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Linking Bayesian networks and PLS path modeling for causal analysis

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ABSTRACT

Causal knowledge based on causal analysis can advance the quality of decision-making and thereby facilitate a process of transforming strategic objectives into effective actions. Several creditable studies have emphasized the usefulness of causal analysis techniques. Partial least squares (PLS) path modeling is one of several popular causal analysis techniques. However, one difficulty often faced when we commence research is that the causal direction is unknown due to the lack of background knowledge. To solve this difficulty, this paper proposes a method that links the Bayesian network and PLS path modeling for causal analysis. An empirical study is presented to illustrate the application of the proposed method. Based on the findings of this study, conclusions and implications for management are discussed.

1. Introduction

In recent years, knowledge management and related strategy concepts are often promoted as important components of organizations' survival strategies (Martensson, 2000). Knowledge management is regarded as a key source of sustainable competitive advantage (Holsapple & Singh, 2001; Liao, 2003), and is also seen as playing a fundamental role in the process of transforming individual knowledge into organizational knowledge (Liebowitz, 2001).

Knowledge is generally considered as intangible, and is difficult to measure, but it is generally accepted that it sometimes increases through use (Wiig, Hoog, & Spek, 1997). More importantly, for the purpose of advancing the quality of decision-making and thereby facilitating a process of transforming strategic objectives into effective actions, causal knowledge based on causal analysis is needed (Lin & Wu, 2008; Nadkarni & Shenoy, 2004; Tan & Platts, 2003). Several creditable studies have placed emphasis on the usefulness of causal analysis techniques. Tan and Platts (2003) conduct an appraisal of causal analysis techniques ranging from fishbone (Ishikawa) diagrams, Why/Why diagrams, influence diagrams, mind maps, to cognitive maps. In an especially relevant study, Lin and Wu (2008) implement a fuzzy DEMATEL method to produce a causal diagram. In addition, Bayesian networks and PLS path modeling are popular causal analysis techniques. Through these causal analysis techniques, causal maps can be created. Causal maps represent the causal knowledge of subjects in a specific domain, and they have been applied widely in the areas of policy analysis and management sciences to demonstrate the relationships between relevant factors, knowledge, and conditions (Nadkarni & Shenoy, 2004).

Among causal analysis techniques, the PLS path modeling is particularly famous for its successful applications in customer satisfaction analysis; both the American Customer Satisfaction Index (ACSI) and the European Customer Satisfaction Index (ECSI) were constructed using PLS path modeling. However, many researchers and experts have experienced a certain amount of difficulty regarding how to establish the causal directions between constructs, due to lack of background knowledge or previous theoretical support. To deal with this difficulty, this paper proposes using the Bayesian network prior to implementing PLS path modeling for causal analysis.

The Bayesian network is a causal map, a kind of graphical representation of an expert's knowledge, based on probability theory (Nadkarni & Shenoy, 2004). The Bayesian network enjoys the advantage that it needs no rigid statistical assumptions: it graphically displays as a directed acyclic graph (DAG), and represents a set of conditional independence constraints among a given number of variables and their related conditional probability distributions (Lauria & Duchessi, 2007). Because of the special nature and merit of the Bayesian network, the DAG can serve as a guide to help us decide the causal directions between constructs when using PLS path modeling. This paper, therefore, suggests a method that links the Bayesian network and PLS path modeling for causal analysis. An empirical study is presented to illustrate the application of the proposed method. The remainder of this paper is organized as follows. In Section 2, the proposed method is presented. In Section 3, the Bayesian network and PLS path modeling are discussed. In Section 4, an empirical study is presented by way of illustration. Finally, based on the findings of this research, conclusions and implications for management are presented.

