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A Hybrid Fuzzy Factor Analysis Model for Evaluation of Fiscal Proficiency

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Abstract

Fiscal Proficiency is one of the most significant priority for mankind as it has a key role in the escalation of the lifestyle. Hence, it plays an important role in the growth of individual, family and finally leads to the growth of the national economy. Here in this manuscript, authors present a fuzzy factor analysis model to determine and evaluate the factors that influence the fiscal proficiency. The application of fuzzy concepts to the statistical analysis deemed appropriate while investigating a nondeterministic report. Resultantly, authors present a Mamdani-based fuzzy model to evaluate the fiscal proficiency through various factors. The proposed model is proved to be an effective model and hence can be widely implemented in real life. Further, authors also recommend that the regulatory authorities should take efforts to promote fiscal proficiency that will lead towards escalation of national economy.

Keywords: Fiscal proficiency, Fuzzy modelling, Mamdani approach, Fiscal planning

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1. Introduction

Fiscal proficiency can be considered as the knowledge of fiscal planning and investment such as various fiscal instruments, budgeting, portfolios, and fiscal markets thus helping the user to make informed decisions regarding outcomes. During the past few decades, the rise in average income of individuals has led to dig deeper into this aspect but unfortunately it is observed that fiscal proficiency is still in the state of infancy [1]. The requirement to have fiscal proficiency becomes more important during this era when the entire world is going through a churning phase in view of pandemic [2][3] [4]. Hence, it becomes important to determine various factors that influence the fiscal proficiency of the individuals so that corrective measures can be adopted to address the associated challenges.

The lack of fiscal proficiency has been primarily witnessed in the uneducated and economically backward section of society [5]. Further, gender of the individual is also witnessed to be a key factor that influences the fiscal proficiency of the individual especially in developing countries [6]. Now it is a matter of grave concern as it forms a huge section of society and thus influences the economic growth of the nation. Consequently, efforts must be taken in this direction as fiscal knowledge and fiscal strength are the leading facets of any economy [7][8]. In particular, these are undoubtedly the most crucial considerations for developing and productive nations like India to emerge as an economically developed country in years ahead [9] [10].

Further, when authors referred to the established findings in the domain, it is observed that fiscal proficiency is impacted by various factors like Socio-economic, behavioral, Demographic Factors, fiscal acumen, and miscellaneous factors [11]. Among these factors, some factors have a direct effect on fiscal proficiency while other factors have an indirect association with fiscal proficiency [12]. Hence, authors have considered these factors in the proposed fuzzy model.

The usage of fuzzy model is advocated by the fact that it is an approach that enables evaluation of results which are non-crisp and non-deterministic in nature. Fuzzy Inference System (FIS) construes the input vector and is based upon a variety of fuzzy rules; it designates equivalent values to the output vector [13] [6]. This is a technique to apply fuzzy logic to map the output from an input. The mapping process is further utilized by the system to determine choices and differentiate patterns. Broadly, there are two main classifications of FISs, namely Mamdani FIS and Sugeno FIS. Since the inception of Mamdani FIS as a way of creating a control system by integrating a set of phonological rules taken from skilled human workers, the method has been used widely applied in numerous business-related problems The Reason that Mamdani FIS constructs more intuitive and understandable rule bases, they are well-suitable to the applications where human intervention is required to create knowledge. Hence, authors propose the application of Mamdani FIS to create a factor analysis model for the determination of fiscal proficiency.

The manuscript has been organized into various sections. The requirement of proposed model is presented in section 1. Section 2 discusses the fuzzy based factor analysis method and the Mamdani FIS modeling for fiscal proficiency is presented in section 3 along with results. Finally, the conclusion and future scope is made in section 4 and section 5 respectively.

2. Proposed Fuzzy Factor Analysis Model

The proposed model works in two phases, namely Factor Analysis, and the second phase involves the application of Mamdani Fuzzy Inference Modelling [14] [15]. The steps mentioned in the proposed model are depicted in Fig.1. Before the application of factor analysis, deciding and further analyzing the adequacy of sample size is crucial. For this purpose, KMO & Bartlett's Test is used. The Kaiser Meyer Olkin & Bartlett's Test is a measure of sample adequacy that indicates the suitability of the data for structure detection. KMO return values between 0 to 1.

