Use of Statistical Methods as an Educational Tool in the Financial Management of Enterprises in the Implementation of International Financial Reporting Standards

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Abstract **– Enterprises that use the international IFRS system usually operate primarily as domestic businesses abroad and this accounting system makes it easier for them to present their financial statements to their partners from abroad. The aim of the paper is to determine clusters for enterprises that report according to IAS / IFRS using statistical analysis - cluster analysis. Also its aim is to prove the possibility of using cluster analysis for accounting data in order to improve management decision-making in financial management issues.**

Keywords **– cluster analysis, IAS, IFRS, financial performance, financial indicators.**

1. Introduction

The adoption of an IFRS accounting system for SMEs also brings a possible change in the structure of assets and sources of its coverage as well as a change in costs and revenues. The reason is the change in accounting policies and in the reporting methods of the individual items of the statement of financial position of the enterprise and the statement of comprehensive profit or loss. The research of authors intended to measure the differences between national accounting rules and the international standards. Using the regression models, a conclusion is made that the coefficient of Return on Equity is significantly (at 10 %) positive and higher at companies which have already adopted IFRS [1]. The authors point to a number of benefits derived by companies from IFRS implementation including the higher quality of financial statements and their comparability, lower costs of capital as well [2]. Similar studies were conducted by Polish researcher on the basis of the annual reports of 255 publicly traded companies. Most companies which implemented IFRS recorded higher equity values, with many of them recording differences within the range of +/-10%. It should be noted that a large number of entities recorded differences above +/-20%. Similar results were recorded for net profits. Most companies recorded financial results at a higher level after transition to IFRS [3].

In the paper we use the cluster analysis method, which enables to organize companies on the basis of selected financial indicators into individual clusters [4]. The use of cluster analysis is broad-spectrum. It is useful in the diagnosis of diseases which have used cluster analysis in a cohort of patients with early stage non-small cell lung cancer [5]. The use of cluster analysis is also possible in the field of transport. It is also possible to use the cluster analysis methodology in the field of education and human resources [7].

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2. Methodology

The objective of this article is to identify clusters of the enterprises based on selected financial indicators using hierarchical agglomeration aggregate analysis based on the financial statements of selected SMEs that have applied the transition from Slovak accounting legislation to IAS/IFRS within two consecutive accounting periods.

The data required for the analysis are based on anonymized financial statements of 30 randomly selected entities (SMEs) that at December 31, 2013 prepared financial statements under Slovak accounting legislation. However, since January 01, 2014, these enterprises have started to use the IFRS accounting system, so the transition from Slovak accounting legislation to IFRS has been the precondition for selecting companies. The financial statements that have been analyzed are compiled as of December 31, 2014 according to IFRS.

We have received the financial statements from the register of financial statements (Ministry of finance of Slovak Republic), under the authority of the Ministry of Finance of the Slovak Republic. The data obtained from this portal is first analyzed by cluster analysis using the mathematical software R. The cluster analysis application procedure will be as follows [8]:

- Entering input data,
- Selecting the type of variables,
- Object names,
- Selection of the agglomeration process,
- Selection of the type of aggregation method,
- Selection of the degree of similarity of objects,
- Determining the number of significant clusters,
- Interpretation of clusters.

We realized selection of the degree of similarity of objects by applying a distance measure called Euclidean distance, formulated as follows:

$$d_{ij} = \sqrt{\sum_{k=1}^{n} \left(X_{ik} - X_{jk}\right)^2} \qquad (1)$$

Where:

X_{ik} is the value of the k^{th} variable for the i^{th} enterprise,

X_{jk} is the value of the k^{th} variable for the j^{th} enterprise.

This distance assumes an orthogonal coordinate system, which means mutual non-correlation of variables. The disadvantages of this type of distance include the significant influence of the absolute value (amount) of input data. This disadvantage can be eliminated by using variables in their standardized shape (form) [6].

