Using Expert-based Bayesian Networks as Decision Support Systems to Improve Project Management of Healthcare Software Projects

Emilia Mendes
Software Engineering Research Laboratory, Blekinge Institute of Technology, Karlskrona, Sweden

Keywords: Software Project Management, Effort Estimation, Decision Support System, Bayesian Networks, Uncertainty, Process Improvement, Cost Estimation, Web Systems.

Abstract: One of the pillars for sound Software Project Management is reliable effort estimation. Therefore it is important to fully identify what are the fundamental factors that affect an effort estimate for a new project and how these factors are inter-related. This paper describes a case study where a Bayesian Network model to estimate effort for healthcare software projects was built. This model was solely elicited from expert knowledge, with the participation of seven project managers, and was validated using data from 22 past finished projects. The model led to numerous changes in process and also in business. The company adapted their existing effort estimation process to be in line with the model that was created, and the use of a mathematically-based model also led to an increase in the number of projects being delegated to this company by other company branches worldwide.

1 INTRODUCTION

Effort estimation, the process by which effort is forecasted and used as basis to predict costs and to allocate resources effectively, is one of the main pillars of sound project management, given that its accuracy can affect significantly whether projects will be delivered on time and within budget (Fenton et al., 2004). However, because it is a complex domain where corresponding decisions and predictions require reasoning with uncertainty, there are countless examples of companies that underestimate effort. Jørgensen and Grimstad (2009) reported that such estimation error can be of 30%-40% on average, thus leading to serious project management problems.

There is a large body of knowledge in software effort estimation (Jorgensen and Shepperd, 2007), and Web-development effort estimation (Azhar et al., 2012). Most of those studies focused on solving companies' inaccurate effort predictions via investigating techniques that are used to build formal effort estimation models, in the hope that such formalization will improve the accuracy of estimates. They do so by assessing, and often also comparing, the prediction accuracy obtained from applying numerous statistical and artificial intelligence techniques to datasets of completed projects developed by industry, and sometimes also developed by students.

The variables characterizing such datasets are determined in different ways, such as via surveys (Mendes et al., 2005), interviews with experts (Ruhe et al., 2003), expertise from companies (Ferrucci et al., 2008), a combination of research findings (Mendes et al. 2001), or even a researcher's own consulting experience (Reifer, 2000). In all of these instances, once variables are defined, a data gathering exercise takes place, obtaining data (ideally) from industrial projects volunteered by companies. However, in addition to eliciting the important effort predictors (and optionally also their relationships), such mechanism does not provide the means to also quantify the uncertainty associated with these relationships and to validate the knowledge obtained. Why should these be important?

Research on effort estimation models built using a technique that incorporates the uncertainty inherent in this domain has shown very promising results relating to improved decision making for project management. This technique is called Bayesian Networks (BNs), and has also been employed successfully in a wide range of other domains (e.g. Pollino et al., 2007); Korb and Nicholson (2004)). Some of the models described in

Mendes E..
Using Expert-based Bayesian Networks as Decision Support Systems to Improve Project Management of Healthcare Software Projects .
DOI: 10.5220/0004434103890399
In *Proceedings of the 8th International Joint Conference on Software Technologies* (ICSOFT-EA-2013), pages 389-399
ISBN: 978-989-8565-68-6

those studies were built automatically from existing datasets on software or Web-development projects (e.g. Nauman and Lali, 2012); Mendes and Mosley (2008)); however, some other models in that literature were built using a structured iterative process in which factors and relationships were identified, quantified and validated (e.g. Mendes et al., 2009) through a process of knowledge creation (Nonaka and Toyama, 2003), where experts' tacit knowledge relating to effort estimation was explicitated (thus leading to models that mirror their mental models), and later internalized (tacit knowledge is modified due to the use of the models) by those employing these models for decision making, in order to obtain effort estimates for projects.

The goal of this paper, and hence its contribution, is to detail a case study in which the process of knowledge creation abovementioned was used to build an effort estimation BN model within a domain that had not been previously investigated in the software and Web-development literature (Jorgensen and Shepperd, 2007); (Azhar et al., 2012) – that of healthcare software project management. This model was built for one of the branches of a large Japanese healthcare software provider, with the participation of seven project managers.

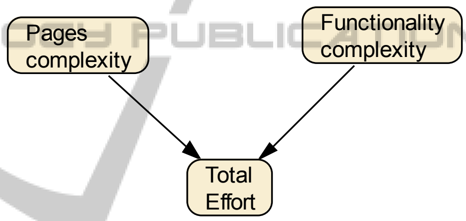
Post-mortem interviews with the participating company showed that the understanding it gained by being actively engaged in building the models led to both improved estimates and project management decision making.

The remainder of this paper is structured as follows: Section 2 provides an overview of BNs, followed by the description, in Section 3, of the general process used to build and validate BNs. Section 4 details this process within the context of the model described herein, followed by a discussion of the results in Section 5, and finally conclusions in Section 6.