Factor Analysis: This is a data reduction method that describes variability among observed $(O_1, O_2, \ldots\ldots, O_m)$ and unobserved $(U_1, U_2, \ldots\ldots, U_k)$ latent variables. It defines the unobservable (latent) variable reflected in the observed variables. The observed variable is assumed to be linearly correlated with unobserved factors as demonstrated in eq (1):

$$O_1 = \beta_{10} + \sum_{i\in 1, j\in 1}^{i\in m, j\in k} \beta_{ij} U_j + \varepsilon_1 \qquad (1)$$

The term β_{ij} known as loadings represent the impact of unobserved variable U_i on the observed variable O_j. The error term to represent the inexactness of the relation is calculated as ε. The model is based upon two assumptions:

Assumption 1: The error terms $(\varepsilon_1, \varepsilon_2, \ldots\ldots, \varepsilon_m)$ are unrelated, having mean as 0 and variance as ${\sigma_i}^2$.

Assumption 2: The unobserved variables are assumed to be independent of each other and to the error terms.

The variance observed variable O_i can be evaluated from the following equation eq. (2).

$$Var(O_i) = {\beta_{i1}}^2(var(U_1)) + {\beta_{i2}}^2(var(U_2)) + (1)^2(var(\varepsilon_i) \quad (2)$$

The covariance between observed variables in terms of factors can be calculated from the eq. (3), eq.(4), and eq.(5).

$$U_i = \beta_{io} + \beta_{i1}Fact_1 + \beta_{i2}Fact_2 + (1)\varepsilon_i + (0)\varepsilon_j \quad (3)$$

$$U_j = \beta_{jo} + \beta_{j1}Fact_1 + \beta_{j2}Fact_2 + (0)\varepsilon_i + (1)\varepsilon_j \quad (4)$$

$$Cov(U_i, U_j) = \beta_{i1}\beta_{j1}var(Fact_1) + \beta_{i2}\beta_{j2}var(Fact_2) + (1)(0)(var + (0)(1)(var(\varepsilon_j) \quad (5)$$

Further, the values obtained are not unique and hence, there needs to be a method to determine the final set of variables. The method employed here is principal component analysis (PCA) method. PCA tries to find the values that bring the communalities close to the observed variables, ignoring the covariances. This is done on based upon the correlation matrix of various factors that are involved, and correlation needs a large size of the sample before stabilization. PCA is done to extract the commonalities. If the factors obtained does not divulge the complete structure, rotation is applied to simplify the data for the purpose of easy interpretation. The method implied here is varimax criterion that rotates the factors in order to maximize the variance among the factors.

