Multivariate determinants of self-management in Health Care: assessing Health Empowerment Model by comparison between structural equation and graphical models approaches.

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ABSTRACT

BACKGROUND: In public health one debated issue is related to consequences of improper self-management in health care. Some theoretical models have been proposed in Health Communication theory which highlight how components such general literacy and specific knowledge of the disease might be very important for effective actions in healthcare system.

METHODS: This paper aims to investigate the consistency of the Health Empowerment Model by means of both a graphical models approach, which is a "data driven" method and a Structural Equation Modeling (SEM) approach, which is "theory driven", showing the different information pattern that can be revealed in a health care research context.

The analyzed dataset provides data on the relationship between the Health Empowerment Model constructs and the behavioral and health status in 263 chronic low back pain (cLBP) patients. We used the graphical models approach to evaluate the dependence structure in a "blind" way, thus learning the structure from the data.

RESULTS: From the estimation results dependence structure confirms links design assumed in SEM approach directly from researchers, thus validating the hypotheses which generated the Health Empowerment Model constructs.

CONCLUSIONS: This models comparison helps avoiding confirmation bias. In Structural Equation Modeling, we used SPSS AMOS 21 software. Graphical modeling algorithms were implemented in a R software environment.

Key words: SEM, graphical models, health empowerment, dependence

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INTRODUCTION

Self-management in patients with chronic conditions is increasingly becoming a health care issue [1]. The literature indicates that improper self-management leads to negative consequences. For example, medication non-adherence is associated with worsening of health outcomes and increased costs for the healthcare system [2, 3 and 4]. To properly address this issue, health status predictors must be understood and theorized in an operative model, defining future health care interventions.

The aim of the paper is to address the complexity of data coming from the health empowerment model by means of two different statistical approaches to data: SEM and graphical models. The comparison between these two models highlights different dependence structures coming from data-driven rather than hypothesis-driven perspectives.

The data set used in these statistical analyses comes from one of such projects. Its aim is to validate the Health Empowerment Model by Schulz and Nakamoto [5] in a chronic low back pain (cLBP) patients population.

Our conceptual framework includes two major constructs: empowerment and health literacy. We draw on the concept of psychological empowerment from the management literature. This perspective highlights the subjective experience of empowerment. Spreitzer [6] identifies in her measure of empowerment four constructs inherent in organizational empowerment: meaningfulness (or relevance), self-efficacy (or competence), self-determination (or choice) and impact [6]. These four cognitions can be summarized in the following four propositions: "I feel that doing this is relevant for me", "I am able to do this", "I can choose between different ways", and "I can make a difference". Within our context, these four propositions reflect individual orientations in dealing with a specific health condition as specified in cognitive literature (se from [7] to [17])

The literature on the second key construct of our study, health literacy, focuses on education as a key to health promotion and disease prevention [18]. For example, the idea of the "expert patient," which emerged recently in UK health policy, describes a patient who is well informed or has access to crucial information regarding his or her own health conditions [19]. Information allows patients to become responsible for their own health, doing activities such as: recognizing their own symptoms, managing acute episodes, using medications, interacting with healthcare providers, seeking information and using community resources [1], both psychologically and situationally empowered.

We intend to use three screening questions developed by Chew et al (2008) [20]. Previous studies have shown that these screening questions are highly correlated to the S-TOEFLA, the traditional test of health literacy. The Italian version of the S-TOEFLA has been validated in a previous study [21]. In this project we will use the Italian version of Chew's screening questions (Schulz et al., under review). In our study we also included measurements regarding declarative, procedural knowledge of the study participants, as well as their judgment skills. Traditional analyses of health literacy focus on basic reading and numeracy skills; however, a literate health consumer needs knowledge beyond these basics [18]. Nutbeam [18] distinguishes this basic, or functional literacy, from communicative/interactive literacy and critical literacy, which involve skills that allow a person to derive meaning from available information, and to use that information to exercise greater control of and responsibility for his or her health. Schulz and Nakamoto [22] seek to clarify the skills and information needed to attain these forms of literacy, suggesting the need to recognize declarative knowledge, e.g. information about health and medicine, and procedural knowledge, i.e. rules guiding reasoned choice about the proper course of action, and finally judgment skills [22]. In order to participate in the manner envisioned for an expert patient, judgment skills are needed, relating both declarative and procedural knowledge to personal experiences and goals. Therefore, we incorporate in our model literacy components, specifically declarative and procedural knowledge in the relevant health domain as specified in Table1.

The Health Empowerment Model theorizes specific relationship among these components, patients' management of cLBP and their health status. They can be summarized in different hypotheses as described in Table 2.

The proposed "theory driven" approach can be visualized in Figure 1.