2 INTRODUCTION TO BAYESIAN NETWORKS

A Bayesian Network (BN) is a model that supports reasoning with uncertainty due to the way in which it incorporates existing knowledge of a complex domain (Pearl, 1988). This knowledge is represented using two parts. The first, the qualitative part, represents the structure of a BN as depicted by a directed acyclic graph (digraph) (see Figure 1). The digraph's nodes represent the relevant variables (factors) in the domain being modeled, which can be of different types (e.g. observable or latent, categorical). The digraph's arcs represent the causal relationships between variables, where relationships are quantified probabilistically (Pearl, 1988).

The second, the quantitative part, associates a conditional probability table (CPT) to each node, its probability distribution. A parent node's CPT describes the relative probability of each state (value) (Figure 1, nodes 'Pages complexity' and 'Functionality complexity'); a child node's CPT describes the relative probability of each state conditional on every combination of states of its parents (Figure 1, node 'Total Effort'). So, for example, the relative probability of 'Total Effort' being 'Low' conditional on 'Pages complexity' and 'Functionality complexity' being both 'Low' is 0.7. Each row in a CPT represents a conditional probability distribution and therefore its values sum up to 1 (Pearl, 1988).



Pages complexity		
Low	*Medium*	*High*
0.2	0.3	0.5

Functionality complexity	
Low	*High*
0.1	0.9

Total Effort (Low, Medium, High)				
Pages complexity	**Functionality complexity**	*Low*	*Medium*	*High*
Low	*Low*	0.7	0.2	0.1
Low	*High*	0.2	0.6	0.2
Medium	*Low*	0.1	0.7	0.2
Medium	*High*	0	0.5	0.5
High	*Low*	0.2	0.6	0.2
High	*High*	0	0.1	0.9

Figure 1: Example of a BN and three CPTs.

Formally, the posterior distribution of the Bayesian Network is based on Bayes' rule (Pearl, 1998):

$$p(X \mid E) = \frac{p(E \mid X)\,p(X)}{p(E)} \tag{1}$$

where:

- $p(X \mid E)$ is called the *posterior* distribution and represents the probability of *X* given evidence *E*;

- $p(X)$ is called the *prior* distribution and represents the probability of X before evidence E is given;
- $p(E \mid X)$ is called the *likelihood* function and denotes the probability of E assuming X is true.

Once a BN is specified, evidence (e.g. values) can be entered into any node, and probabilities for the remaining nodes automatically calculated using Bayes' rule (Pearl, 1988). Therefore BNs can be used for different types of reasoning, such as predictive, diagnostic, and "what-if" analyses to investigate the impact that changes on some nodes have on others.

3 ADAPTED KNOWLEDGE ENGINEERING OF BAYESIAN NETWORKS PROCESS

The BN model presented herein was built and validated using the adapted Knowledge Engineering of Bayesian Networks (KEBN) process (Mendes and Mosley, 2008) (see Figure 2). In Figure 2 arrows represent flows through the different processes, depicted by rectangles. The three main steps within the adapted KEBN process are the Structural Development, Parameter Estimation, and Model Validation. This process iterates over these steps until a complete BN is built and validated. Each of these three steps is detailed in the next Sub-sections.

3.1 Structural Development

The Structural Development step represents the qualitative component of a BN, which results in a graphical structure comprised of, in our case, the factors (nodes, variables) and causal relationships identified as fundamental for effort estimation of healthcare software projects. In addition to identifying variables, their types (e.g. query variable, evidence variable) and causal relationships, this step also comprises the identification of the states (values) that each variable should take. The BN's structure is refined through an iterative process. This structure construction process has been validated in previous studies (Druzdel and van der Gaag, 2000) and uses the principles of problem solving employed in data modelling and software development (Studer et al., 1998). As will be detailed later, existing literature in effort estimation, and knowledge from the domain experts were employed to elicit the Healthcare software effort BN's structure. Throughout this step the author also evaluated the BN's structure to check whether variables and their values have a clear meaning; all relevant variables have been included; variables are named conveniently; all states are appropriate (exhaustive and exclusive). The BN structure may also need to be optimised to reduce the number of probabilities that need to be elicited or learnt for the network. Whenever this is the case, techniques that change the causal structure (e.g. divorcing (Jensen, 1996)) are employed.

3.2 Parameter Estimation

The Parameter estimation step represents the quantitative component of a BN, where conditional probabilities corresponding to the quantification of the relationships between variables (Jensen, 1996) are obtained. Such probabilities can be attained via Expert Elicitation, automatically from data, from existing literature, or using a combination of these. When probabilities are elicited from scratch, or even if they only need to be revisited, this step can be very time consuming. In order to minimise the number of probabilities to be elicited some techniques have been proposed in the literature

