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Strategic management of technical university: structural equation modelling approach

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Abstract

Purpose – The purpose of this paper is to examine the constructs and establish causal relationship between factors for strategically governing a technical university in Indian context. Further, the paper carries out a systemic study to emphasize on the need for these universities to design strategies that are endurable and sustainable.

Design/methodology/approach – A structured questionnaire survey was carried out (207 responses). Factor analysis was carried out to bring out the latent variables representing the attributes, and later, the causality between these variables was established using structural equation modelling (SEM). These relationships between the factors helped in developing a robust system dynamic model for strategic management of technical universities.

Findings – The peak points on the contours for varying strategic orientation revealed the adaptability and the time required for attaining that level of adaptability. The contour plots also revealed the limiting values in each case. Finally, it is concluded that university adaptability increases with increasing strategic orientation. The analysis also revealed that the process by which the technical universities formulate their strategies is an important determinant of various factors.

Originality/value – Universities looking to implement strategic management-related methodologies for the improved management focusing on developing effective methods for developing strategy can be expected to yield better performance, rather than concentrating on the technologies and supporting infrastructures.

Keywords India, Factor analysis, Strategic management, System dynamics, Structural equation modelling, Technical university

Paper type Research paper

Introduction

Strategic management is "the art and science of formulating, implementing and evaluating cross functional decisions that enable an organisation to fulfil its objectives" (David, 1996). The success or the failure of a university critically depends on the way it

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is managed, on the progress of the disciplines, on the student experience and careers of academic and other staff. The objective of strategic management of universities is a holistic process, in which all the interlocking elements need to work together synergistically. The sustained success of managing the university lies much in harmonising the different components of university management to be mutually reinforcing. Strategic management, therefore, is an integrating mechanism which pulls policies and processes together to achieve the best institutional outcomes.

Some of the essential inherent characteristics of strategic management are as follows (Shattock, 2003):

- Senge describes strategic decision-making as "dynamic complexity": […] situations where cause and effect are subtle, and where the effects over time of interventions are not obvious […]. When obvious interventions produce non-obvious consequences, there is dynamic complexity […]. The real leverage in most management situations lies in understanding dynamic complexity (Senge, 1990).
- Belief that the best strategic plan is evolutionary rather than directive (Mintzberg and Walters, 1985).
- Organisations need coherence and integration, Milgrom and Roberts (1995) have described how the implementation of a system of "mutually enhancing elements" are used to raise the performance of an organisation. Whittington *et al.* (1999) and Pettigrew *et al.* (1999) endorse its effectiveness in wider organisational settings.
- Conservative financial control mechanisms can create unnecessary layers of hierarchy and bureaucracy and can choke initiative. (Ghoshal and Bartlett, 1999).

The most successful universities are among those that have adapted best to the new dynamic environment. In the Indian context, the technical universities established by the various state governments are mostly of affiliating type. They have a more bureaucratic approach to manage issues, strictly adhering to regulations, hierarchy and relying on elaborative committee structures. Planning in majority of cases is not strategic in nature, primarily depending on *ad hoc* decisions contingent to the situation, rather than being proactive due to large number of colleges and students in its control.

So taking cue from the Senge on dynamic complexity, development of system dynamics models using empirical data is facilitated in three stages of development:

(1) In the first stage, a framework is developed to find out the various constructs measuring the indicators or attributes.

(2) In the second stage, causal relationship between the constructs or the latent variables has been established with the help of structural equation modelling (SEM).

(3) And in the third stage, the above SEM model evolved, to develop a system dynamics model, which will enable to surface out the effects of the latent factors through the policy analysis.

Therefore, the purpose of this paper is to examine the constructs and establish causal relationship between factors for strategically governing a technical university in the Indian context through exploratory factor analysis. The instrument is designed through an assessment of a combination of 11 factors, which is captured from the perception of members of Board of studies, Board of examiners and faculty.

Methodology

A survey was conducted within institutions offering courses in engineering discipline, which are affiliated to various universities of different states in India. This survey covered a broad range of issues relating to the strategic and operational aspects university management. There were 414 responses received, indicating an estimated response rate of 34.5 per cent. Using SPSS statistical software, exploratory factor analysis was conducted to explore the underlying structure among the variables captured through the questionnaire response using principal component analysis as the extraction method and varimax as the rotation method. The eigenvalues criterion, also called as Kaiser Criterion (Dunteman, 1989) and Scree-test criterion, were used to determine the number of factors, and 11 factors were extracted. These 11 factors explain 65.40 per cent of the total variance as shown in Table I. The variables with higher loadings were considered more important, and had greater influence on the name or label selected to represent the factors.