TABLE 1

LITERACY COMPONENTS
Declarative knowledge: denotes all factual knowledge that patients could acquire via different information sources, such as: health professionals, mass media, colleagues, relatives and friends. This type of knowledge is that which can be expressed verbally, and is basic in learning how to approach a health condition.
Procedural knowledge (or know-how): it was introduced by the philosopher Gilbert Ryle, distinguishing between knowledge in the sense of "knowing that" and "knowing how" [23] and investigating ability to conduct a certain activity. A similar distinction is drawn in the psychology literature as "declarative knowledge" versus "procedural knowledge" [24] and in a related vein "explicit knowledge" versus "implicit" or "tacit knowledge" [25, 26], recognizing that procedural knowledge cannot be verbalized. It is procedural knowledge that enables a person to use information in a specific context and that governs the skilled performance of tasks (in this case relative to the management of health conditions).
Judgment Skills. When confronted with different or novel aspects that appear in everyday life, patients can manage them due to the acquired skill that allow them to judge on the basis of factual knowledge. Therefore, they become autonomous in dealing with new situations. It goes without saying that this often requires practice, time, and also initial support from health professionals. For that reason, integral to our model is patients' progression in managing disease. This progression and acquiring performance skill is an integral part of patients' perceived empowerment.

TABLE 2

HEALTH EMPOWERMENT MODEL HYPOTHESES
H1: The more knowledgeable a patient is, the higher the level of physical exercise.
H2: The more knowledgeable a patient is, the lower the level of medication intake.
H3: The more knowledgeable a patient is, the lower the level of medication misuse.
H4: The more empowered a patient is the higher the level of physical exercise.
H5: The more empowered a patient is, the lower the level of medication intake.
H6: The more empowered a patient is, the lower the level of medication misuse.
H7/8: The higher the level of physical exercise, the lower the level of pain intensity and disability.
H9/10: The higher the level of medication intake, the higher the level of pain intensity and disability.
H11/12: The higher the level of medication misuse, the higher the level of pain intensity and disability.

METHODS

Participants

A sample of 263 cLBP patients participated in a cross-sectional study between January and August 2012 in Lombardy (Italy), the Italian-speaking canton of Ticino, and the French-speaking cantons of Geneva, Friburgo and Vaud (Switzerland). Patients were eligible for participation in the study if they were aged 18 or older, if they had suffered from cLBP for at least three months, if their pain was not caused by cancer, systematic inflammatory disease, or FMS, and if they had sufficient knowledge of Italian. Data on both outpatients and inpatients were collected. Patients signed an informed consent before they completed a self-administered paper-and-pencil questionnaire. An assistant was present to clarify any comprehension problems. This procedure was approved by the ethical committee of the canton of Ticino.

Measures

The self-administered paper-and-pencil questionnaire contained measures based on patients' self-report. Since none of the measures were previously translated and validated in Italian or French, the questionnaire was translated and back-translated by two independent bilingual translators for each

FIGURE 1

HYPOTHESES SYSTEM IN HEALTH EMPOWERMENT MODEL

language, i.e. English-Italian, English-French, to assure linguistic validity [27, 28]. Prior to data collection, the questionnaire was pre-tested in five cLBP patients and assessed by one healthcare provider for face and content validity. The included measures were as follows.

Health knowledge was measured with twelve questions taken from the Low Back Pain Knowledge Questionnaire [29] and based on information from cLBP web sites. Questions addressed both declarative and procedural knowledge related to symptoms, causes, treatments, and the management of cLBP. Each question was followed by a set of four response possibilities and an "I don't know" option. Correct responses were coded as 1 and incorrect responses as 0. The final value was obtained by a mean score calculation with a theoretical range from 0 (no correct response) to 1 (all correct responses).

Psychological empowerment was measured with the Psychological Empowerment Scale, developed and validated by Spreitzer [6] for use in workplace settings. Incorporating multidimensionality in the concept, the scale consists of three items for each of the four sub-dimensions: meaning, competence, self-determination, and impact. The scale was adapted to the context of cLBP and its management. Patients responded on a Likert-scale ranging from 1 (strongly disagree) to 7 (strongly agree), with higher values suggesting higher levels of psychological empowerment.

Management of cLBP was assessed with three indicators. Two indicators assessed patients' medication use: frequency of medication intake in a normal week (number of days) and medication misuse measured with 22 statement items from the Pain Medication Questionnaire [30]. All statement items were followed by a 5-point Likert-scale. Three items were reverse formulated and recoded before calculating a mean score that ranged from 0 (no medication misuse) to 5 (high medication misuse). The third indicator of cLBP management was physical exercise in leisure time measured with the respective sub-dimensions of the Short Questionnaire to Assess Health-Enhancing Physical Activity [31]. A composite score was calculated for the amount of time spent on physical exercise (hours) per week.