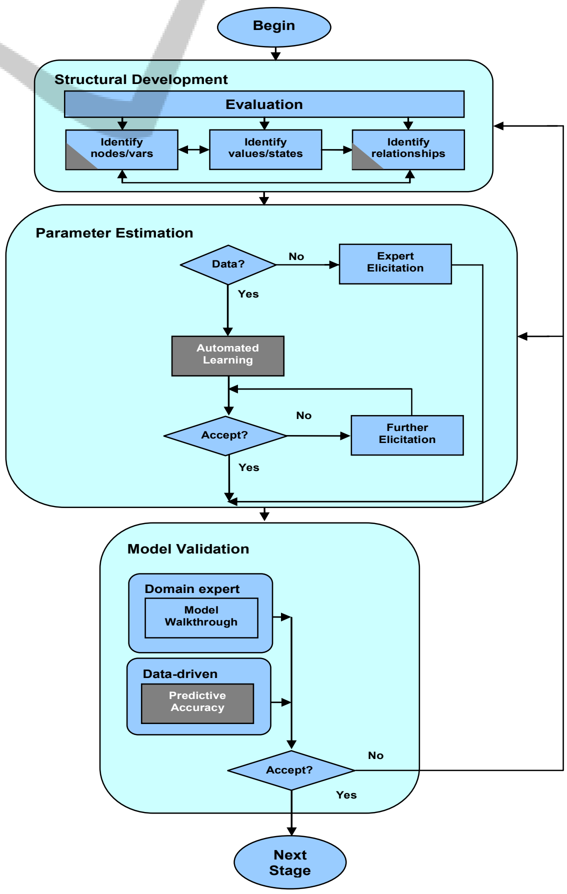


Figure 2: Adapted KEBNs process (Mendes et al., 2009).

(Druzdel and van der Gaag, 2000) (Tang McCabe, 2007).

3.3 Model Validation

The Model validation step validates the BN that results from the two previous steps, and determines whether it is necessary to re-visit any of those steps. Two different validation methods are generally used - Model Walkthrough and Predictive Accuracy.

Model walkthrough represents the use of real case scenarios that are prepared and used by domain experts to assess if the predictions provided by the BN model correspond to the predictions experts would have chosen based on their own expertise. Success is measured as the frequency with which the BN's predicted value for a target variable (e.g. quality, effort) that has the highest probability corresponds to the experts' own assessment.

Predictive Accuracy uses past data (e.g. past project data), rather than scenarios, to obtain predictions. Data (evidence) is entered on the BN model, and success is measured as the frequency with which the BN's predicted value for a target variable (e.g. quality, effort) that has the highest probability corresponds to the actual past data.

4 PROCESS USED TO BUILD THE BN MODEL

Here in we revisit the adapted KEBN process (see Figure 2), detailing the tasks carried out for each of the three main steps, within the context of the effort estimation BN model for healthcare projects that is the focus of this paper. Before starting the elicitation of the model, the seven project managers participating in the model elicitation & validation were given an overview of BNs, and examples of "what-if" scenarios using a made-up BN. This, we believe, facilitated the entire process as the use of an example, and the brief explanation of each of the steps in the adapted KEBN process, provided a concrete understanding of what to expect. We also made it clear that the author was solely a facilitator of the process, and that the Healthcare company's commitment was paramount for the success of the process.

The entire process took 324 person hours to be completed, with seven projet managers participating at 12 3-hour slots, and two other project managers participating at other 12 3-hour slots.

The company for which the model was created, located in the Pacific Rim region, represents one of the several branches worldwide that are part of a larger Healthcare organization, which headquarters in Japan. The company had ~100 employees. The project managers had each worked in Healthcare software development for more than 10 years. In addition, this company developed a wide range of Healthcare software applications, using different types of technology.

4.1 Detailed Structural Development & Parameter Estimation

In order to identify the fundamental factors that the project managers considered when preparing a project quote, and also taking into account that most of the projects managed were Web-development projects, we used, as suggested in (Mendes et al., 2009), the set of variables from the Tukutuku dataset (Mendes et al., 2005) as a starting point (see Table 1). We first sketched them out on a white board, each one inside an oval shape, and then explained what each one meant.

Once the Tukutuku variables had been sketched out and explained, the next step was to remove all variables that were not relevant for the project managers, followed by adding to the white board any additional variables (factors) suggested by them. We also documented descriptions for each of the factors suggested. Next, we identified the states that each factor would take. All states were discrete. Whenever a factor represented a measure of effort (e.g. Total effort), we also documented the effort range corresponding to each state, to avoid any future ambiguity. For example, 'very low' Total effort corresponded to 4+ to 10 person hours, etc. Once all states were identified and documented, it was time to elicit the cause and effect relationships. As a starting point to this task we used the same example used in (Mendes et al., 2009) - a simple medical example from (Jensen, 1996) (see Figure 3).

This example clearly introduces one of the most important points to consider when identifying cause and effect relationships – timeline of events. If smoking is to be a cause of lung cancer, it is important that the cause precedes the effect. This may sound obvious with regard to the example used; however, it is our view that the use of this simple example significantly helped the project managers understand the notion of cause and effect, and how this related to software effort estimation and the BN being elicited.

Table 1: The Tukutuku variables (Mendes et al. 2005).

