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The Impact of Artificial Intelligence Integration on Minimizing Patient Wait Time in Hospitals

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Abstract

Reduced patient wait times benefit not just patients' health but also the overall efficiency of the healthcare system, which is particularly crucial given the aging population and rising demand for medical services in recent decades. Reducing the time that outpatients have to wait is one of the most crucial actions that must be taken to improve the patient experience. Artificial intelligence and machine learning may be applied in health care and medicine to enhance insights, reduce waste and wait time, and increase speed, service efficiency, accuracy, and efficiency. The purpose of this research is to determine whether or not the deployment of AI in hospital management system help reduce the amount of time that patients have to wait for their appointments. The Random Forest Regression, Pairwise multiple regression, and the pairwise Pearson correlation have been performed. This research also included additional features such as the number of the office personnel, the number of doctors, the quantity of equipment, and the health expenses in order to eliminate any potential omitted variable biases. According to the findings of the Random Forest Regression, the integration of AI and ML seems to be required to cut down on the amount of time that patients have to wait. The size of the office personnel, the number of doctors, and the number of pieces of equipment are found to be significant factors in lowering the amount of time spent waiting. It was determined that the aspect of the cost was the least significant in terms of reducing the amount of time spent waiting. According to the findings of our study, the healthcare care center needs to expand the integration of AI in order to cut down on the waiting time for patients and to improve the overall experience they provide for them. The findings also suggest that wait times depend on many factors. Thus, focusing on a few factors does not significantly reduce wait time.

Keywords: *Artificial Intelligence, Correlation, Health care, Machine Learning, Multiple regression, Random forest, wait-time*

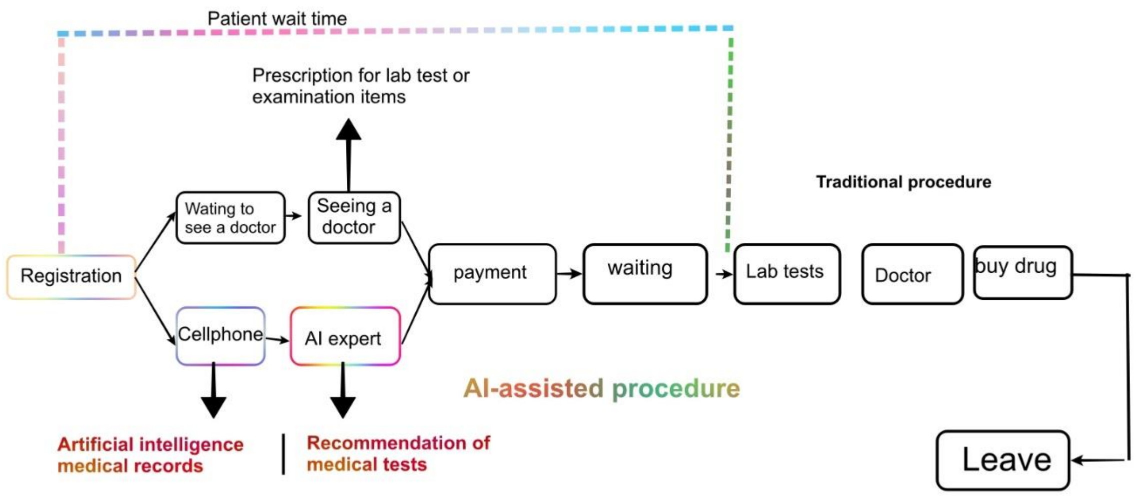
1. Introduction

Historically, hospitals and other types of healthcare facilities competed with one another largely based on the quality of their services, the treatment specializations they offered, and the prices of their care (Devers et al., 2003). Nevertheless, there is a fresh wave of change occurring now: patients coming into the hospital are worried not just about receiving high-quality medical care, which continues to be a top priority, but also about the overall experience they would have during the course of their hospital stay (Porter & Teisberg, 2006).

Waiting time in hospitals refers to the length of time that a patient spends waiting in the hospital before being attended by a participant of the medical staff (Mardiah & Basri, 2013). The amount of time that patients have to wait in hospitals is an important measure of the quality of service provided by the hospital. The amount of time that a person has wait before being seen by doctors and nurses is one factor that might have an effect on their use of healthcare services. Patients often see lengthy wait periods as a barrier that prevents them from accessing care. Maintaining an overly long wait time for patients may be distressing both for patient as well as for the care provider. People will judge health providers more on their waiting times than they would on their knowledge or experience since waiting times are a tangible and annoying component of healthcare (Zhu et al., 2012).

