Predicting Firm Performance and the Role of Top Management Team (TMT): A Fuzzy Inference Approach

Yousif I. Alhosani, Constantine J. Katsanis, and Sabah Alkass

***Abstract*—The combination of business forecasting, Top Management Team (TMT) and Fuzzy Inference System is rarely seen in the literature. Drawing on the Upper-Echelon perspective, we investigated the power of Top Management Team (TMT) composition to forecast firm performance. A Multi Input – Multi Output Adaptive Neuro-Fuzzy Inference System (ANFIS) approach was used in two dimensions, Cross-section and Time Series forecasting. Six input performance enablers were used to forecast a multifaceted firm performance. Two stage analysis was applied, and the results provide empirical evidence of the power of TMT to forecast the firm's performance. This study represents a promising new way for future extension in this field currently understudied, including the possibility of introducing a firm's pre-defined bins or categories classification methods rather than an exact figure forecasting. Also, it is suggested that firm's performance forecasting should be obtained from one region as opposite to multiple regions. This may reduce errors associated with disparities between different regions in terms of overall economic context and TMT composition governance.**

***Index Terms*—ANFIS, Top management team, firm performance, forecasting.**

I. Introduction

While previous research has almost entirely focused on the CEO or the individual leader, a new stream of literature rapidly emerged in the mid-1980s under the name of "Upper Echelon" perspective. In Hambrick and Mason's watershed article [1], "Upper Echelons: The Organization as a Reflection of its Top Managers" they have provided a boost to the empirical research by arguing that top management teams' demographic characteristics (e.g. age, education, tenure, diversity) are good proxies for the underlying traits and cognitive processes of the top executives [2]. Furthermore, the authors manifested that the firm's performance is a consequence of these constructs [3].

In strategic business studies in general, and Upper Echelon Theory in particular, previous studies attempted to present and illustrate the relationships between firm performance and certain contextual characteristics of the TMT (either diversity of / or demographical characteristics). However, [4] reported that "little research in forecasting has been done to aid in understanding the managerial side of forecasting". Also [5] concluded that the use of forecasting in business has greatly lagged behind the development in other fields. This was largely due to the inconsistency between the different propositions of various studies which led to confusion and multiple possible conclusions. In addition to that, those studies were dominated by statistical approaches which may cause a significant problem in considering qualitative factors [6] such like those suggested in Upper Echelon Theory. These statistical methods require arbitrary aspiration levels and cannot accommodate subjective attributes. With focus on construction industry, this paper is proposing a Fuzzy Inference forecasting model that would facilitate the Upper Echelons Theory of TMT demographic characteristics as main unit of measurement of performance. The paper addresses many of the above-mentioned gaps by: a) introducing a multi-dimensional firm performance construct, b) developing a Multi Input – Multi Output Fuzzy Inference model, and c) analyzing six TMT enablers to forecast six firm performance indicators. Some of the limitations of the study and suggested avenues for research are also presented. This paper is essentially tackling one of the basic roles of TMT as indicated by Hambrick and Mason's [6] original theory of how the TMT would assist in predicting the firm future.

II. Background

A. Upper Echelon Theory

Firm capabilities embody those collective insights, knowledge and activities that directly translate a firm's vision and mission into the concrete action steps that produce financial results [7]. Those capabilities are mainly influenced by people within the firm that are responsible for such critical decisions, namely the top managers (e.g. executives, board of directors). The demographic characteristics of those executives can be used as valid, albeit incomplete and imprecise, proxies of executives' cognitive frames. It could well provide useful indicators of company competitive performance [8].

B. Construction Industry

The construction industry (also referred to as, building industry or AEC firms; Architect, Engineers and Contractors) was selected for this paper due to many reasons (a) the bulk of the published work on construction management is on the management of construction projects, rather than on the firm [9] and (b) the need for such strategic decisions, especially amongst construction firms, is due to the volatility of the

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construction market [10].

