Artificial Intelligence Enabled Healthcare Ecosystem Model: AIEHEM Project

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Abstract: The AIEHEM project aims to analyze the data made available by the regional health system, using an unorganized Turing machine model (A-Type) trained with a swarm-evolutionary hybrid algorithm. The goal is to identify the main factors related to certain outcomes that the healthcare organization intends to achieve (which can be economic, organizational, social or environmental). The chosen AI model is used to enhance, not to replace the analytical capabilities of the healthcare system management. The insights of the AI model are in fact used not only to identify the main objects of study to be taken into consideration, but also to define the areas of intervention and consequently also the stakeholders to be involved in the organizational change project to be carried out through the Theory of Change methodology. AI is therefore used to identify the most suitable ecosystem for solving the considered problem.

1 INTRODUCTION

The development of decision support systems (DSS) is a potentially gamechanger for executives and managers of health systems and organizations because they offer the possibility of managing an elevate number of variables (Longaray et al., 2016; Khademolqorani and Hamadani, 2015). These particular DSSs are indeed characterized by a high level of complexity that leads to the definition of groups or hierarchies of variables to be taken into account to solve certain critical issues and problems.

As health is a good of a fundamental and irreplaceable nature (Diaby et al., 2013), there is a high level of responsibility in the decision of adopting IT solutions to support management. This is particularly true if one considers that wrong management decisions can directly endanger patients, but it can also happen that the improvement of the medical state of some patients can negatively affect that of other patients (Marsh et al., 2014).

Unfortunately, such DSSs are often based on machine learning and AI algorithms working as "black boxes", where the assumptions of their predictions and/or choices are concealed (Academy of Medical Royal Colleges, 2019). This increases the difficulty in assessing the degree of reliability of such systems, making them particularly vulnerable to bias and deliberately malicious attacks.

Among the main machine learning and AI models used to implement DSSs are algorithms based on decision trees, linear and logistic regression, Bayesian inference and classification (Bashir et al., 2014; Zandi, 2014; Roumani et al., 2013).

Such systems often use Multicriteria Decision Analysis methods (MCDA) and Multicriteria Decision Making methods (MCDM) (Aghdaiea et al. 2014).

MCDAs are algorithms that allow to simplify complex problems by bringing them back to a series of elementary criteria to be considered in finding the solution (Angelis et al., 2017). In recent decades, MCDAs have been applied in various areas including the management of health systems (Longaray et al., 2016). Specifically, they have been used in the clinical (Gasol et al., 2022; Berner, 2007) and in the health management fields (Marsh et al., 2014; Ju et al., 2012; Wu et al., 2007; Baltussen et al, 2006).

MCDMs are algorithms that allow to find solutions in the presence of multiple objectives (San Cristobal, 2013) and also have been used been used, among others, in the clinical (Bashir et al. 2014) and

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in the health management fields (Narci et al., 2014; Ishizaka and Nemery, 2013).

Both MCDAs and MCDMs work by grouping or ranking possible alternative solutions to administrative problems. For this reason they also behave like decision-making black boxes that hide the criteria that guided the choice of the suggested solution, as well as the biases and all the other factors that influenced the selection. Therefore, it is crucial instead to develop algorithms that may help in explaining the causal links between the variables considered in the identification of the solution. This will allow *a posteriori* to verify whether the automated decision-making process has been based on a sufficient number of data, whether these are characterized by a sufficient level of quality and consistency, whether or not their selection has been influenced by cognitive biases. Indeed, a simplified logical representation of the causal links between the key variables selected by the DSSs, can help human decision-makers in assessing the reliability of the system and in making the most appropriate decisions.

All these considerations led to the definition of the project called "Artificial Intelligence Enabled Healthcare Ecosystem Model" (AIEHEM), a DSS based on an innovative AI model capable of providing not only accurate predictions on the outcome of certain operational or management activities, but also to identify the main critical factors correlated with the achievement of certain organizational objectives.

The example shown in this article is related to the optimization of the management of patients at high risk of death. In this preliminary phase of analysis we decided to use the exceeding the regional expenditure threshold linked to patient treatment as a proxy variable correlated with this organizational outcome.

