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Influence Diagram As a Support Tool for Clinical Decisions In Cardiopulmonary And Metabolic Rehabilitation

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Abstract

An influence diagram (ID) is a method of graphical representation of uncertain knowledge, which can be employed to support decisions in health care using probabilistic reasoning. We aimed to describe the development of an ID to support the decision-making process in phase II at Cardiopulmonary and Metabolic Rehabilitation Program (CPMR). The development of the ID was carried out through the identification of relevant variables and their possible values, as well as the identification of details of each variable, in order to find a network structure that appropriately connects the nodes that represent the variables, with arcs linking acyclic graphs, and to build the graph using specialized knowledge and the conditional probability table for each node in the graph. In spite of the complexity of the interactions, the model obtained with the ID seems to contribute in the decision-making process in phase II CPMR, providing a second opinion to the health pratictioner and helping in diagnostic, therapeutic and decision-making processes, since it is useful in situations with non-linear modeling or with absent or uncertain information.

Keywords:

Cardiovascular diseases; clinical decision support systems; influence diagram; physical and rehabilitation medicine, probabilistc networks; rehabilitation.

Introduction

The Influence Diagram (ID) appeared for the first time in the United States during the 1980's as a way to represent a decision-making problem [1]. It is even more compact than a decision tree and can make explicit the probabilistic dependencies among variables. An ID is a graphical structure that allows the modeling of uncertain variables and decisions that explicitly reveal probabilistic dependency in a flow of information [2].

There are several benefits in the evaluation of a problem through ID operations such as: the algorithm executing the entire inference and analysis automatically; the analysis being made available in a representation which is natural for decision making; and the use of ID resulting in gains in processing, as it considerably reduces the size of intermediary calculations and the need for greater memory spaces.

Recent work has shown the viability in the use of ID in processes where variables are uncertain and decisions need to be taken starting from the probabilistic dependency in a flow of information as, for instance, in the Medical field [3-5], and Risk Evaluation [6].

The ID is presented in this paper is the selection of the best Cardiopulmonary and Metabolic Rehabilitation (CPMR) option for cardiac patients chosen in a safe and effective way.

Many studies about the enormous prevalence of heart disease suggested some treatment possibilities to minimize the negative effects of these disorders in a patient's quality of life [7-9]. There emerged the possibility of a non-pharmacological treatment: the Cardiopulmonary and Metabolic Rehabilitation (CPMR) [10, 11].

CPMR is the sum of the activities needed to ensure patients with heart disease achieve better physical, mental and social conditions [8-10]. Patients who adhere to CPMR programs experience improved quality of life, hemodynamic stabilization, metabolic changes, and improved vascular and psychological states, which are associated with better control of risk factors and improvement in lifestyle [15-16]. Studies have already demonstrated the cost-effectiveness of CPMR, which became necessary for the rehabilitation of patients affected by these diseases [8-9, 12].

However, there are several uncertainties surrounding the professionals who work in CPMR. Although the beliefs are strengthened and the uncertainties are reduced over years of experience and professional practice, there will always be a degree of uncertainty in each decision. A classic example observed in clinical practice is the prevalent use of the treadmill, with the use of the stationary bicycle restricted to patients who have a physical or mental limitation that prevents treadmill training. However, there are still uncertainties about whether the equipment chosen by the professional is suitable for the patient's specific clinical picture [11, 13].

Thus, based on the technological advances, the possibility of building decision support systems, the high prevalence of heart disease and the growth and recognition of the CPMR, this study aims to build a ID to support clinical decision for phase II CPMR in cardiac patients. This aims to assist non-specialist professionals in choosing the best CPMR option for cardiac patients in a safe and effective way.

Methods

This is a methodological study approved by the Research Committee (ComPesq) of the Federal University of Health Sciences of Porto Alegre (UFCSPA) under number 011/2013.

Participants

The data used in this study were obtained from the medical records of a cohort of cardiac patients in phase II CPMR, assigned by a referral center for cardiopulmonary and metabolic rehabilitation in the state of Rio Grande do Sul, Brazil.