In terms of the type of aggregation (clustering) method, we have applied Ward's method (Ward's minimum variance method), which is the most used in practice. According to this method the clusters are formulated based on the maximization of homogeneity within the cluster. The homogeneity measure represents the sum of squares of deviations from the average of the cluster, called ESS (the error sum of squares) and we use the following formula for its calculation:

$$ESS = \sum_{i=1}^{n_h} \sum_{h=1}^{q} \left(X_{hi} - \overline{X}_{C_h}\right)^2 \qquad (2)$$

Where:

n_h is the number of objects in the cluster C_h,

$\overline{X}_{C_h}$ is the vector of the averages of the values of the character in the cluster C_h,

X_{hi} is the vector of the values of the character of ith object in the cluster C_h.

The cluster analysis is designed to create relatively homogeneous groups where it is necessary to determine an appropriate number of these groups based on various criteria, for example based on hierarchical tree - dendrogram [9].

By performing the correlation of the input variables at the significance level of 5 % ($\alpha = 0.05$), we observe the dependence (relationship) between the variables. However, the problem may be a high degree of dependence (relationship) between variables, which can affect the classification results. Deletion of the problem can be accomplished through the main components method, in which input indicators are transformed into the new variables called main components and they are already each other.

Only a few main components can reliably explain a substantial part of the overall spread of the original data. Therefore, several rules are used to determine the optimal number of components, for example:

- The number of main components should explain at least 70 % of the total spread of the data.
- For determination the number of main components to use a graphical representation of the spread explained by main components.

3. Results – cluster analysis of small and medium-sized enterprises

In the following sections, we will analyze the anonymized financial statements of 30 randomly selected entities (SMEs) that prepared their financial statements according to IFRS for the first time at December 31, 2014. As we have mentioned above, the method that was selected for the clustering process was Ward's method (Ward's minimum variance method) and the selection of the degree of similarity of objects was realized by applying Euclidean distance. From the financial statements, we have calculated the selected financial indicators for each of the 30 enterprises, which we identified as variables and they are stated in Table 1.

Table 1. Examined variables

Variable	Financial indicator	Measure
A1	Cash position ratio	coefficient
A2	Quick ratio	coefficient
A3	Current ratio	coefficient
A4	Degree of self-financing	coefficient
A5	Degree of indebtedness	coefficient
A6	Financial leverage	coefficient
A7	Return on assets (ROA)	coefficient
A8	Return on equity (ROE)	coefficient
A9	Return on investment (ROS)	coefficient

A prerequisite for performing cluster analysis is to examine relationships between individual variables. The starting point for us was a correlation matrix that contains Pearson's correlation coefficients (Figure 1.).

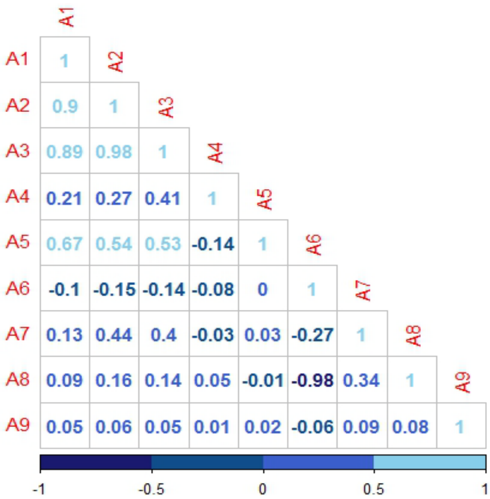

Figure 1. Correlation matrix

From the results of the correlation matrix (Figure 1.), we can determine the relationship between the variables. We can notice that there is a high positive linear relationship between the variables A1 and A2, but there is a high negative linear relationship between the variables A6 and A8. For the needs of cluster analysis, however, it is necessary to exclude statistically significant, but weaker relationships, as they could distort the result of cluster analysis. It is therefore necessary to test the statistical significance of the Pearson's correlation coefficients. The output from the mathematical software R automatically crosses out the statistically insignificant coefficients at the significance level of 5 % as it is shown in Figure 2.

