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The reorganisation decision test: A risk analysis model to increase competitiveness

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Abstract

This article provides a fresh perspective on the essential question: company reorganisation or bankruptcy? Competitiveness constantly reshapes business environments and strategic planning objectives. Any important management tool for increasing competitiveness should be based on effective risk analysis models that can integrate business reorganisation capabilities. Relevant findings regarding the process of choosing an optimal reorganisation pattern are discussed, and the conclusions are based on a study of a representative sample of insolvent companies that conducted a reorganisation. This inductive research process presents valuable insights and findings based on qualitative and quantitative analyses of the characteristics of insolvency procedures, proposing an original risk profile analysis model called the Reorganisation Decision Test (RDT). Cronbach's alpha test, the principal component analysis (PCA), and the receiver operating characteristic (ROC) curve analysis were used to analyse the results and refine the company's risk profile. The RTD was compared with the Altman Z-score to assess whether this classical bankruptcy prediction model is relevant in business reorganisation decisions, a topic that has not yet been thoroughly researched. The shortage of studies, data, and statistics in this area represents a challenge as well as an opportunity. Furthermore, an important information gap has been bridged using statistical indicators that can contribute to public macro-economic disclosures in this field. This model can also add value to professionals in the field of insolvency and provide valuable insights for various decision-making users.

Keywords: *Insolvency, Risk Profile Analysis Model, Reorganisation Plan, Reorganisation Decision Test, Competitiveness*

JEL Classification: M1, M2, M4

1. INTRODUCTION

Recent crises, such as the economic crisis of 2008 and the COVID-19 pandemic, emphasised the increasing importance of business reorganisation for companies facing insolvency (Dinu & Bunea, 2022; Vrabcova et al., 2022) and also affected, to a greater extent, companies' competitiveness (Pech et al., 2020). Countries all over the world have improved their specific regulations regarding insolvency procedures as part of their globalisation strategy, a process that also requires the removal of inefficient companies from the competitive business environment (Petkovski et al., 2022). Recently, through Directive 2019/1023, the European Union (E.U.) has drawn attention to the need for early warning signals to highlight expensive insolvency procedures with high material and social costs and low success rates. This issue is related to the possible extension of insolvency cases based on statistics showing that, in half of all operating entities with a lifespan of up to five years, one in four cases represents cross-border insolvency, with bankruptcy affecting 600 companies per day and resulting in approximately 1.7 million lost jobs (Laitinen, 2011a; Lim, 2013; Marais et al., 2014; Verreydt et al., 2022).

This study contributes to perspectives on sustainable competitiveness (Hermundsdottir & Aspelund, 2021) in the area of business models (Petkovski et al., 2022) and organisational strategic trends (Vrabcova et al., 2022) based on a specific research proposition: assessment of the effectiveness of a company's reorganisation procedures is an important micro- and macro-economic tool. To date, the general macro-economic focus has been on identifying bankrupt companies and eliminating them from the business environment as soon as possible (Mai et al., 2019).

In the last two decades, most studies in the field of company reorganisation through the insolvency procedure have concluded that there is a shortage of studies on this topic because of the lack of public information on companies that undergo this procedure. Insolvency occurs in the court of justice, and as a rule, information is known only by the participants in the procedure—that is, debtors, creditors, syndic judges, and insolvency professionals (Laitinen, 2010; Laitinen, 2011b; Pálinkó & Tóth, 2017; Verreydt et al., 2022).

This pattern of scarce public information is widespread worldwide, as insolvency and reorganisation systems share similar characteristics (Fisher & Martel, 2009; Laitinen, 2011b; Kuttner et al., 2022). Many studies and analysis models based on the Altman Z-score have been developed in order to forecast bankruptcy (Belás & Cipovová, 2011; Ékes & Koloszar, 2014; Tenkasi & Kamel, 2016; Mai et al., 2019; Bărbuță-Mișu & Madaleno, 2020; Kitowski et al., 2022); for decades, this model has been considered the most important benchmark in the field (Roy, 2021).

The estimated small number of companies reintegrated into the economy through a reorganisation procedure has not been documented, thus far, by extensive studies or dedicated research in order to establish some models for analysing the reorganisation capacity of various entities. There is insufficient relevant public national information, data, or statistical indicators regarding the number of successfully reorganised companies (Garrido et al., 2019), as concluded by a comparative study conducted on public insolvency data in countries with a consistent history in this regard (e.g., the United States, France, Germany, and Romania). The Romanian insolvency system is comparable and compatible with other E.U. countries based on European insolvency regulations; therefore, the results generated by this research have worldwide relevance (Duțescu & Stroie, 2018). This study is relevant because of the common technical characteristics of insolvency processes in different geographical areas. Intensive research on a single country can provide general theoretical insights and a comparative framework that can be generalised (Pepinsky, 2019).

Insolvent companies can choose between reorganisation and bankruptcy. Reorganisation is a step in the insolvency process through which companies can remain competitive in the market and continue to operate based on a reorganisation plan. Ram and Wadhwa (2022) argued that, to successfully rescue and restore distressed enterprises and promote entrepreneurship, innovation, competitiveness, and economic growth, it is necessary to mitigate the risks associated with corporate insolvency.

