Decision Support System using Artificial Neural Network for Managing Product Innovation

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Abstract

The firm's capability to develop product innovation and successfully launch new products has been regarded as crucial determinant in sustaining a firm's competitive advantage. Firms have been faced with a complicated problem in selecting innovation development project. From review of the related studies we found two groups of capability; firm's innovative capability and firm's new product development capability together with the external competitive environment factor are the factors influence the successful development of product innovation. We use the Artificial intelligence; Artificial Neural Network (ANN), to develop the decision support system concerning the selecting of product innovation development projects and found that The ANN model provide a fast, flexible and strong predictive ability for selecting the product innovation development project.

Keywords: *Artificial Intelligence, Artificial Neural Networks, Innovation Capability, New Product Development Capability, Product Innovation.*

1. Introduction

It is urged that succeeding in a competitive environment; firms must create and sustain a competitive advantage [1]. The firm's capability to develop product innovation and successfully launch new products has been regarded as a crucial determinant in sustaining a firm's competitive advantage [2], [3]. Firms have been, for a long time, faced with a complicated problem in development project selection decisions, such as go/no-go choices and specific resource allocation decisions. Despite a long list of high potential product innovation for management to choose, pledged support from product champions, and increased attention from researchers on the development problem, there still is a relatively stable success rate near 59% for new products in the marketplace[4], [5].

This paper is aim to 1) review the literature of factors influence the successful product innovation 2) develop the model by using the Artificial Neural Network (ANN) and test its predictive ability in selecting the product innovation development project.

2. Literature Review

2.1 Product Innovation and its Key Success Factors

Because the pattern of the relationships between the independent (input) factors and the dependent (output) factor in our model will be learned from the data by the Artificial Neural Network (ANN) algorithm, the selection of input to the neural networks is an important decision. It is crucial to select factors that fully capture the domain of interest-success factors in the product innovation process. In this session we focuses on a literature review of the factors to provide an understanding of how they affect the successful product innovation development. Also, as our goal is different from that of previous study; therefore, our selection process differs. Instead of adopting a micro approach to understand the specific effects of a few factors, we use a macro approach that examines a broad variety of factors in an effort to capture the complexities of the product innovation development. This macro approach is warranted because we are trying to subsume the intricacies of the process into our model to improve the accuracy of its predictions (Calantone, di Benedetto, and Bojanic 1988) [6]. Furthermore, all the measures were well-validated and accepted measures in the new product literature (see Song and Parry 1997 [7]). In choosing the input for our models, we rely on the resource-based theory of the firm (Wernerfelt 1984, Barney 1991; Conner 1991) [8]-[10]. Resource-based theory provides a unique insight into the situation that faces managers who make project selection and resource allocation decisions. This theory is relatively new in relation to industrial organization theory. Traditional industrial organization theory posits that a firm's strategy and ultimately its ability to create and sustain a competitive advantage are dependent on environmental factors. Resource-based theory takes a different position by viewing firm resources as heterogeneous and immobile. Thus, each firm has a limited, heterogeneous endowment of resources, and its task is to combine the endowment to form capabilities which are the basis for creating a unique, valuable market offering that is not easily imitated or substituted. The central tenant of resource-based theory is that this offering is the mechanism for creating a sustainable competitive advantage for the firm.

A review of literature in the study of factors influence the successful product innovation has shown numerous factors which can be grouped into three main factors: (1) the firm’s innovation capability, (2) the firm’s new product development capability, (3) the external competitive environment.

2.1.1. The Firm’s Innovation Capability

A review of the new product success literature suggests that the firm’s innovation capability is the necessity required to create product innovation.

Absorptive capability is the firm ability to recognize the value of new information, assimilate it and apply it to commercial end [11]. Cooper [12] has found that adopting a transnational new product process is a critical success factor to the product innovation. Organizational learning capability that regarded as the characteristic of absorptive capability of firm also has a significant and positive impact on process innovation [13]. Study also found that R&D process of the successful product innovation is well planned and executed by firm and new product success was more likely when the developing organization is proficient in marketing and commits a significant amount of its resources to selling and promoting the product [14].

