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Neural Network-Based Performance Index Model for Enterprise Goals Simulation and Forecasting

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Abstract

Enterprise Information System management has become an increasingly vital factor for many firms. Several organizations have encountered problems when attempting to evaluate organizational performance. Measurement of performance metrics is a key challenge for a huge number of firms. In order to preserve relevance and adaptability in competitive markets, it has become essential to respond proactively to complex events through informed decision-making that is supported by technology. Therefore, the objective of this study was to apply neural networks to the modeling, simulation, and forecasting of the effects of the performance indicators of Enterprise Information Systems on the achievement of corporate objectives and value creation. A set of quantifiable and sizeable conditionally independent associations were derived using a simplified joint probability distribution technique. Bayesian Neural Networks were utilized to describe the link between random variables (features) and to concisely and easily specify the joint probability distribution. The research demonstrated that Bayesian networks could effectively explore complex logical linkages by employing probability to represent uncertainty and probabilistic rules; and by applying impact models from Bayesian taxonomies to achieve learning and reasoning processes.

Keywords

Neural Network, Bayesian Neural Network, Decision Support, Predictor Forecasting, Decision Support, Enterprise Architecture

1. Introduction

Enterprise Information Systems (EIS) establish the necessary concepts, structures, procedures, tools, knowledge base, and techniques to support the mission of a business [1]. Faced with ambiguity, organizations are increasingly turning to artificial intelligence and expert systems to construct knowledge management systems that may serve as the foundation of an enterprise's Enterprise Information System and its long-term success. Neural networks have presented the potential to be an extremely effective knowledge representation and inference engine for the development and design of Expert Systems [2]. As modeling tools for expert systems, Bayesian Neural Networks (BNN) are already well-established for forecasting under uncertainty [3]. Probabilistic graphical models describe a distribution across a multidimensional space using a graph-based representation, which is a compact or factorized representation of the independence that exists in the given distribution.

Numerous researchers in diverse disciplines have deployed BNN to simulate probabilistic graphical models [3] [4], molecular biology; [2] [4], genomics; [5] [6] and agriculture; [7]. The principal applications of Bayesian Networks (BN) are summarized in [9], and, more recently, in [8]. BNs are well-established probabilistic approaches that have been successfully applied to a variety of problems in a number of disciplines using a variety of machine learning techniques. Probability theory of BN is also one of the most controversial Artificial Intelligence ideas for reasoning in the face of uncertainty. Recently, Bayesian Networks, also known as belief networks or directed probabilistic graphical models, have garnered a great deal of interest and have been effectively applied to a wide range of situations [9]. The bulk of these instances involve modeling and uncertain decision-making. Probabilistic models can also be advantageous for traditional AI-based strategies. Bayesian models have been applied effectively to describe and simulate probabilistic systems in the context of uncertain business scenarios [8]. In exceptional instances, Bayesian models have also been used to handle non-probabilistic issues, such as pattern identification in images [4].

This study aims to build a statistical modeling framework for evaluating and simulating performance indices, as well as a Bayesian network-based implementation of value forecasting for Enterprise Information Systems. Utilizing the universality of Bayesian networks to show and solve choice issues in the presence of uncertainty is the emphasis of the research. It analyzes how Bayesian network concepts may be applied to make accurate forecasts regarding a company's success rate. Using Bayesian Networks as a formal model for detecting and reasoning with ambiguous information based on analytical categorization, this study seeks to develop referential patterns for achieving EIS goals and motivation. It has been demonstrated that Bayesian network models are useful in a variety of AI fields, including medical diagnosis and weather forecasting. Simulating the model is comparable to making predictions about real-world occurrences [8].