C. Input Variables-Performance Enablers

Given the great difficulty obtaining conventional psychometric data on TMTs (especially those who head major firms), researchers can only reliably use information on executives' functional backgrounds, industry and firm tenures, educational credentials, and affiliations to develop predictions of strategic actions [11]. In the group effectiveness literature, diversity is often characterized as a "double-edged sword" which is beneficial only if managed successfully [12]-[14]. From a positive perspective, higher diversity provides more choices, accurate calculation of environmental changes and better assessment of alternatives. The negative aspects include slower decision making, communication breakdowns, and interpersonal conflict. Due to the "mixed blessing" nature of diversity impact [15], the inconsistency between the different propositions of various studies has led to confusion and multiple possible conclusions. For example, [3] argue that TMTs education-level diversity has a negative and significant impact on corporate performance, however, [16] study concluded that differences in educational background and in length of organizational tenure have a positive effect on information processing, task conflict, and learning, and thus may help the team to successfully handle adding new products in a given time period, resulting in improved firm performance. Moreover, [16] findings related to age diversity (negatively moderating effect) is also in conflict with [17] who believe that young, less tenured and heterogeneous TMTs have the composition most likely to produce strategic and structural changes in turbulent contexts. Similarly, [18] results show that higher educational level in the TMT has a positive and direct effect on innovation performance, while functional diversity and diversity in TMT tenure have a direct and negative effect. On the other hand, [14] argue that heterogeneous management teams are better able to handle the simultaneous and conflicting demands of refocusing the organization strategically and keeping up operational performance.

As a consequence, the previous research of Top Management Teams was mainly focused towards exploring the type and strength of the relationship between their diversity parameters and the firm's performance. There was less focus on how to employ those knowable parameters and utilize them to forecast the future performance of a firm. As suggested by [19], we claim in this paper that the relationship of TMT diversity to organizational performance is not positive or negative, yet team diversity in terms of age, tenure, education background and functional background work as enablers to that relationship. Table I show a total of six input variables, which are considered as performance enablers. Those variables were selected after review of TMT literature.

There is almost a consensus between different studies on the way to measure the diversity. Two methods have been widely used for that purpose. Blau's Diversity Index (with categorical variables) and Coefficient of Variation (with quantitative variables).

Blau's Diversity Index expressed as 1-∑Pi2, where P is the proportion of executives that belong to the ith regional category. This formula has been applied by a range of past upper echelons studies to measure TMT diversity in categorical variables [7], [20]-[22]. High values imply more diversified team, while low values indicate more homogeneous team members. This index measures the degree to which there are a number of categories in a distribution and the dispersion of the group members within these categories [23]. On the other hand, Coefficient of Variation (standard deviation divided by the mean) was suggested by [24] as a tool to measure diversity. Different studies used this methodology to measure quantitative values of different TMT attributes; examples are age and organization tenure diversity. Higher scores indicated greater diversity and scores approaching zero indicated greater homogeneity teams.

TABLE I: SELECTED INPUT VARIABLES

Input Variables	Definition (and method of measurement)
TMT Age Diversity	The diversity between the team members in terms of their age (measured by: Coefficient of Variation)
TMT Organizational Tenure	The diversity between the team members in terms of their total length of duration in the organization (measured by: Coefficient of Variation)
TMT Tenure	The diversity between the team members in terms of their total length of duration as a member in the Top Management Team (measured by: Coefficient of Variation)
TMT Educational Diversity	The diversity between the team members in terms of their educational background (measured by: Blau's Diversity Index *)
TMT Functional Diversity	The diversity between the team members in terms of their organizational functions (measured by: Blau's Diversity Index **)
TMT Industry Experience	The degree of diversity among Top Management Teams in terms of their previous experience (measured by proportion of TMT member with previous work experience in construction)

* Eight Categories; sciences, engineering, math, business, economics, law, arts, and others [14], [19]-[20].

** Categories were defined at individual level for each firm, depending on its internal governance system.

D. Output Variables: Organization Outcome in Construction (Domains and Indicators)

Two issues are argued by [25] that should be addressed in any firm performance-related study: (1) the dimension, establishing which measures are appropriate to the research context; and (2) selection and combination of measures; establishing which measures can be usefully combined. [26]. Organizing performance on different dimensions and indicators has been found in previous studies. For example, [27] presented three domains of business performance: (1) financial performance, (2) business performance and (3) organizational effectiveness. Another example is the methodology proposed by [28] where they applied 13 performance indicators under seven dimensions i.e., financial stability, customer satisfaction, business efficiency, learning and growth, job safety, technological innovativeness, and quality management, to measure firm performance. Similarly, [29] proposed the Dominant Dimensions of Performance in building industry. In his research, [29] explored how each enterprise within the building industry (architects, engineers, and general contractors) organizes their business. This paper follows the proposition of [29] that performance within the realms of the building industry is translated into a measure of short to medium term financial performance which has repercussions on firm strategy and structure. However, since this paper considers the construction industry as one unit, regardless of the underling enterprises, we provide a re-grouping concept of [29] Dominant Dimension into a generic performance construct that reflects the common measures of the three enterprises (architects, engineers and contractors). Table II (in Appendix) shows the suggested four (re-grouped) dimensions, namely, Financial Performance, Growth, Reputation and Continuity. Since performance of an industry is a function of its structure, where each industry has its specific variables and performance meaning [30], a total of six economic indicators has been selected as a measurement.