This study covers the literature gap and provides a specific reorganisation decision test, the RDT, as part of a company risk analysis model that is capable of effectively predicting the success or failure of the reorganisation plan. The model is based on a specific risk profile using qualitative and quantitative factors. The relevant qualitative factors that impact the likelihood of successful reorganisation have been identified in a previous study based on an applied questionnaire to insolvency professionals (Stroie & Duţescu, 2019); furthermore, the quantitative indicators used are widely analysed in accordance with insolvency literature (Laitinen, 2011a; Routledge, 2021; Kuttner et al., 2022).

This new model was tested on a relevant sample of companies under the insolvency procedure, and important conclusions have been presented. To establish the RDT minimum score for competitive reorganisation, a random sample of 50 small and medium-sized companies that completed the full reorganisation procedure was used. The RDT model is a useful tool for all parties involved in the restructuring process, including insolvency specialists, creditors, and debtors.

The activities carried out to validate the proposed RDT included tests to clarify whether the Altman Z-score (Altman, 1968) was reliable when assessing a reorganisation scenario. Thus, the RDT results are compared with the Altman Z-score used for bankruptcy prediction, and some relevant results are provided. To analyse the results and refine the company risk profile, this study determined the internal consistency or average correlation of the analysed factors and measured the reliability of the results using the Cronbach's alpha test. PCA and ROC curve analyses were also applied to further investigate and quantify how accurately the RDT can ensure an effective reorganisation and any bankruptcy scenario that could contribute to the straightening of the competitive environment.

The rest of this paper is organised as follows: section two is comprised of a literature review that highlights the state-of-the-art technology in the domain of reorganisation decision making and the conceptual framework used for deciding on reorganisation versus bankruptcy, with an emphasis on the gap between the existing literature and the proposed new model. Section three relates to the research methodology, presenting the main tools and techniques used. The results and discussion are presented in section four, and the conclusions provide a synthesis of the main contributions, perceived limitations, and possible future research.

2. LITERATURE REVIEW

The insolvency procedure provides an opportunity for restructuring when appropriate; this is closely related to competitiveness (Ključnikov et al., 2017). To successfully complete a reorganisation procedure, a company should improve its competitiveness in an economic environment (Routledge, 2021).

When insolvency occurs, creditors and debtors may often have overlapping interests, which may eventually lead to bankruptcy, even in the case of competitive companies. Companies can easily access the restructuring process; however, specific costs contribute to inefficiency, distrust of the process, and an already high economic burden. Consequently, the effectiveness of these reorganisation procedures fosters economic competitiveness as an important strategic priority for governments and other stakeholders (Laitinen, 2010).

Companies' access to restructuring procedures causes material, economic, and social costs; consequently, it is becoming more difficult for these entities to cope with the complexity of the economic environment (Busu et al., 2020). Therefore, under normal circumstances, increasing the competitiveness of small and medium-sized enterprises may be difficult (Sukumar et al., 2020); however, through a complete restructuring process, these organisations gain the possibility of ensuring continuity and asset preservation. Nevertheless, a downsize may occur in the case of some entities, and this may have an artificially prolonged existence. Therefore each 'resilient business component' that is proven to be effective long term becomes relevant (Aziz et al., 2021).

Reorganisation procedures generally involve changes in the business model structure. Insolvency experts and creditors, who make the most important decisions that affect a company's competitiveness, must have ready-to-use tools to support their conclusions. A benchmark framework in this area is the Altman Z-score (Altman, 1968), which is the starting point for many studies. The use of the Altman Z-score for assessing a company's bankruptcy predictability or for grounding management decisions has often been analysed, and its limitations in predicting future business success and an entity's ability to improve performance under normal operating conditions have been highlighted (Marais & Soni, 2014; Lord et al., 2020). According to Verreydt et al. (2022), it may be useful to extend the role of formal prediction models to improve the filtering mechanisms in the reorganisation framework.

Most studies are based on predicting the state and stages of bankruptcy (Bartłomiej, 2021) (Kitowski et al., 2022), while others focus on companies' competitiveness and ability to reorganise through specific procedures; however, these academic efforts are limited, as some authors have concluded (Laitinen, 2011b; Routledge & Morrison, 2012; Pálinkó & Tóth, 2017; Busu et al., 2020).

To analyse corporate restructuring in a competitive environment, the literature highlights useful quantitative and qualitative factors (e.g., solvability, liquidity, company size, industry, specific capital structure, profitability, and so on) (Laitinen, 2011b; Routledge, 2021; Kuttner et al., 2022). Most studies are based on publicly available financial information (Bartłomiej, 2021). Nevertheless, estimating bankruptcy might be difficult if this is based only on financial information. Therefore, qualitative indicators and non-financial variables (such as company size, industry, and the possibility of fraudulent events) have been used in bankruptcy predictions (Garrido et al., 2019; Lungu, 2020).

Recent studies have integrated corporate governance indicators (e.g., ownership structure and board structure) and other qualitative disclosures (e.g., discriminant analysis, neural networks, or a two-stage classification model) (Mai et al., 2019). The use of these new technical prediction models finds its applicability mainly as a theoretical contribution (Segal, 2007; Trittin-Ulbrich et al., 2020). Another important issue that should be disclosed is the fact that these studies did not extract specific explanations or did not enable the design of professional tools for supporting the assessment of insolvent companies' reintegration capacity and their perspective on competitiveness (Tenkasi & Kamel, 2016).

