DOI 10.58423/2786-6742/2023-4-227-239
ETO 343.535

Balázs PATYI
PhD student
University of Sopron, Lámfalussy Sándor Faculty of Economics,
Sopron, Hungary
ORCID ID: 0000-0001-6418-6447

Károly SZÓKA
PhD
Associate Professor
University of Sopron, Lámfalussy Sándor Faculty of Economics,
Sopron, Hungary
ORCID ID: 0000-0003-4880-1715

László PATAKI
PhD
Associate Professor
Neumann János University,
Kecskemét, Hungary
ORCID ID: 0000-0001-8064-0208

APPLICABILITY OF BANKRUPTCY PREDICTON MODELS IN THE WESTERN HUNGARIAN FOOD RETAIL SECTOR

Анотація. *У статті досліджується придатність до застосування існуючих моделей прогнозування банкрутства в секторі роздрібної торгівлі продуктами харчування. Для аналізу була обрана галузь, яка, за даними офіційної статистики, суттєво постраждала від подій останніх років (епідемія Covid-19, економічна криза). Для дослідження була створена база даних з усіма фірмами, які припинили свою діяльність у секторі протягом 11 років у 3 областях (медьє). Для дослідження визначено чотири основні цілі: 1) перевірити, чи існують відмінності в надійності моделей і які моделі найбільше застосовні до вибраного сектора; 2) вивчити точність моделей за часовими межами банкрутства; 3) перевірити точність прогнозування моделей за типом процедури завершення банкрутства; 4) надати пропозиції щодо можливостей застосування моделей прогнозування банкрутства та вказати напрями подальших досліджень. У процесі дослідження виявлено, що не всі розглянуті моделі придатні для точного прогнозування. Дві з п'яти моделей мають дуже низьку точність прогнозування (модель Віраг-Гойду та модель Тафлера). Оцінка точності моделей за межами часових горизонтів банкрутства показала, що існує незначна варіація в точності короткострокового прогнозу з незначним зниженням надійності моделей у довгостроковій перспективі. Перевірка точності прогнозування моделей за типом процедури завершення виявила, що типи процедур впливають на прогноз. Найбільш точні результати отримані для ліквідації, тоді як добровільна ліквідація виявилася найменш точною в кількох випадках. Використання моделей прогнозування банкрутства є важливим для підприємства, оскільки вони є ключовим інструментом для зниження його операційного ризику та попередження фінансових проблем. Дослідження може надати інформацію для підприємств у секторі роздрібної торгівлі продуктами харчування, а результати можуть бути використані для подальших досліджень. Існують додаткові можливості для розширення бази даних підприємств, перенесення дослідження на інші сектори*

економіки і розширення кількості моделей банкрутства для вивчення придатності їх застосування до підприємств різних галузей.
Ключові слова: *моделі прогнозування банкрутства, криза, галузевий аналіз, аналіз часових рядів.*

JEL Classification: G33, C53

Absztrakt. *A cikk az élelmiszerkiskereskedelmi ágazatban vizsgálja a csődelőrejlző modellek alkalmazhatóságát. Az elemzéshez egy olyan iparág került kiválasztásra, amelyet az elmúlt évek eseményei (Covid-19 járvány, gazdasági válság) jelentős mértékben érintettek. Így a döntés a hivatalos statisztikákkal alátámasztva az élelmiszerkiskereskedelem ágazatra esett. A vizsgálathoz kiépítésre került egy adatbázis, amely 11 éves időtávra tartalmazza az ágazatban tevékenykedő összes megszűnt céget 3 megyére vonatkozóan. A tanulmányban négy fő kutatási cél került elkülönítésre. Vizsgálatra került, hogy az egyes modellek megbízhatósága között vannak-e eltérések és mely modellek alkalmazhatók legjobban a vizsgált ágazatra. Ennek alapján kiderült, hogy a vizsgált modellekből nem mindegyik alkalmas a pontos előrejelzésre. A vizsgált öt modell közül kettő esetében nagyon alacsony az előrejelzés pontossága. Szintén a vizsgálat tárgya volt a modellek előrejelzési pontossága a csőd bekövetkezési időtávokra vonatkozóan. Itt megállapításra került, hogy a rövidtávú előrejelzés pontosságában csekély eltérés tapasztalható, hosszú távon kis mértékben csökken a modellek megbízhatósága. Ezt követő vizsgálat a modellek előrejelzési pontosságával kapcsolatos a megszűnési eljárási típusok szerint. Megállapításra került, hogy az eljárási típusok hatással vannak az előrejelzésre. Legpontosabb eredmény felszámolás esetén van, míg a legpontatlanabbnak több esetben is a végelszámolás bizonyult. Végül a kapott eredmények alapján javaslatok lettek téve a csődmodellek alkalmazhatóságára vonatkozóan és ki lett jelölve a további kutatási irány is. A csődelőrejelző modellek alkalmazása a vállalkozások életében nagyon fontos, hiszen a vállalkozás működési kockázatának csökkentése szempontjából és a problémák előrejelzése végett kulcsfontosságú eszköz a csődmodell. A kutatás információval szolgálhat az ágazatban működő vállalkozások számára, valamint további kutatásokhoz is alapul szolgálhat. Az adatbázis bővítése, más ágazatok vizsgálata és új modellek alkalmazása további lehetőségeket rejt a csődmodellek alkalmazhatóságának a kérdéskörében.*
Kulcsszavak: *csődelőrejelző modellek, megszűnés, válság, elemzés, ágazati elemzés, idősoros elemzés.*