2. Review of Literature

Bayesian belief networks, a type of graphical model, are characterized by their probabilistic nature [10]. Probabilistic graphical models (PGMs) are graphical representations of probabilistic models [11]. A graphical representation is composed of discrete entities, referred to as vertices, which are interconnected by edges, also referred to as edges or arcs. In this context, it can be observed that individual nodes serve as a representation of a stochastic variable, or a composite of such variables. Additionally, the interconnecting links between these nodes are indicative of their respective probabilistic correlations. Despite the existence of various categories of graphical models, Hidden Markov Model [12] and Bayesian Network are the most prominently studied [13]. Over the course of the previous ten years, the Bayesian network has emerged as a prominent model utilized for encoding uncertain expert knowledge in expert systems, as evidenced by scholarly literature [4]. In recent times, scholars have developed techniques to infer Bayesian networks from empirical data sources [6] [7] [14]. Although the techniques utilized are innovative and continuously developing, they have demonstrated remarkable efficacy in addressing diverse data analysis challenges. Bayesian networks are noted for their capacity to effectively handle incomplete data sources [9]. The utilization of Bayesian statistical techniques and networks enables the integration of both domain expertise and data. The construction of extensive expert systems that exclusively depend on antecedent information showcases the significant significance of past or domain knowledge, particularly in situations where data is limited or costly. Bayesian inference has been classified as a statistical methodology that involves the assignment of subjective probabilities to the distributions that are capable of generating the data [15]. This approach enables the derivation of more precise conclusions from the data. The collective probabilities amalgamate to generate the Prior distribution [16]. The methodology comprises three distinct phases. Firstly, the qualitative phase involves the identification of conditional independence relationships among variables, which are then represented through a graphical model. Secondly, the probabilistic phase involves the evaluation of the joint distribution of the model. Lastly, the quantitative phase involves the assignment of values to the Conditional Probability Tables (CPT) underlying the model [17]. This study incorporates both expert and data-driven approaches at every stage. The techniques employed in the creation of a model are guided by the discipline in which it is being developed or the accessibility of data, as stated in references [18] and [19]. Various methodologies have been deployed to manually construct the structure and connections of a Bayesian network (BN). These methodologies span from the utilization of idioms and ontologies [20] to more fundamental techniques that entail identifying each variable and its causal influences/influencers [21]. The essential phases of an effective elicitation process have been revealed through an analysis conducted by Meineri *et al.* [22], Han *et al.* [23], and Meyniel *et al.* [24]. Qualitative data was collected and analyzed through the utilization of sampling with intent, as a component of a mixed-methods implementation strategy [23]. This study employs a qualitative research methodology approach, utilizing closed-ended queries in observations and interviews to gather quantitative data. The collated variables are utilized in their original form rather than being modified. The aim of the methodology employed in this study is to corroborate or disprove the conjecture posited in the present manuscript.

3. Method

This work demonstrates the primary method used to integrate the various study components in a cohesive and logical manner, ensuring that the research topic was effectively addressed. It established a framework for data acquisition, measurement, and analysis. To acquire pertinent evidence for the study, it was necessary to identify the types of depositions that would support or refute the work's hypotheses, validate the research theory, and accurately characterize the phenomena outlined in the research's aims and objectives. Therefore, a cross-sectional design procedure is implemented. The cross-sectional method employs research instruments that permit the collection of data on a particular topic. In this study, the evocative artefacts modeled are EIS components as described by The Open Group Architecture Framework's (TOGAF) Technical Architecture [25]. The Open Group Architectural Framework is a prominent framework for enterprise architecture that describes a method for developing, planning, executing, and maintaining enterprise information technology architecture [25]. In the context of this work, the TOGAF's layers of abstraction provide the framework for feature decomposition and serve as nodes in the Bayes network model derived from the TOGAF Technical Architecture. The accumulated data is structured to address each of TOGAF's six layers: strategy, business, application, technology, infrastructure, and implementation [25]. An essential element of the EIS criteria provided an efficient sampling strategy. To determine an organization's success or failure rate, a representative sample was applied.

