Reducing the Psychological Burden of Isolated Oncological Patients by Means of Decision Trees

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Abstract

This century has seen several outbreaks of epidemics caused by a common sub-family of coronaviruses such as the responsible for COVID-19 outbreak. The most ominous variants have developed a peculiar viral mechanisms that allows the virus to directly attack the pulmonary tissues often causing a set of dangerous symptoms. It made quite evident that we need a global response to prepare health systems for future epidemics. Unfortunately, during such kind of diseases' outbreaks a large amount of time is required to the caregivers for sanitization and cleaning operations, therefore tampering with number and duration of visits to patients, especially in oncology wards. Such patients are then left alone for a long time, it follows that their perceived quality of service is greatly diminished, often determining ill-fated consequences also on the psychological side, with significant fallbacks on the recovery possibilities and speed. In this paper we explore an algorithmic approach to automatic communication interfaces that could enhance and enforce the perceived quality of care by the patients in in order to reduce predisposing factors that could potentially tamper with the patient's ability to recover, also preventing the occurrence of precipitating factors that could lead a therapy to complete failure. The proposed interface could be used to connect the patients with a psychological support when it is most needed, and, moreover, to connect them with their physicians and families, and also to the outside world. In particular we aim to provide the psychological support that is actually excluded in pandemics such as the COVID-19 emergency, mainly in order to enforce the healthcare and sanification protocols, due to its potential unsafety related to the introduction of more personnel into the hospital.

Keywords

Psychology, Oncology, Medical Physics, hospitalization, decision support, decision trees.

1. Introduction

This century has seen several outbreaks of epidemics caused by a common sub-family of coronaviruses. The most ominous variants have developed a peculiar viral mechanism that makes use of the angiotensin-converting enzyme 2 (ACE2).

Such a mechanism allows the virus to directly attack the pulmonary tissues often causing a set of dangerous symptoms that can be generalized as Severe Acute Respiratory Syndromes (SARSs). Therefore such viruses are characterized by extreme infectivity, rapid spread, and the concrete risk of developing pulmonary syndromes that may require intensive care unit admission [1]. The spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has taken on pandemic proportions, affecting over 100 countries in a matter of weeks. The healthcare system's capacity to respond has been under enormous pressure, to the point that Intensive care specialists had been considering the possibility to deny life-saving care to the sickest, giving priority to patients with better survival chances [2]. While in several countries such a point of no return has been trespassed [3]. Such events made quite evident that we need a global response to prepare health systems for future epidemics. Official numbers of infected people during the COVID-19 virus outbreak have been indicative of the spread of the infection, and of the challenges that have been posed to Italian hospitals and, in particular, intensive care facilities. The enormous demand for handling the COVID-19 outbreak challenged both the health care personnel and the medical supply system. The COVID-19 emergency has exposed the fragility of many Health Care Systems around the world. Two major critical factors have been related to the management of critical care units as well as of other wards hosting patients with immunological deficiencies such as oncology. COVID-like diseases are generally transmitted by airborne pathogens that grant a high contagion rate and rapidity. Moreover, such pathogens often tamper with the respiratory system causing various lung-related comorbidity.

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These affections can also evolve in acute respiratory syndromes, with variable or uncertain outcomes, such as severe pneumonia, that commonly require hospitalization in intensive care.

Unfortunately, during such kind of diseases' outbreaks a large amount of time is required to the caregivers for sanitization and cleaning operations, therefore tampering with number and duration of visits to patients. Such patients are then left alone for a long time, it follows that their perceived quality of service is greatly diminished, often determining ill-fated consequences also on the psychological side, with significant fallbacks on the recovery possibilities and speed. Most hospitals could not maintain their routine work due to the disaster-related new procedures. In facts medical professionals caring for patients with highly infectious diseases such as COVID-19 are at high risk of contracting such infections. All medical personnel involved in the management of potentially infected patients must adhere to airborne precautions, hand hygiene, and donning of personal protective equipment. All aerosol-generating procedures should be done in an airborne infection isolation room. Double-gloving, as a standard practice at our unit, might provide extra protection and minimize spreading via fomite contamination to the surrounding equipment after intubation. All these necessary safety measures come with an elevated cost, not only on the financial side but also on the amount of time and energy required to enforce such practices, as well as in term of quality of care reduction for the patients, that are often to be left alone for the major part of the day.