Figure 1. Illustration of how AI-assisted method reduces patient wait-time

Artificial intelligence are being employed to estimate patient flow and reduce needless



emergency room visits (Berlyand et al., 2018; Tenhunen et al., 2018). Rapid clinical data interpretation would allow patients to be separated and outcomes predicted in emergency department procedures. As a result, AI has a direct impact on cost, resource efficiency, cost and time, and patient care quality (Ryan et al., 2017; Shah & Chircu, 2018). When patients arrive at the emergency room, AI may categorize them based on their risk, allowing for more effective resource allocation and, as a result, better patient outcomes. In the emergency room, AI may determine a frequent diagnosis based on radiographs and thereby speed the patient treatment plan. At departure, the AI can forecast likely outcomes, particularly unfavorable events, and give the patient with a personalized follow-up prescription (Agarwal et al., 2020).

Uncertainty in healthcare centers, such as patient visits, forms of medical procedures and diagnostic procedures needed, and treatment and test duration, presents particular obstacles in predicting future service needs (Motallebi Nasrabadi et al., 2020). Artificial intelligence offers the ability to alter health center operations and hospital administration at numerous points along the patient care process, from admission to release. The use of ML might enhance healthcare operations by better matching services to patient demands, resulting in lower costs and improved patient outcomes (Morley et al., 2020). Overcrowding is a growing problem in healthcare centers that may have a detrimental impact on patient treatment quality. Forecasting analytics for patient volume might aid in the planning of staffing models as well as the preparation for surge and emergency circumstances. Second, various complex variables make estimating hospital wait times problematic. On a bigger scale, if numerous local hospitals publish accurate wait times, low-acuity patients Machine learning systems that can detect trends in large data sets have the capability to give more precise wait times may be able to choose a health center depending on wait time and commute distance (Levin et al., 2018; Lin et al., 2019).

2. Literature review

(Alam et al., 2018) come to the conclusion that a number of different strategies and approaches, such as computer-controlled queuing technology, tele-pharmacy, robotic pharmacy devices/machines for fast and precise filling and distributing, simulation modelling, and the Six Sigma methodology, are able to uphold client satisfaction, reduce waiting time, attract new customers, decrease workload, and improve the organization's reputation.

(Aburayya et al., 2020) stated that medical clinics should need and adjust the appointment system for routine medical appointments such as follow-up patients, as well as improve scheduling systems. Patients should be made aware of the need of follow-up visits in order to ensure continuity of treatment and strengthen their commitment to planned sessions. Inadequate work processes, severe workloads, inadequate or lack of facilities, and other management issues may need prompt resolution by medical upper executives and medical policymakers (Aburayya et al., 2020). Notably, policymakers must exert more effort to address flaws in the healthcare delivery system.

According to the findings of (Hill & Joonas, 2005) that included 200 patients, the length of time spent waiting may have an impact on patients' views of quality, contentment, and pleasantness, as well as the probability of referrals and further visits. In addition to that, it was shown that money had a substantial relationship to how people responded to unreasonable wait times. These results suggest that there has been a cultural change in patients' views of wait time and highlight the necessity for providers to keep consumers' loyalty by providing faster service.

3. Problem statement and objectives of the research

Studies have indicated that longer wait times are associated with fewer positive outcomes and worse levels of patient satisfaction. Previous studies revealed that unsatisfied visitors might result in a reduction of long-term revenues owing to decreased client retention, fewer return visits, and the spread of their anger with the hospital to others. Because of this, the advantage of having reduced wait times is quite evident, and every healthcare organization need to make this a strategic emphasis of their operations. The study's primary goal is to see whether AI integration in healthcare will decrease wait times and speed up service.

4. Methodology

To see if integrating AI into healthcare centers can improve the speed of service, we used Random forest regression as well as Pearson correlation.

i) Random Forest

The Random Forest is a well-known machine learning method that is included under the umbrella of the supervised learning. Classification and regression are two types of machine learning tasks that might benefit from its use. It is predicated on the idea of ensemble learning, that refers to the practice of integrating numerous classifiers in order to solve a difficult issue and to enhance the functionality of the model. Breiman has demonstrated in a multitude of new papers that significant improvements in classification or accuracy rate can be obtained by utilizing ensembles of trees, in which every tree in the ensemble is expanded in relation to a random vector (Breiman, 2001; Livingston, 2005). These papers were published relatively recently. The final predictions are derived by combining the results of the ensemble's vote, often with weights that are all identical.

