay (in days), department name, physician's name, whether the payment was made by a private party or a guarantor (name of guarantor), patient age, patient gender, patient marital status, city name or village name, diagnosis, case status (urgent or non-urgent), amount of the first advance payment ("Advance 1" if applicable), amount of the second advance payment ("Advance 2" if applicable), amount of the third advance payment ("Advance 3" if applicable), estimated bill amount at the time of patient admission, and the remaining amount unpaid one month after the patient's discharge from the hospital. The status of this remaining amount will be predicted for future patients. This status, as represented in the available data used to create the AI model, is referred to as the "Label" in AI terminology. On the other hand, data for "Urgent Patients" includes all "Features" information available for "Internal Patients" but excludes the following: estimated length of hospital stay, department name, case status, "Advance 1", "Advance 2", and "Advance 3". Patients with an unpaid amount greater than 2 USD one month after discharge from the hospital were classified with a "Label" of "Unpaid Patients". All other patients were classified with a "Label" of "Paid Patients". Furthermore, some data were processed; for example, similar entries with different languages or varying spellings were standardized to ensure consistency, and all cities or villages located far from the hospital were grouped under the same regional name.

The aim of the present study is to develop and test an AI model for each group ("Internal Patients" and "Urgent Patients") based on this retrospective data to predict which future patients are likely to pay their bills within one month after discharge from the hospital. Consequently, for the predicted "Unpaid Patients", more stringent MI procedures can be applied to reduce their number, while the predicted "Paid Patients" can be exempted from these procedures.

2.2. Data partitions, model, training and evaluation

The AI was developed using Python (Van Rossum, 2007) and employs the "KNeighborsClassifier" from the "scikit-learn" library for classification tasks (Kramer, 2016). This algorithm belongs to the "k-nearest neighbors" family, known for its simplicity and effectiveness in solving various classification problems. The "KNeighborsClassifier" classified as a machine learning algorithm, uses training data by storing all "Features" and "Label" pairs without creating a complicated model. During the preparation of the model, each cell representing a value of a "Feature" or "Label" should be filled with an associated integer number. For each test sample with hidden "Label", the

“KNeighborsClassifier” calculates the distance between the test sample “Features” and all stored training samples “Features” to identify the “K” nearest neighbors. It then assigns the test sample to the class that is most frequent among these “K” neighbors. This method relies on direct comparison with stored training data, making predictions based on the similarity of new samples to the examples with known “Labels” in the training set. In the “KNeighborsClassifier”, the “K” value stands for the number of nearest neighbors to consider when making a prediction. Specifically, it refers to the parameter “K”, which determines how many of the closest training samples are used to vote on the class “Label” for a given test sample. In the present study, five values of “K” were tested (K = 1, 2, 3, 4, and 5) on the data, and the value of “K” that produced the best results was used.

Table 1: Adjustment of some performance metrics explanations to fit the context of the present article

Performance Metrics	Explanations
True Positives	Number of patients for whom the AI correctly (“True”) predicted that they would pay (“Positives”) their bills
False Positives	Number of patients for whom the AI incorrectly (“False”) predicted that they would pay (“Positives”) their bills
True Negatives	Number of patients for whom the AI correctly (“True”) predicted that they would not pay (“Negatives”) their bills
False Negatives	Number of patients for whom the AI incorrectly (“False”) predicted that they would not pay (“Negatives”) their bills
Actual Positives	= Real Positives = (True Positives + False Negatives)
Actual Negatives	= Real Negatives = (True Negatives + False Positives)
Predicted Positives	= (True Positives + False Positives)
Predicted Negatives	= (True Negatives + False Negatives)
Sensitivity	= True Positives Rate = (True Positives / Actual Positives)
Specificity	= True Negatives Rate = (True Negatives / Actual Negatives)
Precision	= (True Positives / Predicted Positives)
Accuracy	= ((True Positives + True Negatives) / (Actual Positives + Actual Negatives))

Source: Authors

In the present work, data were prepared and stored using Microsoft Excel. For the “Internal Patients” group, the AI model was trained and tested 10,000 times with the following payment advance “Features” sets: including all advance “Features”, excluding “Advance 3” “Feature”, excluding “Advance 2” and “Advance 3” “Features” and excluding all advance “Features”. Similarly, for the “Urgent Patient” group which have not advance “Features”, the model was also trained and tested 10,000 times. Each time, 90% of the data from each group was used randomly to train the model, while the remaining 10% was reserved as test data to assess model performance. To divide the dataset into two subsets for training and testing purpose, the “train_test_split” function from the “sklearn.model_selection” module in “scikit-learn” was used (Kramer, 2016).