Determining suitable predictive variables that are useful for constructing a reorganisation decision model is not an easily achievable objective because of the lack of a specific framework and the limited availability of relevant data or public statistics on reorganisation files. Indicators specific to insolvency procedures refer mainly to annual insolvency cases and liquidations, reports from the industry on the procedure, and so on. The quality and quantity of data related to the reorganisation procedures should be improved. Insufficient relevant information was identified—that is, the quantitative reports or disclosed ratios on the insolvency percentage or business reintegration weight for reorganised companies (Laitinen, 2011a; Duţescu & Stroie, 2018; Garrido et al., 2019).

This analysis focuses on a balanced mix of qualitative and quantitative factors and examines how these results can improve the quality of the reorganisation decision compared to Altman's Z-score model. A simple and meaningful tool is available to professionals, academic researchers, and regulators, and it can contribute to a better assessment of the reorganisation capacity of various entities (Mai et al., 2019).

3. RESEARCH METHODS

The authors have chosen inductive reasoning to ground ‘bottom-up’ generalisation and to enable the discovery, exploration, and detection of new patterns in the field of company reorganisation. The debate regarding ‘deductive versus inductive research’ has been constantly evolving, with the desirable balance favouring the latter, as it has been highlighted in recent years (Jebb et al., 2017; Spector et al., 2014). This inductive approach provides new knowledge and enhances the contribution of empirical studies to the literature (McAbee et al., 2017).

In this study, exploratory data analysis (EDA) was used (Jebb et al., 2017) as part of the inductive approach in order to reach the main objective: the designing of a risk analysis model for companies undergoing reorganisation in order to assess their capability to reorganise the business and foster its competitiveness in the foreseeable future. The EDA enabled the integration of previously gathered empirical data into a new perspective, filled any relevant literature gaps, and provided a professional tool for practitioners.

The methodology is based on two steps: 1. model development (using both qualitative factors/non-financial variables and quantitative factors/financial indicators); and 2. the model validation.

RDT model development

To create a tool for analysing the risk profile of companies seeking reorganisation, first, qualitative indicators that influence the success of this procedure were examined: a) perception of insolvency procedures, b) quality of management, c) specific laws in the field of insolvency that affect the reorganisation procedure—that is, tax policy and banking policy, d) human resources market, and e) market position. These factors have been generated by previous research (Stroie and Duţescu, 2019) that concentrated on gathering the opinion of insolvency professionals managing more than 200 insolvency cases and more than 15 successful reorganisation cases in different industries (average experience: 15 years in the field). The role and importance of qualitative studies in assessing the perceptions of the target population have been analysed in previous studies (Bardi & Muresan, 2014). Thus, the research methodology is directly influenced by the identity of the researchers; their knowledge; their understanding of the cultural, economic, and social environment; and their professional experience (Pugna et al., 2018). Furthermore, this study explored the perceptions of experts about the major risks associated with insolvent entities by using the grounded theory (Glaser & Strauss, 2017) to determine the impact on the risk profile of companies undergoing reorganisation.

The second focus was on the quantitative information used by professionals, which was widely analysed based on the literature, as an important tool in insolvency procedures (Simanjuntak & Hutabarat, 2019). The following categories were used to provide relevant comparisons and enhance the relevance of the analysis: current assets, current liabilities, total liabilities, and total assets. To ensure data comparability, the dependent variables were transformed into the following indicators: LichC/liquidity (current liquidity ratio = current assets/current liabilities; the indicator has the recommended optimum value at 1.2) and solvability (general solvency ratio = total assets/total liabilities; the indicator has the recommended optimum value at 1).

A risk analysis model was designed for companies undergoing reorganisation and named the Reorganisation Decision Test (RDT). The configuration of this RDT proposed model is presented below:

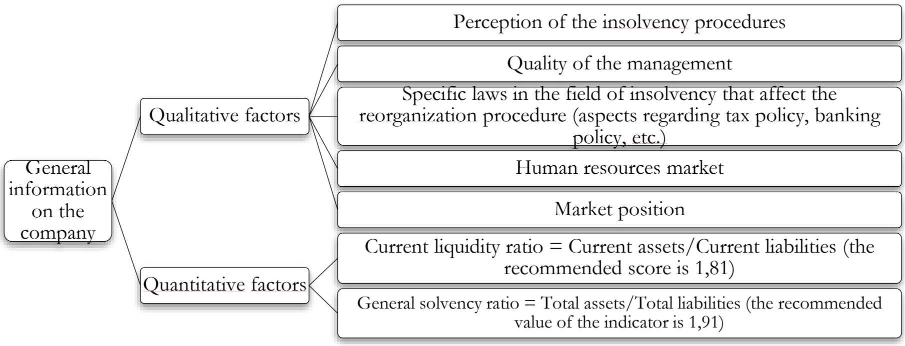

Fig. 1–The RDT – Test Summary. Source: own research

The validity of the RDT should be tested in the process of analysing the company's ability to reorganise in the observation period before a reorganisation plan is proposed and approved by the company's creditors. The person best suited to implementing RDT is the insolvency practitioner, but other beneficiaries may also wish to use it, such as creditors or the management of the insolvent debtor.