	Variable Name	Description
Project Data	*TypeProj*	Type of project (new or enhancement).
	nLang	Number of different development languages used
	DocProc	If project followed defined and documented process.
	ProImpr	If project team involved in a process improvement programme.
	Metrics	If project team part of a software metrics programme.
	DevTeam	Size of a project's development team.
	TeamExp	Average team experience with the development language(s) employed.
Web application	*TotWP*	Total number of Web pages (new and reused).
	NewWP	Total number of new Web pages.
	TotImg	Total number of images (new and reused).
	NewImg	Total number of new images created.
	Num_Fots	Number of features reused without any adaptation.
	HFotsA	Number of reused high-effort features/functions adapted.
	Hnew	Number of new high-effort features/functions.
	TotHigh	Total number of high-effort features/functions
	Num_FotsA	Number of reused low-effort features adapted.
	New	Number of new low-effort features/functions.
	TotNHigh	Total number of low-effort features/functions

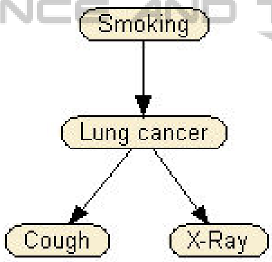


Figure 3: A simple medical example from (Jensen, 1996).

Once the cause and effect relationships were identified the Healthcare software effort & risk BN's causal structure was as follows (see Figure 4). Note that Figure 4 is not a BN based directly on Table 1.

At this point the project managers seemed happy with the BN's causal structure and the work on eliciting the probabilities was initiated. All probabilities were created from scratch, and the probabilities elicitation took 72 hours (one project manager and the author). The complete BN, including its probabilities, is shown in Figure 5. Figure 5 shows the BN using belief bars rather than labelled factors, so readers can see the probabilities that were elicited.

4.2 Detailed Model Validation

Both Model walkthrough and Predictive accuracy were used to validate the Effort Prediction BN model, where the former was the first type of validation to be employed. The project manager used ten different scenarios to check whether the factor Total_effort would provide the highest probability to the effort state that corresponded to the manager's own suggestions. All scenarios were run successfully; however it was also necessary to use data from past projects, for which total effort was known, in order to check whether the model needed any further calibration. A validation set containing data on 22 projects was used. The project manager selected a range of projects presenting different sizes and levels of complexity, where all 22 projects were representative of the types and sizes of projects developed by the Healthcare Company.

For each project, evidence was entered in the BN model (an example is given in Figure 6, where evidence is characterised by dark grey nodes with probabilities equal to 100% (1…)), and the effort range corresponding to the highest probability provided for 'Total Estimated Effort' was compared to that project's actual effort.

The company had also defined the range of effort values associated with each of the categories used to measure 'Total Estimated Effort'. In the case of the company described herein, High effort corresponded to 150 to 1500 person hours. Whenever actual effort did not fall within the effort range associated with the category with the highest probability, there was a mismatch; this meant that some probabilities needed to be adjusted. In order to know which nodes to target first we used a Sensitivity Analysis report, which provided the effect of each parent node upon a given query node. Within our context, the query node was 'Total Estimated Effort'. Within the context of this work, hardly any calibration was needed.

Whenever probabilities were adjusted, we re-entered the evidence for each of the projects in the validation set that had already been used in the validation step to ensure that the calibration already carried out had not affected. This was done to ensure that each calibration would always be an improved upon the previous one. Within the scope of the model presented herein, of the 22 projects used for validation, only one required the model to be re-calibrated. This means that for all the 21 projects remaining, the BN model presented the highest probability to the effort range that contained the actual effort for the project being used for validation. Once all 22 projects were used to validate the model the project manager assumed that the Validation step was complete.

5 DISCUSSION

In terms of the use of this BN model, it can also be employed for diagnostic reasoning, and to run numerous "what-if" scenarios. Figure 7 shows an example of a model being used for diagnostic reasoning, where the evidence was entered for Total Estimated Effort, and used to assess the highest probabilities for each of the other factors.

Six months after the completion of the BN model, the author participated in a post-mortem interview with the company's project managers. The changes that took place as the result of developing the BN model were as follows:

- The model was explained to the entire software development group and all the estimations provided by any team member (e.g. developers, managers) had to be based on the factors that were part of the BN model. This means that the entire team started to use the factors that have been elicited, as well as the BN model, as basis for decision making during their effort estimation sessions.
- Initially, project managers estimated effort using both subjective means and also the BN model. If there were differences between estimates, they would discuss and reach a consensus on which estimate to use. Later both estimates were compared to the actual effort once projects were completed. However, in less than 6 months from using the BN model, managers moved to using the model-based estimates only.

Finally, as a consequence from using this model, this company branch started to increase the number of requests from other branches for software development projects. This occurred when one of the project managers presented the model at a meeting with other company branches, so to detail how their branch was estimating effort for their healthcare projects.

Overall, such change in approach provided extremely beneficial to the company.

We believe that the successful development of this Effort estimation BN model was greatly influenced by a number of factors, such as:

- The company's commitment to providing their time and expertise.
- The use of a process where project managers' participation was fundamental. This approach was seen as extremely positive by the company as they could implicitly understand the value from building a model that was totally geared towards their needs.
- The project managers' excellent experience in managing healthcare software projects.

6 CONCLUSIONS

This paper has presented a case study where a Bayesian Model for effort estimation of Healthcare projects was built using solely knowledge of seven Domain Experts from a well-established Healthcare company in the Pacific Rim. This model was developed using an adaptation of the knowledge engineering for Bayesian Networks process (see Figure 2). Each session with the project managers lasted for no longer than 3 hours. The final BN model was calibrated using data on 22 past projects. These projects represented typical projects developed by the company, and believed by the experts to provide enough data for model calibration.