Abstract. *The article examines the applicability of existing bankruptcy prediction models in the food retail sector. The industry has been chosen for analysis due to the fact, that according to official statistics, it has been significantly affected by the events of recent years (Covid-19 epidemic and economic crisises). For the study, a database was created with all firms that had ceased to operate in the sector over an 11-year period in 3 counties. The main objectives of the study were: 1) to check whether there are differences in the reliability of the models and which models are most applicable to the selected sector; 2) to investigate the accuracy of the models over the time horizons of bankruptcy; 3) to check the accuracy of forecasting models by type of bankruptcy completion procedure; 4) provide suggestions on the possibilities of applying bankruptcy forecasting models and indicate directions for further research. During the research, it was found that not all considered models are suitable for accurate forecasting. Two of the five models have very low prediction accuracy (Virág-Hajdu model and Tafler model). Assessment of model accuracy across bankruptcy time horizons showed that there is little variation in short-term forecast accuracy, with a slight decrease in the reliability of the models in the long term. Examining the predictive accuracy of the models by completion procedure type revealed that the types of procedures affected the prediction. The most accurate results were obtained for liquidation, while voluntary liquidation was the least accurate in several cases. The use of bankruptcy prediction models is important for an enterprise because they are a key tool for reducing its operational risk and preventing financial problems. The study can provide information for businesses in the food retail sector and the results can be used for further research. There are additional opportunities for expanding the enterprise database, transferring the research to other sectors of the economy, and expanding the number of bankruptcy models to study the suitability of their application to enterprises of various industries*

Keywords: *bankruptcy prediction models, crisis, sectoral analysis, time series analysis.*

Problem statement. Covid19 have brought new economic and management challenges all over the world, with new problems which should be solved by new technological and human resource solutions [1]. In Hungary, the economy and the operation of businesses have also been significantly affected by the Covid19 pandemic and the economic and inflationary crisis of recent years. According to Sági and Szennay [2], the Covid19 pandemic brought about significant changes on the demand and supply side. These changes have also affected Hungarian businesses to a large extent. The epidemic and the restrictions affected different sectors of the economy to different degrees, with the result that some sectors experienced much larger declines. Retail trade, and within it food retailing, is a very important sector, because in addition to their role in employment and also their activity is essential for society. This sector has been significantly affected by events in recent years. Figure 1 illustrates the change in the volume of food retail trade from 2019 onwards.