To implement the RDT as a tool for reorganisation or bankruptcy decisions, qualitative factors must be analysed during the observation period. Several subcategories were created to analyse the qualitative factors. For each subcategory, the Likert scale was applied based on the chances of reorganisation (1-without chances of reorganisation, weak, satisfactory, good, and 5 = very good chances of reorganisation). A guide was designed to help interpret these subcategories, which were available to experts, as a ‘best practice’ device. This practical guide contains proposals to assign a score for each of the risks that affect the reorganisation capacity of the insolvent company, and for each factor/subcategory of the risk profile. The practical guide provides a detailed perspective on each qualitative factor, proposing specific relevant subcategories to ground the analysis. Each qualitative characteristic of the RDT contains a pool of relevant ‘subfactors’ to be addressed and estimated by the insolvency practitioners. For example, management quality can be assessed on the basis of management style, the impact of conflicts of interest, and the evaluation of professional training in management positions.
The value assigned to each of the five qualitative factors in the data analysis was the average obtained for each subcategory (minimum = 1, maximum = 5).

For the quantitative factors, for LichC/Liquidity (Current liquidity ratio = Current assets/Current liabilities), we have recommended the optimum value of 1.2, and for Solvability (General solvency ratio = Total assets/Total liabilities), the optimum value of 1.

The RDT model validation
Model validation was performed using a specialised platform (http://www.isondaje.ro/) with the help of insolvency practitioners. Professionals were selected based on their membership in the Romanian Professional Body, the National Union of Insolvency Practitioners in Romania (NUIPR), and their extensive experience with the investigated topic. Statistics on insolvency practitioners, according to NUIPR public data (with 2018 as the reference year), disclosed 2,649 active insolvency practitioners. Out of the 2,649 practitioners analysed, only 20% carry out relevant activities in insolvency, that is, have more than 20 closed insolvency cases. Of the practitioners who conducted insolvency activities, only 20% (106) successfully fulfilled at least two cases of judicial reorganisation.

To test the RDT, insolvency practitioners with more than two years of experience in the insolvency field successfully completed more than 20 insolvency cases and at least two reorganisation files. A sample of 84 experts from the target population was extracted based on a 5% error rate and 95% confidence level. The 84 practitioners were invited to test RDT on companies from their own insolvency portfolio, including in this tested sample the companies with closed judicial restructuring procedures through recovery or bankruptcy. Random sampling of the tested companies is considered a relevant tool because of the lack of public information and macro-economic statistics. This informational scarcity is specific to insolvency procedures worldwide, and data are available from the Trade Register, which is considered limited (Ékes & Koloszár, 2014; Garrido et al., 2019; Nkiri & Ofoegbu, 2022).

The RDT was conducted from January to July 2021, and the total number of companies tested was 50. Incomplete tests were eliminated. The tested companies fulfilled the reorganisation procedure between 2009-2020, of which 26 companies were successfully reintegrated into the economy, and 24 went bankrupt. The validation of the RDT came from professionals with a significant geographical distribution throughout Romania, relevant experience, and a solid professional background. Data bias has been a common limitation in studies forecasting bankruptcy, mainly due to the lack of public information (Laitinen, 2011a; Pálinkó & Tóth, 2017). Thus, some researchers have recommended that these models be constantly readjusted based on new public information available (Tootoonchi et al., 2022). The anonymity of the respondents was ensured, and ethical research standards were adopted. The results were aggregated and analysed. The dataset extracted from the enterprise sample also allowed the aggregation of the Altman Z-scores.

4. RESULTS AND DISCUSSION

The data set resulting from the RDT testing on the sample (50 companies selected from the total number of companies that went through the judicial reorganisation procedure in the period 2009-2020) was centralised and analysed using SPSS.

The Altman Z-score has often been used as an instrument for assessing companies' going concern or ground management decisions, and some studies have highlighted its inability to predict the future successes of companies or improve companies' performance (Lord et al., 2020; Verreydt et al., 2022). The Altman Z-score was also performed on the sample of 50 companies to compare the results with the RDT test and to determine the relevance of estimating the insolvent companies' capacity for reorganisation as part of the overall competitiveness. To assess the reliability and inter-item consistency of the five-point Likert scale, the following qualitative factors were analysed: perception of the insolvency procedures, quality of management, insolvency regulations, human resources market, market position, and Altman's Z-score for the reinserted (R1) and Bankrupt Companies (B0), using the Cronbach's alpha internal consistency test (CA). As shown in Table 1, the Cronbach's alpha values were acceptable, being greater than 0.7, and the significance of the test was considered very good, as the obtained p-value was 0.000 for the chosen variables included in the analysis.

Table 1 – Reliability statistics were performed using the Cronbach's alpha test. *Source: own research*

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
0.702	0.834	7

Qualitative variables were further analysed. Table 2 presents the descriptive indicators, average/mean, standard deviation, minimum, maximum, and percentiles of the analysed items. The analysis of the values highlights the results for each item. The minimum average score obtained for reorganised companies was higher than 3. This value is considered a significant threshold obtained after applying the RDT and indicates that a value higher than three points is consistent with a possible financial reorganisation scenario.