Two of the factors obtained from the factor analysis are pictorially exhibited in Figures 1 and 2. The factor strategic orientation is formed by the six variables which are shown in Figure 1. The value in the bracket indicate factor loading of the variable. The variables, academic senate as a lead body and strategic management of the university, have higher loadings and they influence this factor the most. Similarly, the variables constituting university adaptability along with factor loading are depicted in Figure 2.

The components of a structural equation model were developed using the factors obtained from exploratory factor analysis. From this process, the composition of the factor variables making up the observed and unobserved variables within the model was determined. The initial structure of mental model was based on perceived concepts accrued from the literature review and authors' experience in university administration.

The structural equation model establishes causal relationship among the 11 latent variables (factors) derived from the factor analysis, taking into consideration the reliability and validity of the variables. AMOS version-7 software was used for the

Factor	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	25.929	35.039	35.039	25.929	35.039	35.039	9.759	13.188	13.188
2	6.168	8.335	43.374	6.168	8.335	43.374	5.169	6.986	20.174
3	2.826	3.819	47.193	2.826	3.819	47.193	4.510	6.095	26.268
4	2.696	3.643	50.836	2.696	3.643	50.836	4.420	5.974	32.242
5	2.453	3.315	54.151	2.453	3.315	54.151	4.129	5.580	37.822
6	2.017	2.726	56.877	2.017	2.726	56.877	4.027	5.442	43.264
7	1.931	2.610	59.487	1.931	2.610	59.487	4.013	5.423	48.687
8	1.746	2.360	61.846	1.746	2.360	61.846	3.180	4.297	52.985
9	1.512	2.044	63.890	1.512	2.044	63.890	3.173	4.287	57.272
10	1.442	1.949	65.839	1.442	1.949	65.839	3.117	4.212	61.484
11	1.329	1.795	67.634	1.329	1.795	67.634	2.902	3.921	65.405

Table I. Factor analysis result showing variance explained

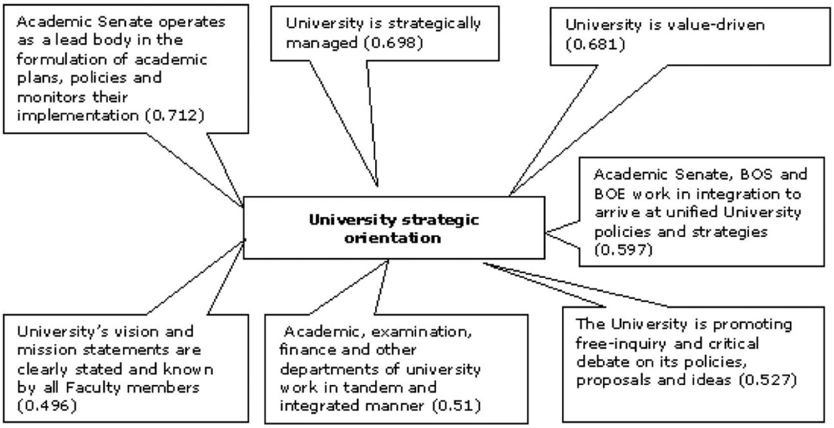

Figure 1. University strategic orientation

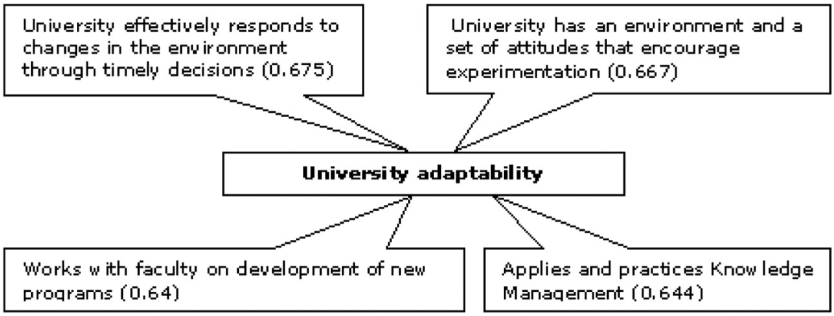

Figure 2. University adaptability

analysis of moment structures to estimate the relationships. The maximum likelihood method of parameter estimation was utilized. The analysis was performed on 207 respondents after excluding the cases with missing data. The process involved in developing a SEM is explained in detail in the following section.

Structural equation modelling

SEM represents the hybrid of two separate statistical traditions (Kaplan, 2000); it contains factor analysis, developed in the discipline of psychology, and regression analysis, evolved in the field of econometrics. SEM is an advanced statistical method that helps provide insight into complex theoretical issues. Structural equation models study causal relationships in observational data assuming the existence of linear relationships, although non-linear relationships can be modelled as well (Shipley, 1999).

