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Modeling the Causes of Business Failure Using Audit Variables: an Interpretive Structural Approach (Case study of agricultural firms in the Tehran Stock Exchange)

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Abstract

Interpretive structural modeling is a method for designing systems, especially accounting and management systems. This approach was first introduced by Warfield and has recently been frequently used by researchers in studies for modeling the relationships between variables. This approach makes it possible for the researcher to illustrate the complex relationships between the variables in a rather complex circumstance. It is now considered to be an important tool for organizing and directing the complexity of the relationships between variables. At first, this technique identifies the variables and then specifies the contextual relationships between the variables using the knowledge of experts and their experiences, and finally, it creates a multi-layered structural model. The present study is an applied research of the mixed type in terms of its purpose. In this study, the aforementioned technique was used to structure the factors explaining the causes of business failure (bankruptcy) of agricultural firms in the Tehran Stock Exchange. For this purpose, experts in this field (auditing-financial managers) in the agricultural firms accepted in Tehran Stock Exchange. In addition, 12 variables of audit report disclosures were identified as factors explaining the business failure. Then, the rate of effectiveness of these variables on one another in the model explaining business failure was coded using the initial access matrix. Finally, they were leveled using the final matrix. The results of interpretive structural modeling showed that the factors explaining business failure were modeled at six levels, with the type of auditing opinion at the highest level and had a greater impact on other factors. The highest degree of effectiveness was associated with other disclosures related to environmental-economic-regulatory factors which were at the lower levels. Therefore, it can be claimed that the disclosures associated with environmental-economic-regulatory factors explained the causes of business failure better than other audit variables.

Keywords: Business failure, audit report disclosures, interpretive structural equations, agricultural firms accepted in Tehran Stock Exchange

Introduction

Researchers in different disciplines of social sciences, including accounting, finance, organizational studies and strategies, have studied the causes of business failure and the consequences of it over the past few decades (Mehrani et al., 2005). Despite the number of studies focused on the causes of business failure, the integration of this research stream into the disciplines of social sciences must be improved (Amini, 2006). For instance, to date, researchers have ignored the intersection between the causes of business failure and audit. A High-quality audit is necessary for beneficiaries to make sure that the provided financial information is quite reliable, so that they could make the right decisions (Agarwal et al., 2006). In this respect, auditors must give a statement regarding their uncertainty about circumstances that might create a serious doubt about the firm's ability to continue to function in the future. If the probability of failure remained high during the one-year period following the issuance of their report, they would need to explain their statements (Makian & Karimi Takloo, 2010).

Auditors provide the company's shareholders with a letter containing a report on the results of their audit process. The audit report is a written statement that sets out the framework of the financial report and the period covered in those statements. This document includes the auditor's opinion, which may be acceptable, conditional or even rejected. It clearly shows the auditor's opinion on the annual financial statements. This document is formed based on the relevant framework, whether or not the annual financial statements comply with the legal requirements. If the auditor was unable to express their audit opinion, the report would contain a waiver of the audit claim. In addition, the report should address that the auditor addresses emphatically without specifying their audit opinion. Furthermore, the auditor should address the financial instability associated with events or circumstances that may raise serious doubts about the firm's ability to continue operating. The current issue is a feature that is usually provided when there are some doubts on the financial stability of the firm (Abzari et al., 2001). Auditing standards specify that the auditor's responsibility is to assess the uncertainty associated with the continuation of the firm's activity (Br´edart, 2014). Thus, auditors should report any evidence found during the audit processes associated with the risk of failure and if the risk still remains strong after the accounting conclusions, the auditors are required to explain their reports (Makian & Karimi Takloo, 2010). Therefore, the audit report could be considered as an early warning of impending failure (Agarwal & Taffler, 2007). Courts, inspectors and analysts use these documents to assess firms facing financial crises (Rama krishnan et al., 2015). Since shareholders of failed companies need to be aware of the current risks when making decisions, it makes sense for auditors, financial advisors and even business journals to feel responsible to provide the shareholders reports on the risks of failure (Yarifard, 2019).

In previous studies in the field of business failure, accounting ratios have been most used to explain business failure. Hence, the ratios do not include all signs of financial failure, and therefore sometimes other types of variables such as macroeconomic data or nonfinancial data could potentially replace them. Nonfinancial data may refer to variables that represent various dimensions of the firm's management. Industry and firm size are among other nonfinancial aspects used to assess the firm. Also, according to the aforementioned data, apart from the financial ratios used to explain business failure, there is evidence of the use of audit variables. Reviewing the research background in Iran shows that so far no research has presented a business failure model based on audit variables and audit report disclosures. Thus, a study in this field is both new and innovative and could improve and enrich the theoretical principles of other researches.