The used AI model is able not only to autonomously identify the independent variables most closely related to the chosen dependent variable, but it is also able to tie them together within a single logical formula. This knowledge representation can be considered as a kind of guideline used to evaluate the possibility of incurring an overrun of care costs.

The advantage of defining a rule expressed through a logical formalism is that it allows a group of human experts to evaluate subsequently the appropriateness of the reasoning followed by the AI model. Just examining the set of independent variables taken into consideration by the system in making its predictions, it is possible to understand if it has left out important factors of analysis and if its reasoning was influenced by the cognitive biases of the human experts who selected the data to be analyzed. Furthermore, once the appropriateness of the logical formula proposed by the AI model is verified, it is possible to identify the stakeholders of the healthcare ecosystem to be involved in order to find a solution to the analysed organizational problem. The next processing of the AI model on the updated database can allow to understand whether or not the healthcare ecosystem has managed to intervene effectively on the critical factors identified by the system and if other critical factors to be taken into consideration have emerged over time. In this way it is possible to establish a Deming cycle (plan-do-check-act) to progressively improve the results achieved by the healthcare ecosystem (Taylor et al., 2014).

The AIEHEM project aims to assess the multidimensional key factors which are related to the strategic goals of a regional health system, by using a specific artificial intelligence model. Strategic goals can be: economic (e.g.: optimize the consumption of system resources in chronicity, etc.), organizational (e.g.: reduce waiting lists, increase the quality of services provided, etc.), social (e.g.: highlight the risk conditions for a pro-active risk management, etc.) and environmental (e.g.: reduce the environmental impact of health facilities, etc.).

The innovation of this project is based on the specific methods, as well as on its global, systemic approach. For the first time, in fact, an AI model will support the identification of the actors, the facilities, the activities, the knowledge, the opportunities, and the most suitable ecosystem to achieve the the regional health system goals, involving the relevant end users.

The AIEHEM project is in line with the "One Health" approach described by the 6th Mission of the National Recovery and Resilience Italian Plan, as it aims to promote interdisciplinarity and inter-professionalism through the enhancement of available health system data and information. The purpose is to enhance the efficacy of planning and decision-making of social and health services through the use of an AI model built to simplify the volume and complexity of social-health interactions. The collection, refinement and processing of the available data will be in compliance with the code for the protection of personal data (GDPR) and with the ethical values and fundamental principles of health promotion and public health, through the involvement of the data protection officer and the regional ethics committee.

2 DSS DESCRIPTION

The recent pandemic crisis has highlighted the problems that can arise from poor healthcare management or unoptimized health system resources. All these problems derive essentially from the lack of effective cooperation strategies between the various regional stakeholders resulting in an insufficient integration of territory services, hospitals and social services in facing health challenges.

The AIEHEM project is aimed at supporting the regional health management with an AI-based DSS to identify the relevant areas of intervention, stakeholders, and resources associated to an effective achievement of their strategic objectives.

As an example, we present here the use of the AIEHEM methodology to optimize the management of system resources for patients at high risk of death in Marche region (Italy). Particularly, we focus on the need of enhancing sustainability by reducing the costs of inappropriate use of resources in the last quarter of life of the patients, which also lead to an unjustified and dangerous delay of the diagnostic services for patients with the right indications.

The strategic aim was to encourage palliative care by avoiding clinical investigations that do not help in improving the prognosis of patients. In order to identify the factors related to an above-average in-hospital consumption of resources in patients in the last trimester of life, the AI model analysed the 2019 hospital discharge records (12344 records). Data relating to the pandemic period were excluded as the allocation of resources for the management of the pandemic could influence the outcome of the analysis.

The variables taken into account by the AI model are the following: gender, age class, type of hospitalization, method of discharge from the previous structure, main diagnosis category, residency, the exceeding the regional threshold for assistance expenditure. The sex variable assumed two values (male or female), the age was divided into 5 strata (0-60, 61-70, 71-80, 81-90, 90+), the type of hospitalization (reqType) was cathegorised in 4 values (scheduled not urgent, urgent, compulsory treatment, scheduled with prehospitalization), the method of discharge (disMode) encompassed 8 values (without the proposal of the family doctor, with sending of the family doctor, scheduled discharge, discharge from public hospital, discharge from accredited private structure, discharge from non-accredited private structure, discharge from other hospitalization regime, discharge from emergency urgency department). In addition, 25 major diagnostic cathegories (MDC) values were taken into account and the regional threshold for assistance expenditure was set by calculating the average diagnosis related group (DRG) value, equal to 4579.71 euros (Mistichelli, 1984).