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2. The proposed method

According to Al-Tabtabai (1998), causal knowledge is a kind of knowledge structure which is concerned with the configuration of a given system and the way its components work together to perform a specific task. Through the use of a causal analysis technique we may obtain a causal map where causal knowledge is exhibited. A causal map is a kind of compact diagram, which captures causal knowledge by picturing relationships among concepts connected with labeled arrows. It is also a method for visualizing the relationships among different concepts within a downward-branching hierarchical structure. A causal map, with its embedded causal knowledge, is an important and useful tool, because it helps us stimulate the generation of ideas, promote creativity, communicate complex concepts, and transform an individual's tacit knowledge into a team's explicit knowledge.

Lin and Wu (2008) note that: (1) cause and effect are two different concepts; (2) causes tell the reason why something happened, whereas effects are the results of that happening; and (3) to capture the cause–effect relationship is not an easy task, because the interaction between cause and effect is often complex and subtle. Fortunately, several causal analysis techniques can be used to produce causal maps (Lin & Wu, 2008; Nadkarni & Shenoy, 2004; Tan & Platts, 2003). Among them, the Bayesian network and PLS path modeling are vital, trend-setting techniques. The former is currently gaining importance as a data mining technique, while the latter is becoming popular as a modeling method.

Many studies have attempted to advance the usefulness of the Bayesian network. Barrientos and Vargas (1998) combine Bayesian networks and case-based reasoning to create a knowledge representation scheme capable of dealing with time-varying processes; Sucar and Martínez-Arroyo (1998) propose a hybrid approach for structure learning of Bayesian networks; Garside, Rhodes, and Holmes (1999) discuss the efficient estimation of missing information in causal inverted multiway trees, and propose a simplified Maximum Entropy model; Kang and Golay (1999) present a Bayesian network-based advisory system for operational availability in complex nuclear power plant systems; Nadkarni and Shenoy (2001) present a Bayesian network approach to making inferences in causal maps; Jurgelenaite and Lucas (2005) propose a method of using equivalence classes of binomial distributions as a means to define very large Bayesian networks; Viaene, Dedene, and Derrig (2005) use Bayesian learning neural networks for auto claim fraud detection; Liu, Sung, and Mittal (2006) propose a semi-fixed model to represent the gene network as a Bayesian network with hidden variables; Cho (2006) uses the linear Bayesian approach to update the distribution of activity duration; Lauria and Duchessi (2007) suggest a methodology for developing Bayesian networks; De Melo and Sanchez (2008) present a knowledge-based representation for maintenance project delays, etc.

As for PLS path modeling, it has been successfully applied to a variety of areas, such as: exploring the human side of client/server system success (Guimaraes & Igbaria, 1997); examining the impact of poor performance on risk-taking attitudes (Lee, 1997); investigating effects of source and participant anonymity and difference in initial pinions in an EMS context (Kahai, Avolio, & Sosik, 1998); performing the technological aspect of environmental scanning (Raymond, Julien, & Ramangalahy, 2001); examining the impact of shared domain knowledge and its unit structure (Ranganathan & Sethi, 2002); satisfying and retaining customers through independent service representatives (Brown & Chin, 2004); discussing the extensions of PLS path modeling (Tenenhaus, Vinzi, Chatelin, & Lauro, 2005); testing the influence of technology on user expectancies (Looney, 2006); investigating the relationship between interpersonal trust, employee satisfaction, and employee loyalty (Matzler & Renzl, 2006); defining relationship quality for customer-driven business development (Roos, Gustafsson, & Edvardsson, 2006); arguing the error term in formative measurement models (Diamantopoulos, 2006); examining the determinants of students' satisfaction and their perceived learning outcomes (Eom, Wen, & Ashill, 2006); arguing the issue of strategic sourcing (Kocabasoglu & Suresh, 2006); making decisions for resource allocation (Andreou & Bontis, 2007); assessing the performance of business unit managers (Bouwens & Vanlent, 2007); performing a modified PLS path modeling algorithm handling reflective categorical variables (Jakobowicz & Derquenne, 2007); examining the role of problem recognition and cognitive bias (Keil, Depledge, & Rai, 2007); discussing competitive and cooperative positioning in supply chain logistics relationships (Klein, Rai, & Straub, 2007); and discussing the relationships among latent variables and residuals in PLS path modeling (Vittadini, Minotti, Fattore, & Lovaglio, 2007); performing a trust-based consumer decision-making model in electronic commerce (Kim, Ferrin, & Rao, 2008); developing an index for online customer satisfaction (Hsu, 2008), and so on.