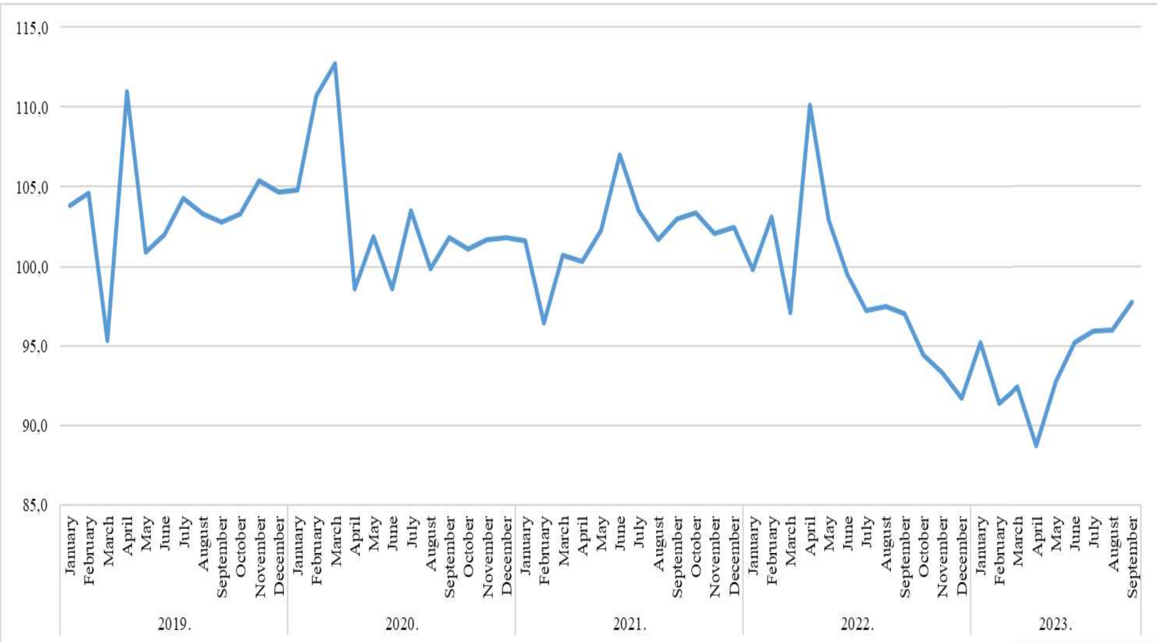

Figure 1. Change in the volume index of retail sales quarterly (same period last year = 100.0%)

Source: Own editing, based on [3].

Figure 1 clearly shows that the COVID-19 crisis caused a smaller and shorter downturn in the sector, but the 2022 crisis has already significantly affected businesses operating in the sector, as turnover volumes decreased significantly compared to the same period of last year. Another important data is the number of businesses operating in the sector, which highlights the consequences of negative effects in the sector. Table 1 provides relevant information about that.

© **B. Patyi, K. Szóka, L. Pataki**

Table 1.

Number of active enterprises in the food retail sector

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Number of enterprises	45 205	43 647	42 640	42 271	40 970	39 960	38 987	38 140	37 392	36 262	34 777

Source: Own editing, based on [4].

Table 1 shows that the number of enterprises in the sector has been steadily decreasing since 2012.From 2019 onwards, the rate of decline accelerated and by 2022, more than 10,000 enterprises had disappeared from the sector compared to 2012. This figure shows that many businesses have closed down recently. Overall, the food retail sector has been significantly affected by the Covid19 epidemic and the economic crisis of recent years and the available data also highlights the importance of analysis and bankruptcy prevention. Analysis is a means of identifying a problem early and finding a solution in time [5].

Literature review. As illustrated in the previous chapter, food retail has been in a period of crisis in recent years. Massey and Larsen [6] deal with crisis management and believe that each crisis should be viewed from a different perspective, as different types of crises require different techniques and approaches. The deployment of early warning systems, including the use of bankruptcy warning models, plays an important role in anticipating and managing the crisis. The use of bankruptcy models is an appropriate tool for reducing risks and avoiding a crisis. Charalambous and co-authors [7] believe that one of the most important characteristics of bankruptcy prediction models is the extent and accuracy of distinguishing between failing and healthy businesses. Virág [8] summarized the characteristics of bankruptcy forecasting models as follows:

- The models are based on financial and accounting statements.
- They provide additional information from the processed data to support decision-making.
- They deal with current and past data, but predict future outcomes.
- There are two possible output states for models: bankrupt or non-bankrupt.

According to Bugár [9], bankruptcy models can be distinguished according to what they deal with. On this basis, he argues that there are models dealing with the risk of bankruptcy and models dealing with credit risk. There are several types of bankruptcy models and they have undergone several changes throughout history. Balázs Imre, in his dissertation [10], details the evolution of bankruptcy models as follows:

- Indicator analysis,
- Discriminant analysis,
- Decision trees,
- Logit and probit models,
- Neural networks.

Nowadays, the development of artificial intelligence provides further opportunities for the development of existing bankruptcy warning models on the one hand, and the creation of new models on the other. Norbert Ágoston [11] investigated the methods of artificial intelligence and machine learning to estimate insolvency. In his paper, he mentions modern possibilities such as neural networks, SVM method, Bagging and random forest method. Kristóf and Virág [12] dealt with Hungarian bankruptcy forecasting models. Hungarian models have evolved up to enterprise rating systems, however, with the use of artificial intelligence, there are still many opportunities in the application of domestic forecasting models. In the following, the bankruptcy forecast models that were examined in the research are presented. When selecting the models, it was considered important that they can be used with simplified balance sheet and income statement data. Thus, for the study, 5 different bankruptcy forecast models were selected.