To identify the analysis variables most correlated with the problem that we intend to investigate, we have chosen to use a single-state type A model of Unorganized Turing Machine (UTM) (Turing, 1948), consisting of a combinatorial network of NAND gates whose optimal configuration is selected by the evolution of a population of individuals each of which represents the encoding of a UTM configuration. In this way the UTM is generated "in an unsystematic and random way" from a set of two-input NAND gates. Turing chose a NAND gate because any other logical operation can be performed by a set of NAND gates. An Unorganized Turing Type A Machine can be considered "a kind of Boolean neural network without a layered structure, since recurrent connections are allowed without constraints" (Teuscher and Sanchez, 2000).

Every possible configuration of the NAND gates that make up the UTM was coded with a binary vector and to identify the optimal configuration, that is the vector that would allow to maximize the predictive accuracy of the model, a swarm-evolutionary hybrid algorithm was used, which we have called the Evolutionary Bait Balls Model (EBBM), in which NAND gate configuration vectors are considered as individual members of a swarm. Each of them is able to perform only three elementary operations (repulsion from others, attraction to another particularly performing individual, orientation towards others). The evolution of this population leads to the appearance of emerging behaviors (the state in which a sort of bubble is formed in which most individuals tend to orient themselves with respect to others), manifesting a kind of collective intelligence (Lella et al., 2022).

The original evolutionary model of the bait ball, which inspired our EBBM, was developed by researchers who found that within the group of fish trying to escape predators a spontaneously generated core constitutes what they called "selfish herd" (Roberts, 2021; Yang, 2018). This denomination comes from the selfish theory of the pack according to which individuals within the population attempt to reduce the risk of predation by placing other conspecifics between them and predators. Returning to the bait ball model, it is precisely this "selfish" behavior adopted by individuals that leads to the formation of the optimal collective configuration. The EBBM algorithm used as an optimization algorithm can be described as follows:

```
Input: Array of individuals I to be updated
Output: The position vectors (binary vectors) of each individual in I will be changed.

call function to alter the positions of each individual
for all i ∊ I do
   perform ZOR, ZOA, ZOO sets calculations
   if individual detected in ZOR then
       perform repulsion (R)
   else if individual detected in ZOO then
       perform orientation (O)
   else if individual detected in ZOA then
       perform attraction (A)
   end if
end for
```

Where ZOR is the Repulsion Zone: one individual cannot occupy the position of another, that is, it cannot be represented by the same binary vector. In this case it assumes another random position (every single bit of the individual is modified with probability RepulsionRate). ZOA is the Zone of Attraction: an individual tends to approach individuals characterized by a greater fitness (with a probability equals to the attraction rate, every single bit of the individual can assume the same value of the bit in the same position of the best performing individual in the ZOA set). ZOO is the Orientation Zone: an individual tends to orient itself, among the individuals close to it, towards the most performing one (with a probability equals to the orientation rate, every single bit of the individual can assume the same value of the bit in the same position of the best performing individual in the ZOO set). To define the sets ZOR, ZOA, ZOO, the parameters ZORrange, ZOArange and ZOOrange were introduced, representing the maximum number of different bits between the vector of the individual considered and that of the individual belonging respectively to the ZOR, ZOA and ZOO zone (attraction rate=0.05, orientation rate=0.3, repulsion rate=0.5, ZOA range=70, ZOO range= 5, ZOR range = 0). The fitness function of the individual is set as the prediction accuracy of the corresponding UTM.

With this swarm-evolutionary hybrid algorithm, better results are obtained in terms of predictive accuracy than other classical evolutionary models such as the genetic algorithm, as demonstrated in (Lella et al., 2022) where the EBBM model was used to implement an expert system capable of diagnosing with a fair level of accuracy the risk of incurring type II diabetes mellitus.