The successful project execution methods are positively associated with development project execution [15], while new product success rates show a strong correlation with project portfolio management performance and project portfolio management methods used [16]. In addition, study has shown that creative capability and creative problem solving processes have significant impact on product innovation [13], [17]. Prajogo and McDermott [17] and Valencia, Valle and Jimenez [18] studied culture of innovation of firm and found that adhocratic cultures could enhance the development of new products or services. In addition, firm culture shows a positive relationship with product innovation. Ragatz, Handfield and Scannel [19] concluded that commitment from top management of companies in supporting new product development is a strategically critical issue impact a successful product innovation.

Study of Prajogo and McDermott [17] also found that decentralization shows a positive relationship with product innovation. Meanwhile, flexibility also shows a positive relationship with product innovation because effective product development execution requires organizational flexibility within a structure [15], [17].

2.1.2. The Firm’s New Product Development Capability

Many studies have pointed to various new product development activities as important determinants of new product success. Cooper [20] reported positive and significant correlations between new product success and development proficiency, which include measures of proficiency in idea development and screening, business and market opportunity analysis, product design, testing, launching and commercialization. A follow-up study reported similar results [21]-[24].

Cross-functional integration has also been identified by study of Song and Parry [24] and Griffin and Hauser [25] as an important determinant of new product success. For Cross-function integration, Study [14] concluded that the probability of new product success rises when the creation, make, and market functions are well interfaced and coordinated. Chakrabarti [26] pointed that product champion is important in the success of product innovation while Hoegl and Gemuenden [27] found that teamwork is important for the success of innovative projects.

From study of Lau [28], customer involvement can lead to better new product performance. More recently, Gruner and Homburg [29] pointed that customer interaction during certain stages of the new product development process has a positive impact on new product success.

Ragatz, Handfield and Scannell [19] in his study found that supplier involvement in new product development is also a strategically critical issue, while Ar and Baki [13] and Lau [28] confirmed that supplier relationship has significantly impact upon product innovation supplier involvement leads to better new product performance.

2.1.3. The External Competitive Environment Factors

Balachandra and Friar [30] urged that a new product development cannot succeed if the environment in which it is introduced is not supportive.

Many studies of new product success directly link the level of competition in the marketplace to the level of new product success. In a recent study of the electronics industry, Zirger and Maidique [31] reported that failures were more likely for products introduced into highly competitive markets. More recently, Parry and Song [32] found strong negative correlations between competitive intensity and new product success ratings in both China and Japan.

Study of Cao, Zhao and Nagahira [33] has shown that market uncertainties is reduced during the front end, the higher is the effectiveness of new product development projects product. Moreover, Balachandra and Friar [30] pointed that the expected growth rate of the market for the product is an important successful factor for the decision to pursue the new.

Cao, Zhao and Nagahira [33] urged that technical uncertainties is reduced during the front end, the higher is the effectiveness of NPD projects. Meanwhile cooperation with industrial agents was found very important for the development of new products [34].

Li, Millman and Chi [35] pointed that Government public R&D subsidies and disembodied technology imports positively and significantly impact on firms' private R&D investment. Study of Hardie and Newell [36] found that the role of government regulators in either inhibiting or driving innovation is regarded as critical by successful innovators.

From the review of the related study, the factors influences the successful product innovation developments are summarized in Table 1:

2.2 Artificial Neural Networks (ANN)

The literature review of ANN suggests several potential advantages that ANN has over statistical methods. ANN can be the good universal function approximations for even non-linear functions and also estimate piece-wise approximations of functions. ANN can be mathematically shown to be universal function approximations. This means that they can automatically approximate best characterizes the data for whatever functional form. ANN can also partially transform the input data automatically.

Table 1: Summary of Factors Affect Successful Product Innovation

The Firm's Innovation Capability
1. Absorptive capacity 2. R & D capability 3. Marketing capability 4. Project Management 5. Creativity Management 6. Culture of innovation 7. Internal commitment 8. Managerial control 9. Flexibility
The Firm's New Product Development Capability
1. Idea development and screening proficiency 2. Business and market opportunity analysis proficiency 3. Product conceptual design and detailed design proficiency 4. Product testing proficiency 5. Product launching and commercialization proficiency 6. Cross-functional integration 7. Teams and champion 8. Customer involvement 9. Suppliers involvement
The External Competitive Environment
1. Competition intensity 2. Market potential and demand uncertainty 3. Technological change & uncertainty 4. Supplier availability and capacity 5. Government support