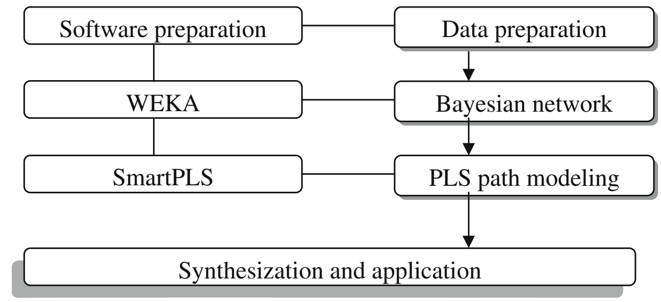

Fig. 1. Causal analysis process.

However, few studies have dealt with the issue of 'theory dependency'. Regarding theory dependency, the Bayesian network is data driven with no restrictions, while PLS path modeling is based on theory (Lauria & Duchessi, 2007). If one uses PLS path modeling in a situation lacking a previous theory, serious problems arise. For example, the task of deciding the causal direction between constructs would become excessively complicated because we need to guess at a huge number of possibilities in terms of causal directions between several constructs. To solve this problem, this paper proposes an effective way to implement the Bayesian network prior to conducting PLS path modeling. Using the proposed method, the execution of PLS path modeling, according to the DAG of the Bayesian network, can be performed smoothly and effectively. For this scenario, the proposed method is shown in Fig. 1. Before carrying out the causal analysis, software preparation is needed. For this purpose, there are a number of free software packages available, such as 'WEKA' for the Bayesian network, and 'SmartPLS' for PLS path modeling.

The proposed method for causal analysis consists of four phases: 'Data preparation', 'Bayesian network', 'PLS path modeling', and 'Synthesization and application'. Data preparation is the preparation phase, in which we are required to cleanse and format the data for the use of the chosen software. The next step is to employ 'WEKA' to obtain a DAG through Bayesian network classifiers with a search algorithm. Based on the DAG, the PLS path modeling phase can be implemented with 'SmartPLS'. Finally, synthesization and application are conducted to support better decision-making and to apply in problem-solving.

3. Bayesian networks and PLS path modeling

Popular data-mining techniques include K-means clustering, decision trees, Bayesian networks, regression models, and neural networks. Such data mining techniques are supported by the software known as 'WEKA', a package which incorporates a large number of machine learning algorithms for data mining tasks. WEKA provides a series of comprehensively practical utilities, such as: Preprocess, Classify, Cluster, Associate, Select attributes, Visualize. Among data mining techniques, the use of the Bayesian network can produce a DAG that models causal relations between attributes. Additionally, the software 'SmartPLS' excels at graphic path modeling with latent variables. As described in the SmartPLS manual, it is a software application to be used for structural equation modeling with a user-friendly graphical interface. More details are as follows.

3.1. Bayesian networks

The Bayesian network is a graphical representation of probabilistic relationships between multiple attributes/variables (Klopotek, 2002). It is more robust for inferring structure than other methods because it is better resistant to noise in data (Wang, Touchman, & Xue, 2004). Moreover, the Bayesian network incorporates probabilistic inference engines that support reasoning under uncertainty (Hruschka & Ebecken, 2007). It is an outcome of a machine learning process that finds a given network's structure and its associated parameters, and it can provide diagnostic reasoning, predictive reasoning, and intercausal reasoning (Lauria & Duchessi, 2007). A Bayesian network is a DAG that consists of a set of nodes/vertices linked by arcs, in which the nodes represent the attributes and the arcs stand for relationships among the connected attributes (Hruschka & Ebecken, 2007). In a DAG, the arcs designate the existence of direct causal relations between the linked variables, and the strengths of these relationships are expressed in terms of conditional probabilities.