Those indicators are specific for the sample of this paper based on publicly listed construction firms. For example, Liquidity is particularly necessary for construction firms because of financial cash flow fluctuations resulting from delay of payment by owners [32], the requirement of financial support [34] and sufficient level of working capital which is often vital to soften the effects of a timing mismatch between cash inflows and outflows. Furthermore, depending on profitability alone will only provide a great view of where the company has been but does not provide much guidance for the future [28]. Therefore, Cash Flow Stability represents how the organization was efficiently managing its cash flow [32]. Finally, Capital Structure is believed to be closely related to risk management because debt per se would impose additional financial risks, such as the risk of bankruptcy, if a firm is unable to meet its debt service obligations.

All of the above indicators are measures of the financial wealth of an organization (whether on the short or medium span). From the Resource-Based Theory, the intangible strategic assets are also to be considered to complement the organization competency [40]. In this study, intangible resources are defined by two main indicators, External Customer Satisfaction and Internal Customer Satisfaction, both of which are considered necessary complementary sources of advantage [32].

III. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Various approaches and models have been applied to describe and explain the relationship between different TMT characteristics and the firm performance. Among those, the economic approach was more extensively applied, while the Artificial Intelligence (AI) (sometimes referred to as Soft Computing models) was rare in this field. Because of the changeable nature of firm performance, using conventional methods may not yield accurate results. Thus, employing soft-computing models can alleviate this problem [42]. Some of the major drawbacks in conventional methods are, 1) statistical models have the restrictions that the number of rules in prediction is limited by the inherent characteristics of the model [43]. 2) Large number of historical data are required to satisfy the results, and 3) most of the conventional methods assume linearity [44], while real-word are rarely pure linear combinations [44]-[45]. Further, a data sequence with a very low correlation implies highly non-linear dynamics such that simple regression is not able to explain adequately a sequence's correlation [46].

By contrast, Artificial Intelligence (AI) models can generate as many rules as they can capture and predict future trends [43]. Also such models are powerful tools for modelling the non-linear structures [44]. Intelligence analysis gives researchers the ability to model both experimental design and data in a number of different forms other than the statistical approaches [47]. The objective of soft computing approaches is to synthesize the human ability to tolerate and process uncertain, imprecise, and incomplete information during the decision-making process [43], which fits the purpose of this study with multiple input – multiple output nature. Given the complexity and the dynamics of real-world problems, such systems should be able to successfully perform incremental learning and online learning, deal with rules and handle large amounts of data quickly [48].

The well-known Adaptive Neuro-Fuzzy Inference System (ANFIS) is a form of artificial intelligence models. It is a fuzzy inference system applied in the form of a neuro-fuzzy system with crisp functions as in the Takagi-Sugeno-type fuzzy system [44]. ANFIS can serve as a basis for constructing a set of fuzzy "If-Then" rules with appropriate membership function to generate the stipulated input–output pairs. The membership functions are tuned to the input–output data [49]. ANFIS is able to "train" systems to generate rules, where those rules would be able to "test" the system if live data are fed into the model to test the rate of accuracy of the model [43]. This feature is of great value in forecasting and understanding behavior, as there can be many rules, and the rules may be unknown to researchers.

IV. Methodology

A combination of Stepwise Regression Analysis and ANFIS methods were implemented in order to demonstrate the appropriateness and capability of the forecasting model. The Stepwise Regression Analysis using SPSS Software to extract the most significant input variables for each of the output pairs (analysis for data points from 2006-2014 individually, averaged over two years and also averaged over three years). Afterwards, ANFIS forecasting was used (for the most recent dataset, i.e. year 2014) to recognize the non-linear relationship between the variables using Matlab Fuzzy Logic Toolbox.