The first model was created by Virág and Hajdu [13]. Their model was developed using data from the 1990 and 91 reports, where the effects of 17 different indicators were examined, but only 4 indicators were used in the final model. Their model is the following:

$$Z = 1{,}3566X1 + 1{,}63397X2 + 3{,}66384X3 + 0{,}03366X4$$

- X1: liquidity flash ratio;
- X2: cash flow/total debt;
- X3: current assets/total assets;
- X4: cash flow/total assets.

If the value of Z is less than 2.61612, the business can be classified as insolvent.

The second model was created by Comerford [14]. The function of Comerford's analysis is:

$$Z = 1{,}44X1 - 1{,}78X2 + 6{,}06X3 + 0{,}62X4 - 2{,}56X5 + 0{,}37X6$$

- X1 = profit after tax/ total assets
- X2 = liabilities/ fixed assets
- X3 = liquid assets/total assets
- X4 = current assets/ current liabilities
- X5 = quick assets/ current liabilities
- X6 = profit after tax/ registered capital

The critical value of the indicator is at 0. The more the result takes on a negative value, the more likely bankruptcy is to occur. The third model was created by Taffler. The content of the model is described in detail by Molnár [15] in his study:

$$Z = 0{,}53\,X1 + 0{,}13\,X2 + 0{,}18\,X3 + 0{,}16\,X4$$

- X1= Result of business activity / Current liabilities
- X2=current assets / liabilities
- X3=Current liabilities / Total assets
- X4=Sales / Total Assets

The fourth model is the Springate model also found in Molnár's [15] study.

$$Z = 0{,}545X1 + 0{,}791X2 + 0{,}270X3 + 0{,}136X4 + 0{,}228$$

- X1=working capital/total assets
- X2= result of business activity /total assets
- X3=profit before tax/current liabilities
- X4=net sales/total assets

If the value of Z is less than 0, then the company is close to bankruptcy.

The fifth model is Zmijewski's model. In Ratting's [16] study can find the formula for the model:

$$P = -4{,}3 - 4{,}5\,X1 + 5{,}7\,X2 - 0{,}004\,X3$$

- X1 = return on assets
- X2 = ratio of liabilities
- X3 = liquidity ratio

Bankruptcy is likely if the value of P is greater than 0.

The research goal. For the research a complex objective was set. The primary objective was to investigate the applicability of selected bankruptcy prediction methods to the food retail sector. This investigation consists of several parts:

1. To see if there are differences between the reliability of the different models and which models are most applicable to the examined sector.
2. The prediction accuracy of models for bankruptcy timeframes was examined. Here the accuracy of short-term and long-term forecasts was discussed.
3. The prediction accuracy of the models by type of termination procedure was examined.
4. Finally, based on the results obtained, suggestions are provided on the applicability of bankruptcy models and further research directions are defined.

Results and discussions. For the research, food retailers operating in the West Transdanubian region were selected. The choice of the region was deliberate, as it was intended to examine a deceloped region at national level, which would allow regional comparability in the future, compared to another regions. The West-Transdanubian region includes the following counties: Győr-Moson-Sopron, Vas and Zala. Thanks to the cooperation between the University of Sopron and ”Céginformáció” , it was possible to retrieve the following datas from their Crefoport system: the balance sheet and profit and loss account data of food retail companies operating in the region. Based on the data obtained, a total of 1072 such enterprises operate in the region. The duration of the study covers 11 years, from 2012 to 2022. The start date of 2012 was chosen because, on the one hand, there was a desire to look at businesses over a longer period of time and, on the other hand, to exclude the short-term consequences of the 2008 economic crisis from the study. The distribution of enterprises is shown in Table 2.

Table 2.

Distribution of investigated enterprises in the region

County	Operational	Bancrupted	Altogether
Győr-Moson Sopron	399	146	545
Vas	167	65	232
Zala	216	79	295

Source: Own editing

The data in Table 2 show that 27 % of enterprises closed down during the investigated period. From the point of view of the research, it is important to examine the data of dissolved companies, since it is possible to be sure of the operation of bankruptcy forecasting models in the case of dissolved enterprises. For operating enterprises, the results of the models could only be verified in the future. So, in the final database of the research, there are 290 companies for which the selected bankruptcy forecast models were tested. In the case of companies that have bankcrupted, the reasons for the closures were examined. Figure 2 illustrates possible ways of termination.