Inferring Bayesian structure from expression data can be viewed as a search problem in the network space (Wang et al., 2004). Thus, to heuristically search the Bayesian network space, it is necessary to employ a variety of search methods such as: simulated annealing algorithm, genetic algorithm, tree augmented Naïve Bayes (TAN). For structure learning through Bayesian networks, the 'WEKA' offers various algorithms such as: hill climbing, K2, simulated annealing, genetic, tabu, TAN, and so on. Among these algorithms, the TAN can produce a causal-effect graph (not just a tree-like graph) in which the class attribute treated as the only and greatest parent node of all other nodes is located at the top in the DAG (Friedman, Geiger, & Goldszmidt, 1997). The causal-effect graph of the TAN is formed by calculating the maximum weight spanning tree using Chow and Liu's method (1968).

The TAN is an extension of the Naïve Bayes: it removes the Naïve Bayes assumption that all the attributes are independent. Moreover, the TAN finds correlations among the attributes and connects them in the network structure learning process. According to Friedman et al. (1997), the TAN provides for additional edges between attributes that capture correlations among them, and it approximates the interactions between attributes by using a tree structure imposed on the Naïve Bayes structure. Davis, Costa, Ong, Page, and Dutra (2004) note that (1) although the Naïve Bayes is more straightforward to understand as well as easy and fast to impart through training, the TAN, on the other hand, allows for more complex network structures than the Naïve Bayes; and (2) the TAN achieves retention of the basic structure of Naïve Bayes, permitting each attribute to have at most one other parent, and allowing the model to capture dependencies between attributes.

Bayesian network classifiers incorporated in WEKA, such as the Bayesian network with the TAN search algorithm, have exhibited excellent performance in data mining (Cerquides & De Mantaras, 2005). In fact, the conditional independence assumption of Naïve Bayes is not real, and the TAN was developed to offset this disadvantage. It does achieve a significant improvement in terms of classification accuracy, efficiency and model simplicity (Jiang, Zhang, Cai, & Su, 2005). Although the TAN may not always perform the best with regard to classification accuracy, this study adopts the TAN because it can create a causal-effect graph in which the class attribute treated as the supreme parent node is located at the top in the DAG.

3.2. PLS path modeling

PLS path modeling and LISREL (LInear Structural RELations) are two main SEM (structural equation modeling) approaches to modeling relationships between latent variables (Tenenhaus et al., 2005; Temme, Kreis, & Hildebrandt, 2006). The LISREL approach focuses on maximizing the explained covariation among the various constructs, while PLS path modeling maximizes the explained variation among the various constructs (Lauria & Duchessi, 2007). Unlike LISREL, with its assumption of homogeneity in the observed population, PLS path modeling is more suitable for real world applications. It is particularly more advantageous to employ PLS path modeling when models are complex (Fornell & Bookstein, 1982; Hulland, 1999). Moreover, a major merit of using PLS path modeling is that its required minimum sample size is a mere 30 (Wixom & Watson, 2001).

Anderson and Vastag (2004) stress that the SEM is likely the preferred method if the objective is only a description of theoretical constructs with no interest in inference to observable variables, while the Bayesian network approach should be selected if objectives include prediction and diagnostics of observed variables. Moreover, although both LISREL and PLS path modeling are SEM, the former highlights theory confirmation while the latter stresses causal explanation (Lauria & Duchessi, 2007). More importantly, PLS path modeling is more suited for analyzing exploratory models with no rigorous theory grounding, it requires minimal assumptions about the statistical distributions of data sets, and it can work with smaller sample sizes (Ranganathan & Sethi, 2002).