Health status was measured with six items from the Chronic Pain Grading Scale [32]. Three items measured pain intensity on an 11-point Likert-scale ranging from 0 (no pain) to 10 (pain as bad as it could be). Another three items measured pain disability on a 11-point Likert-scale ranging from 0 (no interference/ no change) to 10 (unable to carry on activities/

extreme change). Higher values imply worse health status.

The questionnaire also assessed socio-demographics, such as gender, age, highest educational attainment, the number of years patients have been affected by cLBP, and whether respondents were out- or inpatients. These measures served the description of the final sample and, if necessary, as covariates.

Structural Equation Modeling approach

Structural equation models (SEM) are the natural approach to analyze data in a questionnaire, where continuous latent structures are assumed to cause certain patterns in the data.

This family of statistical methods offers different ways to treat latent variables, depending on the nature of observed data. In this study, we worked with continuous data. We also considered Likert-scale, a psychometric scale commonly involved in research that employs questionnaires, as continuous. This might be debatable from a strictly statistical point of view, but it is consistent with SEM literature that considers Likert to be continuous (which does not necessarily mean Gaussian) whenever kurtosis and skewness values range within standard boundaries, and use the appropriate estimation method. For this reason the scales whose kurtosis and skewness fell within the standard boundaries were retained in our model.

SEM are becoming the leading multivariate approach in psychology and social sciences in general [33], due to their interpretability and potential in visualizing the relationships between variables. SEM graphical representations follow the notation of path analysis, developed around 1918 by geneticist S. Wright. According to this notation, rectangles represent observed variables, while unobserved structures are identified by circles. The arrows represent regression relationships between variables and different letters are used to denote endogenous or exogenous variables. The latter terms in causality models are the equivalent of dependent and independent variables in a multiple regression framework.

Since the model requires data augmentation due to the unobserved variables, SEM analyses are divided into two parts: a measurement model and a structural or causal one.

The dataset was large enough to allow for listwise deletion of the missing values.

An exploratory factor analysis (EFA) was conducted on the whole dataset, as well as a reliability assessment of the Likert scales in the questionnaire. Only a few items were kept for each assumed latent variable, and the measurement model was hypothesized in the form of a confirmatory factor analysis (CFA). EFA and CFA differ in both the assumptions and estimation methods. In a CFA framework [34], specific assumptions on the number of factors, on the relations between them, and on the items defining each factor are precisely stated according to existent theories, EFA or the characteristics of the experimental design. This, along with the other required SEM assumptions, motivated the following comparison with graphical models, which are basically data driven.

Moreover, in the measurement model, some parameters are fixed and some are free to be estimated again, according to pre-existing theories. The solution of such estimation, compared to that of EFA, is unique.

The second part of SEM is the structural model, consisting of a system of related equations that describe the direct and indirect effects of exogenous latent factors on endogenous ones.

Although the solution will be visualized by means of a graph, it is possible to state the analytical specification of the graphical model. Using the notation of multivariate regression model, we indicate exogenous variables with X and endogenous ones with Y. In a matricial form the two different measurement models are stated in Equation 1 and Equation 2, respectively for X and Y,:

$$\boldsymbol{X} = \boldsymbol{\Lambda}_x \boldsymbol{\xi} + \boldsymbol{\delta} \quad (1)$$

$$\boldsymbol{Y} = \boldsymbol{\Lambda}_y \boldsymbol{\eta} + \boldsymbol{\epsilon} \quad (2)$$

According to our dataset, $\boldsymbol{X}$ is a vector containing the items related to self-determination, competence, impact and health knowledge, and $\boldsymbol{Y}$ a vector containing the items related to physical exercise, medication misuse and intake, pain intensity and disability. δ and η refer respectively to exogenous and endogenous latent variables, while δ and ε refer to the measurement errors. Furthermore, $\boldsymbol{\Lambda}_x$ and $\boldsymbol{\Lambda}_y$ are matrices of loadings of $\boldsymbol{X}$ on $\boldsymbol{\xi}$ and $\boldsymbol{Y}$ on η, while Θ_{δ}

and Θ_ε refer to the covariance matrices of the two measurement errors.

The assumptions of the measurements model mainly concern the absence of correlations between factors and related errors, and between $\boldsymbol{\delta}$ and $\boldsymbol{\varepsilon}$. No assumptions are made on the correlations among $\boldsymbol{\delta}$ and among $\boldsymbol{\varepsilon}$, allowing for the modeling of panel data.