2.2.1 An Artificial Intelligence Approach Using Neural Networks

Inspired by the neuron-structure of the brain, the collection of mathematical models known as neural networks has developed as an approach to provide algorithmic structures that can interact with the environment in much the same manner as does the human brain. This interaction includes such aspects of artificial intelligence as, for example, learning from experience, generalizing from examples, and abstracting the essence from input data that may contain irrelevant factors. Structurally, the neural network model can be represented as an interconnection of many autonomous individual processing units that behave similarly in certain respects to the interconnections of individual neurons in the brain. Mathematical neural networks function by constantly adjusting the interconnections between individual neural units. The process by which the mathematical network "learns" to change the interconnections, improve performance, recognize patterns, and develop generalizations is called the training rule. One of the popular algorithms that have been used successfully in many applications is the "back-propagation learning algorithm" based on a "feed forward" network, described below. This study uses this algorithm for assessing successful propensity of developing product innovation. Essentially, the feed forward designation indicates that the flow of the network intelligence or information is from input toward output as, for example, occurs in path models and structural equation or maximum likelihood factor analysis causal models.

The structure of the artificial neural networks used in this study is that of the Multilayer feed forward network (MFN) (see Figure 1). In this structure shown there are three parallel layers. The first (input) layer contains the independent variables, the second (hidden) layer contains processing units (called hidden nodes), and the third (output) layer contains the dependent variables. The layers are connected by weighted links.

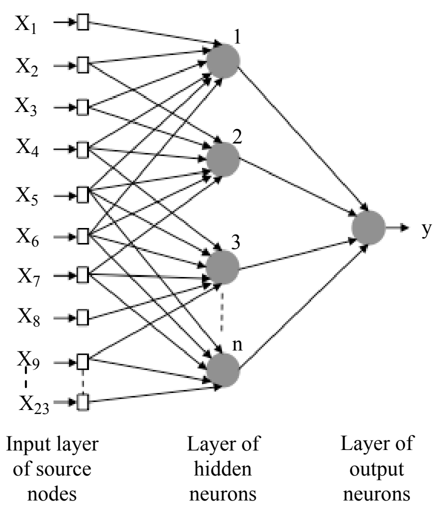

Fig. 1 The Multilayer feed forward network (MFN)

In mathematical terms, we may describe the neural k by writing the pair of equation.

$$u_k = \sum_{j=1}^{m} w_{kj}\, x_j \tag{1}$$

and

$$y_k = \varphi\,(u_k + b_k) \tag{2}$$

where $x_1, x_2, \ldots x_m$ are the input signals; $w_{k1}, w_{k2}, \ldots w_{km}$ are the respective synaptic weights of neural k

y_k is the output signal of the neuron

u_k is the linear combiner output

b_k is the bias, φ is the activation function

As

$$v_k = u_k + b_k \tag{3}$$

We may formulate the combination of Equations. (1) to (3) as follows:

$$v_k = \sum_{j=0}^{m} w_{kj}\, x_j \tag{4}$$

2.2.2 The Back-Propagation Algorithm

The back-propagation designation indicates that the particular learning algorithm updates its abilities by starting at the output, determining the error produced with a particular mathematical structure, and then propagating this error backward through the network to determine, in the aggregate, how to efficiently adjust the mathematical structure in order to improve the ultimate output behavior of the network. Although this is an iterative and possibly somewhat time consuming algorithm, when trained on adequate samples it gives good results in practice. To date, neural network mathematical techniques have been applied in many areas, such as pattern recognition, knowledge data bases for stochastic information, robotic control, and financial decision making. To achieve pattern recognition, the neural network takes a given pattern as input (e.g., a digitized picture) and matches this pattern with an associated output (e.g., one of a class of prototypic patterns or images). The ability to keep both the input and output patterns in the associative memory makes the network, to some degree, insensitive to minor variation in its input. Neural networks also have reconstruction ability. When an input pattern is not complete, the network will attempt to identify it with the most closely related pattern in its memory. It should be noted that, unlike other artificial intelligence methods that train a network deductively by programming in a system of mathematical logic, the neural network model "learns" empirically or inductively by training repeatedly on a given set of sample input data. These training sessions develop an appropriate nonlinear mathematical network model that can essentially repro- duce the observed output from the given input. Thus, the method does not start with an a priori model of the relationship between input and output (as is the case in causal linear statistical models). Indeed, it is discovering the relation- ship (or logic) between the input and output that is one of the primary thrusts of the training exercise on the network. It follows that, in actual applications, learning can continue even while the network is producing predictions. This, of course, allows the network to adapt to new situations (a feature absent from causal models or other static statistical estimation techniques such as discriminant analysis, logistic regression, linear regression, etc.). Information in neural networks is distributed throughout the network. When some pieces of information are lost (such as some processing units are destroyed), this may not cause the whole network to collapse.