The random forest technique has a number of significant benefits when it is used for activities involving classification or regression. First, there is a reduction in the possibility of overfitting. Because decision trees have a tendency to closely match all of the samples included within the training data, they may easily be overfit (Hoyos et al., 2015). When a random forest includes a large quantity of decision trees, its classification algorithm would not overfit because the averaged uncorrelated trees lowers both overall variability and prediction error. This is because the larger number of trees decreases the correlation between them. Because it is capable of handling both classification techniques with a fair degree of precision, random forest is a technique that is quite popular among data scientists. Because of its ability to maintain accuracy even if a section of the dataset is missing, the random forest algorithm is particularly helpful for guessing values that are not present (Sun, 2016). This is made possible by the classifier's use of feature bagging.

Second, it is simple to evaluate the significance of the features: evaluating the contribution of variables to the model, also known as their relevance, is a breeze with random forest. There are a number different approaches that may be used to evaluate the significance of a characteristic. When a feature is omitted from a model, it is usual practice to use the mean drop in impurity (MDI) to evaluate how much the accuracy of the model will decrease. Permutation significance, also referred as mean decrease accuracy, is yet another essential statistic (MDA). MDA determines the mean loss in accuracy by arbitrarily permuting the selected features in OOB samples. This allows for more statistical power (Patel et al., 2014).

While the trees are being grown, the random forest algorithm contributes more unpredictability to the model. When splitting a node, rather than looking for the feature that is the most essential, it seeks for the feature that is the best among a group of features that is chosen at random (Guo et al., 2018) (Trivedi & Patel, 2020). This ends up producing a diverse range of outcomes, the majority of which lead to an improved model. The procedure that is used to divide a node within a random forest only takes into account a randomized subset of the characteristics.

ii) Correlation analysis

The Pearson Correlation is a statistical technique that may be used to ascertain whether or not a linear connection exists between two variables.

$$Correlation(X,Y) = r_{XY} = \frac{Cov_{XY}}{S_X S_Y} = \frac{\frac{\sum(X-\overline{X})(Y-\overline{Y})}{(N-1)}}{S_X S_Y}$$
$$= \frac{\sum(X-\overline{X})(Y-\overline{Y})}{S_X S_Y} \times \frac{1}{N-1}$$

X and Y are both considered to be continuous variables here. The value N denotes the total number of occurrences.

The sample of data was acquired from a variety of hospitals and medical facilities. However, the pace of treatment in the health sector may also be impacted by a variety of other variables. The failure to take into account these aspects may provide misleading findings. Therefore, in order to reach findings that are objective, this research takes into account a variety of additional aspects. The dataset came form various healthcare centers across India and Nepal.

Table 1 contains a listing of all the other features, as well as information about their descriptions, roles, and goals.

Table 1. descriptions of dependent variable and feature.