In this paper we explore an algorithmic approach to automatic communication interfaces that could enhance and enforce the perceived quality of care by the patients in in order to reduce predisposing factors that could potentially tamper with the patient's ability to recover, also preventing the occurrence of precipitating factors that could lead a therapy to complete failure. Tumors represent a nefarious event of high importance. In fact, cancer always represents, for the patient and for his family but also for the treatment system, an overwhelming existential test. This test concerns all aspects of life: the relationship with one's body, the meaning given to suffering, illness, death, as well as family, social and professional relationships. The proposed interface could be used to connect the patients with a psychological support when it is most needed, and, moreover, to connect them with their physicians and families, and also to the outside world. In particular we aim to provide the psychological support that is actually excluded in pandemics such as the COVID-19 emergency, mainly in order to enforce the healthcare and sanification protocols, due to its potential unsafety related to the introduction of more personnel into the hospital.

The paper is organized as follows. After this brief introduction, in the following Section 2 we discuss the related works and compare our contribution to the existing literature. In Section 3 we describe the system, its purpose and aim, while we deepen into the algorithm and topology in Section 4. Finally in Section 5 we will report the simulation results and draw our conclusions.

2. Related Works

In literature the quality of services of a healthcare system is defined as consistently delighting the patient by providing efficacious, effective and efficient healthcare services according to the latest clinical guidelines and standards, which meet the patient's needs and satisfies providers [4]. Healthcare quality definitions common to all stakeholders involve offering effective care that contributes to the patient well-being and satisfaction. As shown in [5] the perceived health service quality is an important determinant for health service satisfaction and behavioral intentions.

A recent study [6] reported that in general the hospitalized patients, while often lacking the education and knowledge regarding isolation, feels that it improves their care.

On the other hand [7] shows that contact isolation is associated with adverse effects in patients and lead to psychological and physical problems, and that hospitalised patients placed under isolation often showed a negative impact on their mental well-being and behaviour, including higher scores for depression, anxiety and anger [8].

Moreover, as showin in [9], isolated patients are visited fewer times than non-isolated patients, moreover such isolated patients generally benefit of a shorter time span with their physicians. Because of the significantly lower contact time observed, particularly among the most severely ill of floor patients, a reexamination of the risk-benefit ratio of this infection control method has been proposed. In facts the attending physicians are about half as likely to examine patients in contact isolation compared with patients not in contact isolation [10].

Similarly, other studies have pointed out the concern that isolation may negatively affect not only the perceived quality of service but also the patients' mental health [11, 12], with a substantial increase in anxiety and stress-related disorders [13, 14]. Finally [15]

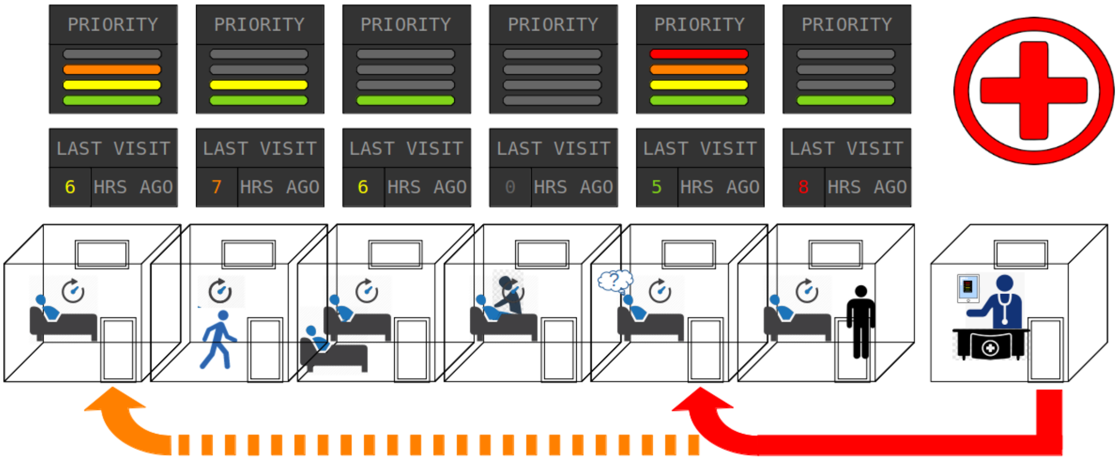

Figure 1: A schematic representation of the developed system's purpose and application.