SEM assumes that there is an underlying mechanism that leads to a theoretical covariance structure between vectors of random variables. The objective is to present and test a model that captures the essence of this underlying mechanism (Malaeb *et al.*, 2000). The causal relationships established in a starting hypothesis imply a series of constraints on the variance/covariance matrix. If the variance/covariance matrix obtained from observational data is compatible with the constraints imposed by the hypothesis, then the model is considered. SEM provides a higher degree of support for the question of causation than other methods like multiple regression and traditional path analysis, because SEM models measure error and can eliminate the bias and distortion in estimates that typically occur with these methods (Pugesek and Tomer, 1995). The results obtained from SEM analysis provide a global picture of the factors affecting the process under study and clarify their relative importance.

The four different types of causal relationships that may make two variables co-vary are (Iriondo *et al.*, 2003):

(1) *Direct causal relationships*: In this, one variable directly causes an effect on the other [Figure 3(a)]. Direct relationships can also be reciprocal [Figure 3(b)].

(2) *Indirect causal relationships*: In this, one variable causes an effect on another through a third variable [Figure 3(c)].

(3) *Spurious relationships*: In this, the two variables of reference have a common variable that cause effects on both of them [Figure 3(d)].

(4) *Association without causation (correlation)*: Two variables of reference have a common variable, but it is not possible to determine if the common variable contributes to the covariation between the two former variables through indirect or spurious relationship [Figure 3(e)].

The arrows with no origin represent the effect of other unconsidered factors that are affecting the endogenous variables.

When SEM methods are used for generating and exploring models, the model is modified by adding paths suggested by the observed correlation structure or by deleting paths that are weakly correlated to optimise the fit of the model. Exploratory analysis under the a posteriori approach has been criticised by some authors because once this is done, data drive the model and not the theory (Petraitis *et al.*, 1996; Pugesek and Grace, 1998).

The SEM definition contains two implied models as shown in Figure 4. The *inner model*, also called structural model, constitutes the causal relationships between the latent variables. The *outer model*, also referred to as the measurement model, defines how each block of indicators relates to its latent variable (Chin, 1998). Figure 4 illustrates the general context of structural and measurement models, where:

- X_1, X_2 and Y_1 = Measured variables from measurement models;
- $\lambda_{11(x)}$, $\lambda_{21(x)}$, $\lambda_{11(y)}$ = Regression coefficients computed by equation (4);

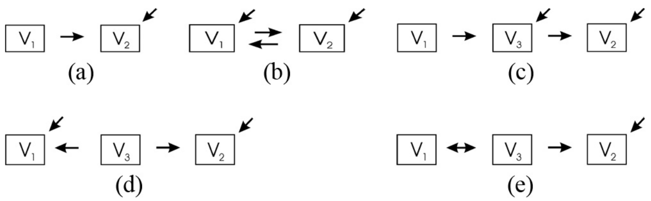

Figure 3.
(a) Direct relationship; (b) reciprocal direct relationship; (c) indirect relationship through a third variable V_3; (d) spurious relationship; (e) association without causation

- δ_1, ε_1 = Measurement error variances computed by equation (5);
- ς_1 = Structural equation errors;
- ξ_1 = Exogenous latent variable;
- η_1 = Endogenous latent variable; and
- γ_{11} = The regression coefficient of exogenous to endogenous latent variable.

Joreskog and Sorbom (1989) showed that it is possible to compute an estimated score (ξ) for each latent variable using factor score regression weights (ω_i), which are given in the output of the SEM statistics program. This is given by equation (1).

$$\xi_i = \sum \omega_i x_i^2 \tag{1}$$

where ξ_i is the estimated score; ω_i the row vector of factor score regression weights; and x_i the column vector of the observed indicator variables.

The reliability alpha (α) for each latent variable can be computed. Given the reliability estimates, this information built into the structural model (path) to establish the relationship between the latent variables. Munck (1979) showed that it is possible to fix both the regression coefficients (λi), which reflect the regression of each measured variable on its latent variable and the measurement error variances (δi) associated with each measured variable.