Since the model's adoption, it has been successfully used to provide effort quotes for the new projects managed by the company.

The entire process used to build and validate the BN model took 324 person hours.

As part of our future work, we plan to compare our model to that from other related research using BNs within the context of software effort estimation.

ACKNOWLEDGEMENTS

We would like to thank the project managers who participated in the elicitation and validation of this model. This work is part of the BESQ+ research project funded by the Knowledge Foundation (grant: 20100311) in Sweden.

REFERENCES

Azhar, D., Mendes, E., and Riddle, P. 2012. A Systematic Review of Web Resource Estimation, *Proceedings of Promise'12*.

Druzdzel, M. J., & van der Gaag, L. C. (2000). Building Probabilistic Networks: Where Do the Numbers Come From?. *IEEE Trans. on Knowledge and Data Engineering, 12(4)*, 481-486.

Jensen, F. V. (1996). An introduction to Bayesian networks. UCL Press, London.

Fenton, N., Marsh, W., Neil, M., Cates, P., Forey, S., and Tailor, M. 2004: Making Resource Decisions for Software Projects, Proc. ICSE'04, pp. 397-406.

Ferrucci, F. Gravino, C., Di Martino, S. 2008, *A Case Study Using Web Objects and COSMIC for Effort Estimation of Web Applications*. EUROMICRO-SEAA, p. 441-448.

Korb, K. B., and Nicholson, A. E. 2004, *Bayesian Artificial Intelligence*, CRC Press, USA.

Jørgensen, M., and Grimstad, S. 2009. Software Development Effort Estimation: Demystifying and Improving Expert Estimation, In: Simula Research Laboratory - by thinking constantly about it, ed. by Aslak Tveito, Are Magnus Bruaset, Olav Lysne. Springer, Heidelberg, chap. 26, pp. 381-404. (ISBN: 978-3642011559).

Jorgensen, M. and Shepperd, M. 2007. A systematic review of software development cost estimation studies, IEEE Trans. Softw. Eng., vol. 33, no. 1, pp. 33–53.

Mendes, E., and Mosley, N., 2008, Bayesian Network Models for Web Effort Prediction: a Comparative Study, Transactions on Software Engineering, Vol. 34, Issue: 6, Nov/Dec 2008, pp. 723-737.

Mendes, E., Mosley, N., and Counsell, S. 2001. Web metrics - Metrics for estimating effort to design and author Web applications. IEEE MultiMedia, January-March, 50-57.

Mendes, E., Mosley, N. and Counsell, S. 2005. The Need for Web Engineering: an Introduction, Web Engineering, Springer-Verlag, Eds: E. Mendes, N. Mosley, pp. 1-26, ISBN 3-540-281 96-7.

Mendes, E., Polino, C., and Mosley, N. 2009, Building an Expert-based Web Effort Estimation Model using Bayesian Networks*, 13th International Conference on Evaluation & Assessment in Software Engineering*.

Nauman, A. B., and Lali, M. I., 2012, Productivity Inference with Dynamic Bayesian Models in Software Development Projects, International Journal of Computer and Electronics, 1(2), 50-57.

Nonaka, I., Toyama, R. 2003. The knowledge-creating theory revisited: knowledge creation as a synthesizing process. Knowledge Management Research & Practice, 1:2-10.

Pearl J. 1988. *Probabilistic Reasoning in Intelligent Systems*, Morgan Kaufmann, San Mateo, CA.

Pollino, C., White, A., and Hart, B.T., 2007, Development and application of a Bayesian decision support tool to assist in the management of an endangered species. *Ecological Modelling* 201, 37-59.

Studer, R., Benjamins, V.R., & Fensel, D. 1998. Knowledge engineering: principles and methods. *Data & Knowledge Engineering, 25*, 161-197.

Tang, Z., & McCabe, B. 2007. Developing Complete Conditional Probability Tables from Fractional Data for Bayesian Belief Networks, *Journal of Computing in Civil Engineering, 21(4)*, 265-276.

Reifer, D. J. 2000, Web Development: Estimating Quick-to-Market Software, IEEE Software, Nov.-Dec., 57-64.

Ruhe, M., Jeffery, R., and Wieczorek., I. 2003, Cost estimation for Web applications, Proceedings ICSE 2003, 285-294, 2003.

Woodberry, O., Nicholson, A., Korb, K., & Pollino, C. 2004. Parameterising Bayesian Networks. Proceedings of the Australian Conference on Artificial Intelligence (pp. 1101-1107).