Influence Diagram development

The methodology used to generate the ID began by reading the selected references and isolating clinical information that may influence the diagnosis [13], prognosis and treatment, or be related to the measures taken. The bibliography search and choice of variables was done by a field expert, with the choice of variables and future connections between them based on his knowledge of the field. This study used the variables listed in the scientific literature through consensus, guidelines and norms for CPMR [7, 10, 14, 17, 18].

The structure building can be carried out manually and was designed precisely this way, taking into account the causal relationships between selected variables [13]. The estimating probabilities was obtained from a cohort of data provided by a referral center for CPMR.

However, this does not invalidate the ID, because remains the exact same principle used by the expert to make the decision in scenarios where the quantitative knowledge of the problem is not known or clear [21, 23-25]. At this point, the cohort data provided by the referral center was critical, because it helped to quantify the frequency of clinical outcomes.

Validation

Data for validation [13] of the ID were obtained from the records of another cohort of patients in phase II CPMR, kindly provided by a referral center for CPMR in the State of Rio Grande do Sul called Instituto de Cardiologia do Rio Grande do Sul. Therefore, to assist with the observed frequencies, both situations were considered: the frequency of observations performed on data from the referral center and the decision based on expert's opinion.

Results

The quantitative data used for modeling the shape ID were obtained from a cohort of patients who attended a referral center from April 2012 to April 2013. Characterization of variables in this sample is described in the tables below.

Table I - Characteristics of the sample of 264 patients in phase II CPMR from a referral center

Variables	Mean	±SD
Age (years)	62	±12.35
Weight (Kg)	81	±16.67
Height (m)	1.65	±0.09
Systolic blood pressure (mmHg)	125	±19.35
Diastolic blood pressure (mmHg)	74	±12.11
Heart rate (bpm)	72	±13.18
Partial pressure of O_2 (%)	96	±10.54
Indirect Vo2	15	±5.61
Maximum voluntary ventilation (L)	51	±23.48
Predicted percentage of maximum voluntary ventilation	90	±46.81
Sits and stands	11	±3.51
Maximum inspiratory pressure	74	±33.08
Predicted percentage of maximum inspiratory pressure	79	±37.95
Maximum expiratory pressure	88	±42.91
Predicted percentage of maximum expiratory pressure	91	±49.29
6-minute walk test (m)	406	108.18
Predicted percentage of 6-minute walk test	82	±35.69
Gender-n(%)		
Male	160	(60.6)
Female	104	(39.4)
Ethnic group - n(%)		
Caucasian	223	(84.5)
Black	32	(12.1)
Other	9	(3.4)
Body Mass Index - n (%)		
Underweight	4	(1.5)
Normal weight	48	(18.2)
Overweight	102	(38.8)
Obesity (Grade I)	71	(26.9)
Obesity (Grade II)	27	(10.2)
Obesity (Grade III)	12	(4.5)
Main complaint -n(%)		
Fatigue	79	(29.9)
Dyspnea	26	(9.8)
Fatigue associated to dyspnea	29	(11)
Pain in lower limbs	13	(4.9)
Thoracic pain	13	(4.9)
Medicated for cardiac condition - n(%)	244	(92.4)
Time from event to recovery - (months)(median - Q1-Q3)	1	(1-3)
Main symptoms - n(%)		
Asymptomatic	72	(27.3)
Dyspnea	115	(43.6)
NYHA CFI	38	(14.4)
NYHA CFII	42	(15.9)
NYHA CFIII	31	(11.7)
NYHA CFIV	4	(1.5)
Cough	64	(24.2)
Orthopnea	7	(2.7)
Paroxysmal nocturnal dyspnea	23	(8.7)
Chest pain	56	(21.2)
Typical chest pain	30	(11.4)
Functional Class I	7	(2.7)
Functional Class II	12	(4.5)
Functional Class III	7	(2.7)
Functional Class IV	4	(1.5)
Palpitations	75	(28.4)
Dizziness	97	(36.7)
Syncope	13	(4.9)
Intermittent claudication	26	(9.8)

Legend: *SD – standard deviation; n=absolute frequency, %=relative frequency.*

Table II – Major etiologies diagnosed in the sample of 264 patients in phase II CPMR reference center