Every possible UTM configuration, which corresponds to a given binary vector, has been coded as follows. The first 59 bits represent the values that can take all the classes of variables that can be selected for the first input of the NAND gates of the UTM model. The following 59 bits represent the values that can take all selectable variable classes for the second input of the NAND gates of the UTM model. The remaining 54 bits were used to encode the architecture of the 18 available NAND gates. The values of these variables were encoded in binary format using a single bit for the sex variables and the exceeding of the regional spending threshold and a "one-hot" encoding for all the others, that is, using n bits for all the n possible values of the variable and valuing to 1 only the bit whose position is associated with the corresponding category. The variable of the exceeding of the regional expenditure threshold is considered as class variable, all the other ones are considered non-class variables.

Each NAND gate has been encoded with three bits. If the value of the first bit is 1 the first input of the NAND gate considered is a first class of input variable, otherwise the first input is connected to the output of the next NAND gate. If the value of the second bit is 1 the second input of the considered NAND gate is a second class of input variable, otherwise the first input is connected with the output of another NAND gate. If the value of the third bit is 1 it means that the inputs of the NAND gates considered are short-circuited and only the first input should be considered. In this way each individual, which represents a possible NAND network configuration, is represented by 59+59+54=172 bits. To represent a combinatorial NAND, when a individual is tested for suitability, all the first classes of input variables, all the second classes of input variables, and all 18 available NAND gates are selected sequentially once. The first NAND gate (NAND#1) of the 54-bit sequence is the network output gate. If the first bit of its code is 1, NAND#1 input 1 is the first input class variable that can be selected. If the first bit of its code is 0, input 1 of NAND#1 is the output of NAND#2, the code of which is represented by the following three bits of the 54-bit sequence. If the second bit of NAND#1 is 1, NAND#1 input 2 is the first input class variable that can be selected. If the second bit of NAND#1 is 0, input 2 of NAND#1 is the output of NAND#3, the code of which is represented by the third bit triplet within the 54-bit sequence.

3 EBBM UTM PERFORMANCE

The performance of the UTM model trained by EBBM (EBBM UTM) was compared with other AI and machine learning models that allow to model an explicit representation of the causal links identified between the study variables considered. All the models were trained using 60% of the available data and tested with the remaining 40% of the data. Table 1 shows the predictive accuracies of the tested models together with precision, recall and F1-score measures. Table 2 reports the number of decision nodes that make up the model and the number of non-class variables taken into account by the models to make their predictions.

The ZeroR model (Witten et al., 2011) was used as a benchmark to verify that all other algorithms used have been configured and used correctly. ZeroR always predicted the most frequent class variable in the presence of any combination of input variables. Given its simplicity it typically had a much lower level of predictive accuracy than the other algorithms that have been tested. Alternatively, the result found may be due to a bad selection and encoding of the input data with which the models were trained and tested or to a bad configuration of the models used.

The OneR, which stands for "one Rule" (Holte, 1993), is nothing more than a one-level decision tree. In various areas and predictive tasks this model has proved to be much more performing than other more complex models, and it is always appropriate to verify whether the problem under consideration can be effectively treated using this model that uses a reduced amount of resources.

The J48 (Witten et al., 2011) is a decision tree based on the "divide and conquer" strategy used recursively. At each training step the node characterized by the highest amount of information is selected and split into a series of nodes corresponding to some possible values that the original node can assume. The process ends when all instances considered reference the same value as the class attribute.

The Bayesian network (Ben-Gal, 2007) is a probabilistic graphic model that represents a set of stochastic variables with their conditional dependencies through the use of a direct acyclic graph.

A random forest is an aggregate classifier obtained by bagging aggregation of decision trees. The name comes from the random decision forests that were first proposed by Kam Ho (1995).

Table 1: Prediction accuracy of the AI tested models.

Model	Prediction Accuracy (%)	Precision	Recall	F1-Score
Zero R	72.11	0	0	0
One R	80.57	0.731	0.48	0.58
J 48	81.29	0.792	0.446	0.571
Bayes Network	80.70	0.745	0.469	0.575
Random Forest	75.92	0.578	0.508	0.541
EBBM UTM	81.14	0.796	0.435	0.563

Compared to the other considered machine learning and AI models, the UTM EBBM allowed to create a predictive model characterized by a limited number of nodes and which also takes into account only a subset of the non-class variables presented in making its predictions.