Analysis of the primary data comes from a case study of the Computing Centre at Veritas University. Unique in nature, primary data provides the required authenticity for research. Data analysis consisted of the collection and classification of data using arithmetic averages to provide context and explanation for observations and to determine the overall trend of a data set. The standard deviation was utilized to determine the dispersion of the data around the mean. A high standard deviation indicated that the data were more dispersed from the mean, whereas a low standard deviation indicated that the data were more concentrated around the mean. The standard deviation was beneficial for evaluating the dispersion of data points in a portfolio of data analysis methods included in this study. In addition, regression models were deciphered in order to identify correlations between dependent and explanatory variables, and scatterplots were generated that were pertinent. Moreover, the regression line indicates whether the relationships are robust or feeble, thereby facilitating the identification of trends over time. This simplified the implementation of probability to convey uncertainty in various statistical model components [20]. Furthermore, it permits a flexible extension of maximum likelihood and is an information-efficient way to estimate a statistical model.

4. Bayesian Theory, Dataset Probability Distribution and Results

Decision theory is an area of mathematics that investigates the logic and mathematical characteristics of uncertain decision-making [11]. It is utilized in a vast array of human endeavors. The notion of maximizing anticipated effectiveness is fundamental to Bayesian decision theory [19]. Fundamentally, the probability of a class or event occurring is calculated based on the likelihood of a feature's value occurring and any prior information about the class or event of interest [24] as given in the conceptual model Equation (1).

$$P\left(\omega_j/x\right)=\frac{P\left(x/\omega_j\right)P\left(\omega_j\right)}{P\left(x\right)}=\frac{\text{likelihood}\times\text{prior}}{\text{evidence}};\text{ Source [11]} \quad (1)$$

Bayesian inference is a method of statistical inference in which Bayes' theorem is used to simulate the probability of a hypothesis as additional evidence or data becomes available [26]. In the dynamic analysis of a sequence of data, Bayesian updating is particularly crucial. In the philosophy of decision theory, Bayesian inference has a close relationship with subjective probability, often referred to as "Bayesian probability" [8]. Each hypothesis includes an exhaustive list of network parameters or features. As applied to this work, satisfaction or dissatisfaction with hypothesis where there is evidence or no evidence is represented by the Bayesian theory as in **Table 1**.

The probability distribution of the dataset indicates the likelihood that the desired event will occur [24]. Each node in the network that represents a variable represents the data as a percentage of probability. These percentages enable the model to accurately predict outcomes based on the simulation requirements [23]. The deterministic variables are defined in the first section of the model, which consists of basic probabilistic attributes and associations as shown in **Table 2** and **Table 3**. Nevertheless, the offspring nodes total the probabilities associated with the variable parameters. This property permits the prediction of responses to changes in parent nodes [19].

To calculate the probability of Efficiency, Speed, and Security, a similar method is employed, in which the scale is derived from the conditional probabilities of the connecting nodes of effects [26], as shown in **Table 4** and **Table 5**. The

Table 1. Generative algorithm for Bayesian inference.

Hypothesis / Evidence	Satisfies hypothesis (Event occurs) ω	Dissatisfies hypothesis (Event does not occur) $\neg\omega$	Summative
Has evidence χ	$P(\omega\|\chi)\cdot P(\chi)$ $= P(E\|\omega)\cdot P(\omega)$	$P(\neg\omega\|\chi)\cdot P(\chi)$ $= P(\chi\|\neg\omega)\cdot P(\neg\omega)$	$P(\chi)$
No evidence $\neg\chi$	$P(\omega\|\neg\chi)\cdot P(\neg\chi)$ $= P(\neg\chi\|\omega)\cdot P(\omega)$	$P(\neg\omega\|\neg\chi)\cdot P(\neg\chi)$ $= P(\neg\chi\|\neg\omega)\cdot P(\neg\omega)$	$P(\neg\chi) =$ $1 - P(\chi)$
Total	$P(\omega)$	$P(\neg\omega) = 1 - P(\omega)$	1

Table 2. CPT for software efficiency.

High	Low	Software_Type	Software_Version
0.9	0.1	Easy	Recent
0.4	0.6	Easy	Old
0.4	0.6	Difficult	Recent
0.1	0.9	Difficult	Old

Table 3. CPT for hardware efficiency.

High	Low	Hardware_Model
0.9	0.1	Recent
0.3	0.7	Old

Table 4. Probability distribution of responsiveness.