The structural part of the model is summarized by Equation 3:

$$\boldsymbol{\eta} = \boldsymbol{B\eta} + \boldsymbol{\Gamma\xi} + \boldsymbol{\zeta} \quad (3)$$

η is a vector, containing the unobserved structures related to empowerment and health knowledge, and $\boldsymbol{\xi}$ is a vector containing the unobserved structures related to medication misuse, physical exercise and pain. Furthermore, $\boldsymbol{B}$ and $\boldsymbol{\Gamma}$ are matrices of structural coefficients reffering to the relations among some of the endogenous latent variables, and between endogenous and exogenous latent variables, while $\boldsymbol{\zeta}$ is a vector containing errors. Finally, $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ are the covariance matrices between exogenous variables and between errors respectively.

The assumptions of the structural model concern the absence of correlation between exogenous variables and error, the non-singularity of matrix I - $\boldsymbol{B}$ and the null diagonal of $\boldsymbol{B}$.

A very important issue when dealing with SEM is the identification of the model, which can be achieved through the *two step rule*, a sufficient but not necessary condition for identification [35]. In our model such rule cannot be used, since errors related to pain intensity and disability, and to medication misuse and intake are not constrained to zero. This implies a non-diagonal $\boldsymbol{\Psi}$. Therefore, the identification of the model was estimated empirically.

Another core issue of SEM is to choose the fit function for the estimation of unknown parameters; in particular, for the purpose of our project, the estimation of the relations among unobserved latent variables.

The purpose of the estimation process is to minimize the fit function. In our case, it was chosen in order to perform generalized least square estimation, since the observed variables cannot be assumed to be normally distributed as in maximum likelihood estimation, but they show no excessive kurtosis.

The drawbacks of SEM, compared to data-driven models are the massive combination of structural assumptions, which lead to strongly theory-driven models, and the difficulty in the adoption of selection methods for the best fit. However, SEM are well accepted and powerful models for the analysis of Likert-scale questionnaires and a broad range of indices exist for the assessment of SEM goodness of fit. In particular, when the purpose is the confirmation of a pre-existing theory, as is the case of the Health Empowerment Model, these tools offer a more adequate framework for a precise and statistically sophisticated analysis of latent structures and their relations.

GRAPHICAL MODELS APPROACH

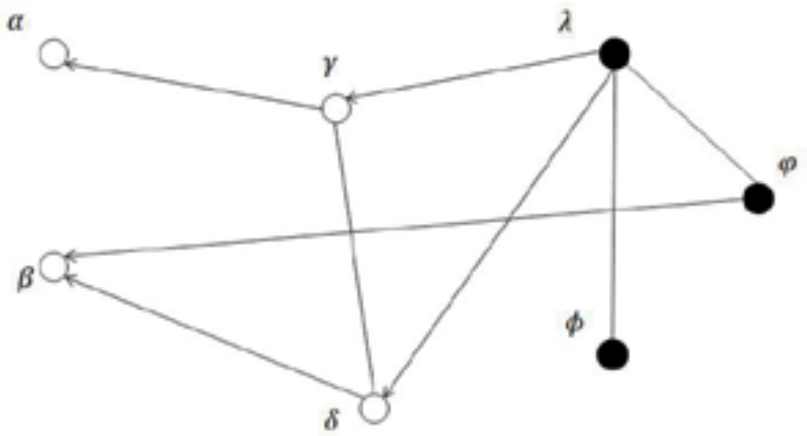
The graphical model approach presents an alternative to SEM. This focuses on the possibility of describing diagrammatically the complex set of relations and dependencies among different variables. Graphical chain models [36] allow for the representation of all these variables by means of a single graph, which in addition emphasises the dependence structure of the variables. Before defining a graphical chain model, it is necessary to give some preliminaries on graphs.

A graph is a pair *G=(V, E)*, where V is the set of vertices, $V=\{1,\ldots,q\}$, and E is the set of edges, that is a subset of the set VxV of ordered pairs of distinct vertices, $E \subseteq V \times V$. The vertices are associated with random variables, while an edge linking two nodes represents an association or causality relationship between the variables corresponding to the nodes. The edges may be of two different kinds: indirect edges (lines) to represent association and direct edges (arrows) to represent causality. Since the analysis of a multifactorial disease involves both discrete and continuous variables, in the following we will deal with marked graphs: graphs whose vertex set is partitioned in two groups D and G, denoting the discrete and continuous vertices respectively. Discrete vertices are represented by dots, while continuous vertices are represented by circles.

A *chain graph* is a graph where the vertex set V can be partitioned into subsets (chain components or blocks) V1,...,Vk, such that the nodes belonging to the same block are joined by lines, and variables belonging to different

FIGURE 2

MARKED CHAIN GRAPH



blocks are joined by arrows. For an example, see Figure 2.

When two nodes, g and d, are joined by an edge, then X_γ and X_δ, i.e. the variables associated with the nodes, can be considered on an equal footing, and attention is focused on the association between them. When two nodes, δ and b, are connected by an arrow as in Figure 2, we say that X_δ is the *parent* of X_β and X_β is the *child* of X_δ. In this case a causal relationship between X_δ and X_β is postulated. Since chain graphs contain both direct and indirect edges, they represent at the same time and by means of one single picture the association structure and the causal relationships.