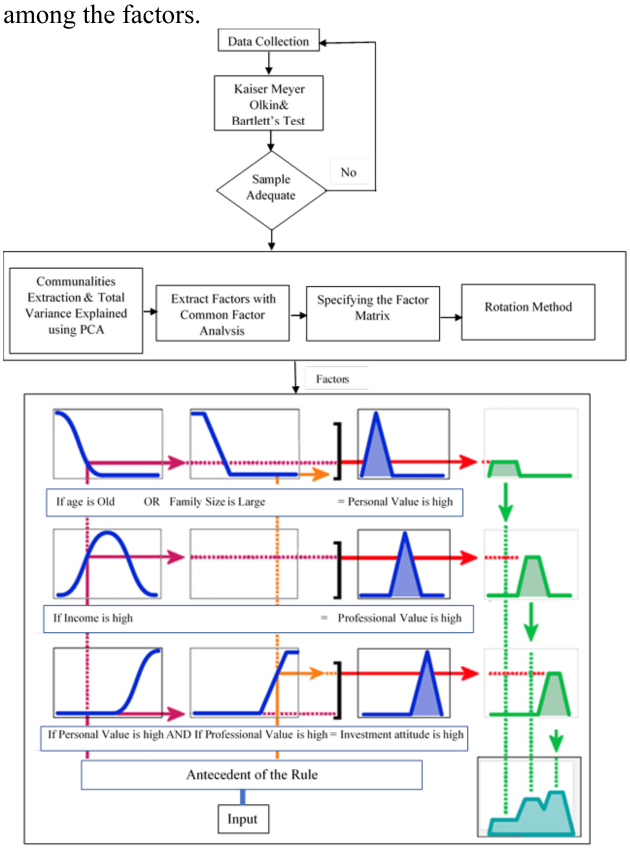

Figure 1. Step-wise Illustration of Fuzzy Factor Analysis Model

Mamdani Fuzzy Inference Model: Given the crisp values of factors as inputs, the Mamdani model works in three steps, namely Fuzzification, Inference composition, and Defuzzification [16] [17]. The proposed model has factors as input, representing the fiscal proficiency of an individual. These factors are normalized into a range [0, 1]. The detailed description of steps in Mamdani Fuzzy Inference Model is as follows:

Fuzzification: The first step involves input fuzzification, wherein the membership values are obtained which is realized using three membership function m_j viz. low, medium, and high. Two separate input FIS are created to represent personal value and professional value and one output FIS is realized for fiscal proficiency. Here, since the antecedent of the rule has multiple parts, therefore membership value is obtained using t-norm.

Inference Composition: Concept of logical operators "and", "or", and "not" is used to create fuzzy rules and such combinations are called as "T-norms". Fuzzy "and" is written as shown in eq. (6).

$$\mu_{A\cap B} = T(\mu_A(x), \mu_B(x)) \quad (6)$$

Here, in eq. (6), μ_A is read as "the membership in class A" and μ_B is read as "the membership in class B". There are many ways to compute "and". One of the most common way is min(μ_A (x),μ_B (x)).

Fuzzy "or" is written as shown in eq. (7).

$$\mu_{A\cup B} = T(\mu_A(x), \mu_B(x)) \quad (7)$$

In eq. (7), There are many ways to compute "or" and one of the most common way is max(μ_A (x),μ_B (x)). Similarly, Fuzzy "not" is written as shown in eq. (8).

$$\mu_{\sim A} = T(\mu_A(x)) \quad (8)$$

Here, there are many ways to compute "not" in eq. (8). One of the most common ways is $(1 - \mu_A(x))$.

Defuzzification: The results obtained through rule compositions are fuzzy in nature and to get the desired crisp results a process, Defuzzification is required. Many techniques of Defuzzification are available in the literature but the most common is Center of gravity (COG)/ Centroid Method.

3. Fuzzy Model for Fiscal Proficiency

In this section, authors present a Mamdani based fuzzy model that determines fiscal proficiency of an individual [14]. This model uses the factors that have been identified by the factor analysis. In the proposed model, the factors have been broadly divided into personal factors and professional factors. Here, personal factors comprise of gender, age, marital status and family size whereas professional factors contain profession, occupation and income. In the proposed model, there is a separate Fuzzy Expert System (FES) for personal as well as professional factors. These two FESs are further combined to give the final output that represents the fiscal proficiency of the individual as shown in Fig. 2. Here, the fiscal proficiency is classified into low, medium and high.

FES Implementation for Personal Value: FES for personal risk value takes 4 input parameters and produces one output value. It gives the output indicating an aggregated value called personal value. The fuzzy classification of various input and output parameters for FES1 of personal value is shown in Table 1. As evident from Table 1, the number of classifications for gender, age, marital status and family size are 2,3,2 and 3 respectively. Hence, there are a total of 36 (2*3*2*3 = 36) rules in rule-base. The rule that is executed is determined by the values of input parameters. The generic fuzzy pattern to evaluate personal value is demonstrated in Fig. 3.