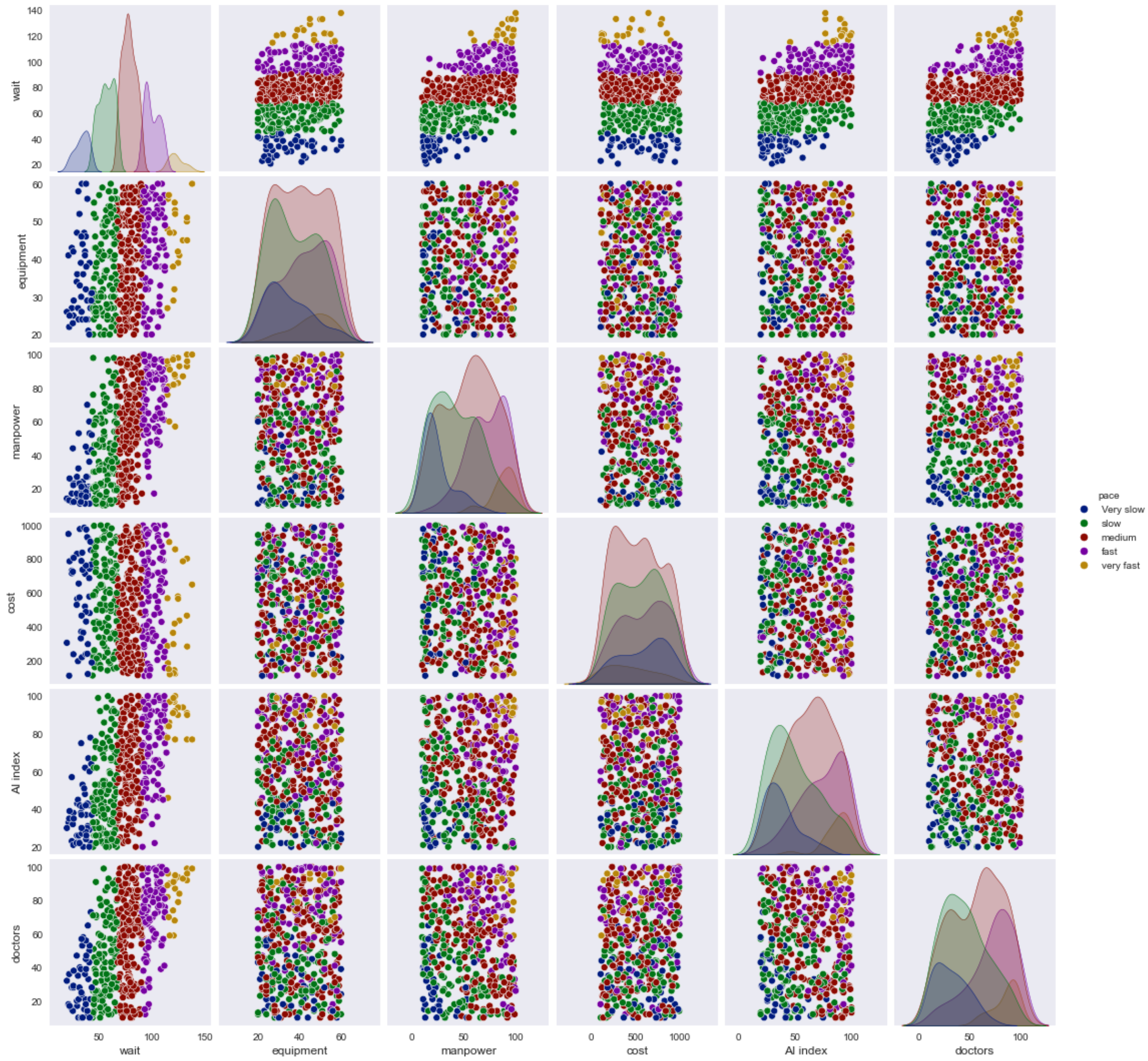
Variables	Definition	Calculation	Role	Purpose
Service Pace Index	Indicates the rate at which the medical facilities deliver their services to their patients or customers.	The value of the index may range anywhere from 0.0 to 100. The numbers that are close to 0 indicate that the rate of service will be slower. The principles. The authors derive the numbers by subtracting the average wait time from zero (AWT)	Target	To evaluate the swiftness of service delivery in light of the many features.
Equipment	Refers to the number of operational medical devices available in a health facility.	Continuous data type	Feature	To determine whether the amount of equipment in a health facility is related to the service speed.
Manpower	Specifies the quantity of workers and communication personnel in healthcare facilities.	Continuous data type	Feature	To determine whether there is a relationship between the quantity of personnel and the speed of service in health facilities.
Doctors	Represents the number of physicians and healthcare facilities	Continuous data type	Feature	To determine if the number of physicians in a health facility corresponds to the speed of service.
Cost	This includes fees and other post-arrival healthcare-related expenses.	Continuous data type	Feature	To determine whether the number of expenses in health care facilities has a relationship with service speed.
AI	Indicates the extent to which a health care facility uses artificial intelligence to deliver its services.	The range of the index is 0 to 100. The numbers around zero imply a low amount of AI integration, while values near 100 indicate a high level of integration.	Feature	To determine if the degree of AI integration in health facilities has a connection with service speed.

5. Results

This research starts by exhibiting the pairplots among the factors. The pairplots are displayed in figure 2 with hue= degree of pace in service. The dark dots represent extremely slow speed while the orange dots represent quick pace. Looking at the various pair, we can observe that blue dots are located at the origin of plots. This suggest that the pace of service is sluggish if number of devices, physicians and staffs are insufficient. Most notably, the speed of service is delayed if the level of AI approach is lower.

The results of this research showed a satisfactory level of accuracy, scoring 94.56 percent overall. The quantity of employees is the factor that matters the most for providing speedy service, as determined by the results of the random forest. The quantity of available medical professionals is the element that comes in second place. The results also shows that the third and fourth most significant aspects are the individual's overall health and their respective pieces of equipment. According to the findings, the cost is the element that is the least significant. Table 2 presents the findings of this investigation. Figure 4 presents a graphical representation of the relevance of the factors in consideration.