To find the appropriate chain graph we used the R software (version 2.15.3), specifically a package called gRapHD [37].

The algorithm implemented in the gRapHD package is the extended Chow-Liu algorithm, to find the maximum likelihood tree model for multivariate mixed data[38, 39 and 40].

In modern terminology, tree models are discrete graphical models whose graphs are trees. Trees and forests are special cases of acyclic undirected graphs.

The problem of finding such trees can be reduced to the computationally easier search of the maximum weight spanning tree, using the Kruskal algorithm to find it. This starts with the null graph and successively selects edges {e1, …, er}. If edges e1, …, ek have been selected, the algorithm selects a new edge e such that:

i) $e \notin \{e_1, \ldots, e_k\}$ $\{e_1, \ldots, e_k, e\}$ and is a forest, and

ii) e has maximum weight among all edges satisfying i)

This algorithm can be extended in various ways to apply it to mixed discrete and continuous data . By modifying the weights appropriately, it can be adapted to find the minimal AIC or BIC forest, by limiting the search space in i) to strongly decomposable forests (with no paths between non-adjacent discrete nodes passing through continuous ones). Restricting search space to a decomposable model corresponds to an improved computational efficiency.

Once the minimal BIC forest is found, another function in the same package implements forward search through decomposable models to minimize BIC. At each step, the edge giving the greatest reduction in BIC is added.

RESULTS

Health Empowerment Model and SEM

The following results refer to the SEM performed to validate the Health Empowerment Model, according to the twelve hypotheses listed in Section 1.

We started from the model with all the latent factors defined in section 1, and we checked for significance of the coefficients and for the main goodness of fit indices. We selected the best model in terms of goodness of fit, also adopting the modification indices

approach. A modification index is a univariate Lagrange Multiplier, in this case expressed as a chi-square statistic with a single degree of freedom, or X^2 (1). The value of an LM, in the form of a modification index, *estimates* the amount by which the overall model chi-square statistic, X^2_M, would decrease, if a particular fixed-to-zero parameter was freely estimated. That is, a modification index *estimates* X^2_M (1) for adding a single path. Thus, the greater the value of a modification index, the better the predicted improvement in overall fit if that path was added to the model. Likewise, a multivariate LM estimates the effect of allowing a set of constrained-to-zero parameters to be freely estimated. Amos allows the user to generate modification indexes for specific parameters, which lends a more a priori sense to this statistic. Figure 3 and Table 3 below show the features of the selected model.

As shown in Figure 3 and Table 3, health knowledge does not significantly predict physical exercise (p=,161). Thus, H1 cannot be confirmed. H2 and H3 cannot be confirmed. Health knowledge in the SEM model presents the mean of twelve variables (know01, know02, etc.) as described in Section 2. This could bias the significance of the regression coefficient.

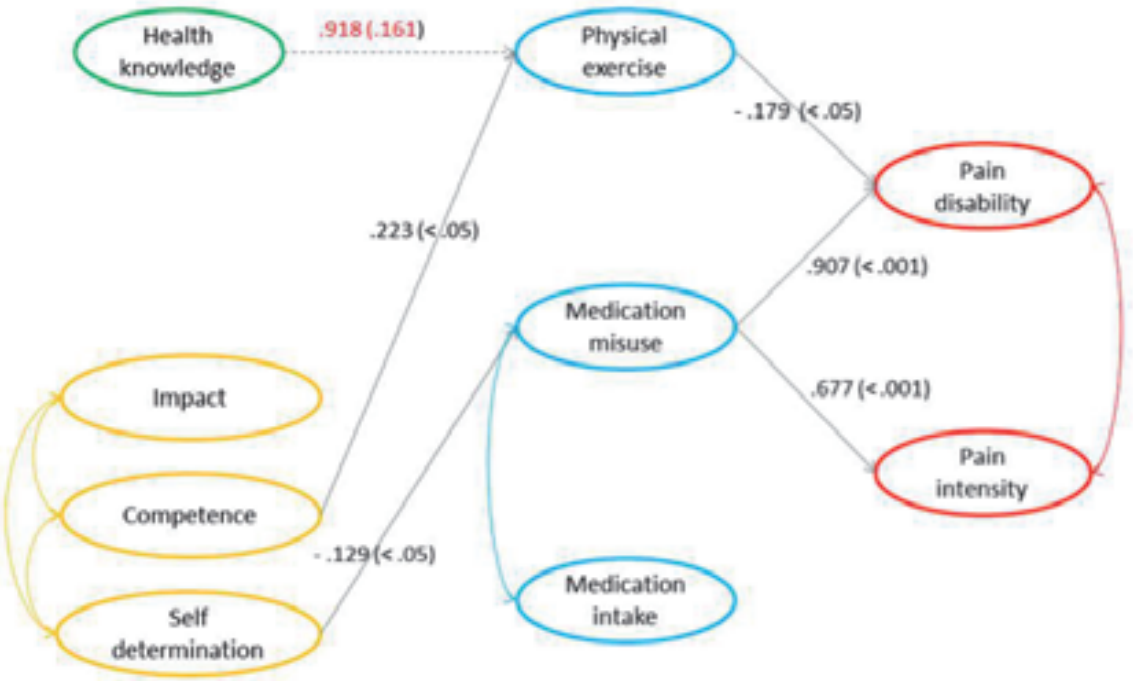
The other hypotheses [H5-H12] are all confirmed by significant regression weights. Results show that higher levels of competence, impact and self-determination correspond to a lower level of medication intake, a higher level of physical exercise (p<,05) and a lower level of medication misuse (p<,001). A higher level of physical exercise, corresponds to lower levels of pain intensity and disability (p<0,5). The higher the levels of medication intake and misuse, the higher the level of pain intensity and disability (p<,001).