Munck showed that in situations where the matrix to be analysed is a matrix of correlations among the measured variables, the parameters of λ and δ can be computed using equations (2) and (3), respectively. The variances of the composite variables in this case are equal to 1.

$$\lambda = \sqrt{\alpha} \tag{2}$$

$$\delta = 1 - \alpha \tag{3}$$

However, in situations where the matrix to be analysed is a matrix of covariances among the measured variables, Munck showed that the parameters of λ and δ can be computed using equations (4) and (5), respectively:

$$\lambda = \sigma\sqrt{\alpha} \tag{4}$$

$$\delta = \sigma^2(1 - \alpha) \tag{5}$$

where λ is the regression coefficients; δ is the measurement error variances; α is the reliability coefficient for each latent variable; σ is the standard deviation (SD); σ^2 is the

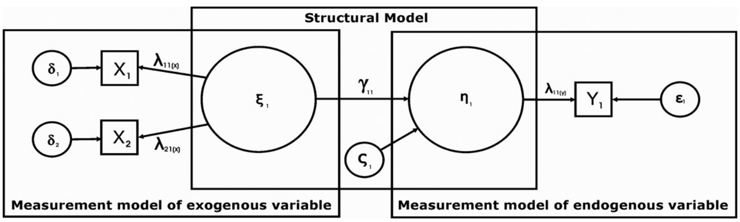

Figure 4.
General structural and measurement model

variance and of measured variable; and σ^2 is the variance of composite measure. AMOS is used in this paper; equations (4) and (5) are used to compute λ_i and δ_i estimates.

The SEM procedure

The section discusses the SEM procedure, and is collated to our study. Six main steps broadly identified in the basic SEM procedure (Bollen and Long, 1993; Batista and Coenders, 2000) are:

- specification of the model;
- model identification;
- data collection;
- parameter estimation;
- testing model fit; and
- respecification of the model.

Specification of the model

The specification of the model consists of the translation of the concepts into a series of equations represented in the form of a causal or a path diagram.

The path diagram shows the causal relationships among the latent variables in the system. It should be based on a prior knowledge of such relationships with previous experience or based on theoretical basis (Batista and Coenders, 2000). Thus, the path diagram represents the working hypothesis about the causal relationships among latent variables. Relationships between these latent variables are unidirectionally causal (indicated by a straight, single-headed arrow on path diagrams), correlations (indicated by a double-headed arrow on path diagrams) or residual unexplained variances (arrows not originating in a variable). Unexplained variances are unanalysed components of the diagram, which show our current ignorance of the variables that determine them. The relative effect of one latent variable upon another is shown through standardised path coefficients, which are equivalent to standardised partial regression coefficients.

Figure 5 shows the conceptual interrelation between the factors affecting strategic management of technical university from the perspectives of Board of Studies, Board of Examiners and faculty members and its important stakeholders.

The relationships illustrated in the path diagram are primarily derived from knowledge based on previous studies (Bhushi, 2007), field experience and also the authors' experience of seven years as a special officer in a technical university since its inception. Because the path diagram proposed is too large, only one factor is indicated below (Figure 6).

Identification of the model

The second step involves checking whether the parameters of the model can be derived from the observable set of variances and covariances. A necessary condition is the use of possibly over-identified models where the degrees of freedom are greater than 0 (d.f. > 0).

Parameter estimation

The purpose of this stage is to estimate the value of the unknown parameters, such as the standardised path coefficients, in such a way that the observed variance–covariance matrix is optimally adjusted to the predicted moment matrix. There are several estimation methods available, such as Unweighted Least Squares (ULS), Generalised Least Squares (GLS), Maximum Likelihood (ML) and Generally Weighted Least Squares (WLS or ADF). The most frequently used is ML. ML or ULS is also consistent for categorical variables under multivariate normality (Babakus *et al.*, 1987). The use of these variables allows experimental constraints to be included in the models as new exogenous variables with as many categorical levels as treatment levels. The ML method has been adopted in this study.

Testing model fit

This is the statistical process of assessing whether or not the model fits the data appropriately. This is accomplished by a goodness-of-fit test, in which the covariance in the observed data is compared with that expected if the model were true. The test statistic is asymptotically distributed as a chi-square under the assumption of multivariate normality (Mitchell, 1994). The goodness-of-fit of the model to data may be tested by several different measures. The measure most frequently used is the likelihood chi-square value. However, it is generally accepted that the chi-square test should be interpreted with caution and supplemented with other goodness-of-fit indices when data depart from multivariate normality and sample sizes are small (Bollen, 1989; Loehlin, 1992; Bollen and Long, 1993). Therefore, Bentler and Bonett's normed-fit index (NFI), Bentler's comparative fit index (CFI) and/or the goodness of fit index (GFI) are also used.