Table 2 – Statistics details. *Source: own research*

		Insolvency Perception	Management Analysis	Insolvency Regulations	HR Analysis	Market Share	R 1/F 0	Z-Score Altman
N	Valid	50	50	50	50	50	50	50
	Missing	0	0	0	0	0	0	0
Mean		3.3875	3.2771	3.3600	3.2900	3.0914	0.520	0.98
Median		3.3750	3.5714	3.7500	3.5000	3.0714	1.000	0.81
Std. Deviation		0.75730	1.19781	1.30034	.95346	1.11995	.5047	1.896
Minimum		1.50	1.00	1.00	1.50	1.00	0.0	-6
Maximum		4.50	5.00	5.00	5.00	4.86	1.0	6
Percentiles	25	2.7500	2.4286	2.0000	2.5000	2.1429	.000	-0.13
	50	3.3750	3.5714	3.7500	3.5000	3.0714	1.000	0.81
	75	4.0313	4.1786	4.3333	4.0000	4.1429	1.000	2.00

The inter-item correlation matrix provides an image of the correlation between variables, and the p-values provide useful results. Table 3 presents the items that were significantly correlated with other variables and the statistical significance of each correlation. The focus of the analysis at this point is to evaluate the reorganisation capacity or bankruptcy (R1/B0) and how the other variables relate to this. According to Table 3, all qualitative variables of the RDT have a strong positive correlation with the variable of the reorganisation scenario (R1 / B0), indicating that the qualitative variables (the scores calculated based on the answers given to the RDT) are appropriate for providing valuable clues about the possibilities of reorganisation. Based on the selected sample, another conclusion is that the Altman Z-score is not relevant for forecasting possible reorganisation or recovery through the insolvency process.

Table 3 – Inter-Item Correlation Matrix. *Source: own research*

		Insolvency Perception	Management Analysis	Insolvency Regulations	HR Analysis	Market Share	R 1/F 0	Z-Score Altman
Correlation	Insolvency Perception	1.000	0.634	0.596	0.548	0.725	0.717	-0.123
	Management Analysis		1.000	0.364	0.536	0.790	0.668	-0.037
	Insolvency Regulations			1.000	0.464	0.531	0.683	0.001
	HR Analysis				1.000	0.670	0.634	-0.227
	Market Share					1.000	0.843	-0.115
	R 1/B 0						1.000	-0.131
	Altman Z-score							1.000
Sig, (1-tailed)	Insolvency Perception		0.000	0.000	0.000	0.000	0.000	0.198
	Management Analysis			0.005	0.000	0.000	0.000	0.400
	Insolvency Regulations				0.000	0.000	0.000	0.496
	HR Analysis					0.000	0.000	0.056
	Market Share						0.000	0.214
	R 1/F 0							0.182
	Z-Score Altman							

Table 4 presents the relevant results for variables that were deleted according to the Cronbach's alpha test. Since a Cronbach's alpha of 0.702 indicates very good results for qualitative variables, it seems that if the Altman Z-score was removed (0.879), the value of Cronbach's alpha would increase, which is significant for the reliability of qualitative variables. In conclusion, the qualitative variables were consistent with company reorganisation or recovery through insolvency.

Table 4 – Item – Total Statistics. *Source: own research*

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Insolvency Perception	14.5202	19.290	0.683	0.613	0.632
Management Analysis	14.6305	16.701	0.640	0.651	0.605
Insolvency Regulations	14.5477	16.805	0.554	0.544	0.627
HR Analysis	14.6177	19.111	0.526	0.496	0.647
Market Share	14.8162	16.358	0.750	0.824	0.580
R 1/B 0	17.3877	20.585	0.779	0.795	0.649
Altman Z-score	16.9261	22.883	-0.114	0.096	0.879

Principal component analysis (PCA) was used to emphasise a large dataset. In the preliminary analysis, the independent variables of the quantitative indicators are excluded, and only the liquidity and solvability ratios are used to ensure data comparability. The main components (the factorial axes) are presented in descending order depending on their weight explained by them. The main objectives of this method are as follows: 1. description of the correlations between the variables and similarities/differences between the statistical units; 2. selection of the most important variables that explain the similarities and differences between statistical units; 3. selection of factors and their use in other types of statistical analyses.

The first, second, and third components (factorial axes) explained 47.07, 15.82, and 9.78% of the variance, respectively. The variables that explain the first component better explain the similarities and differences between statistical units. To test the hypothesis of independence between the statistical variables, we used test statistics $\chi 2$ (KMO output and Bartlett's test). A KMO value of 0.792 indicates a good solution obtained by the PCA, as shown in Table 5.

Table 5 – KMO and Bartlett's Test. Source: own research

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		**0.792**
Bartlett's Test of Sphericity	Approx. Chi-Square	226.601
	df	36
	Sig.	<.001

In our study, the first three components (factorial axes) together explained 72.68% of the total variance (total variance explained by output; cumulative% column). The coordinate values of the variables were presented as the component matrix output. The obtained values indicated the positions of the variables along the factorial axes. For example, the variable 'market share' has a positive coordinate on the first factorial axis (+0.921), a negative coordinate on the second factorial axis (-0.017), and a positive coordinate on the third factorial axis (0.040). The variable 'insolvency perception' has all three positive coordinates.