Etiologies	Yes n	%
Ischemic	153	(58.0)
Valvular	11	(4.2)
Myocardiopathic	24	(9.0)
Others	76	(28.8)
Total	264	(100.0)

Legend: *n=absolute frequency, %=relative frequency.*

Table III – Major risk factors presented by 264 patients in phase II CPMR reference center

Risk Factor	**Yes n**	**%**
Dyslipidemia	150	56.8
Systemic hypertension	210	79.5
Sedentary	186	70.5
Diabetes mellitus	78	29.5
Obesity	73	27.7
Smoker	17	6.4
Former smoker	116	44.0
Active alcoholism	34	12.9
Ex-alcoholic	16	6.1
Positive family history	173	65.5

Legend: *n=absolute frequency, %=relative frequency.*

From the variables defined according to the guidelines and consensus and the data obtained in the cohort of patients, we obtained the ID below:

Figure 1: Influence diagram structured to assist in decision making to perform cardiopulmonary and metabolic rehabilitation.

The DI can represent the mutual and hierarchical relationships among many variables using probabilistic rules and therefore, in many cases, their application is more suitable for prognosis and diagnosis.

Figure 2: Influence diagram structured to assist in decision making (after entering the cardiopulmonary and metabolic rehabilitation program) regarding type of equipment and training to be used.

We present 3 randomly selected cases from the database to display the variables, the decision of the expert and the decision of the ID.

1. Patient W.L.B., male, 86 years old, 83Kg, 1.60 m height, BMI (body mass index) = 32 kg/m2, resting HR (heart rate) 41bpm. Main complaint is fatigue that comes to feel dizzy, but also refers severe pain in lower and upper limbs. Has positive family history of CAD, is sedentary, stress test is abnormal, predicted maximum inspiratory pressure at 115%. The decision of the expert is to send this patient for the following conduct:. Stretches (flexibility), bike to a HR of 96bpm working with the Borg scale below 3. There is no need for FES (functional electrical stimulation) and IMT (inspiratory muscle training) at the time and would not tolerate the treadmill.
   The decision proposed by the ID was: In failure to perform treadmill, perform bike; indicates the FES, with lower value indicates the RML (located muscle strengthening), does not indicate the IMT and indicates the flexibility. ID also makes reference to the preferable aerobic intensity.
2. Patient L.A.P., male, 48 years old, 76.5 kg, 1.68 m height, BMI (body mass index) = 27kg/m2, resting HR 67 bpm. Main complaint is chest pain. Patient referred not having other symptoms or risk factors such as dyslipidemia, hypertension and family history. Was treated with beta-blockers, anticoagulants and statins; lacked effort and the predicted maximum inspiratory pressure is 105%. The decision of the expert is to send this patient for the following conduct: Stretches (Flexibility); if the patient was not on betablockers, he could be working at a HR of 130bpm, with a range of less than 4 borg There is no need for FES and the IMT. The decision proposed by the ID was: Biggest indication to perform the wake of that bike, indicates the FES, with lower value indicates the RML, and does not indicate the IMT; indicates flexibility. The most indicated type of training is aerobic rather than anaerobic.
3. Patient A. D. S., female, 58 years old, 142Kg, 1.60 m height, BMI = 55Kg/m2, resting HR 136 bpm. AP (arterial pressure) 190/140. Main complaint is fatigue associated with shortness of breath at rest, chest pain, which in some cases reaches fainting and dizziness. Among the risk factors are dyslipidemia, hypertension, decompensated DM, smoking, family history of CAD. Patient states that she has prescriptions but forgets to take the medication. Referred pain in MIE; when the expert did a physical examination he noticed swelling, heat, redness and increased local temperature. The decision of the expert is to send this patient to consult with the specialist because he believes that under such conditions the patient is not able to perform CPMR. The decision proposed by ID contraindicated CPMR.

The predictions obtained with this method can inform the patient and the health practitioner whether a given treatment is being effective or whether a given condition is under control.