The present study aims to answer the question of whether or not the causes of business failure explained in audit report disclosures; meaning whether or not causes of business failure could be predicted in advance. Since business failure could take as much as 5 to 6 years and it is not a sudden and one-time phenomenon (Azar, 2013). Therefore, auditors could identify early warning signals of crisis in a company so that users of the audit reports could prepare to react to the phases following these warnings. Given what was mentioned, the present study has aimed to present a business failure model using audit variables and audit report disclosures in firms accepted in Tehran Stock Exchange.

Research background and theoretical framework

Business failure (firm's bankruptcy)

It is quite efficient to predict the risk of financial bankruptcy using neural network techniques based on accounting/market/integrated models. The integrated model is more precise in predicting bankruptcy (Takata et al., 2017). The market model is more precise in predicting bankruptcy than the accounting models (Barboza et al., 2017). The accuracy of the analysis plays a very significant role in predicting the firm's bankruptcy based on characteristics of the industry as a whole entity is lower than each industry is assessed separately (Salehi & Azimi Yancheshmeh, 2016). Additionally, prediction of the firms' bankruptcy using the decision tree model has also been examined (Salehi & Azimi Yancheshmeh, 2016). Comparing the ability of the models in predicting bankruptcy using the receiver operating characteristic (ROC) analysis method showed that the risk model presented by (Campbell et al., 2008) was significantly better at predicting the bankruptcy of nonfinancial corporations and it was more precise than (Ra'ei & Fallahpour, 2008) accounting model in predicting bankruptcy. However, the difference between the aforementioned model and the model presented by (Shumway, 2001) in terms of their precision and accuracy was not significant. Many studies have examined the effect of financial and nonfinancial variables in predicting bankruptcy. The results obtained from examining the role of financial ratios in predicting bankruptcy in different industries using the Z-Kramer method showed that this impact could vary in different industries. Furthermore, bankruptcy prediction based on neural models, regression, genetic algorithm relative to the current ratio variables, working capital and profit before interest and taxes showed that neural networks are more accurate in predicting bankruptcy (Talibnia, 2016). In a study, the economic value of risk models has been compared with the accounting approach to bankruptcy prediction of the risk model presented by Shamui (2001) and (Campbell et al., 2008) and the accounting-based model presented by (Shumway, 2001). The results showed the risk models were economically more valuable than accounting approaches and the model presented by (Campbell et al., 2008) was the most economical model. (Farajzadeh Dehkordi, 2007) have used modern learning patterns (e.g. multivariate analysis, logistic regression, classification and regression tree and artificial neural networks) to identify the most effective method for predicting the bankruptcy of Russian manufacturing companies. They found out that the neural networks were more accurate than any of the other studied methods. They also studied the prediction of bankruptcy using neural networks in commercial banks as well as the probability of bankruptcy up to three years prior to its actual occurrence. They came to the conclusion that bankrupt banks were more focused on real estate loans and set more rules and regulations. This circumstance increases the risk to some extent, which in turn decreases the equity of shareholders and the income obtained from the loan interests (Iturriaga F. & Sanz I. (2015). Sayari & Mogan (2016) found in an article that using financial ratios leads to the development of industry-specific financial bankruptcies. They also used the logistic regression technique and concluded that financial ratios are in fact reflective of the characteristics of the industry and that the information content of certain ratios varies in different industries. In addition, their findings were indicative of the divergent effect of industry characteristics on the companies and as a result, there is a need to construct industry-specific financial bankruptcy models. (Yarifard, 2019) argued that the difference between bankrupt companies and unbankrupted companies could be specified using a combination of accounting ratios and audit data. Other auditors believe that audit data, such as the auditor's comment, accumulation of conditional comments and auditor's high turnover help the assessment of business failure (Campbell et al., 2008). (Back et al., 2019) have evaluated various methods for bankruptcy prediction, including Support Vector Machine, Boosting, Bagging and Random Forest. They have also compared the results with linear audit analysis, logistic regression and neural networks. In their study, they reviewed the data used by American companies from 1985 to 2013. Their results were indicative of a 10% improvement in the accuracy of modern methods in comparison with traditional methods. The accuracy of the Random Forest, logistic regression and audit analysis methods were reported to be 87%, 69% and 50%, respectively. Furthermore, the results indicated that the Support Vector Machine was less precise than other models. In the following section, the studies published in Iran will be discussed. In a study, Muñoz-Izquierdo et al. (2019) have explained the causes of business failure or bankruptcy using audit report disclosures. They have considered the disclosure of internal and external factors in the audit reports to explain bankruptcy and have showed that the audit report disclosures were able to significantly explain bankruptcy.

Interpretive structural modeling

Interpretive structural modeling, introduced by Warfield, is a methodology for establishing and understanding the relationships between the elements of a complex system (Azar, 2013). This modeling system is a suitable technique for analyzing the effect on an element on another. This technique focused on the order and the direction of the complex relationships between the elements of a system. Additionally, it is an interpretive method, meaning that the relationships between the variables are determined based on the experts' comments and opinions. It is also a structural method, in the sense that it extracts an overall structure from a complex system of variables based on relationships and connections. It is also a modeling technique, as it shows the specific relationships between the variables as well as an overall structure in a graphical model (Fallahpour & Reza, 2004). Administration of this interpretive structural modeling technique has seven steps. Firstly, the criteria associated with the problem have to be identified and the elements of the will then be obtained. The initial and final access matrix will then be extracted and matched in the next step. What follows is the leveling of the elements of the access matrix and finally, the model will be illustrated and all key criterial will be determined (Azar, 2013).