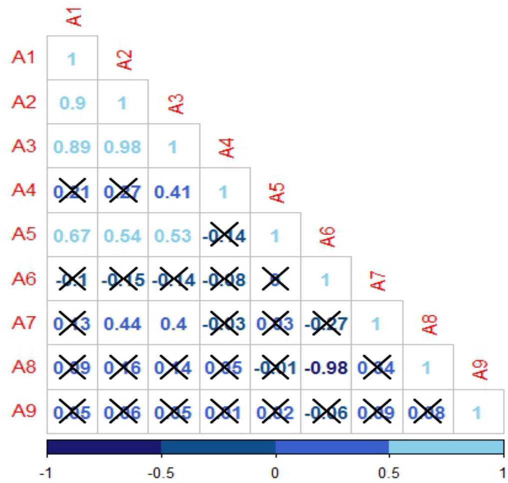

Figure 2. Statistical significance of correlations

Figure 2. shows that for example in the case of the variables A6, A7, A8 and A9, all coefficients are statistically insignificant. But in case of the variables A5, A3, A2 and A1, some of their correlations are statistically significant. This means that there may be a problem with cluster formation in cluster analysis. Therefore, it is necessary to use the main components method (to analyze the main components). We used the type of main components analysis that works with standardized variables. For the purpose of identifying the optimal number of main components (number of significant components), we calculated the shares of component variability in the total variability of the data from which we calculated the components (Table 2.).

Table 2. Selected statistics of components

Indicator	C1	C2	C3	C4	C5	C6	C7	C8	C9
Standard deviation	1.891068	1.424731	1.066808	0.9989366	0.9420133	0.5446866	0.2188478	0.1413256	0.07817247
Proportion of spread	0.397350	0.225540	0.126450	0.1108700	0.0986000	0.0329600	0.0053200	0.0022200	0.00068000
Cumulative	**0.397350**	**0.62289**	**0.749340**	**0.8602200**	**0.9588200**	**0.9917800**	**0.9971000**	**0.9993200**	**1.00000000**

From Table 2., we can see that the first component explains the most and the last component explains the least variability. At the same time, we see that in order to clarify 99.178 % of the variability of the original data, we need only 6 components. So, we can say that we have met a rule that says the number of main components should explain at least 70 % of the total spread of data. Subsequently, we explained the variability of the original data by the components also graphically using screen plot (Figure 3.), where is a graphical representation of the spread explained by main components and we found a break in the graph.

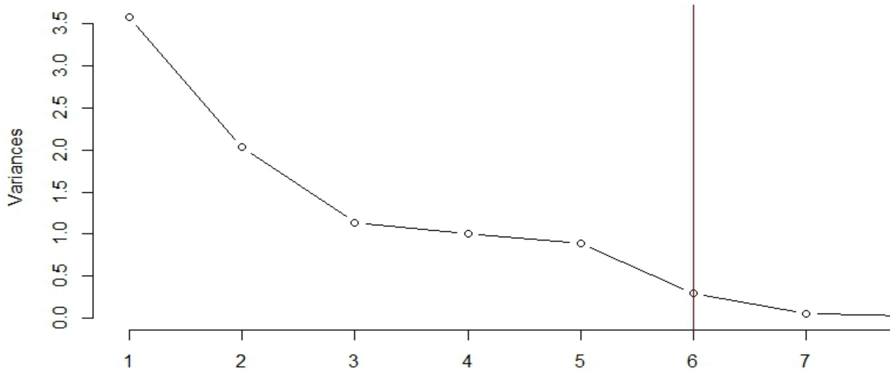

Figure 3. Screen plot of the main components

In Figure 3., we can observe a break by the third component, which explains 74.934 % of the total variability of data. It would be possible to select this number of main components, as these 3 components explain more than 70 % of the total spread of data, but the 6 selected components can analyze the variability of original data much more (74.934 % < 99.178 %). The next step was determination of the number of significant clusters of enterprises in our analysis. Based on the heuristic approach, we grouped the enterprises into 8 clusters. For this determination we also used the screen plot of number of clusters (Figure 4.), where the number of clusters is shown on the x-axis and the within cluster sum of squares is shown on the y-axis. The decisive criterion is to minimize the within cluster sum of squares, which represents the optimal situation.