In conclusion, the only non-significant coefficient turns out to be coefficient of the regression of physical exercise on knowledge.

With regard to the goodness of fit issue, we used Chi-square which was significant. Although for models with about 75 and less than 200 cases the Chi square test is a reasonable measure of fit, however for models with larger number of cases (above 200), the chi square is almost always statistically significant and unreliable. Moreover, Chi square is also affected by the size of the correlations in the model: the larger the correlations, the poorer the fit which is the case in our analyses. A key

FIGURE 3

HEALTH EMPOWERMENT MODEL SEM RESULTS



consideration in the choice of a fit index is the penalty it places for complexity. That penalty for complexity is generally measured by how much chi square needs to change for the fit index not to change. This is the case for the Bentler-Bonett Index and other comparative fit indeces (CFI). In fact, one of the most used fit measures is the RMSEA. If X^2 is less than df, then the RMSEA is set to zero. Its penalty for complexity is the chi square to df ratio. The measure is positively biased (i.e., tends to be too large) and the amount of the bias depends on smallness of sample size and df, primarily the latter. A key advantage of the RMSEA is that confidence intervals can be constructed around the point estimate because the RMSEA asymptotically follows a rescaled noncentral X^2 distribution for a given sample size, degrees of freedom, and noncentrality parameter [41]. Thus, we reported the RMSEA index, together with the PCLOSE measure which provides a one-sided test of the null hypothesis that the

TABLE 3

HEALTH EMPOWERMENT MODEL SEM ESTIMATION RESULTS AND GOODNESS OF FIT INDEX

			ESTIMATE	S.E.	C.R.	P	LABEL
Misuse	←	selfdet	-,129	,059	-2,192	,028	
Exercise	←	compet	,223	,110	2,040	,041	
Exercise	←	health	,918	,655	1,401	,161	
Painint	←	misuse	,677	,162	4,171	***	
Paindis	←	misuse	,907	,214	4,241	***	
Paindis	←	exercise	-,179	,078	-2,299	,021	
paindisability02	←	paindis	1,033	,085	12,176	***	
painintensity02	←	painint	,907	,120	7,536	***	
paindisability03	←	paindis	,984	,083	11,826	***	
paindisability01	←	paindis	1,000				
painintensity03	←	painint	1,267	,146	8,675	***	
painintensity01	←	painint	1,000				
medsmisuse12	←	misuse	1,000				
medsmisuse09	←	misuse	,892	,110	8,076	***	
medsmisuse07	←	misuse	,792	,101	7,813	***	
medsmisuse04	←	misuse	1,066	,119	8,980	***	
competence01	←	compet	1,167	,103	11,334	***	
selfdetermination03	←	selfdet	1,335	,111	12,050	***	
selfdetermination02	←	selfdet	1,258	,119	10,614	***	
selfdetermination01	←	selfdet	1,514	,110	13,745	***	
impact03	←	imp	1,533	,103	14,828	***	
impact02	←	imp	1,453	,109	13,367	***	
impact01	←	imp	1,535	,098	15,614	***	
competence02	←	compet	1,506	,108	13,894	***	
medsintakefreq	←	intake	1,000				
phys_ex	←	exercise	1,000				
health_know	←	health	1,000				
MODEL	RMSEA	LO 90	HI 90	PCLOSE			
Default model	,047	,036	,057	,698			
Independence model	,084	,076	,092	,000			

RMSEA equals .05, which is called a close-fitting model.