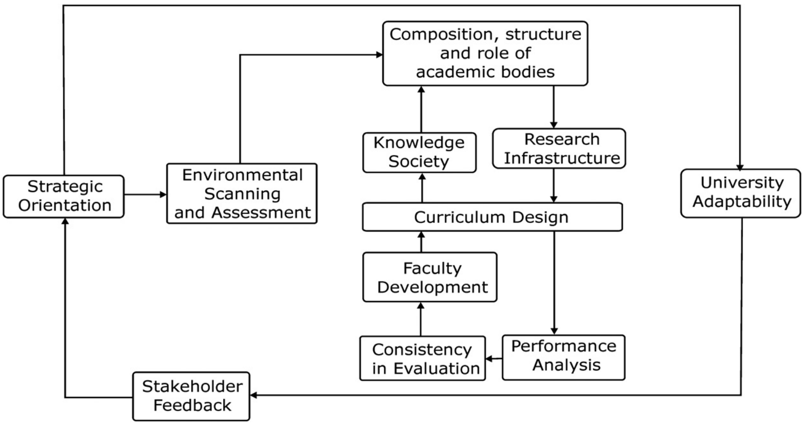

Figure 5.
Conceptual interrelation between the factors of strategic management of university governance

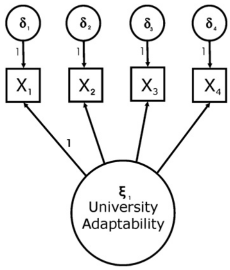

Figure 6.
Latent variable university adaptability defined by the constituent measured variables

Values of NFI, CFI and GFI range between 0 and 1, and values > 0.9 indicate an acceptable fit of the model to the data (Bollen, 1989). CFI is more reliable than NFI with small sample sizes (Palomares *et al.*, 1998). Table III gives the values obtained for the final model.

The respecification of the model

SEM is an intrinsically confirmatory technique, but in practice, it is often used in an exploratory way. Various tools have been developed for adapting this confirmatory technique to exploratory uses (MacCallum, 1986). These include the use of modification indices and Lagrange multiplier tests for selectively adding parameters to a model, and the use of *z* statistics (also called critical ratios) and Wald tests for selectively eliminating parameters (Bentler, 1989; Jöreskog and Sörbom, 1989).

Tools for model evaluation

When conducting a specification search, the primary concern is model comparison, rather than the evaluation of a single model by itself. For the purpose of model comparison, the following tools are available:

- tabular and graphic summaries of comparative model fit and its relationship to number of parameters;
- rescaled versions of AIC, Akaike information criterion (Akaike, 1973, 1987); BCC, The Browne and Cudeck (1989) criterion; and BIC, The Bayes information criterion (Schwarz, 1978; Raftery, 1995);
- Akaike weights based on either AIC or BCC;
- Bayes factors; and
- a Scree test similar to the Scree test used in factor analysis (Cattell, 1966).

The global evaluation of goodness of fit along with a detailed analysis also includes the examination of the parameter estimates and the residuals. The Wald test is used to identify the parameter estimates that are not significant. This test locates the set of path coefficients that can be considered 0 without worsening the fit of the model (without significantly increasing the chi-square statistic of the model) (Buse, 1982; Bentler, 1989). Non-significant parameters are eliminated from the model, especially if their theoretical interpretation is weak. The coefficient of determination R^2 indicates the proportion of observed variance explained by each equation and constitutes another useful statistic for detailed diagnosis (Mitchell, 1992). The effect of unexplained causes on each variable is measured as $(1 - R^2)^{1/2}$. Low R^2 values for a variable suggest that the equation for this variable may be omitting relevant explanatory variables.

In the respecification process, the results of ten models tested are presented in Table II. The tenth model is considered as the best fitting model which has AIC_0, BCC_0 and BIC_0 values equal to 0 and has lowest critical ratio, C/df equal to 1.809.

Chi-square is sensitive to sample size, and tends to be significant in large samples; a relative likelihood ratio between a chi-square and its degrees of freedom was used. According to Eisen *et al.* (1999), a relative likelihood ratio of five or less was considered an acceptable fit. Estimation of structural analysis indicated relatively good fitness, $\chi^2/\text{df} = 1.849$. Post hoc model modifications were performed in an attempt to develop a better fitting, more parsimonious model. On the basis of modification index (MI)

Table II.
Specification search results

Model	Parameters	df	C	C − df	AIC_0	BCC_0	BIC_0	C/df	p
1	156	2,400	4,437.278	2,037.278	95.03	91.806	85.032	1.849	0
2	157	2,399	4,364.092	1,965.092	23.844	21.695	17.179	1.819	0
3	157	2,399	4,384.599	1,985.599	44.351	42.202	37.686	1.828	0
4	157	2,399	4,384.599	1,985.599	44.351	42.202	37.686	1.828	0
5	157	2,399	4,397.423	1,998.423	57.176	55.027	50.51	1.833	0
6	158	2,398	4,352.217	1,954.217	13.969	12.894	10.636	1.815	0
7	158	2,398	4,359.901	1,961.901	21.654	20.579	18.321	1.818	0
8	158	2,398	4,359.901	1,961.901	21.654	20.579	18.321	1.818	0
9	158	2,398	4,360.723	1,962.723	22.476	21.401	19.143	1.818	0
10	**159**	**2,397**	**4,336.247**	**1,939.247**	**0**	**0**	**0**	**1.809**	**0**

recommendations and theoretical relevance, some error terms were added, and few paths were deleted in the respecified model.