To determine the AI model performance metrics, a Python script was developed to automatically perform 10,000 tests, and initially collecting the values of “True Positives”, “False Positives”, “True

Negatives”, and “False Negatives” into lists. It then calculates the average and standard deviation (SD) for these values. Finally, “Sensitivity”, “Specificity”, “Precision” and “Accuracy” of the AI model, as well as the averages and SD for “Actual Negatives” and “Predicted Negatives” were deducted manually (Trevethan, 2017). Table 1 adjusts the explanations of some performance metrics to fit the context of the present article.

3. Results

For the “KNeighborsClassifier” applied to the data used in this research, the best results were found with a “K” value equal to 2.

For the 683 “Internal Patients” and the 753 “Urgent Patients”, the values and the number of values for each cell representing a “Feature” or “Label” are shown in Table 2. As stated in the “Methods” section, the following “Features” were excluded from the “Urgent Patients”: estimated length of hospital stay, department name, case status, “Advance 1”, “Advance 2”, and “Advance 3”. For this reason, Table 2 shows a “Number of Values” equal to zero for these features. On the other hand, these “Features” were richer and more diverse for the “Internal Patients”, with their number of values being 17, 7, 2, fewer than 683, fewer than 683, and fewer than 683, respectively. In addition, the physician's name “Feature” was richer for the “Internal Patients” (“Number of Values” equal 55 compared to 3 for the “Urgent Patients”); and the diagnosis “Feature” was richer for the “Internal Patients” (“Number of Values” equal 198 compared to 128 for “Urgent Patients”). The “Values” and the “Number of Values” for the remaining “Features” and “Label” were the same for “Internal Patients” and “Urgent Patients”.

Table 2: Values and number of values for each cell representing a “Feature” or “Label”

“Feature” or “Label”	“Internal Patients” Number of Patients = 683		“Urgent Patients” Number of Patients = 753	
	Values	Number of Values	Values	Number of Values
Estimated length of hospital stay (in days)	1 - 11, 14, 17, 19, 23, 38, 44	17	X	0
Department name	0 - 6	7	X	0
Physician's name	0 - 54	55	0 - 2	3
Private party or name of guarantor	0 - 4	5	0 - 3	4
Patient age	1924 - 2023	99	1924 - 2023	99
Patient gender	1 or 0	2	1 or 0	2
Patient marital status	0 - 2	3	0 - 2	3
City name or village name	0 - 48	49	0 - 52	53
Diagnosis	0 - 197	198	0 - 127	128
Case status (urgent or non-urgent)	1 or 0	2	X	0
Advance 1	Between 0 & 5000	Fewer than 683	X	0
Advance 2	Between 0 & 4700	Fewer than 683	X	0
Advance 3	Between 0 & 5150	Fewer than 683	X	0
Label: “Paid Patients” or “Unpaid Patients”	1 or 0	2	1 or 0	2

Source: Authors

Table 3 shows the performance metrics of the AI model for the “Internal Patients” and “Urgent Patients” groups when the AI was trained and tested 10,000 times. The “Internal Patients” group was divided into four subgroups based on the payment advance “Features” sets: including all advance “Features” (“With Advances 1, 2, & 3”); excluding “Advance 3” “Feature” (“Without Advance 3”); excluding “Advance 2” and “Advance 3” “Features” (“Without Advances 2 & 3”); and excluding all advance “Features” (“Without Advances 1, 2, & 3”). The absolute number of patients (“Number of Patients”) was converted to percentages relative to the testing data (“% of Patients When Testing Data Is 100%”) to normalize the values, represented as grey colon in Table 3. As shown in Table 1, the percentage of “Actual Negatives” represents the proportion of patients in our dataset who did not actually pay their bills. In Table 3, this percentage was 9.82% (mean of: 9.86, 9.78, 9.84, and 9.80) for “Internal Patient”, compared to 5.57% for “Urgent Patients”. The percentage of “Predicted Negatives” was 18.27% (mean of: 18.09, 17.99, 18.17, and 18.83) for “Internal Patients”, compared to 10.16% for “Urgent Patients”. The “Specificity”, representing the “True Negatives Rate”, is calculated as the number of patients correctly predicted that they would not pay their bills (“True Negatives”), divided by the “Actual Negatives” (Table 1). In Table 3, this value was slightly higher among "Internal Patients" in the "With Advances 1, 2 & 3" subgroup at 46.75%, compared to 41.62%, 39.63%, and 41.73% in other subgroups within "Internal Patients," and significantly higher compared to "Urgent Patients" (15.44%). As a result, for “Internal Patients” with “With Advances 1, 2 & 3”, the AI predicted that 18.09% of patients would not pay their bills. Within this 18.09%, 4.61% (46.75% of 9.86%) actually did not pay their bills, and the remaining 13.48% (calculated as 18.09% - 4.61%, or 13.48% from Table 3) paid their bills but were incorrectly predicted as not paying (“False Negatives”). Similarly, for “Urgent Patients”, the AI predicted that 10.16% of patients would not pay their bills. Within this 10.16%, 0.86% (15.44% of 5.57%) actually did not pay their bills, and the remaining 9.30% (calculated as 10.16% - 0.86%, or 9.30% from Table 3) paid their bills but were incorrectly predicted as not paying (“False Negatives”). However, “Sensitivity”, “Precision”, and “Accuracy” were highest for “Urgent Patients”, with values of 90.15%, 94.76%, and 86.00%, respectively.