The interpretive structural modeling examines the dynamic effect of various components of a system, and semantically, it has three dimensions corresponding to each letter. The interpretive dimension is based on the judgement and opinions of a group of experts associated with whether or not the variables have internal relationships and if so, what is the nature of this relationship. The structural dimension extracts the entirety of the structure from a set of complex variables based on the contextual relationships between the variables. The modeling dimension shows the specific relationships between the variables and the structure of the system as a whole. In other words, in interpretive structural modeling, the interpretive aspect is the result of judgment and opinions; the structural aspect is the output of the conclusions associated with a set of variables, and the modeling aspect is a (Figure 1) of the specific relationships in the overall structure. This analysis includes various steps (Porzamani, 2009). The interpretive structural modeling technique is an interactive learning process. In this technique, a set of various elements are structured in the form of a comprehensive systematic model (Azar, 2013). When such a model is formed, the structure of a complex issue or a problem is illustrated as an accurately designed pattern. This technique is an interpretive model, in that a group of experts decide whether there is a relationship or a connection between the elements and what the nature of this relationship is. It is also a structural model, in the sense that an overall structure is extracted from the complex components of the system based on the structural relationships between them. In this technique, the specific relationships between the elements and the overall structure of the system are illustrated as a graphical model. This technique is used as a tool to bring order to the complex relationships between variables and it is also an appropriate option for dealing with complex issues, especially when a systematic and logical approach is chosen (Sharma & Gupta, 2017). Interpretive structural modeling is a well-established methodology for identifying the relationships between special elements that define an issue or a problematic subject. For any complex issue under examination, there may be a number of factors related to the issue or the subject. However, the direct and indirect relationships between these factors describe the circumstance rather better and much more accurately than individual factors. Therefore, interpretive structural modeling helps develop a collective understanding of these relationships. In other words, structural interpretive modeling is an interactive process in which a set of various and interrelated elements are structured in a comprehensive systematic model. In general, interpretive structural modeling is a technique that makes it possible to study complex systems and structures a system in an easily understandable manner (Azar, 2013). Interpretive structural modeling is quite effective in identifying the internal relationships between variables and it is a suitable technique for analyzing the impact on one variable on another. In addition, interpretive structural modeling can prioritize and level the elements and components of a system, which in turn helps managers to better execute the designed model (Huang & Tzeng, 2005).

Steps of implementing the interpretive structural modeling technique

To implement the interpretive structural modeling technique, the internal relationships between the elements of a system and the prioritization of these elements have to be done by following these steps (Azar, 2013).