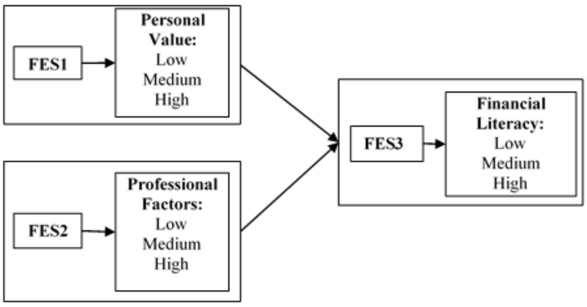

Figure 2. Illustration of Mamdani Fuzzy Model for Fiscal Proficiency

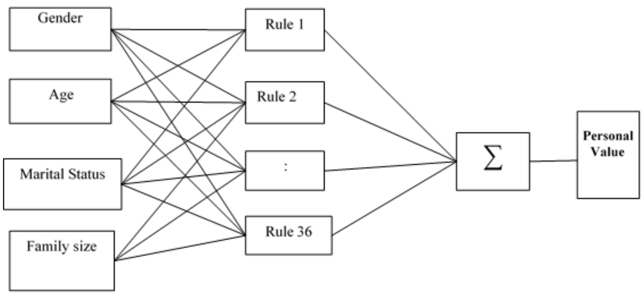

Figure 3. Fuzzy pattern to calculate Personal Value

Table 1. Fuzzy classification of input and output for Personal variables

	Parameters	Membership Functions		
Input	Gender	Male [0 0]	Female [1 1]	
	Age	Young [0 18 25]	Adult [16 30 50]	Old [45 60 100]
	Marital Status	Unmarried [0 0]	Married [1 1]	
	Family Size	Small [1 2 4]	Medium [3 4 6]	Large [5 7 10]
Output	Personal Value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

Thus, Fig. 4 to Fig. 7 illustrates that different value of input parameters leading to different value of personal aspect in respect to fiscal proficiency. For instance, in the implementation, it is observed that when gender is 0 (male), age = 50 years, Marital status = 0.00311 and family size is 5.5, the personal value for fiscal proficiency is 3.35. The relationship of different input and output parameters can be understood by the 3-d surface view as shown in Fig. 4 to Fig. 7. These figures represent the surface view for 2 different input parameters in order to have a better understanding of the fiscal proficiency. From the 3-d surface view of personal value for fiscal proficiency shown in Fig. 4, it is evident that male members have higher index of fiscal proficiency. Moreover, it is also clear that age does not have any significant impact on fiscal proficiency as in Fig. 6, it is observed that members have high personal index for fiscal proficiency across all age groups.