PLS path modeling handles two models at the same time: (1) a measurement model called the outer model relating the MVs (manifest variables) to their own LVs (latent variables), and (2) a structural model called the inner model relating some endogenous LVs to other LVs. The measurement model is tested by the reliability and validity analyses, and the structural model is tested by path coefficients between constructs in the model (Matzler & Renzl, 2006). There are at least two important tasks in conducting PLS path modeling: checking convergent reliability and validity, and explaining path coefficients and predictive ability. Through PLS path modeling, we can obtain standardized regression coefficients for the paths, R^2 values for endogenous variables, and factor loadings of indicators.

4. Empirical study

The effectiveness of decision-making depends largely on the ability of decision-makers to analyze complex cause–effect

Table 1
Attribute information.

Attribute	Characteristics	Description
Vendor name	Symbol	
Model name	Symbol	
MYCT	Integer	Machine cycle time in nanoseconds
MMIN	Integer	Minimum main memory in kilobytes
MMAX	integer	Maximum main memory in kilobytes
CACH	Integer	Cache memory in kilobytes
CHMIN	Integer	Minimum channels in units
CHMAX	Integer	Maximum channels in units
PRP	Integer	Published relative performance
ERP	Integer	Estimated relative performance from the original article

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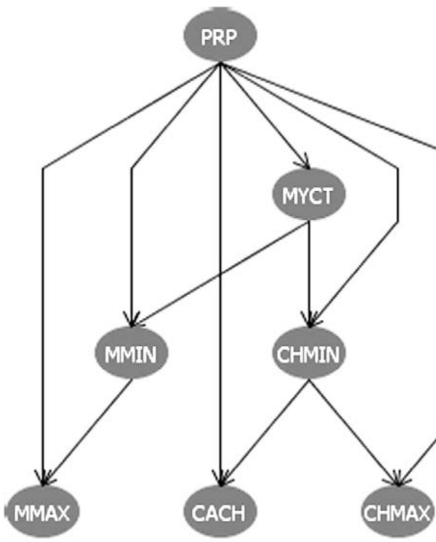

Fig. 2. The causal relationship diagram.

relationships and to take productive actions based on the causal analysis (Lin & Wu, 2008). In this section, an empirical study is presented to illustrate the application of the proposed method for causal analysis. Phase 1 is data preparation. This study adopts the Computer Hardware Data Set selected from the UCI Machine Learning Repository. As shown in Table 1, this dataset has 209 instances regarding relative CPU performance between vendors. This study sets out to model the relationships between six independent attributes (MYCT, MMIN, MMAX, CACH, CHMIN, and CHMAX) and the dependent attribute (PRP).

In phase 2, the Bayesian network classifier with the TAN search algorithm was implemented with WEKA, using a test mode of 10-fold cross-validation. As a result, the causal relationship diagram (Fig. 2) can be obtained. In Fig. 2, it is apparent that MYCT (machine cycle time in nanoseconds) is the most important factor, because it plays a core role, and one that further affects MMIN (minimum main memory in kilobytes) and CHMIN (minimum channels in units). However, the MYCT does not directly affect MMAX (maximum main memory in kilobytes), CACH (cache memory in kilobytes), and CHMAX (maximum channels in units).

In phase 3, referring to the causal relationship diagram (Fig. 2), the task of deciding the causal directions between attributes