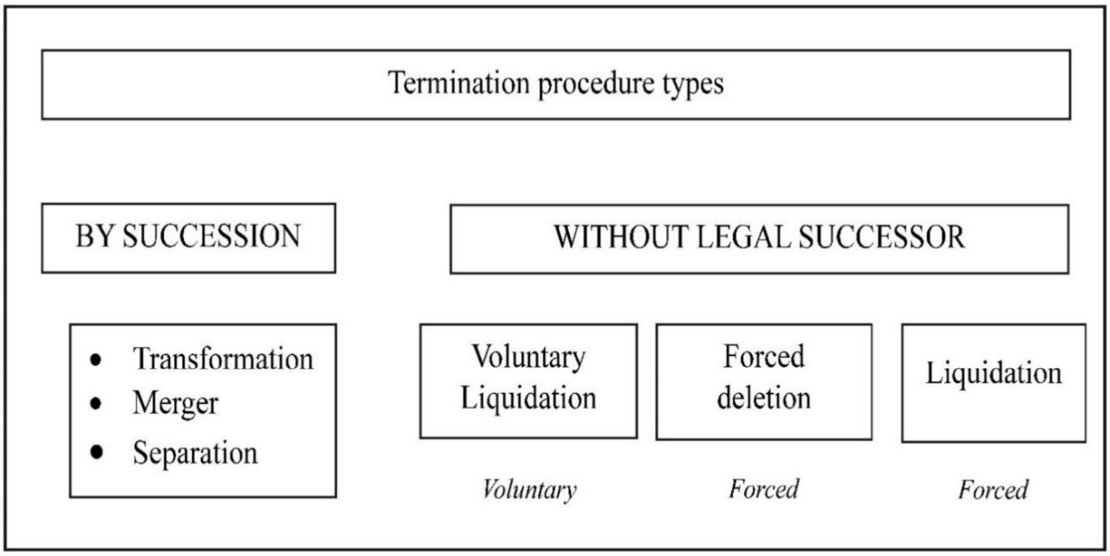

Figure 2. Types of termination proceedings

Source: [17, p. 15.]

Figure 2 shows that it is important to examine the effectiveness of bankruptcy models in the case of dissolution without a legal successor. After performing the calculations, it was necessary to exclude 6 more companies from the database, because even though they bankrupted on paper during the period under review, they did not even have balance sheet and profit and loss account data on the electronic report portal between 2012 and 2022. After that, the distribution of types of termination proceedings in the database is shown in Table 3.

Table 3.

Number of companies bankrupted by method of termination

County	Voluntary liquidation	Liquidation	Forced deletion	Total
Győr-Moson-Sopron	44	59	40	143
Vas	24	21	20	65
Zala	30	27	19	76

Source: Own editing

The data in Table 3 show that the proportion of forced termination procedure types in the examined database is higher than the proportion of voluntary procedures. In the first part of the research, it was examined whether there are differences in the reliability of the different models and which models are best suited to the selected sector. The results are presented in Table 4.

Table 4.

Result of the application of bankruptcy models (t = year of termination)

Virág-Hajdu model	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t
Predicts bankruptcy	0	1	6	7	9	18	20	32	38	41
Not predict bankruptcy	0	3	11	19	38	47	69	85	107	139
Not applicable	0	2	1	1	5	6	20	34	43	61
Comerford's analysis	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t
Predicts bankruptcy	2	11	21	34	46	65	88	114	141	188
Not predict bankruptcy	2	6	6	13	18	26	30	35	46	45
Not applicable	0	0	0	2	3	7	15	24	34	51
Taffler model	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t
Predicts bankruptcy	1	2	4	8	9	13	12	18	17	33
Not predict bankruptcy	3	15	23	38	51	77	116	146	193	244
Not applicable	0	0	0	2	3	7	15	24	35	52
Springate model	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t
Predicts bankruptcy	1	3	6	15	21	40	54	75	96	138
Not predict bankruptcy	3	14	21	32	43	51	64	74	91	95
Not applicable	0	0	0	2	3	7	15	24	34	51
Zmijewski model	t-9	t-8	t-7	t-6	t-5	t-4	t-3	t-2	t-1	t
Predicts bankruptcy	4	9	14	24	37	54	83	103	137	160
Not predict bankruptcy	0	8	13	23	27	37	35	46	50	73
Not applicable	0	0	0	2	3	7	15	24	34	51

Source: Own editing

Based on Table 4, the following results are obtained:

- In the models, it can happens that for an indicator the denominator is set to zero (e.g. there is no sales revenue in a given year) and in this case the model does not make sense. These cases are marked with a label that not applicanle.
- In the case of the Virág-Hajdu model, since cash flow value is included in certain indicators, the change in financial instruments had to be examined. As data were available from 2012 onwards, the cash change in 2012 could not be examined in the absence of data for 2011 and these data were excluded. For the model, usability is high, however, forecast accuracy is low. In the case of the model, it should be mentioned that for many small enterprises there was a minimal difference between the size of current assets and the size of assets, which may somewhat "distort" the X3 (current assets/assets) indicator of the model, which has the greatest weight in the model.
- Comerford's analysis predicts the probability of bankruptcy very accurately and there are few cases in which it is not applicable.
- For Taffler's model, usability is high, but forecast accuracy is low.
- Springate model has relatively high prediction accuracy and usability.