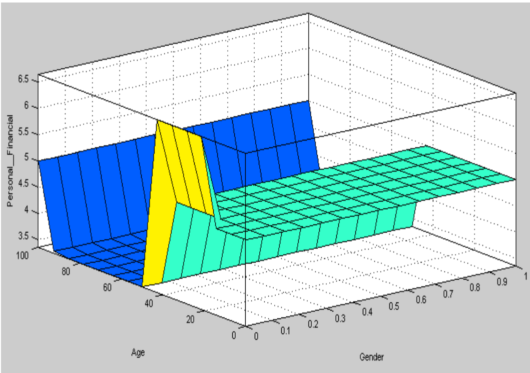

Figure 4. 3-d surface view for Age and Gender

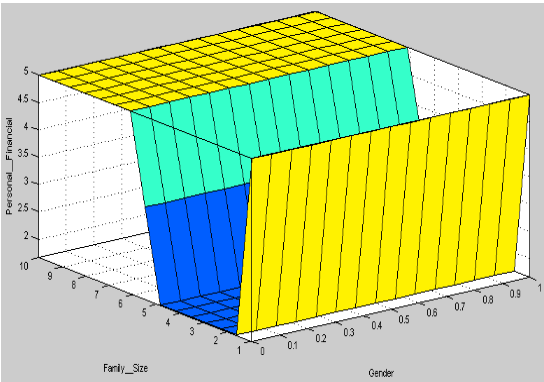

Figure 5. 3-d surface view for Gender and Family size

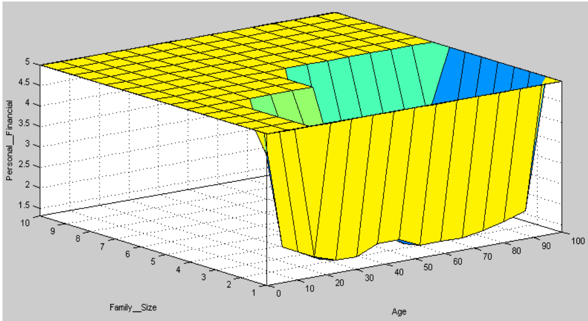

Figure 6. 3-d surface view for age and Family size

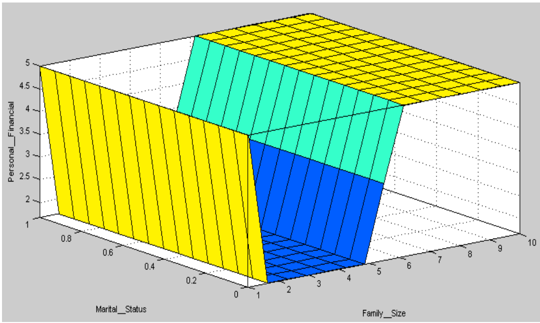

Figure 7. 3-d surface view for marital status and Family size

FES Implementation for Professional Value: FES for professional values considers 3 input parameters and produces one output value i.e professional value for fiscal proficiency. The fuzzy classification of various input and output parameters for FES2 of professional value is shown in Table 2.

Table 2. Fuzzy classification of input and output for Professional variables

	Parameters	**Membership Functions**		
Input	Qualification	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
	Occupation	Student	Working	Retired
	Income	Low 0 to 2 lakhs	Medium 2 to 6 lakhs	High >6 lakhs
Output	Professional Value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

From the classifications of input and output parameters, it is evident that the number of rules is 27. Here, the 3-d surface view of FES for professional value is shown in Fig. 8 and Fig. 9 that shows the influence of different input parameters on professional aspect of fiscal proficiency.

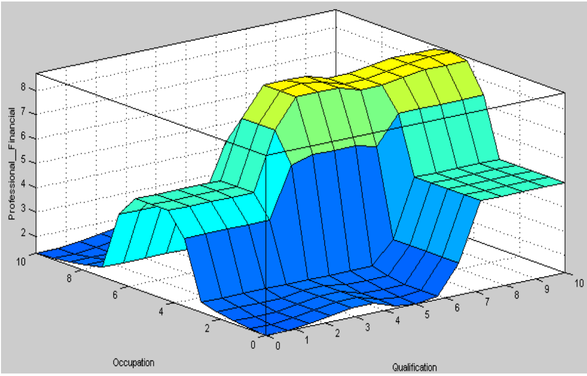

Figure 8. 3-d surface view for Occupation and qualification

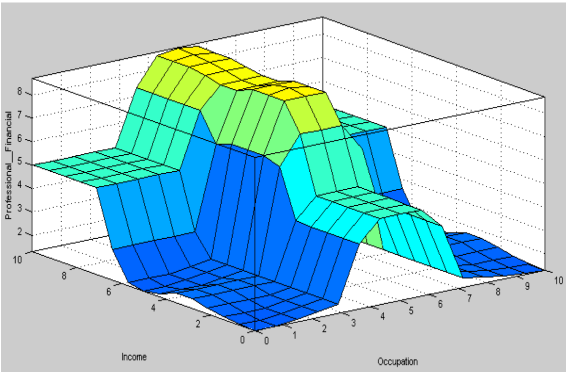

Figure 9. 3-d surface view for Income and Occupation

FES for Fiscal Proficiency (Investment Attitude): The final FES takes 9 input parameters viz. personal index (derived from FES1), professional index (derived from FES2) and socio-economic factors and finally produces an output representing the fiscal proficiency or investment attitude. The fuzzy classification for this FES3 is shown in Table 3.

Table 3. Fuzzy classification of input and output for Investment Attitude

	Parameters	Membership Functions		
Input	Personal Value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
	Professional Value	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
	Socio-economic factors	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]
Output	Investment Attitude	Low [0 0 4]	Medium [3 5 7]	High [6 10 10]

The final FES3 considers these input parameters and evaluates the investment attitude. The influence of personal, professional and socio-economic factors on fiscal proficiency can be easily understood by 3-d surface view as shown in Fig. 10 and Fig. 11.