Speed:				
High	Low	Hardware_Efficiency	Network_Efficiency	Staff_Efficiency
1	0	High	High	High
0.7	0.3	High	High	Low
0.8	0.2	High	Average	High
0.6	0.4	High	Average	Low
0.6	0.4	High	Low	High
0.2	0.8	High	Low	Low
0.8	0.2	Low	High	High
0.2	0.8	Low	High	Low
0.4	0.6	Low	Average	High
0.1	0.9	Low	Average	Low
0.2	0.8	Low	Low	High
0	1	Low	Low	Low

Table 5. CPT forecast for enterprise goals.

Successful	Unsuccessful	Efficiency	Speed	Security
1	0	High	High	High
0.9	0.1	High	High	Low
0.5	0.5	High	Low	High
0.2	0.8	High	Low	Low
0.2	0.8	Low	High	High
0.1	0.9	Low	High	Low
0	1	Low	Low	High
0	1	Low	Low	Low

BN modelling technique begins with a detailed declaration of the model's purpose and scope, followed by the accumulation of information about the system being modelled and its representation as a conceptual model. This conceptual model contributes to the development of the taxonomy of lean Bayesian Networks [20].

The Conditional Probability Tables and states associated with each node are individually described in order to extract expert knowledge (**Table 4** and **Table 5**). The stated dependencies are associated with all assumptions established during the BN development process, including uncertainties, justifications, and explanations for each node and connection, as well as information and data sources. This increases model transparency and enables users to identify the foundations and assumptions of the model in their entirety. It also facilitates the evaluation, reconstruction, replication, and modification of the model [26].

The foundation of Bayesian learning is the concept of allocating probabilities to hypotheses and revising them based on observed evidence. Predictions can be made for every conceivable hypothesis by evaluating their individual forecasts based on the likelihood that the hypothesis generated the observed data and then summing the predictions [9]. If the set of alternative hypotheses is extremely complex, approximations can be used to reduce the graphical model complexity. Bayesian models are a practical and well-researched method for characterizing and reasoning about ambiguous issues [4]. The widespread use of Bayesian Networks is primarily attributable to their ability to deconstruct a complex joint probability distribution into a succession of smaller conditional probability distributions [9].

Prior, Evidence, Likelihood, and Posterior are the four components of Bayes' theorem [26]. The prior distribution of an undetermined quantity is the probability distribution that reflects an individual's pre-evidence beliefs regarding the quantity [23]. The prior is a probability distribution that represents the proportional business value that will be gained or lost due to changes to predictive indices in this study. The unidentified quantity could be a model parameter or a concealed variable. Bayes' theorem is concerned with the probability of an event and its inverse, while the use of evidence is related to the probability of discovering evidence in a given circumstance [9]. The likelihood function describes the joint probability of the observed data as a function of the parameters of the statistical model [17]. Given the pertinent data or context, the conditional probability is the posterior probability of a random event or ambiguous claim. A fundamental principle of Bayesian decision theory is the notion that when evaluating data-based evidence, the consequences of actions linked to the data can be explicitly evaluated [26].

5. Simulation and Discussion

The model in **Figure 1** depicts how the components of EIS may be utilized to predict the success rate of a company. To verify the model, a simulation of highly