- Zmijewski model also has high prediction accuracy and usability.

The prediction accuracy of the models is shown in Figure 3.

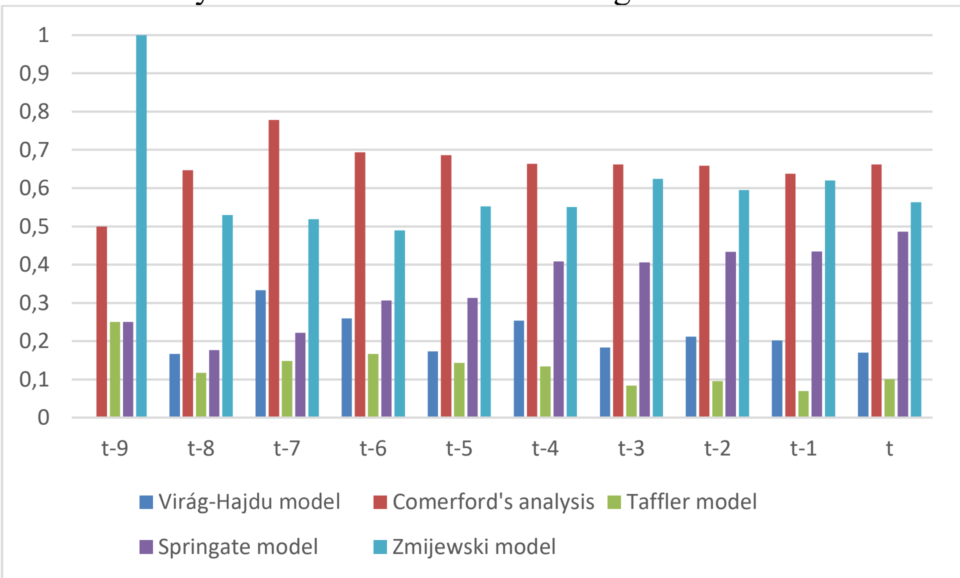

Figure 3. Model reliability (t=year of termination)

Source: Own editing

Figure 3 shows that the prediction accuracy of 3 models is relatively high: Zmijewski's model, Comerford's analysis, and Springate's model. However, it was also considered appropriate to illustrate how reliable the model is, if it can be used. This is illustrated by figure 4.

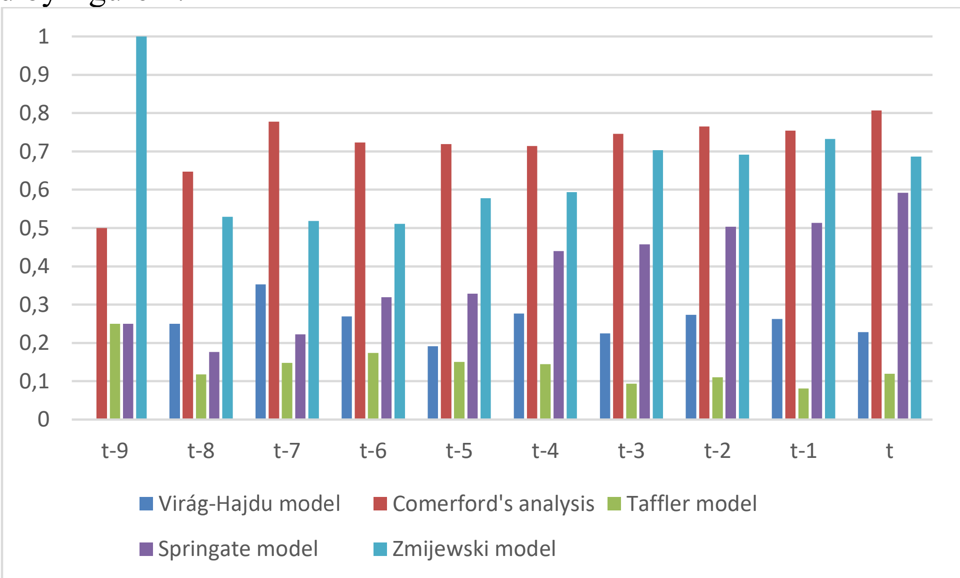

Figure 4. Reliability of models, excluded when they cannot be used (t= year of termination)

Source: Own editing

Figure 4 shows that, if considering only the possibilities where the models can be used, the 3 models already mentioned are the best ones to use for predicting bankruptcy. With the results obtained, it is possible to answer the first point of the research objective. On the basis of the database examined, it can be state that not all bankruptcy prediction models are applicable to the food retail sector. The most applicable models are Zmijewski's model, Comerford's analysis and the Springate model.