APPENDIX

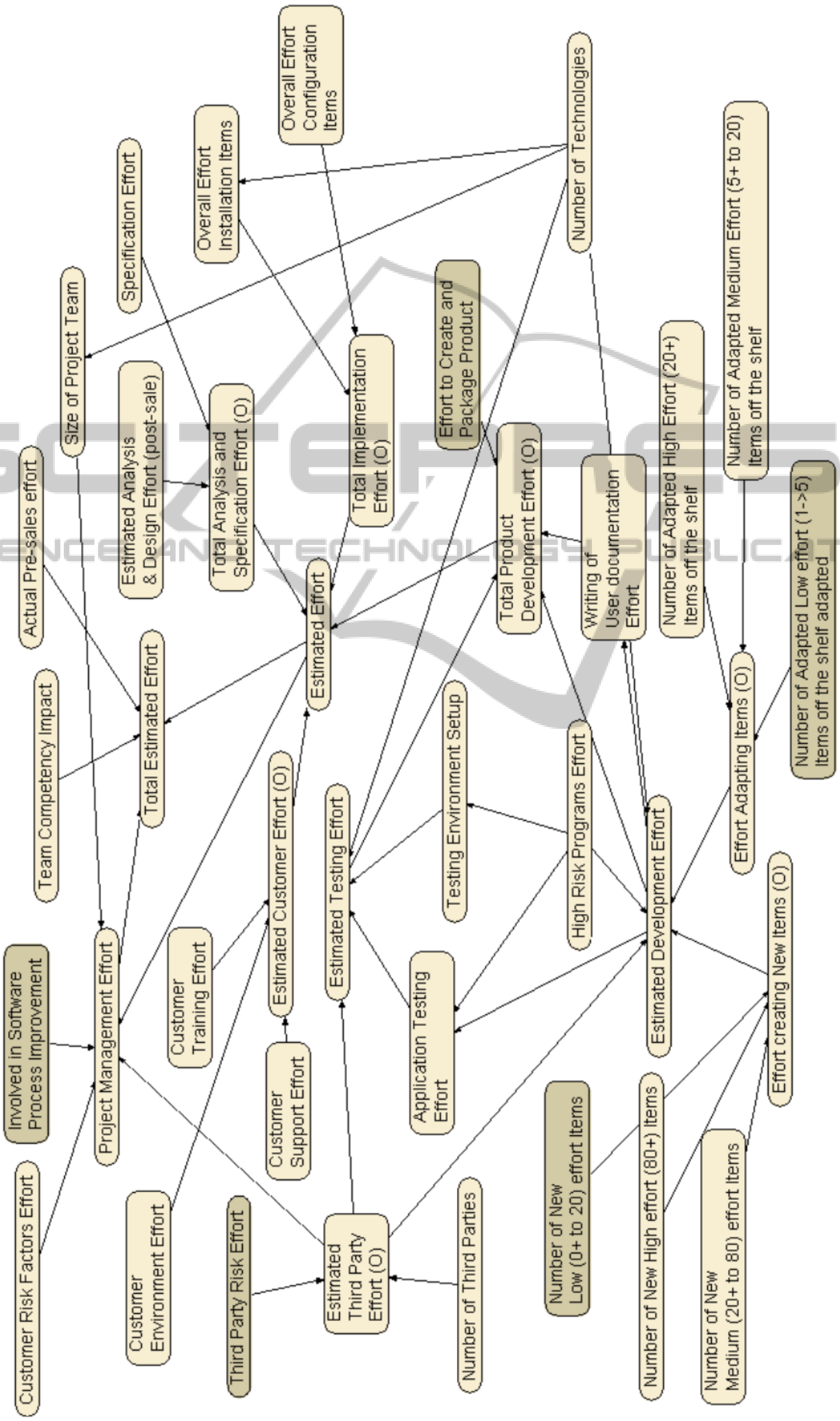


Figure 4: BN model’s Causal Structure.