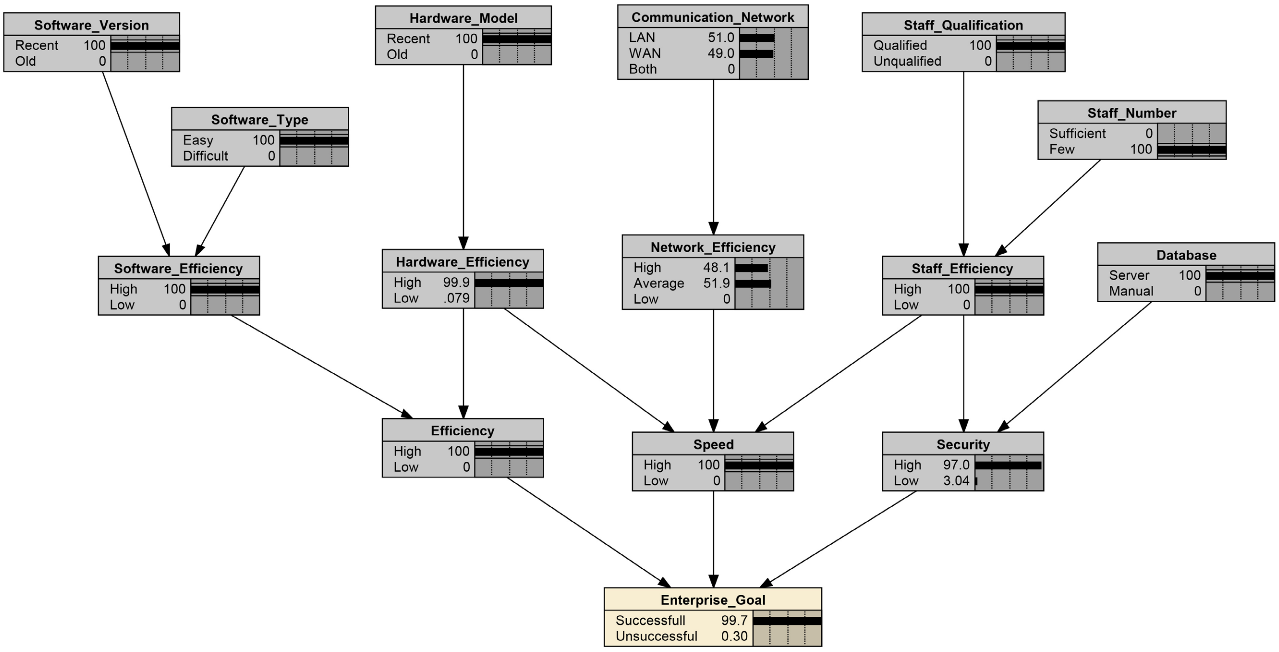

Figure 1. Bayesian network model for positive boundary value evaluation.

predictive elements across all nodes achieve 100 percent corporate objective achievement. Efficiency, speed, and security of the nodes all contributed to a significant portion of the company's objective.

Compiled into 10 cliques, the total table size (including sepsets) is determined as 158. Nodes that conditional probabilities are unspecified explicitly e.g. Network_Efficiency are taken as having uniform probabilities. Simulated case yields. Probability of findings = 2.18089e−14%., Horizontal spreading 23%: Probability of findings = 6.43418e−14%. Percentage of case data to be missing: 0. An exhaustive case file, listing every possible case and its exact frequency of occurrence is given as Probability of new finding = 100%, of all findings = 3.56611e−12%.

Figure 2 illustrates a simulation that compares the effects of superior technology and unskilled labour on corporate objectives. The presence of advanced technology without proficient human resources can potentially impede the achievement of organizational objectives. Although advanced technology has the potential to enhance efficiency, productivity, and overall performance, untrained personnel may not possess the necessary skills to fully exploit or harness the technology's capabilities. The utilization of technology by unskilled labour may necessitate additional training and support, thereby potentially escalating the company's expenses. Furthermore, inadequate utilization of technology may necessitate additional maintenance or repairs, thereby resulting in escalated expenses. Test with cases indicates the Scoring Rule Results for performance index of Communication_Network Logarithmic loss as 1.084, Quadratic loss as 0.7702 and Spherical payoff = 0.506. For Software_Efficiency, Scoring Rule Results were Logarithmic loss = 0.6014. Quadratic loss = 0.4094 and Spherical payoff = 0.7701. Calibration was indicated as High for a range of 0 - 40: aggregated at 22.7;