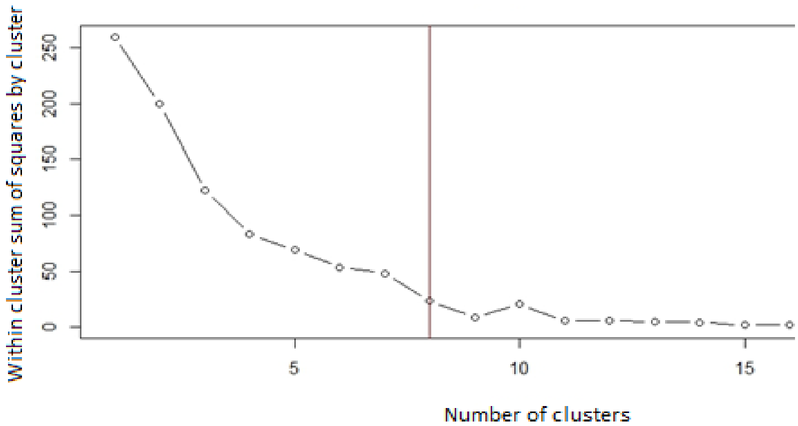

Figure 4. Screen plot of number of clusters

In Figure 4. the line dividing the x-asis determines 8 clusters – the optimal situation – when the within cluster sum of squares has an optimal value. If we decide for more clusters, we can see that the within sum of squares would cause the number of enterprises in the cluster to be too small. Conversely, a small number of clusters would cause the within sum of squares to be too high.

Subsequently we have plotted the clusters in the hierarchical tree diagram, where the individual clusters are marked. Each enterprise is marked with a number (from 1 to 30 enterprises). We can see that 8 clusters have been created, which are mutually heterogeneous but enterprises within their cluster are homogeneous. This means that enterprises in one cluster have similar characteristics in terms of liquidity ratios, debt ratios and profitability ratios, while having different characteristics of indicators (ratios) with enterprises in other agglomerations (clusters).

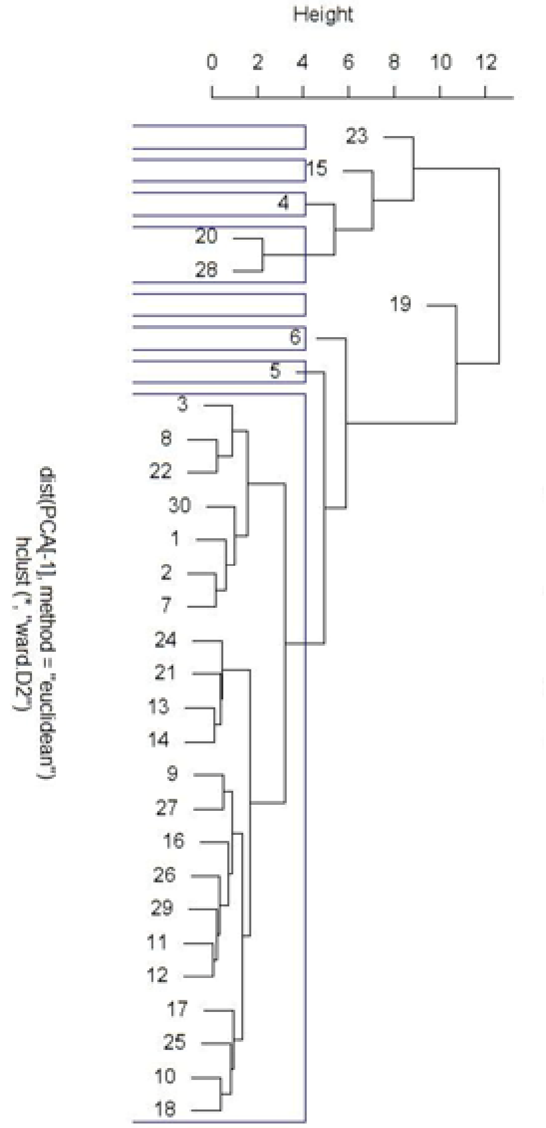

Figure 5. Hierarchical cluster tree dendrogram

According the dendrogram (Figure 5.) we can say that the set of our 30 enterprises has been divided into 8 clusters through cluster analysis. The largest cluster (Cluster No. 1) represents 22 enterprises, followed by a cluster of two enterprises (Cluster No. 7) and 6 remaining clusters represent separate enterprises. At the same time, these enterprises are numbered according to their order.