HEALTH EMPOWERMENT AND GRAPHICAL MODELS

With SEM, we analyzed data on the Health Empowerment Model by testing the dependencies and links imposed by the researchers, in terms of outcome variables and explicative variables. This can be called a "theory driven" approach.

With Graphical Models, we showed results based on the data without assuming any dependence, thus learning about the real structure and relationships among the constructs of the Health Empowerment Model directly from the data. This is the so-called "data driven" approach. Although graphical models deal with conditional dependence rather than causality, chain graph models allow dividing variables in blocks whose mutual ordering may be consequently user defined. The aim of the analysis is to model the data while respecting some constraints (block ordering) that must be consistent with the main fundamentals in Health Empowerment frameworks, without any assumption of an order within each block.

This proved to be the right choice since our work concerns the validation of a pre-existing theory according to which three blocks are defined and relate in a precise causal fashion.

The chain graph shown in Figure 4 was constructed using two graphical models: the first is for the block of variables related to incorrect medication use and physical exercise (sky blue), and health knowledge (green), given the block of psychological empowerment (white); on the other hand, the second is for pain measurements (red) given the former block.

To model the distribution of the block for misuse, physical exercise and health knowledge conditional on the block of psychological empowerment variable, we focused our attention on graphs in which all variables are connected in the latter block. As initial model we set the forest containing this complete sub graph and associated with the minimum BIC, and from this graph started to find the minimum BIC decomposable model through a forward selection process.

The model for conditional distribution in the pain block, given the other variables, is built following the same approach: we found the minimal forest and then used this as the initial model in a forward selection process. As mentioned above, we restricted the search space to conditional models by connecting all prior variables in the models considered and, through the forward selection process, we found the decomposable model with minimum BIC in this search space.

According to a recursive procedure, which starts from these two graphs, we finally built the final chain model by adding those edges in the second that have a vertex in the pain block to the first graph. This model is displayed in the plot below.

As expected, the block of variables related to wrong beliefs on how to decrease back pain are well connected and they directly influence both the attitude to physical exercise of patients and their medication intake. This latter variable seems to play a central role in the model, since it is connected both to all variables concerning the misuse of medications and to the block of pain intensity and disability. More specifically, the block of pain variables is independent from both the block of empowerment and the block of medication misuse.

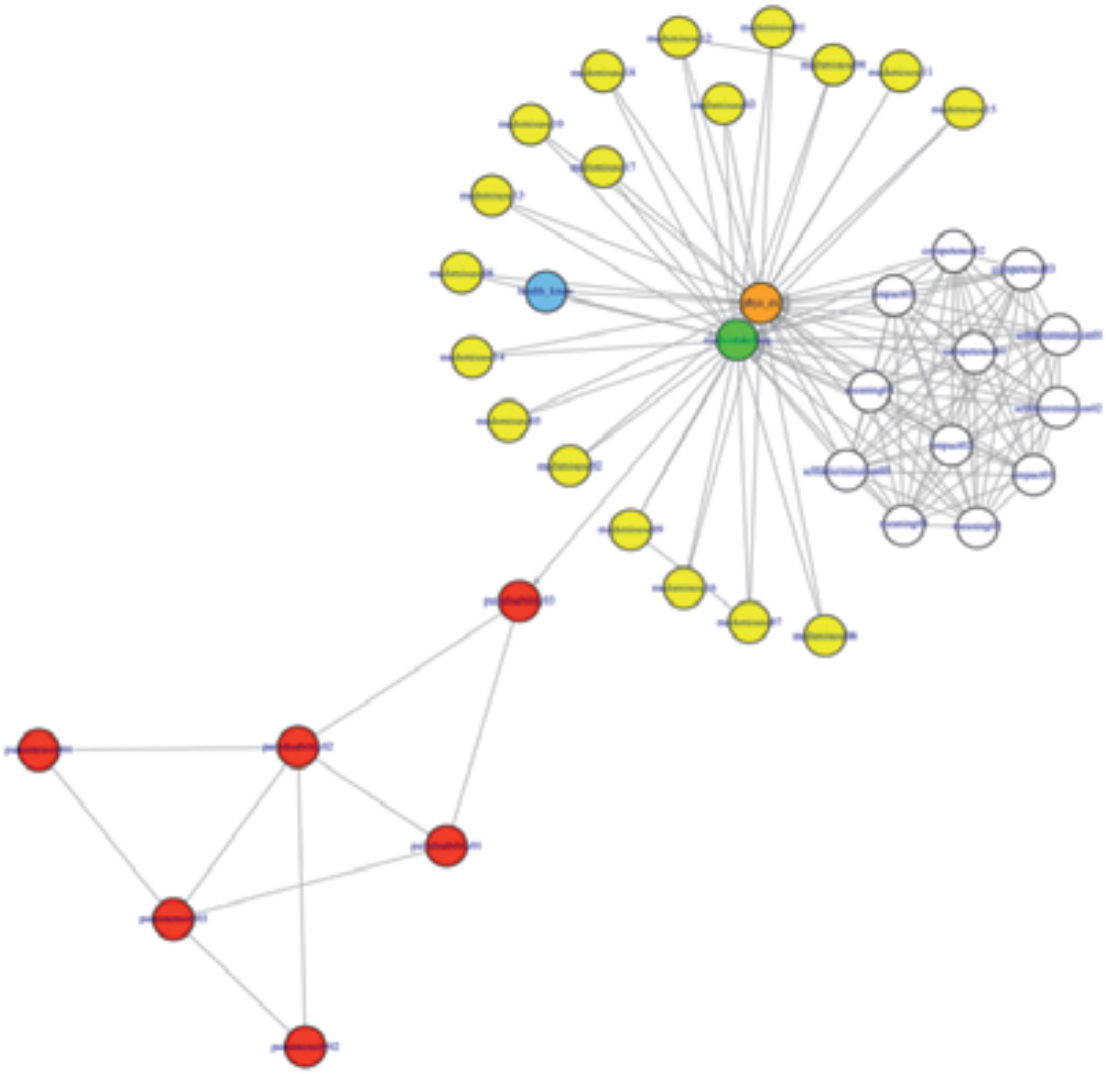
Moreover, it is interesting to notice the directed arrows from health knowledge to medication intake and physical exercise. They confirm some of the hypotheses underlying the empowerment model that were not validated by the SEM, and the conditional independence of physical exercise and health knowledge from the block of pain, given medication intake.