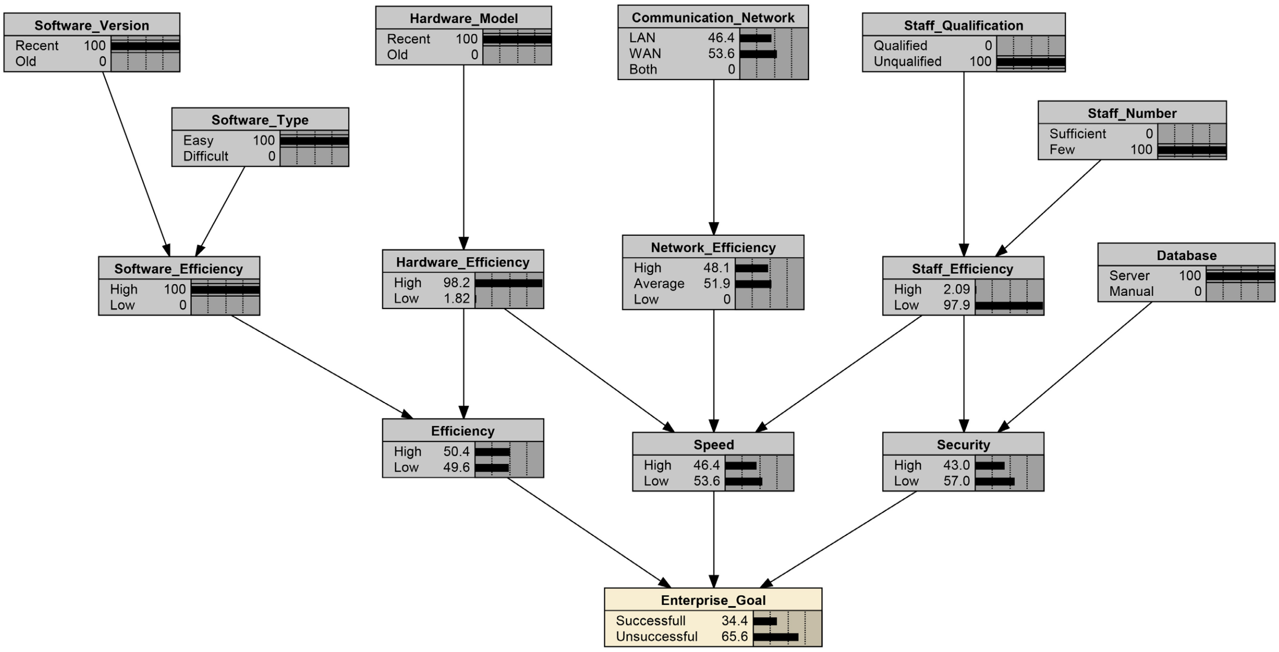

Figure 2. Simulating the effect of excellent technology versus incompetent manpower on enterprise goal.

Low for the range of 0 - 70: aggregated at 77.3 and Totaled as 0 - 40: 22.7 and 40 - 70: with overall aggregate as 77.3. The Quality of Simulation Test for state "High" is given in Table 6:

Figure 3 depicts the Simulation of minimum definitive CPT composition for 100% Success of Enterprise Goal. For the simulation of the minimum definitive conditional probability tables required to represent the probability of 100% success of an enterprise goal, the model relied on several factors as presented in the nodes and the level of uncertainty associated with each variable. Specifically, the conditional probability table for enterprise goal identifies all the relevant variables that impact the success of the goal, estimates their probabilities, and determines how these probabilities are related to each other. The predictive indices were indicated as successful for simulation variance of 45 and unsuccessful at 55 with Error rate = 45.17%. Scoring Rule Results for Logarithmic loss = 0.7086, Quadratic loss = 0.5144 and Spherical payoff = 0.6979. Simulated Calibration indicative for Successful ranged from 0 - 40: aggregated at 45.2 and Unsuccessful ranged from 0 - 70: aggregated at 54.8. Quality of Test for state "Successful" is given in Table 7.

Figure 4 shows the entire network with a simulation to test the boundary cases to ensure that the model predicts and forecasts as delineated. It shows a simulation in which all the factor nodes are at extremely high boundaries.