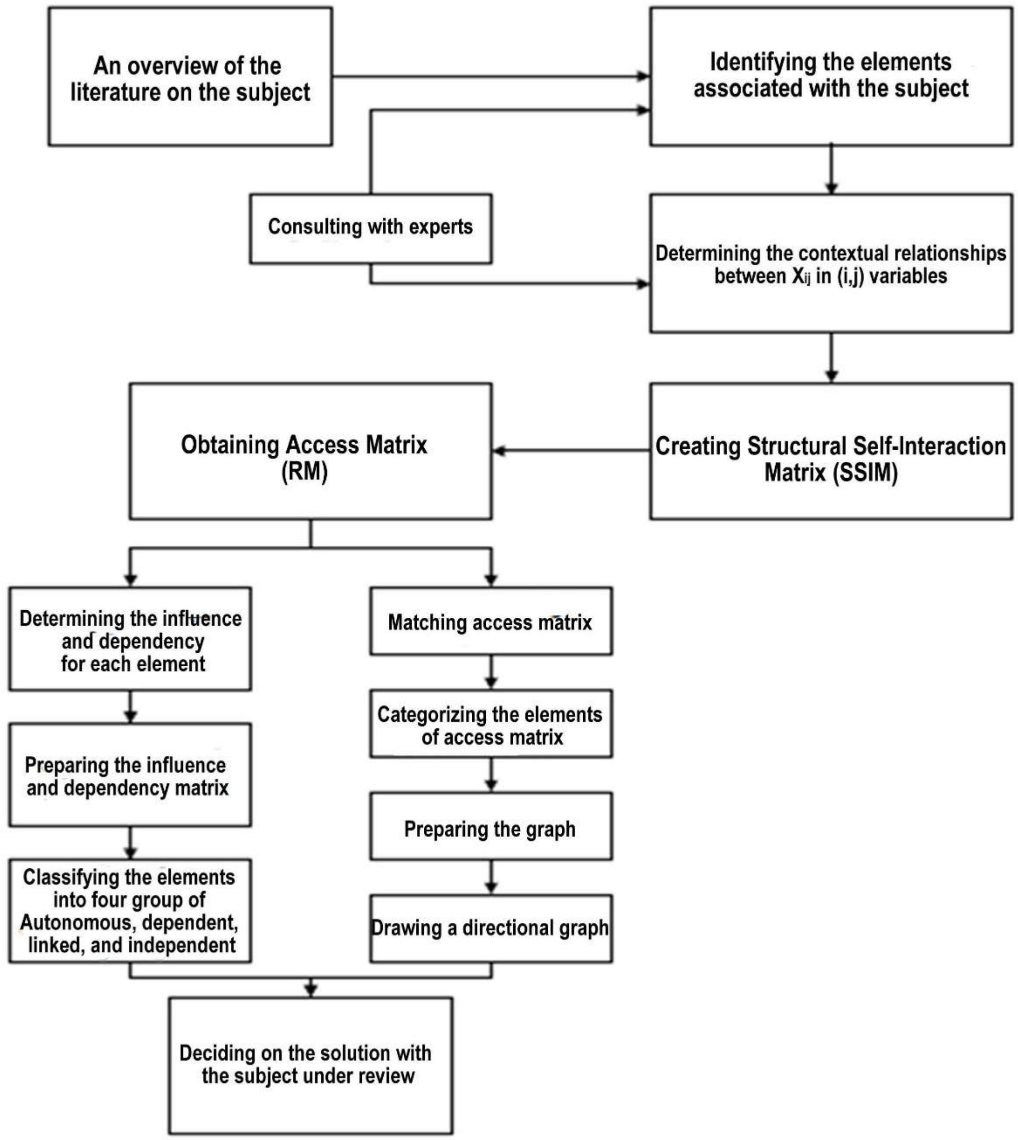

Figure 1. Steps of implementing the interpretive structural modeling technique

The interpretive structural modeling technique contains various stages which have all been displayed in the (Figure 1). These steps ultimately lead to creation of an interpretive structural model which will later be described:

Step 1: identifying the variables associated with the issue

The interpretive structural modeling technique begins with identifying the variables associated with the issue or the subject under discussion. These variables are obtained by studying the literature on the topic, previous studies and also by consulting experts using a questionnaire (Faisal et al., 2007).

Step 2: forming the structural matrix of the variables' internal relationships

This matrix (the structural self-interaction matrix) is a matrix with as many dimensions as the number of variables, where the variables are put in its first row as well as the first column. The, the two-by-two correspondences of the variables are specified by the symbols presented in the (Table 1) (Azar, 2013). The structural self-interaction matrix is created based on the discussions and commented made by a group of industry, organization and university experts (Faisal et al., 2007). To determine the type of relationships between the variables, it is recommended to consult experts based on various management techniques including brainstorming, nominal group techniques and so on (Warfield, 1974). The symbols presented in the (Table 1) are used to determine the type of relationship between the variables.

Table 1. Conceptual relationships in the formation of structural self-interaction matrix

Symbol	The symbol's meaning
V	i leads to j (component in row i leads to the obtainment of column j)
A	j leads to i (component in row j leads to the obtainment of column i)
X	There is a mutual relationship between i and j (both lead to each other)
O	There is no relationship between elements i and j.

Based on the interpretive structural modeling technique, the contextual relationships between the elements are determined based on the results of paired comparisons; in the sense that if most experts (i.e. N/2+1) vote on the existence of a relationship between two components, then the relationship is taken into account and otherwise, no relationship would be considered between the two components. To reach a collective agreement, the structural matrix of the internal relationships between the variables must be discussed more by experts so that it would be finalized with much more expertise and accuracy.

Step 3: creating the access matrix

By converting the symbols of the internal relationships between the variables in the structural matrix into ones and zeroes, the initial access matrix will be formed by following these steps (Azar, 2013).

Step 4: matching the access matrix

After creating the initial access matrix, it has to be internally matched. For instance, if variable 1 leads to variable 2 and variable 2 leads to variable 3, then variable 1 leads to variable 2 as well. If this was not the case in an initial access matrix, then the matrix should be reformed and the missed relationships should be replaced. Various methods have been recommended to match the matrix, two of which will be mentioned as follows:

First method: asking the experts to fill out the questionnaire again and to examine it thoroughly once more, this has to go on as many times as necessary until the matching is done perfectly. There have been some studies in which the first method has been used; namely, (Faisal et al., 2007), Ravi T. & Shankar R. & Tiwari M. (2005.