Table III presents the models tested with various goodness-of-fit indexes. Although the estimation of the final model resulted in an overall χ^2 value of 4,336.247 that was statistically significant, $p < 0.05$, all other measures of goodness of fit, GFI = 0.982, AGFI = 0.980, PGFI = 0.910, RMR = 0.065, provided support for this model (Table III).

The standardised regression weights, standard error of regression weight, critical ratio and level of significance for regression weight at the 0.001 level (two-tailed), obtained from the SEM are given in Table IV.

A schematic representation of this final structural model that includes the standardized path coefficients is depicted in Figure 7.

Exploration of the relationships between the factors and the background established in the path analyses. The structural equation model depicts the complex interactions among the latent variables emerged from the analysis. The specification search in AMOS enhanced the understanding of the interaction more sensibly. The standardised regression weights and critical ratios are represented on the holistic structural equation model. There are several loops emerging out of this SEM model. Three of the important loops are presented.

Causal loops obtained from SEM

Loop 1 is shown in Figure 8. This is a positive loop. The strategic orientation of the university is positively influenced by the stakeholder feedback. In turn, strategic orientation improves the role of BOS and BOE through their well-defined structure and composition. The clearly articulated composition, structure and role of BOS and BOE will enhance the adaptability of the university, which in turn results in balanced vibrant curriculum design. The vibrant curriculum design further improves the stakeholder feedback as it better caters to their needs.

Table III.
RMR, GFI values for SEM

Model	RMR	GFI	AGFI	PGFI
Default model	0.065	0.982	0.980	0.910
Saturated model	0.000	1.000		
Independence model	0.453	0.100	0.075	0.098
Zero model	0.501	0.000	0.000	0.000

Paths	Estimate	S.E.	C.R.	*P*
Environmental scanning and assessment ← performance analysis	0.165	0.064	2.580	0.010
Environmental scanning and assessment ← stakeholder feedback	0.450	0.084	5.338	***
Faculty development ← consistency in evaluation	1.033	0.265	3.900	***
Faculty development ← environmental scanning and assessment	0.250	0.071	3.532	***
Faculty development ← strategic orientation	0.111	0.066	1.691	0.091
Knowledge society ← curriculum design	0.635	0.089	7.097	***
Knowledge society ← faculty development	0.176	0.068	2.596	0.009
Knowledge society ← composition, structure and role of BOS	0.147	0.070	2.095	0.036
Knowledge society ← performance analysis	0.179	0.054	3.335	***
Strategic orientation ← stakeholder feedback	0.458	0.094	4.876	***
Curriculum design ← University adaptability	0.517	0.093	5.589	***
Stakeholder feedback ← curriculum design	0.504	0.089	5.663	***
Performance analysis ← curriculum design	0.571	0.095	6.020	***
University adaptability ← composition, structure and role of BOS	0.195	0.099	1.969	0.049
Composition, structure and role of BOS ← strategic orientation	0.391	0.083	4.729	***
Research infrastructure ← curriculum design	0.685	0.127	5.390	***
University adaptability ← strategic orientation	0.572	0.102	5.584	***
Composition, structure and role of BOS ← consistency in evaluation	0.503	0.215	2.340	0.019
Stakeholder feedback ← performance analysis	0.274	0.063	4.318	***
Consistency in evaluation ← curriculum design	0.199	0.044	4.511	***
Research infrastructure ← University adaptability	0.183	0.120	1.525	0.127
Composition, structure and role of BOS ← research infrastructure	0.125	0.054	2.301	0.021

Notes: Estimate = estimate of regression weight; SE = standard error of regression weight; C.R. = critical ratio for regression weight = z = regression weight estimate/estimate of its standard error; P = level of significance for regression weight at the 0.001 level (two-tailed)

Table IV.
SEM regression weights

Loop 2 is shown in Figure 9. Vibrant curriculum design demands an improved or higher consistency in evaluation which will lead to more focussed faculty development. Through the process of evaluation, faculty members can understand the extent to which the students have gained the knowledge. It gives a better feedback on teaching learning process that the student and faculty members have undergone. This helps the teachers to adopt new methods of teaching and improve teaching effectiveness. This may also help in suggesting the modifications in the syllabus. A well-defined, clearly articulated composition, structure and role of academic bodies such as BOS and BOE are essential for the good health of the university. The transparent and healthy academic structure of the university will enhance the development of the students for much broader knowledge society. This in-turn will help to achieve university vision and mission through curriculum design. This will also provide the students methods and styles for