The second question of the research concerned the prediction accuracy of the models in relation to the timeframes of bankruptcy. Table 4 and Figures 3 and 4 also help to answer this. Based on the results, it was concluded that in the short term (1-3 years) there is no significant change in the prediction accuracy of the models. In this time frame, the prediction accuracy of models is approximately at the same level, regardless of whether usability is taken into account. In the long term, there is a decrease in forecast accuracy for most of the examined models. It is important to note that in the case of long-term testing, the low number of elements in the 7, 8 and 9 years before termination distorts the assessment of accuracy. For example, this distortion is responsible for the increase in the accuracy of the Zmijewski model.

The research third goal was to examine the prediction accuracy of the models according to the types of termination procedures. It had been previously expected that the estimation of the models would be significantly less precise for companies with forced deletion procedures, as such procedures are not necessarily linked to the effectiveness of companies. During the comparison, the usability of the models was also examined, so cases where the models cannot be used were not excluded. Accordingly, the results are illustrated in Figures 5, 6 and 7.

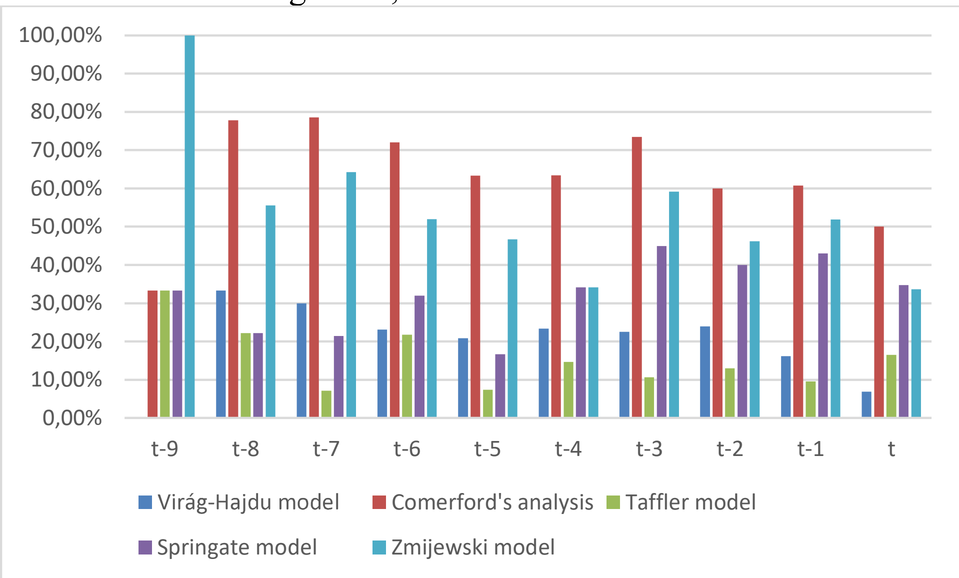

Figure 5. Reliability of models with voluntary liqidation procedure (t=year of termination)

Source: Own editing

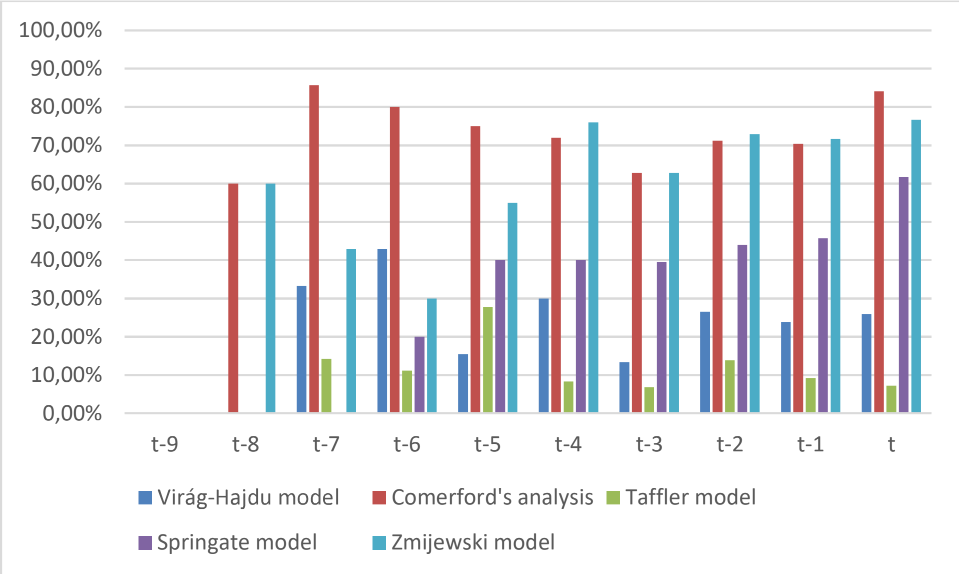

Figure 6. Reliability of models with liqidation procedure (t=year of termination)