Second method: after the initial access matrix is obtained, the final access matrix can be obtained by adding the transferability of the relationships between variables. The final access matrix can be obtained based on the theory proposed by Euler, where the adjacency matrix added to the unit matrix and then this matrix is raised to the power of n if its entries do not change (Azar, 2013). The formula below shows the way to determine the access matrix using the adjacency matrix:

Step 1: A+1

Step 2: $M = (A + I)^n$

Matrix A is the initial access matrix, I is the ad joint matrix and M is the final access matrix. Raising the matrix to the power has to happen based on the Boolean rule, based on which: $(1 + 1 - 1, 1 * 1 - 1)$

Step 5: determining the level and priority of the variables

At this stage, the output and the input for each variable is obtained using the final access matrix (Watson, 1978). To determine the level and priority of the variables, the access set (output) and the prerequisite set (input) are determined for each variable. The output set of a variable consists of the components in the system from which that specific component is derived. To determine the output set associated with each component, its corresponding row has to be examined.

The number of "1s" in this row shows directed lines that enter that component (Azar, 2013). After determining the output set (access) and the input set (prerequisite) for each variable, the elements that exist in both sets are identified for each variable. After determining the output and the input sets and the mutual elements, it is now time to obtain the level of the variable (element). In the first table, we have the variable with highest level in the hierarchy of the interpretive structural model. We can see that the two sets are similar in this regard (2). After identifying this variable or these variables, they get deleted from the (Table 1) and the (Table 2) is created with the remaining variables. In the second table, much like the first one, the variable at the second level is identified. This procedure has to be repeated for all variables (Azar, 2013).

Step 6: illustrating the model

After determining the relationships between the variables and their levels, they can be illustrated as a model. For this purpose, first the variables are ordered from top to bottom based on their levels (Azar, 2013). At this stage, given the level obtained from the variables and the final matrix, the initial model is drawn and the final model is obtained by deleting the transferable components from the initial model. The relationships between the variables and the direction of the arrow are specified based on the final matrix.

Step 7: analyzing the penetrative influence and degree of dependence

The purpose of this analysis is to identify and evaluate the influence and dependence of the variables. At this stage, the influence of the variables is obtained by collecting the inputs (1) in one row and the degree of dependence of the variables is obtained by collecting the inputs in one column (1). Accordingly, the influence – dependence (Figure 2) is illustrated (Azar, 2013). In this analysis, variables are classified into four groups based on their influence and degree of dependence:

a) Autonomous variables (independent): these have weak influence and dependence. These variables are to some extent separated from other variables and have little and weak relationships with the system (Azar, 2013).
b) Dependent variables: these have a low degree of influence, but a high degree of dependence (Azar, 2013).
c) Joint (connected) variables: these have strong influence and dependence. These are non-static variables, because any change in them can affect the system altogether and ultimately, the system's reaction can change these variables again. In fact, any types of impact on these variables affect other variables (Azar, 2013).
d) Independent variables: these have a high degree of influence and a low degree of dependence. Variables with a high degree of influence are called (key variables). These variables are either put in the independent or connected variables (Azar, 2013).

Although many studies have focused on predicting bankruptcy and the factors affecting it using financial ratios, financial and nonfinancial variables (accounting, auditory, management, etc.) through mathematical and statistical models and so on, but there has been no research focused on modeling effective factors (explaining the causes plus predictions) on bankruptcy through interpretive structural. This approach has not been used in the field of bankruptcy predictions. Therefore, in the present study, the variables explaining the causes of bankruptcy (business failure) using this modeling approach.

Research questions:

- What are the factors explaining the causes of business failure in firms listed in Tehran Stock Exchange?
- How are the factors explaining the causes of business failure in firms listed in Tehran Stock Exchange ranked?
-

Methodology

The present study is an applied research of the mixed type (qualitative-exploratory) in terms of its purpose. It is a descriptive research in terms of its data collection technique. At the first stage, the explanatory variables were extracted by referring to research background and theoretical framework. These factors (variables) were specifically extracted from the research and presented to experts in this field (auditing-financial managers) in the firms accepted in Tehran Stock Exchange. Then, the experts were asked to fill out a questionnaire, based on which, 12 variables were analyzed and used for modeling. In this study, the interpretive structural modeling technique will be used to model the 12 selected variables explaining business failure in firms listed in Tehran Stock Exchange.

Results

In this section, to show the efficiency of the interpretive structural modeling technique, the relationships between the variables explaining the causes of business failure in the firms listed in Tehran Stock Exchange have been examined. According to the steps of this technique described in the previous sections, step 1 is identifying the variables associated with the issue. In this research, 12 factors explaining the causes of business failure were identified by experts. The next step is to create the self-interaction matrix between the variables based on the comments made by experts.