shows that isolation precautions are associated with adverse effects which may result in poorer hospital outcomes, a longer hospitalization, an higher cost of care, as well as an higher rate of readmission to hospital within a month. The spread of COVID-19 is of particular concern in this vulnerable population, given the fatality rate and the potentially increased severity of the disease course [16]. For this reason, as stated in [17], a multitude of precautionary steps are implemented by hospitals, departments of radiation oncology to provide uninterrupted radiation treatment for most patients with cancer amid the current COVID-19 pandemic. The main care services in several countries has implemented clinical psychology units to cope with the COVID-19 emergency outbreak. The unit's main goal has been to support and protect health care professionals, relatives of hospitalized patients, and patients themselves from further psychological distress. Details and insights are shared [18].

Among such measures an extensive application of isolation protocols has been applied in onclology and radiotherapy units [19].Patients with cancer are known to be at an increased risk for community-acquired respiratory viruses, such as influenza, because of their frequently observed immunocompromised state [20].

Unfortunately for cancer patients the psychological burden of isolation is heavier with respect to isolated general medicine patients [21]. As pointed out in [22], radiation oncology clinics have always functioned as an interdisciplinary team of support staff, nurses, therapists, dosimetrists, physicists, and physicians, all aiming to help patients with cancer. Heading into the fight with COVID-19, that team nature and vision to protect patients with cancer remain critical. Therefore the implementation of a psychological support within such units appear natural, as well as agreeable. In fact, in [23] it has been shown that during the COVID-19 outbreak, using online multimedia psychoeducational intervention on perceived stress and resilience of patients hospitalized in quarantine had a beneficial impact on the before-mentioned undesirable psychological effects.

Differently from other fields of medicine, psychology does not base its protocol on drugs and prescription, and neither on standard surgical procedures [24, 25], on the contrary it build the intervention around the patients needs starting from standardized protocols. While standardization comes with a price, since it results in a lack of customization for the developed therapy, it also presents great advantages in terms of comparability and results testing among different patients.

Moreover trough standardization the caregivers are guided in making decisions regarding the more appropriate therapeutic plan for a specific conditions, while the medical practices can be rationalized improving, in the end, the general outcome for the therapy at full advantage of the patient's well being. Other fields of medicine can rely on very effective clinical prediction rules in order to reduce the uncertainty inherent the medical practice by defining how to use clinical findings to make predictions [26]. Finally, it must be said that in certain cases it is uttermost difficult to draw methodology-proof clinical practice guidelines due to the extreme statistical and subjective variability of the matter at hand [27].

3. Purpose of the developed system

Finally relevant focus should highlight the situation of patients with cancer may have compromised immunity due to their malignancy and/or treatment, and may be at elevated risk of severe COVID-19. Community transmission of COVID-19 could overwhelm health care services, compromising delivery of cancer care. This interim consensus guidance provides advice for clinicians managing patients with cancer during the pandemic. [28]. Among the experts that take care of the patient with cancer a peculiar figure is constituted by the medical physicist: a specialist who applies the principles and methods of both physics and medicine, focusing on the areas of prevention, diagnosis, and treatment, as well as ensuring quality services and prevention of risks to the patients, and members of the public in general. Unfortunately the work of the MP, as well as the other oncology team members, has been tremendously affected by the COVID-19 outbreak. In fact the MP shares the responsibility to plan the radiotherapy and radiosurgery intervention also for patients with potentially compromised immunity system.

As it will be shown in the following, the psychological and emotional status of the patients it is paramount to determine the therapeutic outcome, and, often, this is strongly affected by the isolation protocols that deprive the person of human contact and relationships.

Therefore in this work we explore the development of a decision three for oncology patients deployed from the collaboration of different figures such as computer scientists, psychologists and radiation oncology physicist. The first responsibility of the radiation oncology physicist is to the patient, trying to assure the best possible treatment given the state of technology and the skills of the other members of the radiation oncology department. A radiation oncology physicist brings a unique perspective to the clinical team in a radiation oncology program: he shows his abilities as a scientist who trained in physics, including radiological physics, and also in clinical, basic medical, and radiobiological sciences. The physicist performs an important role working along with the radiation oncologist, the radiotherapy technologist and others, to assure the accurate delivery of all aspects of a treatment prescription. In radiation oncology, physicists have the primary responsibility for the following for planning the resource allocation with radiation oncologists, administrators, and technologists, takes care of the physical aspects of all radiation sources (radioactive materials and radiation producing machines) used in a radiation oncology program, enforce the radiation safety program (possibly shared with an institution's radiation safety officer), focuses on the physical aspects of patients' treatments and interacts with the medical community.