Table 2: Complexity level of the final knowledge representations.

Model	Number of nodes	Considered variables
Zero R	0	-
One R	1	MDC
J 48	31	MDC, type of hospitalization, residency, mode of discharge, age, gender
Bayes Network	26	MDC, type of hospitalization, residency, mode of discharge, age, gender
Random Forest	30	MDC, type of hospitalization, residency, mode of discharge, age, gender
EBBM UTM	17	MDC, type of hospitalization, mode of discharge

This model allows human experts to evaluate the criteria used by the model, explaining possible biases in the selection of the data used for its training. Because of its simplicity, the model obtained through the UTM EBBM, could also be used, after a proper validation by a team of human experts, to write decision-making guidelines to be adopted by managers or clinicians (figure 1).

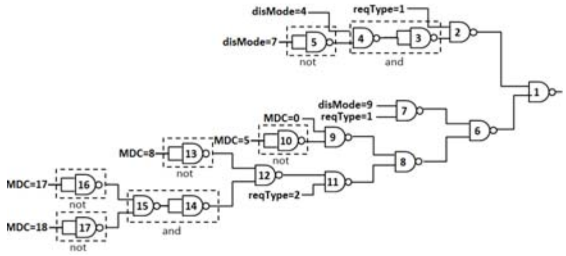

Figure 1: UTM forecast model selected through EBBM.

Only the UTM EBBM model was able to establish that sex, age and residency were negligible variables. Consequently, this finding allows to exclude the referents of the territorial districts as stakeholders to be involved. Also no sex-based or age-based inequalities were observed, therefore the involvement of associations of patients who deal with them may not be necessary. The same AI model built in this first analysis suggested to involve psychiatric and hospital services in the management of certain types of scheduled hospitalizations.

However, to be noted that the choice to use the exceeding of the regional spending threshold as a class variable may have introduced cognitive bias. We will repeat the analysis of the UTM EBBM model using different proxies to assess the appropriateness of the assistance that has been provided to patients close to death. Alternative proxies could be given by the number of accesses to the emergency room or the cost of drug therapies that have been administered to patients close to death. These new simulations will allow to validate or not the predictive model that has been defined.

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4 CONCLUSIONS

The AIEHEM project has the ambitious goal of suggesting to the organizational management the most suitable strategy to undertake in achieving a certain long-term outcome, using the support of an AI model.

The chosen model (EBBM-based UTM) is able not only to identify the critical factors related to the achievement of a certain strategic objective, but through the extrapolation of a rule that binds them it can help to better understand the phenomenon that underlies the achievement of the objective, suggesting which stakeholders to involve in defining an adequate intervention strategy.

The main beneficiary of the outcomes deriving from the adoption of the AIEHEM methodology is the patient. In the given example aimed at optimizing the system resources in the care of patients at risk of death, the medium-long term advantages are mainly the improvement in the quality of palliative care and the reduction of the waiting lists for specialty visits and instrumental examinations. As a matter of fact, our analysis revealed the use of unnecessary investigations, perhaps deriving from defensive medicine practices.

Therefore, the insights obtained with the AIEHEM methodology may support the staff operating in the territorial and hospital structures to better coordinate their activities and optimize the use of their resources. The enhanced quality of services will therefore affect not only the patients, but also their family members and caregivers who would be given more precise instructions on how to manage these patients.

It should be underlined that the AI model taken into consideration, however, must serve to extend, complement and support, not to replace, the analytical skills of human experts who must in any case prepare the best lines of intervention to achieve the specific management goals. In a wide perspective, the EBBM UTM model may give its best as a support tool in structured strategies of management of change. The "Theory of Change", as used by UNICEF and other UN organizations, has proved particularly effective in finding solutions to contingent problems that require political, administrative and organizational interventions (ToC Center, 2021) and may be an ideal framework to enhance AI-driven decision support tools.

An estimate of the potential savings by optimizing the system resources for patients in their fourth quarter of life with the AIEHEM methodology is 16 million euros per year.

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