Table 2. Self-interaction matrix of the factors explaining the causes of business failure

Factor/Index	1	2	3	4	5	6	7	8	9	10	11	12
Disclosures related to accumulated losses of previous years	-	V[1]	V	O[2]	O	X[3]	A[4]	A	X	X	X	O
Disclosures related to assets	-	-	V	X	A	O	X	A	V	V	A	O
Disclosures related to the disapproval of all the report s on financial statements	-	-	-	X	A	X	X	A	X	A	A	A
Condition clauses of audit report	-	-	-	-	X	O	X	O	O	A	V	X
Disclosures related to filing and legal actions of the company	-	-	-	-	-	V	X	V	X	A	V	O
Disclosures related to long-term debts or contingent liabilities	-	-	-	-	-	--	V	A	X	X	V	O
Type of audit statement	-	-	-	-	-	-	-	O	X	V	X	O
Disclosures related to economic and regulatory factors	-	-	-	-	-	-	-	-	O	A	A	X
Disclosures related to the results of the current period (income and expenses)	-	-	-	-	-	-	-	-	-	A	V	O
Disclosures related to the company's future events	-	-	-	-	-	-	-	-	-	-	X	O
Team work	-	-	-	-	-	-	-	-	-	-	-	O
Disclosures related to negative working capital	-	-	-	-	-	-	-	-	-	-	-	-

[1] Variable i lead to variable j.
[2] Variable j leads to variable i.
[3] There is a mutual and two-sided relationship between variables i and j.
[4] There is not relationship between the variables i and j.

Next, the matrix above has to be converted to a binary matrix (initial access matrix). We enter the code zero for symbols A and O and the code one for symbols V and X. it must be noted that if there was the symbol A for variable i, there would be the symbol V for its corresponding variable, i.e. variable j, and vice versa. By applying the rules, the initial access matrix is obtained as follows:

Table 3. Initial access matrix of the factors explaining the causes of business failure

Factor	1	2	3	4	5	6	7	8	9	10	11	12	Driving force
Disclosures related to accumulated losses of previous years	1	1	1	0	0	1	0	0	1	1	1	0	7
Disclosures related to assets	1	1	1	1	0	0	1	0	1	1	0	0	7
Disclosures related to the disapproval of all the report son financial statements	0	0	1	1	0	1	1	0	1	0	0	0	0
Condition clauses of audit report	0	1	1	1	1	0	1	0	0	0	1	1	7
Disclosures related to filing and legal actions of the company	0	1	1	1	1	1	1	1	1	0	1	0	9
Disclosures related to long-term debts or contingent liabilities	1	0	1	0	0	1	1	0	1	1	1	0	7
Type of audit statement	1	1	1	1	1	1	1	0	1	1	1	1	10
Disclosures related to economic and regulatory factors	1	1	1	0	0	1	0	1	0	0	0	1	6
Disclosures related to the results of the current period (income and expenses)	1	0	1	0	1	1	1	0	1	0	1	0	7
Disclosures related to the company's future events	1	0	1	1	1	1	0	1	1	1	1	0	9
Disclosures related to the implemented management plans	1	1	1	0	0	0	1	1	0	1	1	0	7
Disclosures related to negative working capital	0	0	1	1	0	0	0	1	0	0	0	1	4
Dependent force	8	7	12	8	5	8	8	5	8	6	8	3	

From the matrix above, it can be understood that there is not one incompatibility in the initial access matrix and there is no need to match it again. In fact, this is the final matrix.

In the following section, the factors explaining the causes of business failure will be leveled. At this stage, the final access matrix is used to obtain the input and output set for each variable. To determine the level and the priority of the factors, the access set (output) and the prerequisite set (input) is specified for each variable.

The output set of a variable consists of variable consists of the components in the system from which that specific component is derived. To determine the output set associated with each component, its corresponding row has to be examined. The number of "1s" in this row shows directed lines that enter that component.

The input set of a variable consists of variable consists of the components in the system from which that specific component is derived. To determine the output set associated with each component, its corresponding column has to be examined. The number of "1s" in this column shows directed lines or the arrows that enter that component.

After determining these two sets, it is now time to obtain the mutual elements and to determine the level of each factor (element). In the first table, the input and the output sets are the same for the factor at the highest level in the hierarchy of the interpretive structural model. After identifying this variable or these variables, they get deleted from the (Table 3) and the (Table 4) is created with the remaining variables. In the second table, much like the first one, the variable at the second level is identified. This procedure has to be repeated for all variables (Azar, 2013).

From the (Table 3), it can be seen that the driving force score for "type of audit statement" is equal to 10, which is the highest driving force score among the variables of audit report disclosures. This means that this variable has the greatest influence on other variables than any of the other audit variables or audit report disclosures. On the other hand, the driving force score of the "disclosures associated negative working capital" is 4, which is the lowest amount among all variables. This means that this variable has the least impact on other variables, and it thus has the least significance.

In addition, in the (Table 3), it can also be observed that the depending force score of the "disclosures associated with the rejection of all financial statement reports" is 12 which is the highest score. This means that this variable is most effected by other variables of audit report disclosures. Also, the depending force score of the "disclosures associated with negative working capital" is 3 which is the lowest score; which means that this variable is least affected by other variables. The (Table 4) shows these repetitions and the levels of each variable.