Table 3: AI model performance metrics

		Internal Patients								Urgent Patients	
		With Advances 1, 2 & 3		Without Advance 3		Without Advances 2 & 3		Without Advances 1, 2 & 3		Without Advances 1, 2 & 3	
		Number of Patients	% of Patients When Testing Data is 100%	Number of Patients	% of Patients When Testing Data is 100%	Number of Patients	% of Patients When Testing Data is 100%	Number of Patients	% of Patients When Testing Data is 100%	Number of Patients	% of Patients When Testing Data is 100%
Per Test	Testing Data	69	100	69	100	69	100	69	100	76	100
	Training Data	614	889.86	614	889.86	614	889.86	614	889.86	677	890.79
	All Data	683	989.86	683	989.86	683	989.86	683	989.86	753	990.79
Per 10000 Tests	Average of True Positives ± SD	52.90 ± 3.24	76.67 ± 4.70	52.65 ± 3.27	76.30 ± 4.74	52.36 ± 3.28	75.88 ± 4.75	52.07 ± 3.34	75.46 ± 4.84	64.71 ± 2.85	85.14 ± 3.75
	Average of False Positives ± SD	3.62 ± 1.83	5.25 ± 2.65	3.94 ± 1.88	5.71 ± 2.72	4.10 ± 1.89	5.94 ± 2.74	3.94 ± 1.88	5.71 ± 2.72	3.58 ± 1.78	4.71 ± 2.34
	Average of True Negatives ± SD	3.18 ± 1.61	4.61 ± 2.33	2.81 ± 1.51	4.07 ± 2.19	2.69 ± 1.50	3.90 ± 2.17	2.82 ± 1.52	4.09 ± 2.20	0.65 ± 0.75	0.86 ± 0.99
	Average of False Negatives ± SD	9.30 ± 2.82	13.48 ± 4.09	9.60 ± 2.93	13.91 ± 4.25	9.85 ± 2.92	14.28 ± 4.23	10.17 ± 3.02	14.74 ± 4.38	7.07 ± 2.55	9.30 ± 3.36
	Average of Actual Negatives ± SD	6.8 ± 2.44	9.86 ± 3.54	6.75 ± 2.41	9.78 ± 3.49	6.79 ± 2.41	9.84 ± 3.49	6.76 ± 2.42	9.80 ± 3.51	4.23 ± 1.93	5.57 ± 2.54
	Average of Predicted Negatives ± SD	12.48 ± 3.25	18.09 ± 4.71	12.41 ± 3.30	17.99 ± 4.78	12.54 ± 3.28	18.17 ± 4.75	12.99 ± 3.38	18.83 ± 4.90	7.72 ± 2.66	10.16 ± 3.50
	Sensitivity	85.05%		84.58%		84.16%		83.66%		90.15%	
	Specificity	46.75%		41.62%		39.63%		41.73%		15.44%	
	Precision	93.60%		93.04%		93.04%		92.97%		94.76%	
	Accuracy	81.28%		80.37%		79.78%		79.55%		86.00%	

Source: Authors

4. Discussion

MI assisted by AI is a new area that has not been well studied, particularly in surpassing the limits of MI when aimed at reducing the number of unpaid patient bills. In fact, MI alone encounter limitations in reducing the number of unpaid patient bills (as noted in section 1.1.3 of the current article). Implementing stronger MI procedures on all patients to overcome these limits is associated with negative effects on patients, employees, and the hospital. For example, if a hospital decides to implement MI procedures that forbid patient admission without full payment in advance: patients may become anxious and uncomfortable, even though they typically pay their bills before discharge; employees may become overloaded with their workload; and the hospital may admit fewer patients because some cannot pay at the time of admission, even though they can pay later (within one month for example). The aim of this study is to develop and evaluate an AI model that predicts early which patients will not pay their bills within one month after discharge from the hospital. Therefore, this prediction allows for implementing stronger MI procedures only on predicted unpaid patients, thereby ensuring that other patients will not be adversely affected by these procedures.