We analyzed historical data of publicly listed Architecture, Engineering and General Contractor Firms. Listed international firms usually require the inclusion of highly capable TMT, and such firms are considered to be high discretion / highly prudent, characteristics that affects both managerial attention patterns and the relationship between attention and strategic choice [50]. In addition, as publicly-traded firms, they are required to file documents with the Securities and Exchange Commission which enables access to the appropriate performance and demographical information according to certain standards and procedures [51].

Two main databases were used to collect the data, the Bloomberg real-time market and economic database

(Bloomberg Terminal) and the ENR (Engineering News-Record), sometimes referred to as Fact Books, which are collections of publicly available data containing information specific to each of the firms studied. These books contain a number of reports, articles and analyses prepared by analysts, journalists, or researchers studying the particular firm of interest [7]. Fact Books are useful for extracting information for different measures and attributes including firm performance as well as TMT demographical and biographical information, and provide information with a high degree of reliability [36].

For the firm to be included in the sample, it had to satisfy the following various guidelines, and those were: (a) the firm should be continuously publicly listed in its home country market during the period 2006 – 2014, (b) also the firm should be continuously ranked in (ENR) List in either 225 Top International Design Firms or 250 Top International Contractors, (c) The firm had a fiscal year-end of December 31, which allowed appropriate reporting on all financial records and, (d) all required accounting, company and individual data to be available.

TABLE III: SAMPLE DISTRIBUTION

Region	Firms Code (as per Bloomberg Terminal)	Total
United States (US)	ACM, JEC, FLR, KBR, TTEK, AEGN, EEI, RCMT, ENG, TPC, GLDD, LAYN, MTRX	13
Australia (AU)	WOR, CDD, AAX, LLC	4
Netherlands (NA)	ARCAD	1
Canada (CN)	WSP, SNC, STN	3
United Kingdom (LN)	AMFW, ATK, PFC	3
France (FP)	TEC, DG, EN, FGR	4
Spain (SM)	TRE, ANA, ACS, FER, OHL, SCYR	6
Sweden (SS)	SWECA	1
Finland (FH)	POY1V	1
Italy (IM)	MT, SPM, SAL, DAN	4
India (IN)	LT, PUNJ	2
China (CH)	601800, 601390, 601186, 601618, 601668, 600875, 601117, 601727	8
Japan (JP)	1954, 6366, 1963, 9621, 2325, 1812, 1821, 1802, 6330, 1803, 1801, 1944, 1860	13
New Zealand (NZ)	OIC	1
Germany (GR)	HOT	1
Thailand (TB)	TTCL	1
South Korea (KS)	023350, 006360	2
Turkey (TI)	ENKAI	1
Austria (AV)	STR	1
19 Regions	Total	70

From all (417) companies explored initially by ENR list, the sample was reduced to n =70 based on above established guidelines. Reference to Table III shows the final collected data that are satisfied the above guidelines. All of the inputs and output data are measured dimensionless and ratio based.

V. MODEL SETTING

Step 1: Stepwise Regression Analysis

ANFIS is based on the input–output data pairs of the system under consideration. The size of the input–output data set is very crucial when the data available is much less and the generation of data is a costly affair. Under such circumstances, optimization in the number of data used for learning is of prime concern [52]. Since a simple ANFIS structure is always preferred [49], in this paper, the number of data pairs employed for training and testing were selected by the application of the statistical tool known as Stepwise Regression Analysis. By employing our proposed method, the match between the Input and Output variables for learning in the ANFIS network were reasonably identified, and thereby computation time and complexity were reduced. Two rounds of Stepwise Regression Analysis have been adopted to select the most significant variables as our input variables. The Input-Output pairs were processed, then selection of input variables was based on a threshold of p-value (<0.05) and the highest score of the Adjusted Determination Coefficient (adjusted R2) provided understanding whether the selected input variables could explain the output variable and achieve the regression equation at the same time [49]. On the second round, those selected pairs were tested again using the Stepwise Regression to confirm the results. Table IV shows the overall results of Step 1.