Table 4. Leveling of the variables explaining the causes of business failure

Factor	Output Set	Input Set	Intersection	Level
1	1-2-6-7-8-9-10-11	1-2-3-6-9-10-11	1-2-6-9-10-11	5
2	1-2-4-5-7-8-11	1-2-3-4-7-9-10	1-2-4-7	3
3	1-2-3-4-5-6-7-8-9-10-11-12	3-4-6-7-9	3-4-6-7-9	4
4	2-3-4-5-7-11-12	2-3-4-5-7-10-12	2-3-4-5-7-12	5
5	2-3-4-5-6-7-8-9-11	4-5-7-9-10	4-5-7-9	3
6	1-3-6-7-9-10-11	1-3-5-6-7-8-9-10	1-3-6-7-9-10	5
7	1-2-3-4-5-6-7-9-10-11	2-3-4-5-6-7-9-11	2-3-4-5-6-7-9-11	6
8	1-2-3-6-8-12	5-8-10-11-12	8-12	1
9	1-3-5-6-7-9-11	1-2-3-5-6-7-9-10	1-3-5-6-7-9	5
10	1-3-4-5-6-8-9-10-11	11-10-7-6-2-1	11-10-6-1	3
11	11-10-8-7-3-2-1	11-10-9-7-6-5-4-1	11-10-7-1	3
12	12-8-4-3	12-8-4	12-8-4	2

Discussion

Now, the desired structural model of the issue can be created based on the final matrix. The final diagram has been obtained by deleting duplicate modes and also by using level segmentations.

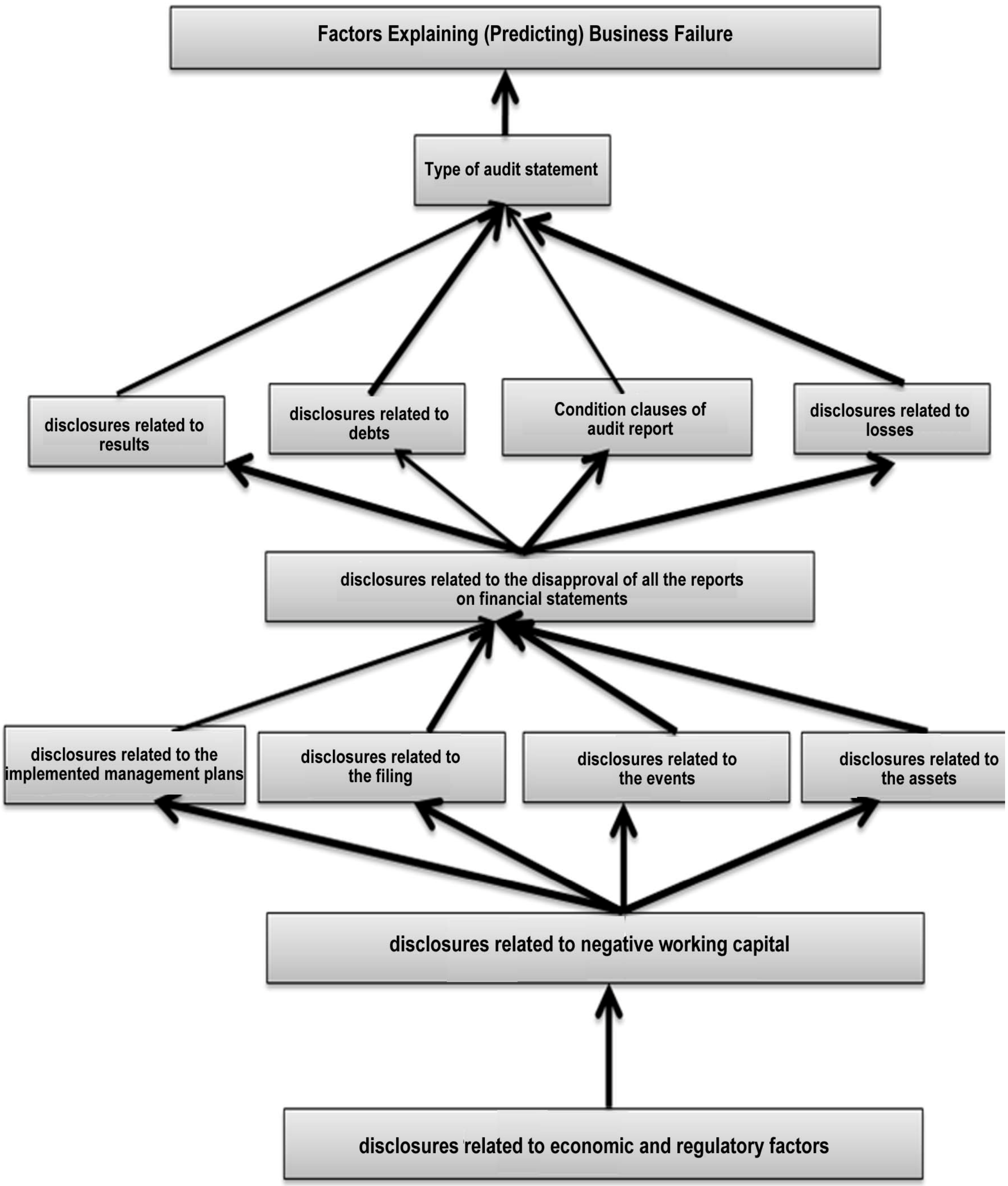

Figure 2. Structural model of the variables explaining the causes of business failure

Based on (Figure 2), it can be understood that the variables explaining the causes of business failure are at six levels, with disclosures associated with environmental-economic-regulatory factors and the disclosures associated with negative working capital is right next to it. Type of audit statement is at the highest level, which means that it is most affected by other factors and special attention has to be focused on this variable.