For the use of all our “Internal Patients” data (“With Advances 1, 2, & 3”), approximately 10 patients out of 100 will not pay their bills in reality. Our AI model predicts that out of every 100 patients, around 18 will not pay their bills. Among these 18 predictions, only about 5 actually do not pay their bills in reality. Hence, in this scenario, leveraging AI predictions allows us to implement stronger MI procedures on only 18 out of 100 patients, resulting in reducing the number of unpaid patients by 5 out of 10 (from 10 to 5 patients). In addition, upon applying the same logical analysis, results based on our “Urgent Patients” data are less significant: implement stronger MI procedures on only 10 out of 100 patients, resulting in reducing the number of unpaid patients only by 1 out of 6 (from 6 to 5 patients). This was primarily due to the low “Specificity” value (15.44%), despite “Sensitivity”, “Precision”, and “Accuracy” values being the highest for “Urgent Patients” (90.15%, 94.76%, and 86.00%, respectively). Compared to “Internal Patients”, the low “Specificity” value in “Urgent Patients” (15.44% vs. 46.75%) could be attributed to the richer and more diverse “Features” available for “Internal Patients” (see Table 2).

Compared to other studies predicting patient payment behaviors using three machine learning algorithms, Davis et al. (2021) achieved the best result for “Specificity” among performance metrics, with a value of 87.2% (47.9% for “Sensitivity” and 71.7% for “accuracy”). They utilized data from 1,055,941 patients across 27 blinded emergency departments in 13 states. In our study, we achieved a better performance metric value for “Precision”, which is 94.76%, despite having a smaller data volume (only 753 patients in 1 department) compared to Davis et al. study. In addition, big data is highly recommended for machine learning algorithms to uncover more detailed patterns and make more timely and accurate predictions (Zhou et al., 2017). Hence, a potential limitation of our study was the size of the data. The availability of more data could significantly improve the overall performance of our model, particularly regarding the low “Specificity” value (15.44%). Additionally, it would be interesting to test on our data, the performance of machine learning

algorithms other than the “KNeighborsClassifier” used in our study, and evaluate them in a prospective setting.

A major limitation in the study by Zurada and Lonial (2005), as well as in the study by Davis et al. (2021), was the restricted access to patients' financial information, including payment history, within the hospital. In our study, we partially overcame this limitation for “Internal Patients”, by including data on three types of advance payments made at the hospital (“Advance 1, 2 & 3”). However, collecting for “Features” values from “Advance 1”, “Advance 2”, and “Advance 3” may be challenging for the MI application in some cases. For example, collecting data on advances may not be feasible if the hospital decides to implement a MI approach that involves not accepting patients who do not provide full payment in advance before admission (as detailed in the first paragraph of this section). In this case, the performance metrics for “Internal Patients” decrease slightly from those using data with all advances (“With Advances 1, 2, & 3”) to those using data without advances (“Without Advances 1, 2, & 3”). Therefore, implementing these MI procedures on 19 out of 100 patients (compared to 18 out of 100) resulted in reducing the number of unpaid patients by 4 out of 10 (from 10 to 6 patients, compared to the previous reduction from 10 to 5 patients).

Finally, applying the current machine learning model to other hospitals or different situations within the same hospital should be revalidated, as datasets often have unique characteristics such as varying “Features” types, distributions, and noise levels. No single algorithm is universally optimal for all data types, so customizing and tuning models to fit specific datasets can significantly enhance performance and accuracy. While general machine learning software provides foundational tools, tailoring these tools to the particular dataset ensures that models are optimized for specific patterns and requirements, thereby improving their effectiveness and generalization.

Conclusion and perspectives:

To overcome the limitations of MI in reducing unpaid patient bills, in each hospital, an AI model can be developed to predict which patients are likely to default on their payments. By identifying these patients early, more targeted MI strategies can be applied, thereby reducing the number of unpaid bills and avoiding the adverse impact on patients who are expected to fulfill their financial obligations. For instance, in our case, applying more targeted MI procedures to just 18 out of 100 internal patients resulted in a decrease in unpaid patients from 10 to 5. Similarly, focusing on only 10 out of 100 urgent patients reduced the number of unpaid patients from 6 to 5. However, further improvements could be achieved by using a larger patient dataset and testing additional AI models in a prospective setting.

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