The back-propagation algorithm can be viewed as a gradient search technique where the objective function is to minimize mean square error between the computed outputs of the network corresponding to the given set of inputs in a multilayer feed forward network and the actual outputs observed in the data for these same given inputs. The network is trained by presenting an input pattern vector X to the network, performing the calculations sequentially through the network until an output vector 0 is obtained. The output error is computed by comparing the computed output 0 with the actual output for the input X. The network attempts to learn by adjusting the weights at each individual neural processing unit in such a fashion as to reduce the observed pre- diction error. Mathematically, the effects of prediction errors are swept backward though the network, layer by layer, in order to associate a "square error derivative" (delta) with each processing unit, compute a gradient from each (delta), and finally update the weights of each processing unit based upon the corresponding gradient. The process is repeated starting with another input/output pattern. After the training set is exhausted, the algorithm starts over again on the training set and readjusts the weights throughout the entire network structure until either the objective function (sum of squared prediction errors on the training sample) is sufficiently close to zero or the default number of iterations is reached. The computer algorithm implementing the back-propagation technique used in this study is from Eberhart and Dobbins (1990) [37]. The mathematical formulations required for implementing the analysis are shown on figure 2.

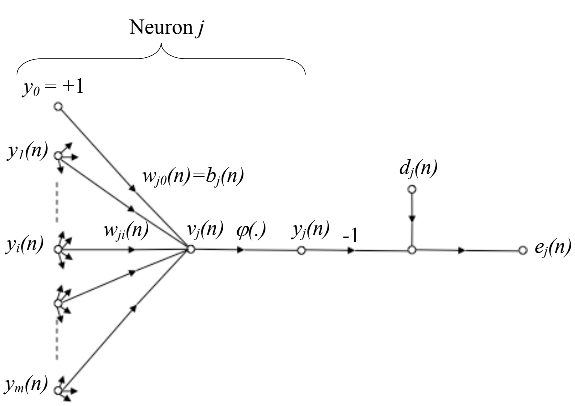

Fig. 2 The Back-Propagation Algorithm

Consider Figure 2, which depicts neuron *j* being fed by a set of function signals produced by a layer of neurons to its left. The induced local field $v_j(n)$ produced at the input of the activation function associated with neuron *j* is therefore:

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n) y_i(n) \tag{5}$$

Where *m* is the total number of inputs (excluding the bias) applied to neuron *j*. The synaptic weight w_{jo} equals the bias b_j applied to neuron. Hence, the function signal $y_i(n)$ appearing at the output of neuron at the iteration *n* is:

$$y_i(n) = \varphi_j(v_j(n)) \tag{6}$$

From Figure 2, the correction $\Delta w_{ji}(n)$ is defined by

$$\begin{pmatrix} \textit{Weight} \\ \textit{correction} \\ \Delta w_{ji}(n) \end{pmatrix} = \begin{pmatrix} \textit{learning-} \\ \textit{rate parameter} \\ \eta \end{pmatrix} \times \begin{pmatrix} \textit{local} \\ \textit{gradient} \\ \delta_j(n) \end{pmatrix} \times \begin{pmatrix} \textit{input signal} \\ \textit{of neuron j,} \\ y_i(n) \end{pmatrix} \tag{7}$$

Where local gradient $\delta_j(n)$ is defined by:

$$\delta_j(n) = e_j(n)\ \varphi'_j(v_j(n)) \tag{8}$$

From Equation (8), local gradient $\delta_j(n)$ for the output neural j is equal to the product of the corresponding error signal $e_j(n)$ for that neural and the derivative $\varphi'_j(v_j(n))$ of the associated activation function is defined by

Finally, we get the back-propagation formula for the local gradient $\delta_j(n)$ described by

$$\delta_j(n) = \varphi'_j(v_j(n)) \sum_k \delta_k(n) w_{kj}(n), \text{ neuron j is hidden} \tag{9}$$