TABLE IV: RESULTS OF STEPWISE REGRESSION

Output Variables	Significant Input Variables
Profitability	TMT Age Diversity
Liquidity	TMT Tenure, TMT Educational Diversity, TMT Functional Diversity
Cash Flow Stability	TMT Age Diversity, TMT Educational Diversity, TMT Functional Diversity, TMT Industry Experience
Capital Structure	TMT Organizational Tenure, TMT Tenure, TMT Educational Diversity
External Customer Satisfaction	TMT Organizational Tenure, TMT Tenure, TMT Industry Experience
Internal Customer Satisfaction	TMT Age Diversity, TMT Organizational Tenure, TMT Tenure

In order to properly study the relationships and accurately identify the significant input enablers for each output of firm performance, the following fixed contextual variables were controlled; (TMT Size, Economy Dynamism, Degree of Internationalization, Degree of Diversification and Past Performance). After defining the significant input variables, they were used to build the ANFIS forecasting model in Step 2.

Step 2: Forecasting by ANFIS

In this step, two ANFIS structures were constructed and trained. Utilizing the year 2014 dataset, the first Cross-Section structure was trained and tested. Three membership functions were evaluated (Generalized Bell-Shaped, Spline Curve Π-shaped, and Triangular-Shaped membership functions). The forecasting capabilities for all three were evaluated through Root Mean Squared Error (RMSE). The smaller the value of RMSE, the better the

ANFIS prediction capability. Since Generalized Bell-Shaped Membership Function (GbellMF) provided an overall smaller RMSE, GbellMF was used for the second ANFIS structure. A total of 15 firms (with completed data from 2006 to 2014) were used to forecast Time-Series output values for each of those firms individually.

In ANFIS, the data are divided into training (used to build the model), and testing (used to check and validate the model, sometimes referred to as the memory recall in the terminology of neural fuzzy models). Usually training data set contains 70–90% of all data and remaining data are used for the testing data set [42]. In this paper, the first ANFIS structure was developed with random selection data for training and testing done based on (70/30) ratio. The ANFIS system will identify the input data to be sent for training and testing based on the occurrence of an event. The training dataset is used to train the ANFIS model whilst the testing data set is subsequently used to evaluate the performance of the trained ANFIS model. The training and testing data are mutually exclusive and data used for training would not be used for subsequent testing. In the second ANFIS structure, data from 2006-2013 were used as training, while the most recent data (2014) was the testing basis.

VI. Results and Discussion

The aim of this study is building on TMT literature and knowledge in order to advance understanding regarding the predictability power of TMT composition to firm performance. The core idea of Upper Echelon Theory is that those collective executives personalized interpretations of the strategic situations are a function of the executives' experiences, values, and personalities. A multi-input multi-output construct capturing the upper echelon′s ability to forecast the firm's future outcome was applied.

In the first ANFIS model, we investigated three fuzzy functions (Generalized Bell-Shaped, Spline Curve Π-shaped, and Triangular-Shaped membership functions), and reported the best membership function for the comparison study. Root Mean Squared Error (RMSE) was used as performance measure, it reflects the goodness of model fit adjusted for the number of estimated parameters. The forecasting results using three membership functions are summarized in Table V (in Appendix). Generally, the best fuzzy function of the ANFIS model for all data (except Profitability) is Generalized Bell-Shaped.

(192) Fuzzy rules were processed in the first ANFIS structure suggesting that a cross-section forecasting is not yielding satisfactory results. Fig. 1 shows an example (Liquidity) of the error in trained data, compared to the error in tested data. Although the error in training is minimized, the testing data didn't provide a good prediction match. However, the second ANFIS structure results suggest that the construct has good validity and provides opportunity for further research.

About 47% of two outputs (Liquidity and Capital Structure) provide a good prediction accuracy (above 80%). Fig. 2 provides an example of the surface view as predicted by the ANFIS rules. Cash Flow Stability is fairly predicted (33% accurate), while the amount of error in predicted Profitability, Internal Satisfaction and External Satisfaction is high. It may suggest two reasons: a) that the selected input variables (Top Management Team characteristics) are not strongly correlated with those output variables, or b) those output variables are not explanatory of the firm performance. The results obtained in the second ANFIS structure confirm the arguments of [19], that the relationship of TMT diversity to firm performance is not positive or negative, yet team diversity in terms of age, tenure, education background and functional background work as enablers to that relationship.