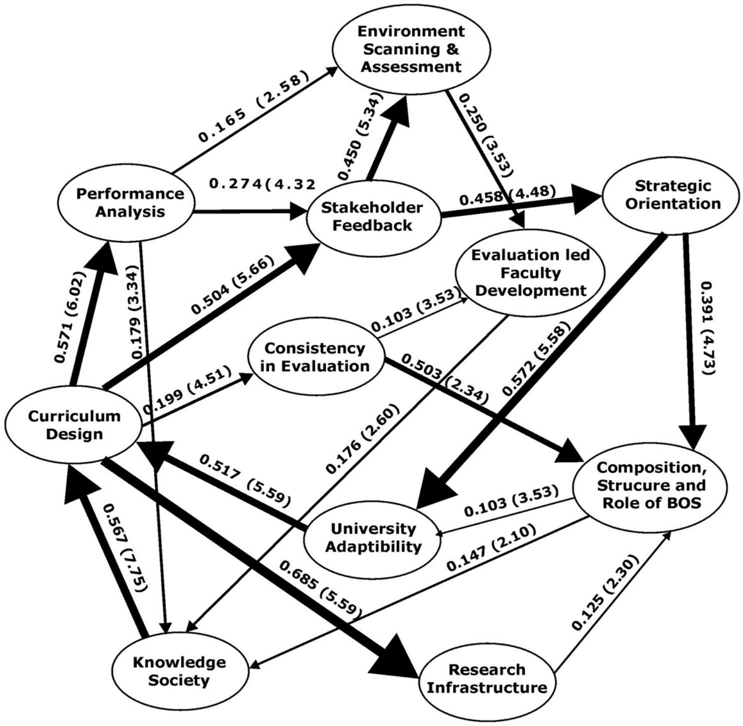

Figure 7.
Structural equation model of strategic management of technical university

Notes: Arrows depict causal relationship, numbers near (on) the paths indicate standardised path coefficients and numbers within the brackets represent critical ratio (C.R). The thickness of lines is proportional to the size of the path coefficient. $\chi^2/df = 1.849$, GFI = 0.982, AGFI = 0.980, PGFI = 0.910. All the paths shown are statistically significant at $p < 0.05$

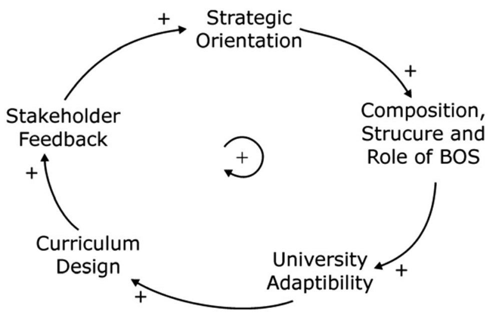

Figure 8.
Causal loop 1

life-long learning. The development of knowledge society has significant influence on curriculum design which has to strike a balance between rationalisation, innovation and preservation. The courses offered need to reflect the "Memorandum of Understanding" between industries and the university, curriculum to be inclusive of inter-disciplinary perspectives. It also has to inculcate the awareness of the possible impact of technology on the environment and its sustainable development. And finally, university focus on the concept of "Learner centred and learning oriented curriculum" should be reflected in the curriculum, where the role of the teacher is changed from transmitter of knowledge to facilitator and motivator of learning.

The holistic development of curriculum improves the performance analysis by adopting sophisticated techniques to capture the quantum of fruitful knowledge imparted.

Loop 3 is shown in the Figure 10. The performance in the examination is analysed and taken as a feedback to devise new teaching methods using information and communication technology, reorganise/shuffle the subjects in different semesters to ascertain precedence and its continuity, bring reforms in evaluation processes. With the insight into the teaching learning process and its requirement in entirety through performance analysis, it enhances focussed environmental scanning and scenario assessment. This includes analysis and forecasts of occupational requirements, alumni feedback, industry and societal needs. This process of environmental scanning leads to focussed faculty development, which in turn enhances the knowledge society. The broader perspectives of the knowledge society will further spread the horizon of the curriculum.

All these loops are self-reinforcing, where an increase in the value of a variable would trigger an exponential rise in the values of other variables. Conversely, a decrease in the level of one variable would trigger exponential fall in the values of the other variables. Figure 7 depicts the integrated construct model.