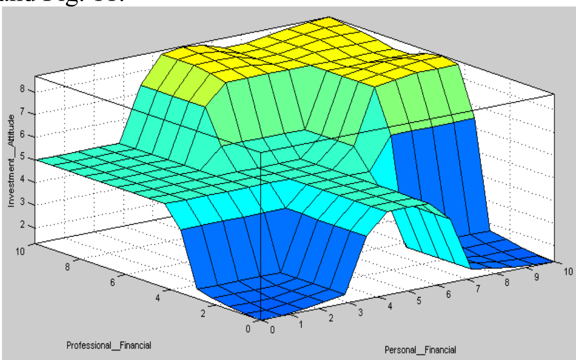

Figure 10. 3-d surface view for personal and Professional factors

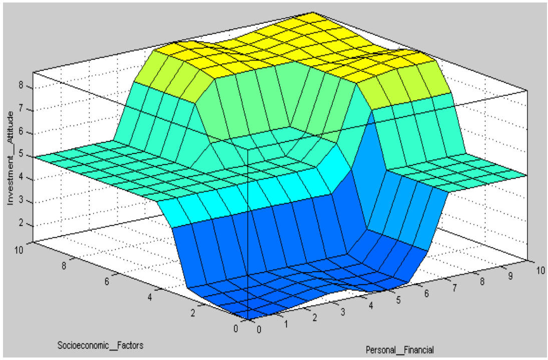

Figure 11. 3-d surface view for personal and socio-economic factors

From Fig. 10, it is clear that the most significant aspect of fiscal proficiency is personal fiscal index that in turn depends upon gender, age, marital status and family size. The classification of respondents against various factors is as shown in Table 4. Table 4 depicts the demographic profile of the respondents. The percentage of male and females is almost same. Majority if the respondents fall under the age group of 18-25 yrs. 50% of the respondents have completed their post-graduation. Majority of them are unmarried. Most of the respondents have 3-5 members in their family and the respondents having income group of 1,00,000 or below are relatively more (29.5%) which is followed by income group of 4,00,000 and above (24.5%).

Table 4. Demographic Profile of Respondents

Parameter	Classification						
Gender	Male 50.5	Female 49.5					
Age groups	18-25 45.0	26-35 28.0	36-50 18.0	> 50 9.0			
Marital Status	Married 35.0	Unmarried 65.0					
Educational Qualification	10th 3.5	12th 8.0	UG 34.5	PG 49.5	Diploma 3.0	Others 1.5	
Occupation	Business 23.5	Govt. Job 8.0	Private sector 26.5	Housewife 6.0	Student 30.0	Unemployed 3.5	retired 2.5
Family Size	< 4 ppl 16.5	4-5 65.0	> 5 18.5				
Family income	< 1 lac 30.0	1 to 2 lac 24.0	2 to 3 lac 12.5	3 to 4 lac 10.0	> 4 lac 23.5		

4. Conclusion and Future Scope

Fiscal proficiency enables the people to have a better understanding of the various fiscal instruments and thus helps them to make informed choices thus improving the poor (economically) situation of individuals. Considering the widespread urgency of fiscal proficiency, regulatory authorities must take proper initiatives to enhance the fiscal health of the individual which eventually leads to fiscal growth of society and nation. In an attempt to aid in this direction, authors in this manuscript have proposed a Mamdani fuzzy model which is validated using factor analysis. It is witnessed that the proposed fuzzy model is an efficient model to evaluate fiscal proficiency. The proposed model may prove to be helpful for governing authorities to work in the direction of enhancement of fiscal proficiency of the society as fiscally literate public will contribute towards growth multidimensional growth of the county.

The proposed work can be extended in the direction to address various strategies for data reduction techniques like t-SNE in view of plethora of data. Efficient methods for data reduction will also contribute towards streamlining the factor analysis process.

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