A graphical representation of the variables in the factorial axis system is presented in Figure 2 and was obtained by choosing the rotation option of the varimax axes. It was noticed that by choosing this option, a pivoting of the axes occurred while maintaining the independence of the main components. This option maximises the variance of factors and facilitates the interpretation of the axes: the 'ambiguity' of some variables is eliminated, and their 'separation' is reflected in the explanation of the factorial axes.

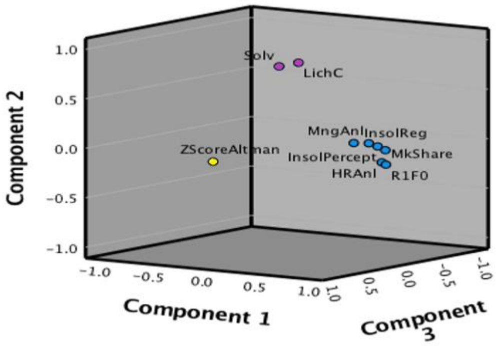

Fig. 2 – Component plot in Rotated Space. Source: own research

To further verify the capacity of Cronbach's Alpha Test and the PCA method to perform a differentiated and accurate evaluation of the qualitative indicators in relation to the indicator of the possibility of financial reorganisation (R1/B0), we tested whether a connection could be identified between all chosen indicators and the R1 /B0 indicator using econometric analysis of the receiver operating characteristic (ROC) curve. As noted in the previous stages, the quantitative indicators used by professionals during the insolvency procedures–LichC, solvability, and Altman Z-scores–were not excluded from the analysis. The purpose of previous tests was to improve the understanding of the use of prediction indicators in the process of identifying the reorganisation possibilities of a company, as they are currently used, and to demonstrate the empirical and theoretical effectiveness of qualitative RDT risk analysis. In addition to the analyses performed in the previous stages, the five qualitative indicators were combined into a single indicator and calculated as a simple average. The new indicator obtained was called the Risk RDT Qualitative Score and was included in the next stage of testing. As a result of the previous stages of the study, the condition for validating the RDT Risk Qualitative Score was that each of the five qualitative indicators considered in the calculation had scores higher than three. We examined whether the foreshadowing of restructuring possibilities or the onset of bankruptcy can be related to the qualitative factors of RDT, the quantitative factors used generically in practice (liquidity and solvability), or the Altman Z-score. At this stage, the qualitative and quantitative indicators considered are associated with the nominal indicator R1/B0. The respondents' empirical assessments of the RTD tests were related to the practical and verifiable dimensions of the concrete situation of the sample of companies in insolvency proceedings. In all cases where the analysed companies benefited from a reorganisation procedure, the nominal indicator was 'yes', and if the companies opened the bankruptcy procedure, the nominal indicator was 'no'. The null hypothesis (H0) tested was that there is no significant connection between the RDT qualitative indicators calculated in the previous stages, Liquidity, solvability, and the Altman Z-score, and the possibility of determining the chances of reorganisation or bankruptcy of a company (R1/B0). The alternative hypothesis (H1) is that the RDT qualitative indicators are related to (R1/B0) and have practical and robust applicability. The distribution of cases related to the real reorganisation situations of insolvent companies included in the analysed sample is presented in Table 6. In 26 cases, the companies benefited from financial reorganisation, and in 24 cases, the companies went bankrupt.

Table 6 – Case Processing Summary. Source: own research

R 1/F 0[a]	Valid N (listwise)
Positive[b]	26
Negative	24

Higher values of the test result variable(s) indicate stronger evidence of a positive actual state.

a. Variable(s) of the test result: The Z-Score Altman has at least one connection between the positive actual-state group and the negative actual state group.
b. The positive actual state is 1.0.