4. Summary - overall assessment of the analysis

Based on a hierarchical agglomeration aggregate analysis, we identified clusters for selected enterprises with respect to selected financial indicators. In this analysis, we have calculated 9 financial indicators (liquidity ratios – A1, A2, A3; debt ratios – A4, A5, A6 and profitability ratios – A7, A8, A9) for selected Slovak enterprises. Selection of the degree of similarity of objects we realized by applying a distance measure called Euclidean distance. In terms of the type of aggregation (clustering) method, we have applied Ward's method (Ward's minimum variance method).

By using the main components method, we have created clusters of enterprises that are mapped in a dendrogram that has ranked enterprises on the basis of selected financial indicators. Enterprises have thus been organized into clusters that have similar characteristics and differ from those of other clusters (agglomerations). Before we proceeded to aggregation, we examined the relationships between the variables.

In our case, the characteristics of the enterprises are represented by the characteristics of the selected financial indicators (variables). To determine the optimal number of clusters, we used a heuristic approach supplemented by a graphical assessment using scree plot, which showed the number of clusters and within cluster sum of squares. The result is the identification of 8 clusters. Centroids (means) of individual original variables in individual clusters are listed in Table 3.

Table 3. Centroids (means) of individual original variables in individual cluster

Cluster	A1	A2	A3	A4	A5	A6	A7	A8	A9
1	0.3172	0.9549	1.1764	0.9673	0.9815	4.0170	0.0596	0.1613	0.0593
2	0.4976	4.1595	4.6429	3.1040	0.1631	1.9746	1.2094	2.3883	0.1708
3	0.1178	0.2139	0.2338	1.4632	0.4059	1.6834	0.0759	0.1278	5.7052
4	0.0315	0.0555	0.0630	1.1068	0.4746	1.5986	0.0000	-0.442	-6.365
5	2.4806	3.8359	5.8861	61.016	0.0160	1.0209	0.0115	0.0117	0.0517
6	0.1593	0.38313	0.7436	0.0083	0.9480	125.70	-0.205	-25.80	-0.490
7	3.2887	4.6236	4.6939	3.0344	0.2745	2.4879	0.2139	0.4172	0.2181
8	6.6939	7.4461	8.4116	0.0783	9.7812	1.3041	0.2114	0.2757	0.2271

On the basis of the dendrogram, we found out that after the transition to IFRS from 30 Slovak enterprises, the majority of enterprises contain Cluster No. 1, which represents 22 enterprises. This most numerous and dominant cluster has the average value of cash position ratio (A1) of 0.3172 (Table 3.), which is in the optimum state and suggests that 1 euro of short-term liabilities should amount to 0.3172 euros in financial accounts. In case of indicators quick ratio (A2) and current ratio (A3) the average values are just below the recommended value (Table 4.). In terms of debt ratios, indicator degree of indebtedness (A5) shows an acceptable average value of 0.9815 (Table 4.), because a value of 1 represents an equal share in financing of enterprise between the owners and the creditors. We can state, according Table 4., that returns ratios in the Cluster No. 1 reached satisfactory average values. Indicator ROA (A7) reached an average value of 0.0596 (5.96 %,) indicator ROE (A8) reached an average value of 0.1613 (16.13 %) and indicator ROS (A9) reached an average value 0.0593 (5.93 %). In Table 5., we can see medians for individual clusters. The use of medians is due to the fact that in the previous table (Table 3.) the means (averages) can be affected by an extreme value for individual enterprises. For a median, this threat is eliminated as the median is the value which is found by ordering the set from lowest to highest and finding the exact middle.