For activation function, the continuously differentiable nonlinear function commonly used in multilayer perceptrons is sigmoid nonlinearity logistic function as described by:

$$\varphi_j(v_j(n)) = \frac{1}{1+\exp(-av_j(n))}, \quad a > 0 \qquad (10)$$

2.2.3 Network Generalizability

Our focus in evaluating our system's performance will be generalization. Generalization refers to the ability of a trained artificial neural network to respond correctly to input not used during the training process. Therefore we train our model with one partition of the data set and test with another partition not used during the training. Network generalizability is related to the concepts of underfitting, overfitting, and smoothing in polynomial curve fitting. Underlearning and overlearning in neural networks are analogous to underfitting and overfitting, respectively, in the degree of the polynomial. One reason for underlearning can be that the complexity of the network (in terms of the number of hidden nodes and weights) is lower than the complexity of the phenomenon being modeled. Overfitting is the opposite and can occur when network complexity exceeds the complexity of the phenomenon being modeled. Thus, complexity in neural networks is analogous to the flexibility that can be achieved by changing the power of the polynomial in line fitting. Study of the statistical properties of network generalization error led to valuable insight regarding methods and strategies for attacking the generalization problem in neural networks.

Consider the expression for the expected value of the SSE function (Geman, Bienenstock, and Doursat 1992) [38]; Bishop 1995 [39]:

$$SSE = E\{[y(x) - tlx]^2\} \qquad (11)$$

where E[.] is the expected value of the argument, y(x) is the output of the network for a given input vector x, and tlx is the conditional average of the target vector given an input vector x. Adding, subtracting, and expanding terms leads to the following expression:

$$E\{[y(x) - tlx]^2\} = E(\{y(x) - E[y(x)]\}^2) + E(\{E[y(x)] - tlx\}^2) \qquad (12)$$

The first term on the right-hand side is the variance, and the second term is the squared bias of the expected value of the SSE of the network output.

In statistics, the mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The error is the amount by which the value implied by the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate.

The MSE is the second moment of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. Like the variance, MSE has the same units of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root mean square error or root mean square deviation (RMSE or RMSD), which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard deviation.

The MSE of an estimator with respect to the estimated parameter θ is defined as

$$\mathrm{MSE}\,(\hat{\theta}) = E[(\hat{\theta} - \theta)^2] \qquad (13)$$

The MSE is equal to the sum of the variance and the squared bias of the estimator

$$\mathrm{MSE}\,(\hat{\theta}) = \mathrm{Var}(\hat{\theta}) + [\mathrm{Bias}\,(\hat{\theta},\theta)]^2 \qquad (14)$$

Variance in this case represents the network's sensitivity to the particular data set used in the training process. Conversely, the bias of the network represents the difference between the target (actual) output of the network, t, given a set of input, and the average output of the network over all possible data sets. Increasing the generalizability of a given network involves reducing variance and bias. Network complexity, as a function of the number of weights and hidden nodes in the network's structure, affects both variance and bias. Bias is negatively related to network complexity, but variance is positively related to complexity. Therefore, to achieve good generalizability in a network, we seek the optimal network complexity that minimizes the trade-off between variance and bias.

2.2.4 Cross Validation

The Use of v-Fold Cross-Validation is for achieving good generalizability. To control for the bias-variance dilemma in our study, we use a v-fold cross-validation procedure in the learning process, which is a popular and powerful tool for improving generalization properties in neural networks (Bishop 1995 [39]; Hassoun 1995 [40]; Masters 1995 [41]; Ripley 1996) [42]. In this method, the data are split into training and evaluation partitions, and the training data are further split into v (in our case v = 10) equal-sized sub- sets. The procedure begins with a simple network structure (one hidden node). This structure is trained v times, and each time one of the v subsets is left out for validation. Validation error is calculated as the total error over the ten data subsets. Summing the errors from each of the holdout subsets generates an estimate of the network's generalization error for that particular network structure. Next, another hidden node is added to the network, and the cross-validation process is repeated for an estimation of the network's generalizability for this network structure. This continues until a network structure is identified that maximizes the network's expected generalizability.