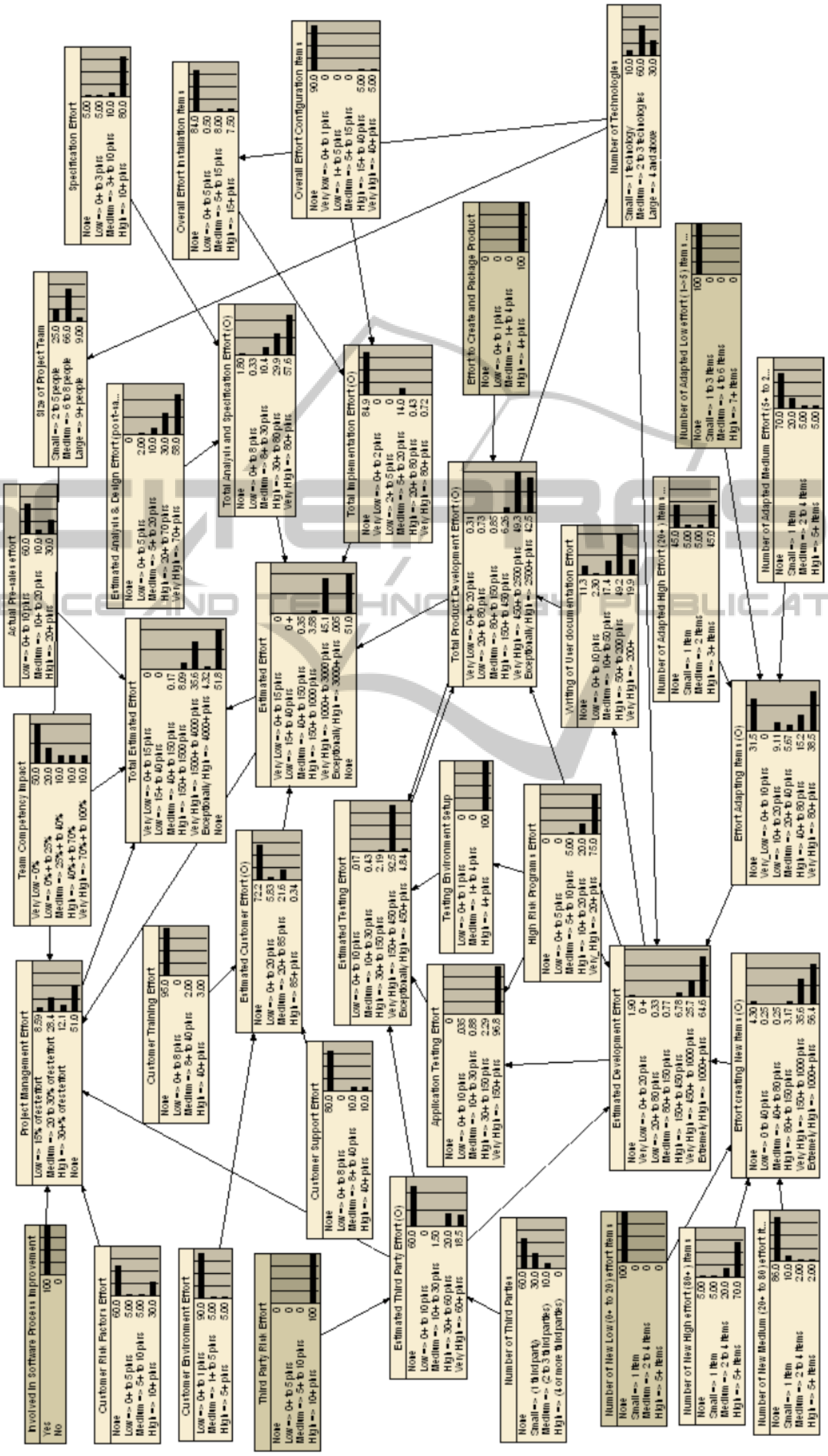


Figure 5: Effort estimation BN model for Healthcare software development.