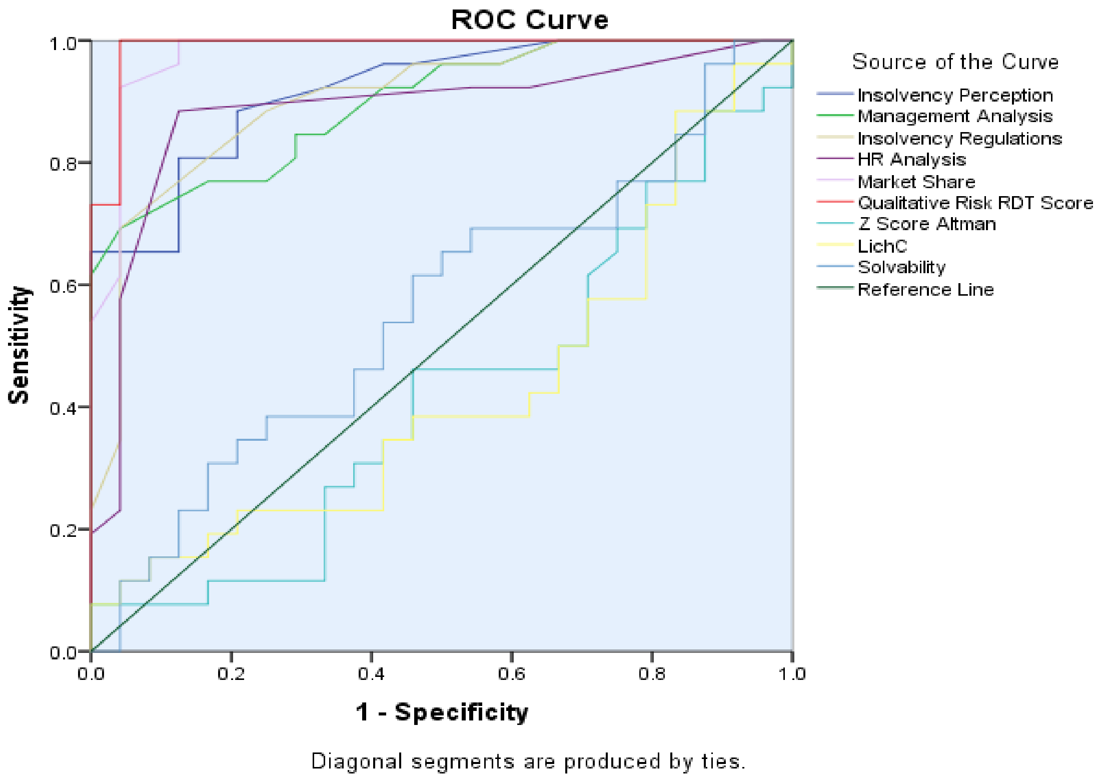

Fig. 3 – Representation of the ROC curve. Source: own research

Figure 3 presents the dynamics of ten ROC curves, with one curve drawn for the connection between each analysed indicator and R1/B0.

As can be seen from the graph, the qualitative indicators calculated as determinable scores based on the RDT have strong connections to determining the chances of competitively reorganising a company. The proximity of the quantitative indicators liquidity (LichC), solvability and Z-Score Altman to the diagonal axis indicates the lack of a statistically significant connection between these indicators and R1 /B0. The analysis performed using the ROC curve identified statistically significant results for all associations between the RDT qualitative variables and the prediction for reorganisation or bankruptcy (R1/B0), according to Table 7. F for each connection, the calculated areas under the curve (AUC) were > 0.8, and the values were p = 0.000. For AUC values> 0.5 and P values <0.005, the null hypothesis (H0) was rejected. In other words, for scores higher than three obtained based on the answers to the RDT for companies in insolvency procedures, for which it is necessary to correctly estimate the chances of reorganisation or the prospect of bankruptcy, there are significant opportunities for competitive reorganisation.

Table 7 – Analysis of Area under the Curve. Source: own research

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
Insolvency Perception	0.918	0.037	0.000	0.846	0.991
Management Analysis	0.897	0.043	0.000	0.814	0.981
Insolvency Regulations	0.903	0.043	0.000	0.818	0.988
HR Analysis	0.885	0.052	0.000	0.783	0.988
Market Share	0.978	0.019	0.000	0.940	1.000

Risk RDT Quality. Score	0.989	0.012	0.000	0.965	1.000
Altman Z-score	0.419	0.082	0.327	0.259	0.579
LichC	0.426	0.083	0.372	0.264	0.589
Solvability	0.558	0.082	0.485	0.396	0.719

The test result variable(s): Insolvency Perception, Management Analysis, Insolvency Regulations, HR Analysis, Market Share, and the Z-Score Altman have at least one connection between the positive actual state group and the negative actual state group. Statistics may be biased.
a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

For quantitative indicators (liquidity, solvability, and the Altman Z-score), the calculated AUC values <0.5 and the p values > 0.05, the results suggest that the statistical relevance of formulating a significant connection between these quantitative indicators and the prospects of reorganisation or bankruptcy in insolvency scenarios is statistically insignificant. The optimum recommended value for the current liquidity ratio is 1.2, but the results obtained after testing the indicator on the sample indicate an optimal reorganisation decision, with an average of 1.81. For the general solvency ratio, the recommended optimum was 1; however, the average result obtained was 1.91. Although the indicators of solvability and liquidity are not relevant to the reorganisation decision, it is important to analyse the stage and evolution of the insolvency process; therefore, the recommendation is to take these indicators into account.

The results obtained can be compared with those of studies focusing on prediction models in different environments. This pilot study is based on an effective model to assess competitive companies' abilities to successfully reorganise and recover from bankruptcy. However, it would be interesting to compare the results with the Altman Z-scores in the context of insolvency procedures, particularly judicial restructuring proceedings. Lord et al. (2020) used a dataset from 2009-2016 of reorganisations under Belgium's jurisdictions and quantified the amount of time in reorganisation before being transferred to liquidation bankruptcy without mentioning whether the Altman Z-score could estimate the future success of the reorganisation proceedings. Our study clarifies this area and confirms the conclusion of Marais and Soni (2014); however, in an insolvent environment, the Altman Z-score cannot estimate the future success of a reorganisation procedure.

As Verreydt et al. (2022) specified, for a competitive filtering mechanism in the reorganisation framework, it is useful to extend the role of formal prediction models as a tool for professionals; however, these professionals (e.g., insolvency practitioners or creditors) are not highly technical, do not have formal training in software engineering, and do not have the necessary knowledge for the implementation and use of recent statistical prediction models (based on logistic regression, discriminant analysis, textual disclosures, or others), even though researchers claim to reveal the practical implications of these statistical models. Previous studies indicated a need for simple but effective tools (Stroie & Duțescu, 2019), and understanding these problems is an essential precondition for designing new instruments to support professional development (Segal, 2007).