3. Data

The data consist of 87 product innovation projects introduced by entrepreneurial firm in Thailand. To assess the validity of the project performance and avoid potential bias, we asked the contact people and other company executives to assess the project's performance and classify the project as either a success or a failure using the following criteria: The project should be considered a success if the new product has been completely launched and gained an expected market share; the project should be considered a failure if the new product failed the product testing, or manufacturing, or launching.

Network's input layer has 23 nodes, corresponding to an independent variable. All inputs are measured on a 0-to-10 scale. The output of the networks is dichotomous success, or failure. The target during training is a dichotomous variable that represents a self-selected successful or unsuccessful project as determined by the informant. This MFN model simply predicts project success or failure.

4. Analysis

In MFN model, we use nonlinear sigmoid functions, specifically, the logistic function:

$$f(x) = 1/(1 + \exp^{-x}) \qquad (15)$$

as activation functions for all hidden nodes and linear activation functions at the output. We perform the training and evaluating the model using the WEKA open software package, Version 3.6.3. Because our goal in constructing the networks that constitute a MFN model is to achieve good generalizability, we perform a v-fold cross-validation procedure (v = 10) for a network using dichotomous success/failure as the output.

5. Result

Table 2: Predictive Performance of the Model

Stratified cross-validation		
Correctly Classified Instances	84	96.551%
Incorrectly Classified Instances	3	3.4483%
Kappa statistic		0.9286
Mean absolute error		0.0444
Root mean squared error		0.1867
Relative absolute error		9.135%
Root relative squared error		37.869%
Total Number of Instances		87

Table 3: Summary of Performance Based on Success/Failure Prediction

	Predict Success	Predict Failure	Correct Predictions in Evaluation Sample (n=87)
Actual Success	50 (98%)	1 (2%)	87 (96.5%)
Actual Failure	2 (5.6%)	34 (94.4%)	

To address our research objective to develop artificial neural network decision support systems that have a strong predictive ability for selecting the product innovation developments, we evaluate the artificial neural network system using our holdout sample, which consists of 87 product innovation development projects. Performance is measured in terms of Kappa Statistic (K) and Mean Square Error (MSE), where error is the absolute value of the difference between the actual project success and the predicted project success. The results in Table 2 indicate that our MFN model has the very high the Kappa Statistic at 0.9286 (1 mean 100% accuracy) and very low value of MSE $(0.1867)^2$ or 0.0348. Thus, using Kappa Statistic and MSE as performance criteria, our neural network decision support system has a strong predictive ability for selecting product innovation development on the basis of success/failure criteria.

We also construct 2 x 2 confusion matrices that indicate the types of errors that were made. These results in Table 3 indicate that the MFN model has the strong prediction power, correctly predicting 96.5% of the 87 product innovation projects in our evaluation sample. The results show the MFN model's predictive power. The numbers on the diagonal from the upper left-hand corner to the bottom right-hand corner of each confusion matrix indicate correct predictions or 98% on success cases and 94.4% on failure cases, whereas the numbers on the off-diagonals indicate misclassification which is 2% on success cases and 5.6% on failure cases.

6. Conclusions

This objective of this study is to develop the model concerning factors influencing the successful product innovation and the utilizing of artificial intelligent methodologies and applications. We conclude that firm's innovation capabilities, firm's new product development capability and external competitive environment are three groups of factors that influence the successful product innovation. In searching for the alternative and more effective tools to the statistic analysis method traditionally used, we selected the Artificial Neural Network (ANN) model, which is particularly useful for modeling underlying patterns in data through a learning process. We developed the model using the ANN and trained with 23 inputs and data from 87 product innovation projects to recognize patterns consistent with success and failure. From the measure of the predictive ability of the model through the variance measurement (MSE) and the accuracy of the predictive ability (Kappa Statistic), the resulting strong prediction ability of the network is recognized.

From the practitioner's view, our set of MFN models demonstrates how neural networks can be used for managerial guidance in project screening and diagnostic evaluation in the management of product innovation projects. The MFN models developed here exhibit consistently strong predictive performance, as regarding to the criteria used for performance evaluation. However, event ANN methodologies have attractive predictive properties; they have limited applications in interpretation and explanation due to the characteristics of the unknown hidden layers of the model. For future study, we recommend the classifying of output not limit to the dichotomous value of success and failure but we can classify into more level of success such as technical success (which means successful product development but limited commercial success) and commercial success (which means success in both product development and commercialization). This will help managers to clearly understand the stage of failure of the development project.

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