The main objective of the treatment of the cancer patient must be to improve the quality of life and to limit the risk of psychopathological consequences such as to affect the future life of the patient and his family. Social support therefore represents a constitutive element of the treatment of the cancer patient and falls within the responsibility of each therapeutic figure.

The adaptation to the disease and to the treatments depends largely on the quality of the relational approach of the treating team, which is the author above all through the control of the side effects of the therapies, the control of pain, anxiety and depressive symptoms. This is possible through an individualized care of the patient, through information on the various aspects of the pathology as well as through the evaluation of his needs, his possibilities of choice, his family and social situation.

The psychological and relational dimension represents an element of particular importance in oncology. In fact, the carers must from time to time be able to tolerate and contain the emotional and affective reactions of patients and their families on a daily basis, developing a particular sensitivity with respect to the perception of signs of discomfort and the inherent limits in the possibility of adaptation of the patient himself to the disease.

Following the dramatic COVID-19 pandemic, the activities of the operators in oncological radiotherapy department have been extensively remodelled, so as to ensure greater safety for the entire staff operating in the facility. First of by applying social distancing, equipping the staff equipped with personal protective equipment, installing sanitizing gel dispensers in every hallway and waiting room, but also determining a maximum limit of two people at the same time in the same room.

Even in the waiting room of an oncology department, patients are subjected to limitations, in order to maintain the correct social distancing. Their relatives have to wait upstairs, thus avoiding further gatherings, and sometime they are not admitted in the ward. The effect of these necessary limitations is to increase the isolation effect on the oncological patient.

Therefore, while the patient follows a cure protocol, he must also be helped, with the same accuracy, by means of a parallel protocol that takes care also of the solitude experienced by the person. In the following

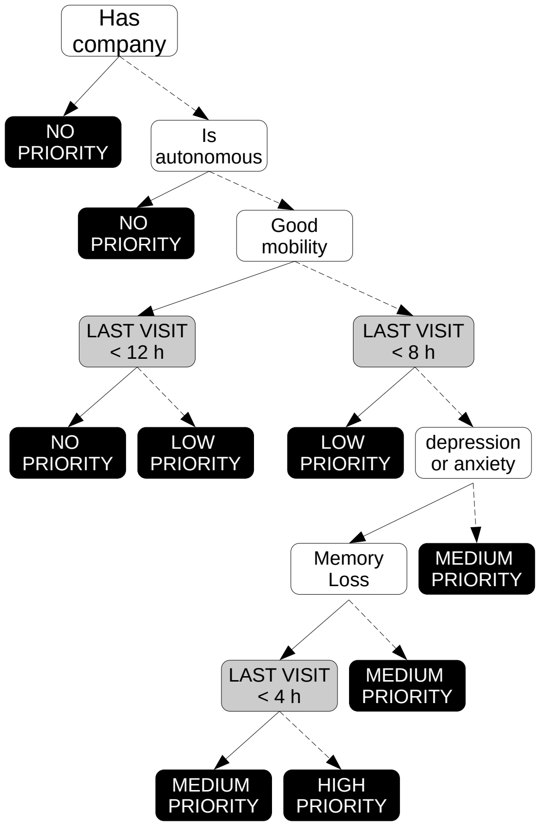

Figure 2: The topology, attributes and nodes of the implemented decision tree.

we will describe how a decision tree can take responsibility for the latter.

4. The implemented decision tree

Decision making rules have been adopted since many years and with different purposes. E. g. in [29] descision making rules have been developed as a guide for hospitalization of patients presenting community-acquired pneumonia, while in [30, 31, 32] decision making rules are adopted to define when x-rays are needed in acute ankle injuries. In facts such a support tool is often used for trauma treatments and when diagnostical imagery is involved [33, 34].

There are many works in literature about the extraction and formulation of decision making rules. In [35] decision making rules have been extracted by means of a decision tree [36, 37, 38, 39] for the diagnostic workup of patients with Meniere's disease, vestibular schwannoma, traumatic vertigo, sudden deafness, benign paroxysmal positional vertigo, and vestibular neuritis. In [40] the authors present the results of a prospective, cross-sectional study involving patients with acute headache and demonstrate that their best bedside decision rule identified all cases of subarachnoid hemorrhage among emergency department patients presenting with new, isolated headaches.