Figure 2 . Pairplots among the features.



The multiples regressions were performed and Research -square were computed for each pair of features with AI-index. As can be seen in figure 3, when combining with AI-index with manpower and doctors, the predictability increases, and the model perform well.

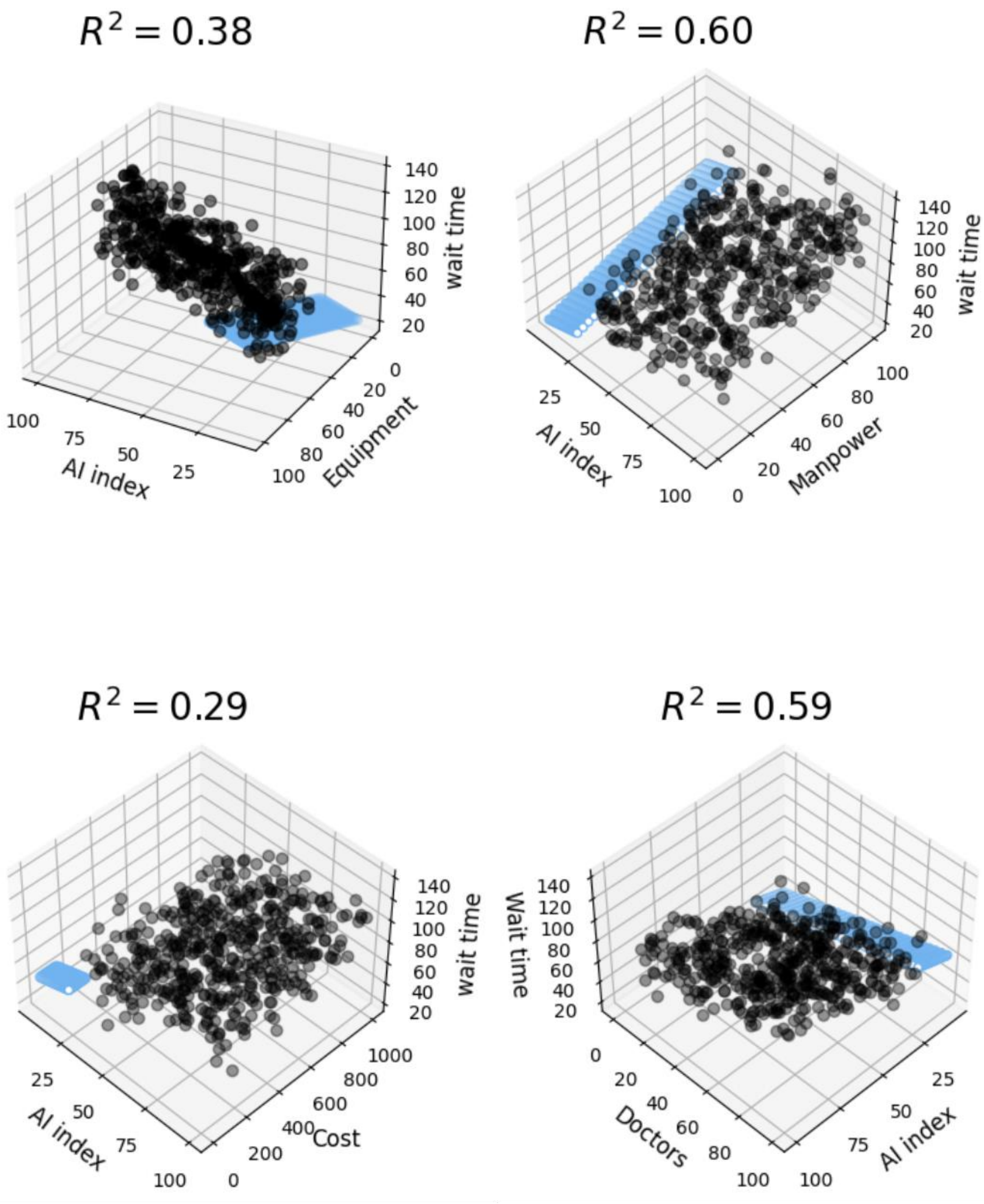


Figure 3. Multiple regressions and Research -square for different feature with AI-index

Table 2. MAE, accuracy score and feature importance in Random Forest Regression

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Mean Absolute Error: 4.02 degrees.

Accuracy: 93.87 %.