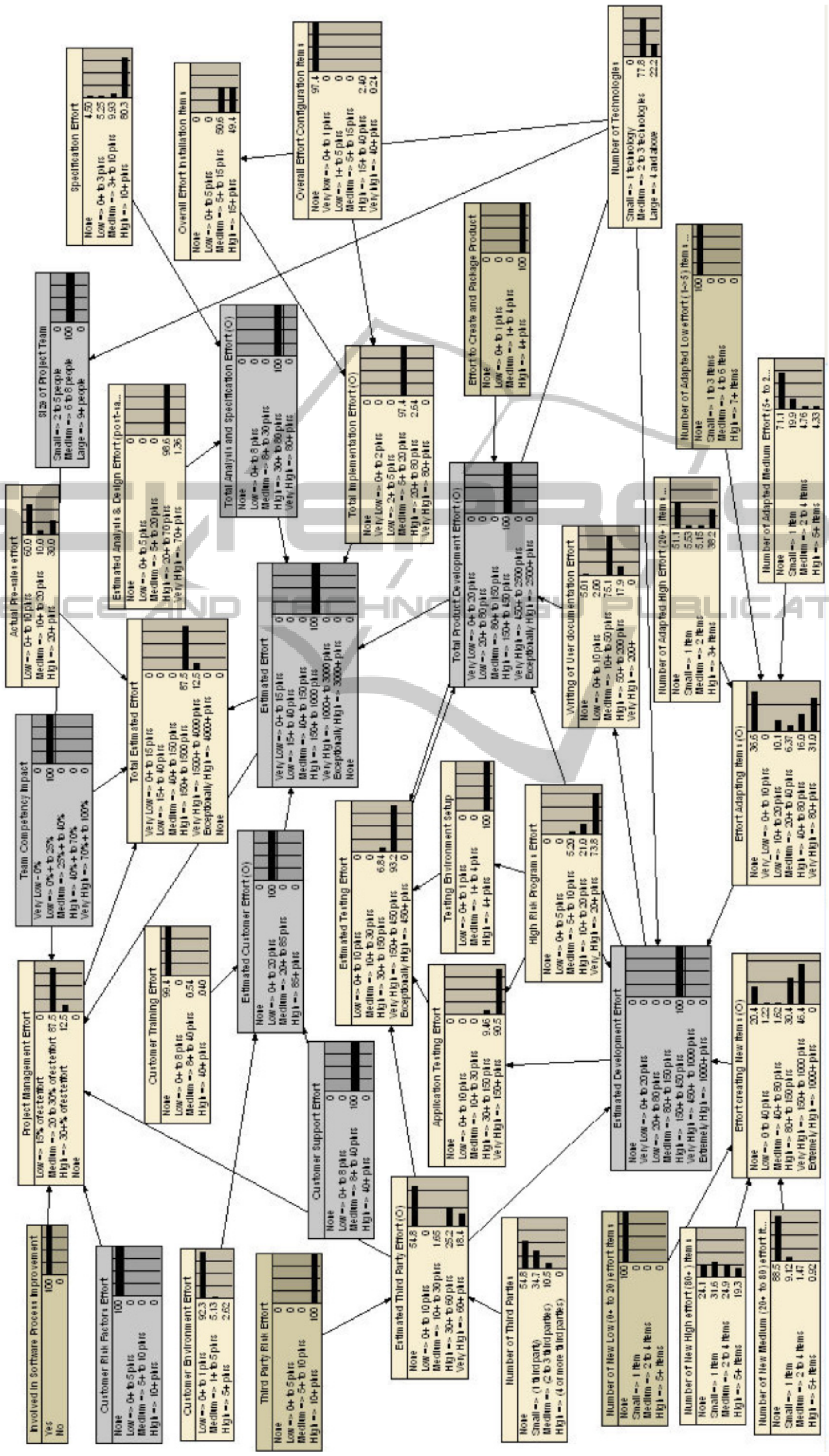


Figure 6: Entering evidence in order to predict effort

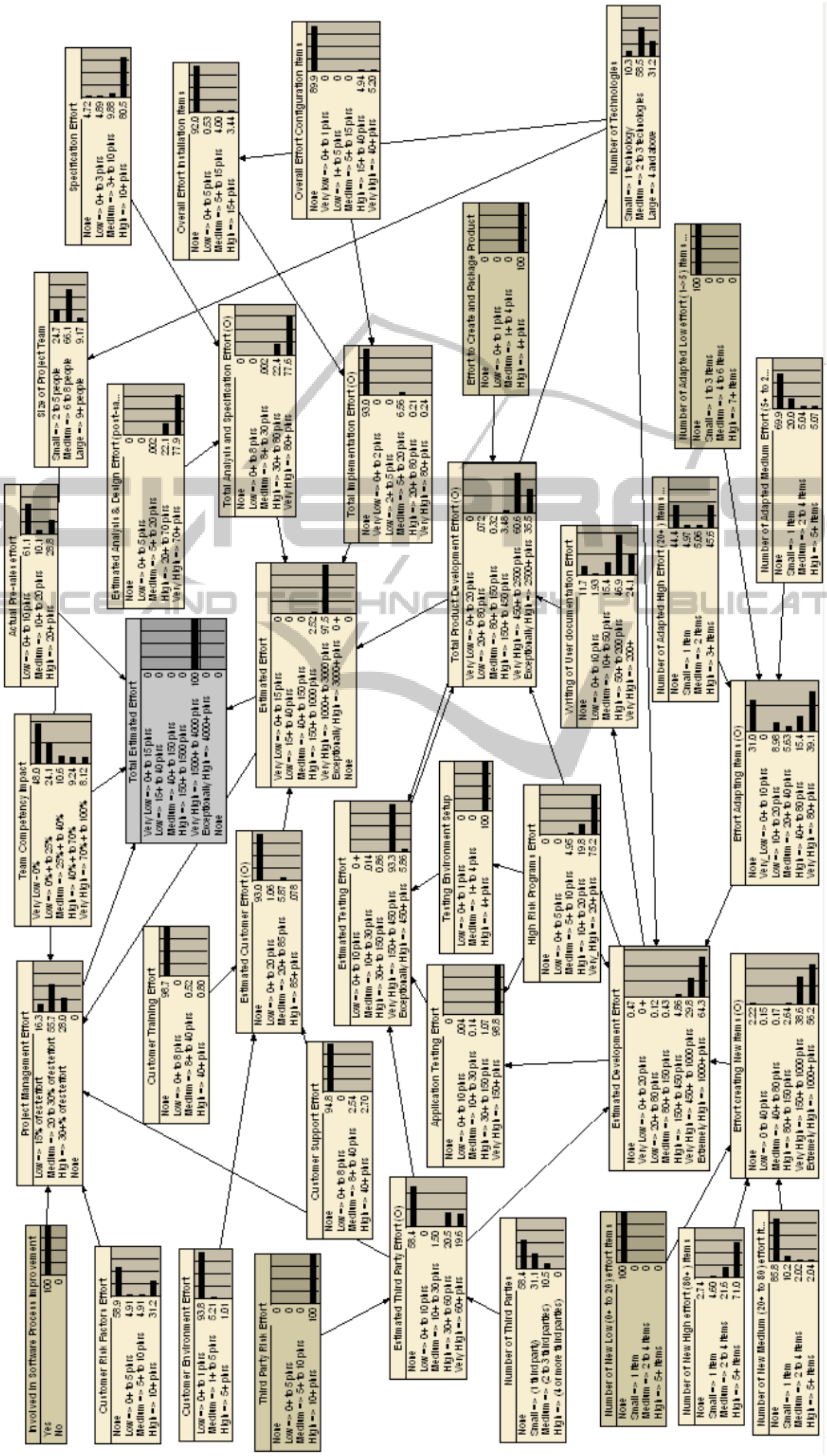


Figure 7: Diagnostic Reasoning.