Accurate corporate success rate forecasts are advantageous for providing a business with the resources required to resolve business issues and maintain a strong corporate culture [7]. This model emulates every aspect of predictive indices, specifically modifying the parameterized EIS components used for autonomous performance prediction. The Bayesian network parameters were determined using

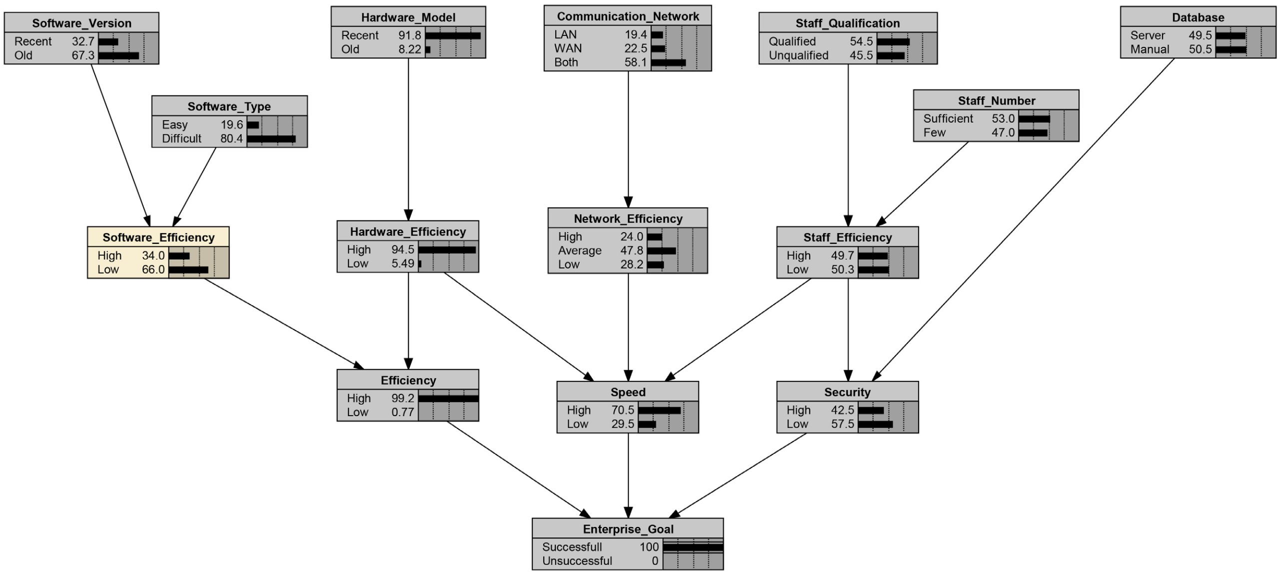

Figure 3. Simulation of minimum definitive CPT composition for 100% success of enterprise goal.