DISCUSSION

The purpose of this work was to explore and validate the health empowerment model, as an important theoretical setting to investigate self-medication and to better understand the line of intervention in healthcare. To this end, we used data from a study involving patients who suffered from lower back pain. In order to draw more accurate information from these data, we compared two statistical approaches that are set in completely different statistical perspectives. In fact, SEM is the most common model used in social sciences to investigate relationships among variables, defining dependent latent factors. It requires a strong initial assumption of the model. On the other side, graphical models

FIGURE 4

HEALTH EMPOWERMENT MODEL GRAPHICAL MODEL RESULTS



let the data "decide" what are the significant connections between variables, without resorting to latent structures.

In both cases, most of the crucial hypotheses of the health empowerment model were confirmed, with the exclusion of the meaning block in SEM, leading to a weakening of the empowerment concept. Results suggest that there is a significant relationship between the block of empowerment variables and medication habits, and between this latter and the block of pain variables. Health knowledge is slightly connected in the graphical model, and a non-significant variable in SEM, since the p value associated with the coefficient representing the causal relationship between this variable and physical exercise is above 0.15.

The advantages of SEM over the more flexible chain graph model are its fewer computational demands and more straightforward implementation and interpretation. These qualities have made SEM very popular in psychometric literature. SEM assumes the latent structure underneath the item responses, which is also a broadly accepted methodology when Likert-scales are used. On the other hand, the mixed graphical models described are a very flexible tool to explore dependencies among the whole set of items, and treats them as discrete variables in accordance with their nature.

These methods could be seen as complementary if we consider a two stage model. The first stage where a graphical model is implemented to explore the dependencies among the variables, either continuous or discrete, and the second one where, exploiting both the prior assumptions of the phenomenon and the explorative suggestions, where the latent structures underneath the ordinal data and their relations could be inferred through a SEM. In addition, as we noticed in our empowerment model, some relationships which were not significant in the SEM were caught by the search algorithm in the graphical model. Therefore, a more precise and interesting conclusion can be drawn by a joint look at the two methods. To this extent, graphical models can also be seen as hypothesis generating approach. With respect to a SEM approach, graphs can be interpreted using conditional distributions, so that we can better address connections between the mathematical framework and causality. Indeed, causal relationships cannot be inferred from a data set by running regressions and association analysis like in SEM, unless there is substantial prior knowledge about the mechanisms that generated the data.

According to this idea, we could conclude that, combining information arising from both SEM and the graphical model, the causality among the three blocks can be investigated. As main result health knowledge, which was not significant in SEM, is connected both to medication intake and physical exercise in the graphical model, confirming the a priori health empowerment model assumptions. Regarding the Health Empowerment Model we conclude that both volitional and cognitive components have a significant impact on patients' health status. Patients' perceived self-determination does translate to lower levels of medication intake and misuse, and their perceived competence impact physical exercise; both, increased level of physical exercise and reduced medication misuse lead to an improved health status of patients, indicated by a lower level of pain disability as well as pain intensity. The conditional role of health knowledge as it emerges in the graphical models approach is particularly interesting.

Further analyses could help to clarify the dependence structure connecting health knowledge and empowerment to volitional components.

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