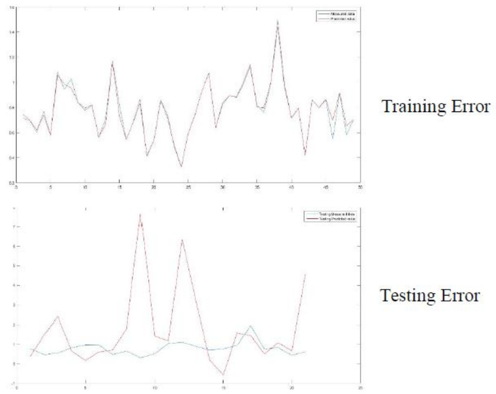

Fig. 1. Liquidity – ANFIS results: Training vs. testing error.

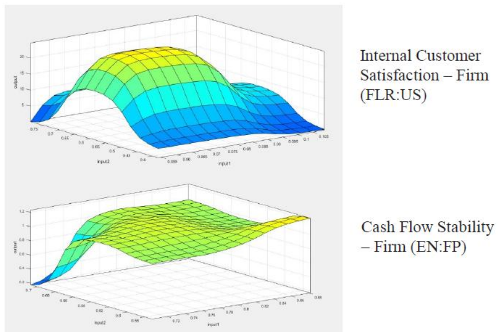

Fig. 2. Examples of ANFIS surface view – time series forecasting.

VII. Conclusion, Limitations and Future Research

Business organizations today have employees that are increasingly more diverse [53]. As [37] currently manifest: "Top Management Teams have become increasingly diverse over the past several decades, yet the performance implications of TMT diversity are not clearly established in the literature". This study has made three important contributions. Firstly, we reduced the effect of the black-box or "causal gap" as suggested by the Upper Echelons [20], [50], [54]. This refers to the mechanism of executives' cognitive capabilities and processes in taking the corporate decision. Secondly, we have shown that the stepwise regression if combined with the ANFIS structure may provide a good forecasting tool rather than statistical methods. Thirdly and most importantly, the ultimate results of this study provide empirical evidence that TMT observational demographic characteristics represent a new tool to forecast the firm future performance.

Despite all efforts and cautions taken to minimize and control any possible compilations, this study has several limitations, thus providing opportunities for further research. Firstly, rather than using ANFIS to forecast the exact value of output variables, a model can be built to provide a "Classification Forecast" depending on pre-defined bins, or categories. Considering the black-box nature of TMT processes, a classification forecast may provide a better approach specifically in forecasting a cross-section date. Secondly, in addition to the sample collection guidelines established for this paper, data available for firm's executives and most specifically in construction industry, is difficult to obtain. Therefore, researchers are advised to focus on industries where historical data are available, unlike the construction industry where it was noted that historical information is very limited.

Finally, further research should attempt to study the forecast accuracy from samples obtained from one region as opposite to multiple regions. This may reduce errors associated with disparities between different regions in terms of overall economic context and TMT composition governance.

APPENDIX

TABLE II: OUTPUT VARIABLES

Dimension	Indicator	Definition	Measurement Method	Example Reference
Financial	Profitability	positive financial performance, profit margin, growth in revenue, effective capital investment	Net Profit after Tax as a Percentage of Total Sales.	[28], [31], [32], [33]
	Liquidity	Access to Capital, leverage, relative measure of nearness to cash	Ratio of the Total Debt of the Organization	[13], [32], [34], [35], [36], [37]
Continuity	Cash Flow Stability	financial stability of an organization	Ratio of Annual Revenue to Total Asset	[28], [32], [33], [38]
	Capital Structure	proportion of the assets of a firm financed by debt rather than equity	Proportion between Debt and Equity	[36], [39]
Reputation	External Customer Satisfaction	Client satisfaction, reflecting its importance in a project-based and various stakeholders involved industry	Organizations' Outcome in the largest sector revenue	[10], [26], [28], [40], [41]
Growth	Internal Customer Satisfaction	Shareholder Value, increasing the shareholders' economic wealth	Price / Earnings Ratio	[31], [55]

TABLE V: RMSE ANFIS RESULTS

Membership Function	Profitability	Liquidity	Cash Flow Stability	Capital Structure	External Satisfaction	Internal Satisfaction
gbellmf' *	3.502147	**0.032747**	**0.000438**	**0.000974**	**0.004543**	**1.521444**
pimf' **	3.457851	0.054383	0.001184	0.046576	0.096834	7.718842
trimf ***	**3.445847**	0.101638	0.000463	0.027361	0.061352	7.222274

* Generalized Bell-Shaped ** Spline Curve Π-shaped *** Triangular-Shaped membership functions

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