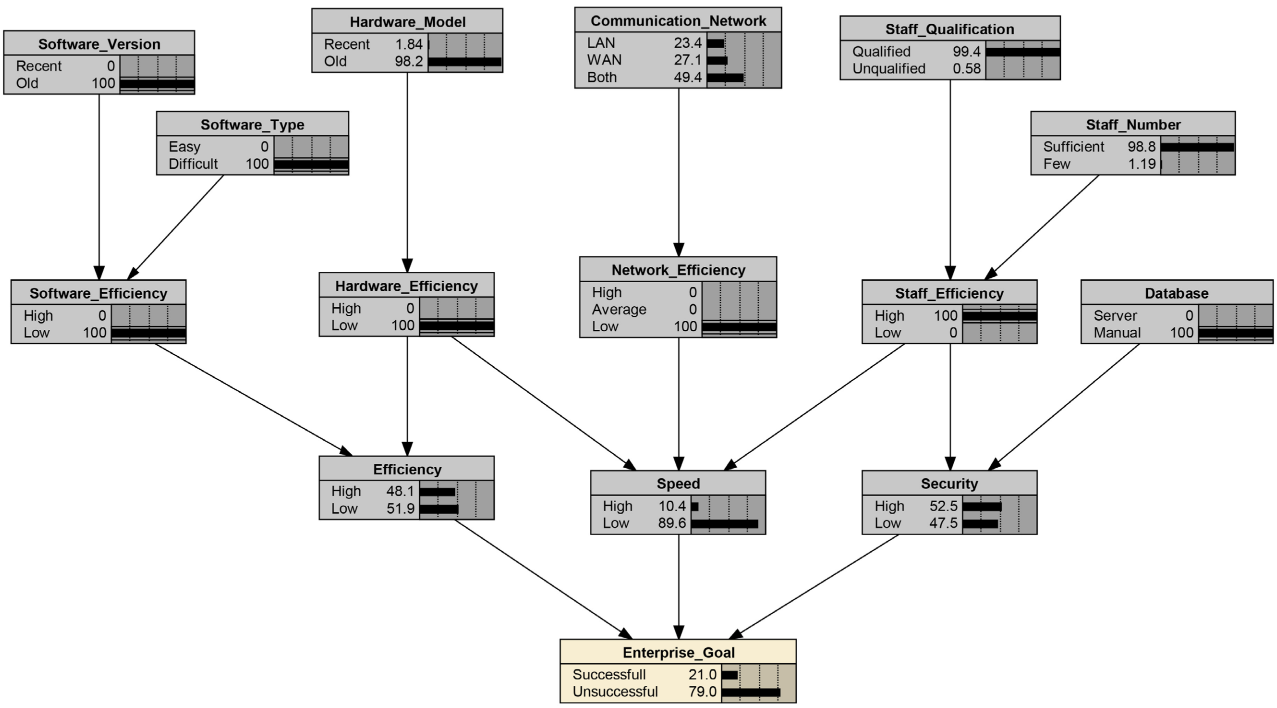

Figure 4. Simulating the effect of poor technology versus proficient manpower on enterprise goal.

Table 6. Quality of test for state "High".

Cutoff	Sensitivity	Specificity	Predictive	Predict-Neg	Error-Rate
0	100.00	0.00	22.73	100.00	77.27
40	0.00	100.00	100.00	77.27	22.73
100	0.00	100.00	100.00	77.27	22.73

Gini Coeff = 0; Area Under ROC = 0.5.

Table 7. Quality of test for state "Successful".

Cutoff	Sensitivity	Specificity	Predictive	Predict-Neg	Error-Rate
0	100.00	0.00	45.17	100.00	54.83
40	0.00	100.00	100.00	54.83	45.17
100	0.00	100.00	100.00	54.83	45.17

Gini Coeff = −1.11e−16; Area Under ROC = 0.5.

the maximum likelihood method. The results indicated that they provided an accurate response to the question, indicating that they are less knowledgeable than an expert group. Before implementing a business plan, simulations of the model can assist organizations in predicting success rates and determining whether organizational objectives are met. BNs are well-suited for modelling business systems due to their ability to incorporate data and knowledge from a wide range of predictive elements.

6. Conclusion

This study evaluates and quantifies the impact of Enterprise Information Systems on business objectives using Bayesian Networks. According to [11], performance is the end result of an activity, while organizational performance is the total of all work procedures and activities. Because it enhances asset management, the capacity to provide value to customers, and the evaluation of organizational expertise, managers monitor and supervise organizational performance. When evaluating the performance of an organization, past management decisions affecting investments, operations, and financing are examined to determine if all available resources were utilized efficiently, if profitability targets were met or even exceeded, and if financing decisions were prudent. Common organizational performance indicators include efficiency, productivity, efficacy, and innovative technology adoption [11]. Computer software, computer hardware, telecommunications, database management systems, and personnel are EIS components that contribute to the success of an organization [26]. Verifying that the criteria are effective, relevant, attainable, and verifiable requires the use of accessible techniques for identifying or enumerating these elements. This study created a network using Bayesian networks to investigate complex logical links using probability to express various types of uncertainty and probabilistic rules in order to enhance forecasting with machine learning modelling for business process management and reasoning. This study investigates the success rate of businesses that have implemented the appropriate EIS model/component using Bayesian networks. A Bayesian network model has been developed and simulated to evaluate the complex logical relationships uncovered by EIS and to illustrate their impact on the organization. A characteristic of Bayesian networks is that a limited collection of direct interactions and local distributions is simpler to conceptualize than joint distributions as a whole. Consequently, future research into Joint distributions with sparse dependencies is feasible. Each example plan should be used for different components based on the likelihood that their effects will differ between when they are applied and when they are independently developed.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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