Laitinen (2011b), Routledge (2021), and Kuttner et al. (2022) emphasise the need to determine suitable prediction variables, useful for reorganisation decision-making, but this area has limited available data or public statistics on reorganisation files.

The RDT model uses specific qualitative factors (Stroie & Duțescu, 2019) and combines them with commonly used quantitative factors (Simanjuntak & Hutabarat, 2019) to analyse how the ability of companies to reorganise can be better predicted or whether this combination of factors provides a higher degree of predictability. In contrast to the practice of using financial information to estimate bankruptcy status, the accuracy of reorganisation is better revealed using qualitative factors.

Discussions on financial information-based bankruptcy prediction models versus reorganisation forecast mix models provide a different perspective. Unlike normal operating conditions, when a company enters insolvency procedures, it must deal with a number of specific factors that affect the reorganisation capacity (Stroie & Duțescu, 2019). As a rule, the financial indicators specific to these companies are usually negative. The use of financial bankruptcy forecast models based on negative indicators does not contribute to the assessment of a company's potential reorganisation. According to Ram and Wadhwa (2022), to successfully rescue companies and promote competitiveness and growth, it is important to reduce the risks associated with insolvency; therefore, the analysis of these specific risks is essential for making a reorganisation decision.

The findings of this study, in line with Laitinen (2010), highlight the need to integrate statistical information on reorganisation procedures at the macro-economic level. The following proposed indicators are considered to provide relevant incentives for competitiveness at the local and global levels and to encourage the development of specific regulations and standards in the field of business reorganisation:

a) The annual reintegration rate for companies organised through insolvency procedures (Rrr), a ratio based on the total number of companies reorganised and reintegrated into the economy (Re), and the total number of companies in business reorganisation (R) with a confirmed reorganisation plan: $Rrr = \frac{Re}{R} * 100$
b) The extended rate of reintegration for companies reorganised through insolvency procedures (Rerr), a ratio based on the total number of companies reorganised and reintegrated in the economy (Re) and the total number of insolvency cases in reorganisation (R), including insolvency cases opened with the explicit intention of reorganisation (Ri) but for which no reorganisation plan has been confirmed: $Rerr = \frac{Re}{(R+Ri)} * 100$
c) The general reintegration rate (Rgr) is the ratio between the total number of companies reorganised and reintegrated (Re) and the total insolvency files for period (I): $\text{Rgr} = \frac{Re}{I} * 100$

To fill the information gap related to statistical indicators, it is appropriate to disclose these indicators in national statistics or in the reports of professional bodies. Regular disclosure of these indicators (e.g., on an annual basis) can provide a better view of the universe of insolvency and its impact on macro-economics.

The results of this study may be integrated into the development of a specific conceptual framework, revealing possible filter mechanisms in the reorganisation processes of companies.

5. CONCLUSIONS

One of the most widely used approaches to improve filtering mechanisms in the reorganisation framework and enhance competitiveness is the use of prediction models as tools for assessing the validity of applications at the beginning of the process. Professionals need simple and meaningful tools to aid their endeavours and to help them estimate, as accurately as possible, the reorganisation's future success and, therefore, the long-term competitiveness of the entities. Another positive aspect is increased efficiency and confidence in the insolvency system, which are important for ensuring a healthy business environment. The RDT can be used as a barometer for a company's reorganisation capacity, and eventually also as a financial and managerial 'health' indicator. This study combines specific insolvency factors and quantitative indicators to build a relevant information system for analysing reorganisation success. It also proposes a new model for reorganisation research that provides a different perspective on the topic. The results confirm that the Altman Z-score cannot predict the future success of an insolvent company's reorganisation procedure. In reorganisation decisions, the analysis of specific factors is more relevant than the assessment of liquidity and solvency indicators; the latter ratios have inadequate value in the case of insolvent companies.

The RDT was designed to conduct an examination of the risks taken on by a company during the insolvency process, from the observation period to the moment of the reorganisation plan proposal. A predefined reorganisation model should be an integral part of a relevant professional and academic framework to guide experts through an effective reorganisation project and enable researchers to consider a more comprehensive analysis pattern, better serving overall competitiveness development. We also designed a detailed guide for RDT users to aid professionals during the specific steps of the reorganisation process as an important component of the integrated procedure.

This study contributes to improving the perspective on insolvency taxonomy worldwide and highlights the importance of a more relevant and detailed database in this area. This model can be used successfully in different jurisdictions based on the similarity of the insolvency system and the expertise of Romanian insolvency professionals.

The limitations of our research are mainly driven by the scale of the sampling and the lack of public information on companies undertaking reorganisation procedures. However, this scarcity is the main denominator of all the relevant research papers in this field. The sample size should be expanded in further studies. Possible future research in this area may lay the foundation for the further investigation and testing of RDT and refine developments by insolvency experts in various geographical areas in order to acquire long-term validation and general sustainability. Other developments that researchers may want to consider could include environmental, social, and governance (ESG) and circular economy effects on the proposed RDT.

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