Discussion

In the simulation of case 1, ID agreed with the expert regarding CPMR and all conducts suggested by the expert are also suggested by the ID, such as opting for bicycle due to advanced age and dizziness presented by the patient. However, the expert, in his daily routine practice, does not normally use the FES as a therapeutic resource and neglects this feature. Nevertheless, the ID patterned to act as an expert does not rule out the possibility of using the FES, and it indicates the treatment since there is no absolute contraindication [17] for possible use. The ID suggests the most appropriate type of training against HR proposed work, which is too often overlooked to the detriment of a care with the Borg scale and not HR work.

In case 2, the expert, based on information obtained from the patient, opted for the treadmill rather than the bike [19], but the ID, while proposing higher value which realizes the treadmill it, also elected the bicycle as an option. This is because for the ID there is a contraindication to prevent the person from doing bicycle, and only values the use of the treadmill by the patient's condition as favorable for further improvement when using the treadmill. The specialist professional unconsciously and routinely chooses the treadmill over the bike, forgetting that this is also a treatment option in some moments [20]. Since the patient has no inspiratory muscle weakness, both the expert and the ID do not suggest the use of IMT [18, 19].

In the third case, the instability presented by the patient is so great that the expert believed that the risks outweighed the benefits and chose not to indicate the CPMR. The expert guided the patient to return to the doctor and redo the query to stabilize her clinical condition, and then return to CPMR only after that [20,21]. The proposed ID according to the consensus of cardiac rehabilitation when informed with the information available on the patient also indicated that the ideal choice is to not perform CPMR at the moment [8, 10, 11, 14, 16, 22].

In the present study, we attempted to integrate the information obtained in the consensus guidelines, the current scientific literature, and the data obtained in a cohort of patients with the interpretation by experts in order to propose a model to implement a ID. This method explains all the relationships between the predictors and outcomes in a graphical model that incorporates uncertainty through the conditional probability associated with each node [21, 23-25].

The ID subsequently provides the possibility to interpret the relations between the variables and the possibility of intervening in the one that is actually negatively influencing the others. Despite the complexity of interactions, the model obtained in the implementation of an ID seems to be able to adequately describe the relations among the variables.

We understand that the BN and ID can be used in decision support systems in the CPMR. The influence diagram, which is a BN modified [22] for decision making, can provide the necessary tools to generate ideas about the decisions to be made [24, 25].

After defining the outcomes to be considered and the observed frequencies, the ID was modeled to support decision making regarding two moments in the CPMR process. At first, the ID was modeled to help decide whether the patient should perform CPMR. In a second stage, another ID was modeled so that if the answer to the first is "YES", the patient performs CPMR, while the second ID should help to define the modalities of CPMR and what type of equipment and training are best recommended to the studied patients.

Our study was limited regarding validation and statistical analysis of the first ID, since it considers the variables from medical records prior to CPMR and this information was not available in the databank. The databank was exclusive for patients already assigned to CPMR, and theoretically the first ID answered “yes” to follow to the second propagation.

It is expected to continue in the evolution of this research and to associate the ID built to the Simulator of Clinical Cases in Health, in order to obtain a tool to be used in cardiac rehabilitation classes. We also intend to develop an application software for smartphones based on this ID, and make it available to academic students of physical therapy to assist in the learning of phase II CPMR.

Furthermore, our research group aims to improve the development of this ID for CPMR and to develop an ID that addresses all phases of CPMR.

Our group will continue with this form of work and wants to further address the temporal matter. The temporality of the relations between the nodes of the BN is known and generates problems in building them due to false causal effects.

This difficulty is already known and described, and is especially important for networks that express this type of causal relationship between variables (nodes) over time. However, causality can arise from multiple contexts where every node has an influence on a child node. The structural contingencies that may modify these influences, if modified over time, make it more difficult to adequately represent the knowledge in the form of a BN. Many clinical decisions have temporal relationship. Appropriate measures in the initial phase of a condition may be inadequate in the late phase, and vice versa.

Conclusion

It is believed that the ID can significantly contribute to the construction of knowledge, assist in the decision making process and encourage future physical therapists to associate health with biomedical informatics.

Despite the complexity of the interactions, the model for the implementation of the ID seems to be able to predict the scenarios in which the new variables can be incorporated or analyzed, contributes in the health customization process, and ultimately provides a second opinion for the health professional helping the diagnostic, therapeutic process and decision making of the physiotherapist.

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