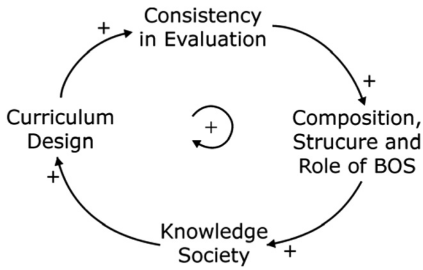

Figure 9.
Causal loop 2

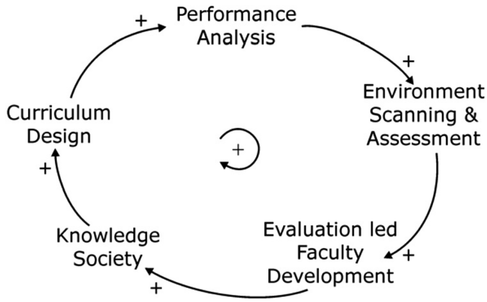

Figure 10.
Causal loop 3

Simulation and analysis of dynamic behaviour using system dynamics

A system dynamic model was constructed with the help of the causal relationships established in the above structural equation model to study the dynamic behaviour of the system. The behaviour of the individual latent variables with respect to time as well as interaction among them is simulated. The simulation results provide scope for policy analysis, and are the tools which provide insight into the dynamic nature and complexity of the university system to university administrators. The interaction of two parameters over a period could be better understood in contour plots, where time is used as the third dimension into the analysis. One such behaviour is depicted in Figure 11.

Some of the important observations from Figure 11 are as follows. University adaptability increases with strategic orientation. If you wish to know for a given value of strategic orientation of 0.1, and desired university adaptability of 0.5, then it takes nearly 10 years. It is shown in Figure 8, with thin dotted line. The contour plots can also indicate the limiting values that could be attained and the span of time required for the same. For example, from the Figure 8, strategic orientation cannot reach beyond a value of 0.31 within a time span of 25 years. The limiting value of strategic orientation is 0.31 in 25 years' time. Similarly with strategic orientation of 0.14, maximum of university adaptability could be obtained is 0.7, and it could be reached in 10 years. For the policy-makers, it depicts that if the same strategic orientation is continued, then the university adaptability decreases. Hence, this peak point denotes the time to change the strategic orientation. This becomes a critical information is facilitated through the SD analysis.

Conclusions

For the organisations to develop, a competence in the management and integration of processes is of strategic importance. The development of this competence is not a widespread phenomenon in technical universities in India. This may be due to lack of strategy; lack of alignment and integration between university strategy with other functional strategies; rigid and bureaucratic organisational structure; lack of dissemination of power at different levels; and auditing is stringent only on financial matters. The technical universities established by various state governments in India are of affiliating type and are still in the infant stage. The state-wide jurisdiction of these

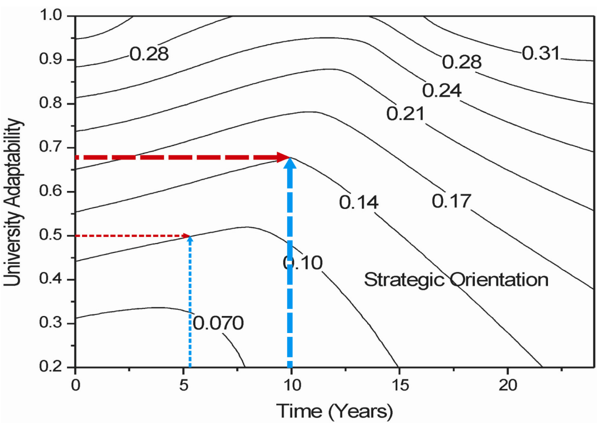

Figure 11.
Contours of SO with UA and time in the base run

universities results in large number of students pursuing engineering education in constituent as well as private institutions affiliated to technical universities. This creates a complex system. To understand the dynamic nature of the system, through this study, a methodology is developed using latent variables which are captured through measurable variables from factor analysis. These measured variables are obtained from the questionnaire survey among the members of academic bodies and faculty. The causalities between the latent variables is established by the SEM using AMOS 7. These causalities are helping to understand the dynamic nature and behaviour using system dynamic model.

The importance of organisational cognition in strategic management of technical university is highlighted in this paper. The data indicate that (within the limitations of this model) the process by which the technical universities formulate their strategies is an important determinant of various factors.

In this study, an empirical framework to assess the causal relationship among the factors, namely environmental scanning and assessment, stakeholder feedback, performance analysis, strategic orientation, composition, structure and role of BOS and BOE, curriculum design, university adaptability, consistency in evaluation, faculty development, adaptability, research infrastructure and knowledge society, have been established with respect to strategic management of technical university in India.

The implication for universities looking to implement strategic management related methodologies for the improved management focusing on developing effective methods for developing strategy can be expected to yield better ultimate performance, rather than concentrating on the technologies and supporting infrastructures.

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