In the ISM, the interrelationships and the effectiveness of the criteria on one another and the relationships between the criteria at different levels are well shown. This provides the managers with a better understanding of the issue and helps them make better decisions. The factor at the sixth level (lowest level) has the most significant impact on the model (system) and as the changes, the whole system changes. Criteria in higher levels are less effective and therefore more affected by other factors. Therefore, it can be argued that the disclosures associated with the environmental-economic-regulatory factors are the most effective among all factors explaining the causes of business failure. In other words, this variable is able to explain the causes of business failure more than other variables.

Conclusion

As seen, the causes of business failure were studied using the recommended approach based on audit variables and the desired results were obtained. Based on the research background, 12 audit variables were considered. It can be argued that there was more or less an acceptable understanding of the issue, its variables and the relationships between them in the organization under study. In this research, the ISM Figure (Interpretive structural model) was illustrated so that a comprehensive network would be obtained and prioritization (level) of the variables would be graphically displayed. In this way, we could have a more complete understanding of the relationships. Also, based on the analysis of self-interaction matrixes, the type of variables was determined according to their impact on other variables and also how they were affected by other variables. It seems that this type of research can be useful for studies with a large number of variables whose nature and relationship with each other and even their type is not well known. This is because, we can simplify the issue with the help of experts and gain a good understanding of the issue, which will eventually lead to better decision-makings.

In the ISM graph, the relationships between the variables and their impact on one another as well as the relationship between the variables at different levels are well displayed, which helps us to have a better understanding of the issue and to make better decisions. The factor at the sixth level (lowest level), i.e. disclosures associated with environmental-economic-regulatory factors, has the most significant impact on the model (system) and as the changes, the whole system changes.

Criteria in higher levels are less effective and therefore more affected by other factors. Therefore, it can be argued that the disclosures associated with the environmental-economic-regulatory factors are the most effective among all factors explaining the causes of business failure. In other words, this variable is able to explain the causes of business failure more than other variables.

At the fourth level, we have disclosures associated with assets, disclosures associated with the firm's future events, disclosures associated with management plans implemented in the firm and disclosures associated with the firm's paper work and legal actions. These variables have a mutual relationship with one another. However, there is no mutual relationship between disclosures associated with the firm's the future events and disclosures associated with assets; disclosures associated with management plans implemented in the company and disclosures associated with the firm's paper work and legal actions. There are also four similar variables at level one. These four variables are disclosures associated with accumulated losses of previous years, disclosures associated with the results of the current period (income and expenses), conditional clauses of the audit report and disclosures associated with short-term and long-term debts. There is a mutual relationship with all of these four variables as well.

In general, based on the self-interaction matrix table, variables such as disclosures associated with management plans implemented in the company, disclosures associated with accumulated losses of previous years, conditional clauses of the audit report, disclosures associated with long-term or probable debts, disclosures associated with the results of the current period (income and expenses) are impressionable variables in the model. On the other hand, the following variables are considered to be the influential variables in the model: disclosures associated with the future events of the company, type of audit statement, disclosures associated with environmental-economic-regulatory factors, disclosures associated with management plans implemented in the company and disclosures associated with paper work and legal actions.

Recommendations

However, in this study, a model of the causes of business failure was presented. It was also shown that disclosures associated with environmental-economic-regulatory variable have the greatest impact and significance in explaining business failure. It was also seen that disclosures associated with the accumulated losses of previous years, disclosures associated with the results of the current period (income and expenses), conditional clauses of the audit report and disclosures associated with short-term and long-term debts can have the least impact on the business failure system. Nonetheless, the results of this study are somewhat inconsistent with the results of empirical studies. In empirical researches, it has been concluded that variables that have the least impact on business failure, can predict a large percentage of changes in business failure, which is rather incompatible with the results of this study. This inconsistency may be due to the nature of the statistical population and research tools (questionnaire-interview) and the data analysis method (structural equations). It is suggested that since the ISM network is a comprehensive network, the weight of all the mentioned variables should be calculated using the analysis network process (ANP). Also, by combining ANP with the proposed research model, a framework can be created for evaluating issues with an unknown structure; in the sense that first, the relationships and network of relationships are created through ISM and then, one can choose the most effective alternative (if the goal is set) using ANP.

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