Variable: manpower, Importance: 0.41

Variable: doctors, Importance: 0.3

Variable: AI index, Importance: 0.25

Variable: equipment, Importance: 0.05

Variable: cost, Importance: 0.02
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Figure 4. Importance of the features in Random forest regression.

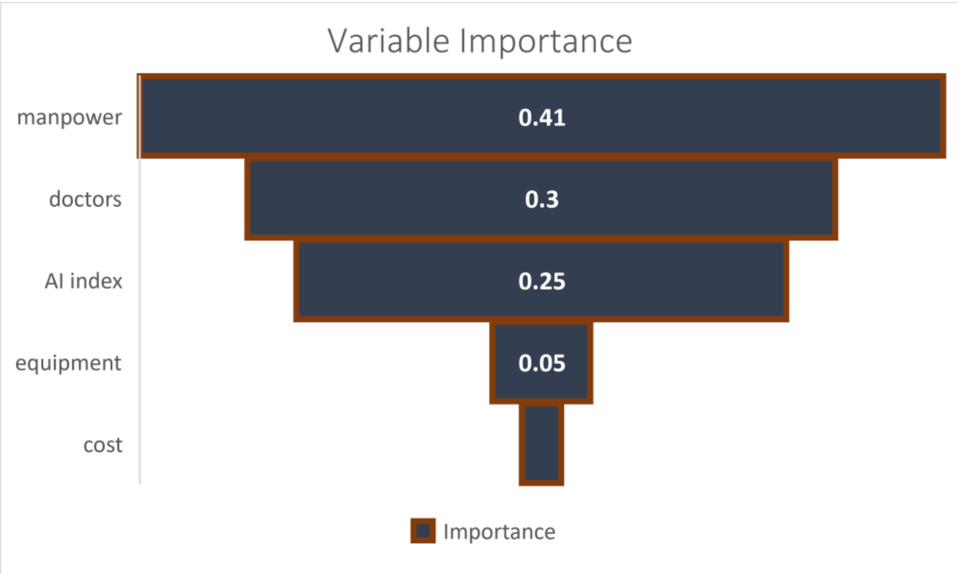

Table 3 highlights the association between the outcome variable speed and the attributes variables by putting that correlation in boldface type. The investigation's findings indicate that a positive and substantial association exists between pace/speed and the most of the other criteria, with the exception of one element known as cost. This indicates that the association between quickness of service as well as the other qualities, with the exception of cost, is positive and strong.

Table 3. Correlation results

	wait	equipment	manpower	cost	AI index	doctors
wait	1.000000	0.262808	0.600973	-0.017781	0.538716	0.528610
equipment	0.262808	1.000000	0.039131	-0.072760	-0.055890	0.017948
manpower	0.600973	0.039131	1.000000	-0.077950	0.091418	-0.064247
cost	-0.017781	-0.072760	-0.077950	1.000000	-0.039900	0.115467
AI index	0.538716	-0.055890	0.091418	-0.039900	1.000000	-0.029036
doctors	0.528610	0.017948	-0.064247	0.115467	-0.029036	1.000000

5. Conclusion

Patients often wait quite a long time at clinics for their scheduled appointments with doctors and other medical professionals. Wait times at medical facilities need to be controlled effectively by entities in the healthcare industry that seek to deliver excellent services. If aspects that are driven by patients are not integrated into the layout of the waiting experience, it may result in dissatisfaction on the part of both patients and providers. This approach is efficient for automating a variety of workflow frameworks, and it recognizes the patient as an important participant in the process. There is less paperwork, manual labor, and manual allocation of resources, which leads to a greater utilization efficiency and lower wait times for patients. However, like with any substantial new technology, adoption is crucial. Despite the immense promise of AI in the healthcare industry, trust remains a significant barrier to adoption. Although automation will never be able to take the position of medical professionals, the use of data, specialized knowledge, and technological advancements may bring about significant improvements in the way we administer the services.

The computing capacity of machine learning, which already outperforms the human mind in many data operations, makes it a good candidate for detecting and forecasting complicated and noisy events, such as waiting times, as demonstrated in this paper. Using AI seemed like the most obvious and straightforward option to us. On the other hand, ML is not without its own set of restrictions. The most obvious of these problems is a decrease in interpretability, which occurs when the sophistication of ML procedures makes it almost hard to express them using straightforward language. Even while these interpretation constraints may not have an impact on our work with estimating patient times, they might be obstacle in certain other areas where interpretation is very important. Therefore, ML should not be used arbitrarily only just because of a trend; rather, it should be viewed as one of several tools for problem-solving, and utilized only when it actually makes sense to do so.

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