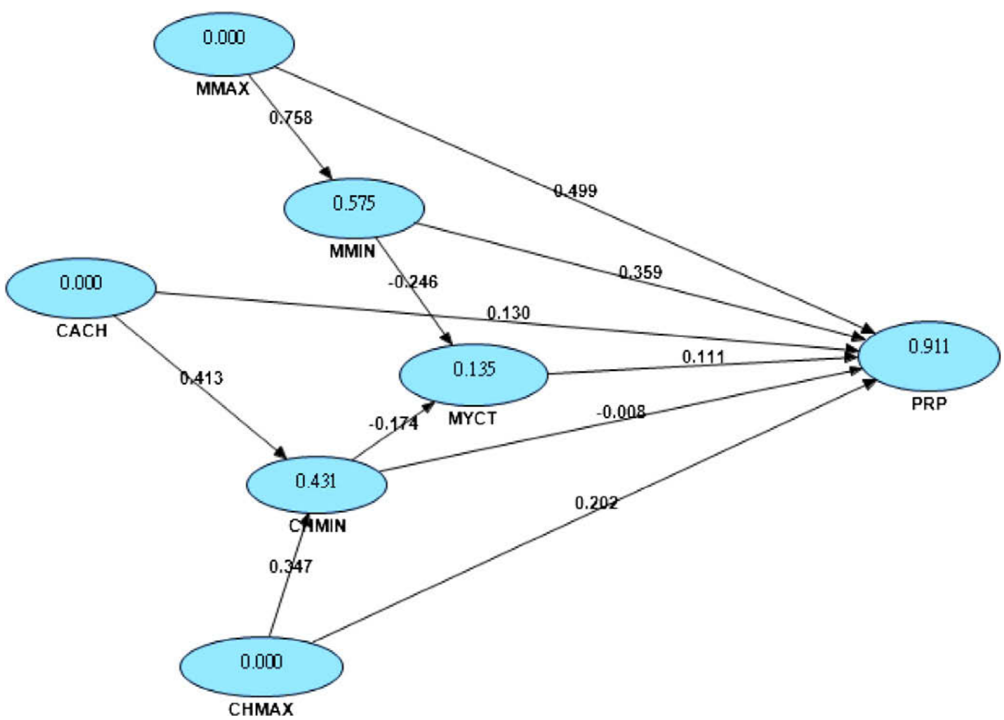

Fig. 3. Relations between attributes.

Table 2
Path coefficients.

	Original sample (*O*)	Sample mean (*M*)	Standard deviation (STDEV)	Standard error (STERR)	*T* statistics (|*O*/STERR|)
CACH → CHMIN	0.413	0.415	0.118	0.118	3.497
CACH → PRP	0.130	0.156	0.087	0.087	1.488
CHMAX → CHMIN	0.347	0.374	0.135	0.135	2.562
CHMAX → PRP	0.202	0.163	0.135	0.135	1.490
CHMIN → MYCT	−0.174	−0.196	0.060	0.060	2.892
CHMIN → PRP	−0.008	0.033	0.093	0.093	0.082
MMAX → MMIN	0.758	0.756	0.058	0.058	13.071
MMAX → PRP	0.499	0.481	0.130	0.130	3.839
MMIN → MYCT	−0.246	−0.242	0.089	0.089	2.769
MMIN → PRP	0.359	0.335	0.158	0.158	2.272
MYCT → PRP	0.111	0.094	0.020	0.020	5.627