Table 4. Medians of individual original variables in individual clusters

Cluster	A1	A2	A3	A4	A5	A6	A7	A8	A9
1	0.1265	0.7421	0.8015	0.4003	0.5698	2.0175	0.0249	0.0446	0.0079
2	0.4976	4.1595	4.6429	3.1040	0.1631	1.9746	1.2094	2.3883	0.1708
3	0.1178	0.2139	0.2338	1.4632	0.4059	1.6834	0.0759	0.1278	5.7052
4	0.0315	0.0555	0.0630	1.1068	0.4746	1.5986	0.0000	-0.442	-6.365
5	2.4806	3.8359	5.8861	61.016	0.0160	1.0209	0.0115	0.0117	0.0517
6	0.1593	0.3831	0.7436	0.0083	0.9480	125.70	-0.205	-25.80	-0.490
7	3.2887	4.6236	4.6939	3.0344	0.2745	2.4879	0.2139	0.4172	0.2181
8	6.6938	7.4461	8.4116	0.0783	9.7812	1.3041	0.2114	0.2757	0.2271

In case of the most numerous Cluster No. 1, we see the differences in almost all financial indicators (examined original variables) and we notice their deterioration compared to the means (averages).

Table 5. Differences between centroids and medians for individual clusters

Cluster	A1	A2	A3	A4	A5	A6	A7	A8	A9
1	0.1907	0.2128	0.3749	0.5670	0.4117	1.9995	0.0347	0.1167	0.0514
2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

In Table 6., there are listed differences between centroids and medians for individual clusters. Based on the values in Table 6., we can say that the averages for Cluster No. 2 until Cluster No. 8 do not record any changes when comparing centroid values (Table 5.) and median values (Table 6.). The reason is that Cluster No. 2 until Cluster No. 6 as well as Cluster No. 8 contained only one enterprise, Cluster No. 7 included two enterprises.

Only in case of the most numerous Cluster No. 1 (where 22 enterprises are included) we observe the differences between centroids and medians and these differences are presented in Table 6.

Table 6. Differences between centroids and medians for cluster No. 1

Cluster No. 1	A1	A2	A3	A4	A5	A6	A7	A8	A9
Centroids	0.3172	0.9549	1.1764	0.9673	0.9815	4.0170	0.0596	0.1613	0.0593
Medians	0.1265	0.7421	0.8015	0.4003	0.5698	2.0175	0.0249	0.0446	0.0079
Difference	0.1907	0.2128	0.3749	0.5670	0.4117	1.9995	0.0347	0.1167	0.0514

For all ratios, the medians were lower, which confirms that there is one or there are more extreme values among 22 enterprises that slightly distort the results in Table 4. with the mentioned centroids. But this one or more of the extreme values of a given enterprise, still by its characteristics of variables is similar to that of the variables of enterprises in Cluster No. 1 and different from the characteristics of variables in other aggregates (clusters).

In case of the liquidity indicators, the value for indicator cash position ratio (A1) declined by 0.1907 to value 0.1265, the value for indicator quick ratio (A2) declined by 0.2128 to value 0.7421 and the value for indicator current ratio (A3) declined by 0.3749 to a new value of 0.8015. This decline can be characterized as deterioration in the values of the liquidity indicators. Indicator degree of self-financing (A4) decreased by 0.5670 and reached new value 0.4003, which is very far from the ideal/optimum state. Indicator degree of indebtedness (A5) as well decreased by value 0.4117 to new value 0.5698. The most significant change of 1.9995 is recorded for indicator financial leverage (A6) to new value 2.0175. In case of all profitability indicators there was a radical deterioration. Indicator ROA (A7) declined to 0.0249 (2.49 %) and indicator ROE (A8) declined by value 0.1167 (11.67 %) to new value 0.0446 (4.46 %). Indicator ROS (A9) decreased to new value 0.0079 (0.79 %) from value 0.0593 (5.93 %).

Conclusion

We devoted this paper to the cluster analysis method, which enables to organize the enterprises on the basis of the selected financial indicators into individual clusters that have similar characteristics and differ from the characteristics of enterprises in other clusters (agglomerations). We try to use this method in terms of financial data, when we analyzed the anonymized financial statements of 30 randomly selected Slovak enterprises (SMEs) that prepared their financial statements according to IFRS for the first time at December 31, 2014. In this area it would be interesting to explore some more objectives:

1. *Has there been a change in the values of the selected financial indicators before and after adoption of IAS/IFRS?*
2. *Is the number of companies in clusters similar to those prior to adoption of IAS/IFRS?*

These research questions will be the subject of our further exploration and we will be able to compare our results with the results of similar mentioned studies.

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