In [41] uses fuzzy decision-making rules adapted to classification problems by using the methodology of exploratory analysis followed by unification of particular decision rules into fuzzy groups. On the other hand clinical decision rule must be based on evidences, when no evidence-based guideline exists, i.e. due to the extreme variability of a disease, then a consensus-based clinical practice guideline is the best option [42]. This latter is often used for psychological treatments planning, sometime also along with more orthodox clinical decision rules.

It follows that physicians, therapists, psychologists, and caregivers in general could obtain great advantages from specific support systems in order to be informed of the existing decision making rules. When such rules are not available the implementation of decision threes could be of great advantage.

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. It is one way to display an algorithm that only contains conditional control statements. The decision tree consists of three types of nodes: decisions, chances and endings.

Decision trees are commonly used in operations research and operations management. One advantage of decision threes is the possibility to linearize them into decision rules. From a decision tree it is possible to extrapolate a chain of decision that are basically driven by the comparison of measurements at a constant time. If such measurements are coming from a set of observation regarding the psychological state of an isolated hospitalized patient, then the decision tree can be used to understand when it is needed a psychological help to improve his mental status.

Decision Tree is a classification algorithm that decides whether a specific value should be accepted or rejected, and it provides with the set of the IF-THEN rules for transforming present state to future state [43]. The tree structure is used to represent decision tree in which variant types of the nodes are connected by the branches where the topmost node is called as root node and the leaves are called decision node [44, 45, 46].

In our implemented model (see Figure 2) we aimed to discriminate whether or not a patient should urge a visit by a physician, not only regarding the therapeutic routine, but also in order to decrease the patient's psychological burden. In our model we used simple observable variables that could be easily recorded during the patient's hospitalization period also by means of scarce automation. These variable take into account whether or not the patient has a company, both in terms of a related, a visitor, or a conscious and interactive roommate, as well as the degree of autonomy and mobility of the patient jointly with his mental status (with particular focus on depression and anxiety). Finally a special attention is given to patients with memory loss or mental impairment. In our approach the data can be collected automatically and stored in the form of an input vector

$$\vec{x} = (x_i)_{i=1:N} = (x_1, x_2, ..., x_{N-1}, x_N) \tag{1}$$

in order to feed the training algorithm of our decision stream. Given a set of known samples, the decision three has can be trained with a C4.5 algorithm [47], using the Kullback–Leibler divergence [48] to measure the homogeneity of the target variable within the subsets. In this manner For a value v_k taken by the attribute x_k of the input vector $\vec{x} \in X$, given a related training set S_k, and the conditional entropy as

$$H(X|v_k) = \sum \frac{|S_k|}{|X|} \cdot H(S_k) \tag{2}$$

the expected information gain is the change in information entropy from a prior state, mediated by the a pirori Shannon entropy $H(X)$, to a state that takes some information, mediated by the conditional entropy. Therefore it is possible to compute the information gain as

$$\Gamma(X, v_k) = H(X) - H(X|v_k) \tag{3}$$

therefore obtaining a good measure for deciding the relevance of each attribute in our recursive partitioning.

5. Results and conclusions

In our approach we used a modified version of the C4.5 algorithm, introducing time and causality, in order to manage the visiting time of the caregivers in an oncology ward. I our simulations (see Table 1) the results has showed an enhanced and improved time distribution and time-consumption efficiency, with a shortened isolation time for the most needful classes of patients. It is possible to state that the patients should

Table 1
The table shows the simulated results obtained by the implemented decision support system in terms of elapsed time between visits. The last column shows the relative variation which represent a beneficial reduction of time intervals for the most needful classes of patients.

	Standard Average Time	Simulated Average Time	Δ	Δ%
Patients with company	~ 10 h	~ 12 h	+2 h	+20 %
Autonomous pateints	~ 10 h	~ 8 h	−2 h	−20 %
Depressed or anxious	~ 10 h	~ 6 h	−4 h	−40 %
Mentally Impaired	~ 6 h	~ 3 h	−3 h	−50 %

then benefit of a positive fallback on their mental status which also improves their remission, therefore reducing hospitalization and relieving also the general burden for the healthcare service, with a positive feedback loop that should exponentially benefit the caregiving system.

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