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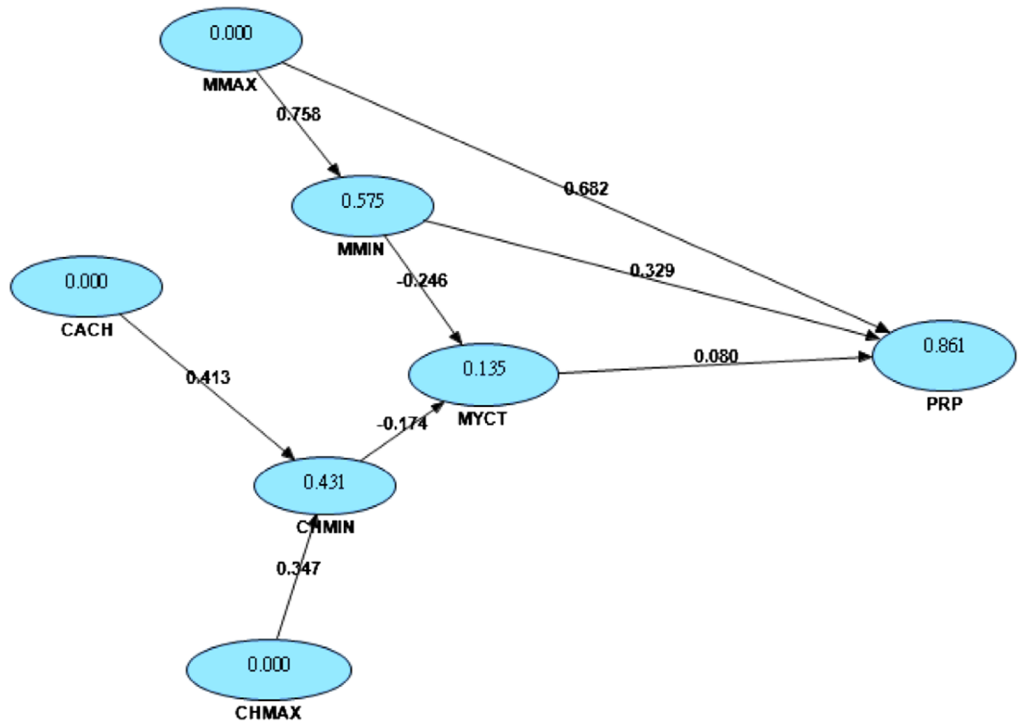

Fig. 4. Significant relations between attributes.

becomes quite easy. Therefore, after setting up the causal directions, implementation of PLS path modeling can be promptly performed. As a result, Fig. 3 is produced to display the relations between attributes. Because each of the independent attributes and the dependent attribute is measured by one item, both the CR (Composite Reliability) value and the AVE (Average Variance Extracted) value for each attribute is acceptable. Table 2 shows path coefficients between attributes. Except for 'CACH → PRP', 'CHMAX → PRP', and 'CHMIN → PRP', all path coefficients are significant. In particular, the highest path coefficient is the "MMAX → MMIN" of 0.758. As for the R^2 value, the PRP exhibits the best ability to explain (91.1%) in this model. On the whole, the combination of MYCT, MMIN, MMAX, CACH, CHMIN, and CHMAX has predictive ability for 91.1% of the PRP. If non-significant path coefficients are removed, then Fig. 4 exhibits relations between attributes more clearly and, in this way, the MYCT is depicted outstandingly. Finally, synthesizing and application of the above analysis results is required in order to achieve better decision-making.

5. Implications and conclusions

Profoundly reasoned decision-making relies greatly on the ability of decision-makers to model complex cause–effect relationships, and thus to undertake constructive actions based on dependable causal knowledge. Causal knowledge based on causal analysis can improve the quality of decision-making and facilitate the transformation and conversion of strategic objectives into effective actions. Several studies have suggested various causal analysis techniques to achieve causal knowledge. Among causal analysis techniques, PLS path modeling is one of the most powerful and popular causal analysis techniques.

However, few studies have concerned themselves with the issue of theory dependency in implementing PLS path modeling. When using PLS path modeling in a situation lacking the support of an underlying previous theory, serious problems may arise. This is because the task of deciding the causal direction between constructs tends to become so complicated so we are compelled to guess at enormous numbers of possibilities for causal directions. In an effort to solve this difficulty, this paper proposes an effective method of pursuing a causal analysis process, i.e. the author suggests implementing the Bayesian network prior to conducting PLS path modeling. Additionally, an empirical study is presented to demonstrate the successful application of the proposed method.

The proposed method embodies a successful combination of the Bayesian network with the TAN search algorithm and PLS path modeling for causal analysis. Although this methodology is successful in that the task of deciding the causal directions between attributes becomes easy through use of the proposed method, this study has some limitations. For instance, although the proposed method can save us from countless instances of trial and error in deciding causal directions, it is not necessarily the best solution when using the TAN search algorithm to settle on the causal directions. This is a significant issue calling for further future research.

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