Source: Own editing

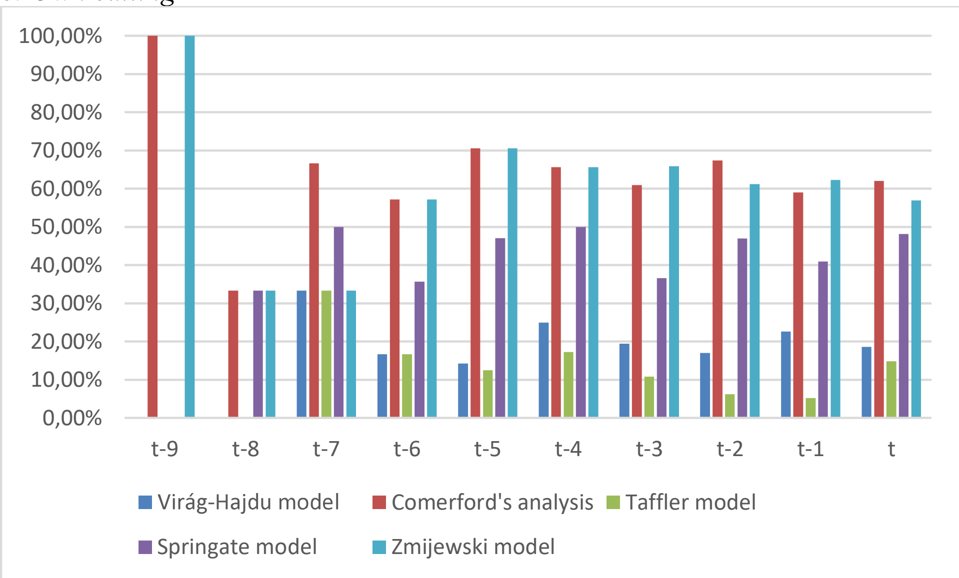

Figure 7. Reliability of models with forced deletion procedure (t = year of termination)

Source: Own editing

It was considered important to present the figures of the results one after the other for easyer comparison. By rejecting the initial expectation, it can be seen that the prediction is not more inaccurate for forced deletion procedures. This assumes that most companies dissolved in forced deletion procedures already had operational problems in the examined database, what the bankruptcy models were able to detect. Another conclusion is that the highest prediction accuracy in the sample is in the case of liquidation proceedings. In the case of voluntary liquidation, which is initiated voluntarily by business owners, in most cases the accuracy of forecasting models is the least accurate.

Conclusions and prospects for further research. The sector that was heavily affected by the Covid19 crisis, as well as by the inflation and economic crisis of recent years was selected for the purpose of the study. At the beginning of the study, the negative effects in the sector were presented and substantiated, and the literature on bankruptcy models was introduced. After presenting the database, 4 goals for the research were set, the results of which were as follows:

In the examined database, bankruptcy forecasting models cannot be used uniformly to detect a crisis situation. Based on the sample, the probability of bankruptcy can be predicted relatively accurately for three out of five models. These three models are: Zmijewski's model, Comerford's analysis, and the Springate model.

For the models, there is no major change in forecast accuracy in the short term, within 3 years before termination, with values remaining close to the same level. In the long term, most of the models showed a decline in forecast accuracy, but the longer the time horizon, the more low number of elements distorts the assessment of accuracy.

The type of liquidation procedure affects the accuracy of the forecast. The most accurate forecast was obtained in the case of liquidation, while the most inaccurate was in many cases in the case of voluntary liquidation.

Based on the results obtained, the selected bankruptcy prediction models are not fully adequate in identifying the critical situation. However, in the short term, 3 out of the selected 5 models provided an accurate prediction in more than half of the cases. It is advised that firms use more than one model at a time to obtain a more accurate prediction of the firm's condition. The use of bankruptcy prediction models is very important to reduce the operational risk of the firm and to anticipate problems. In order to obtain more accurate results from the research, it is necessary to increase the size of the database in the future, to include other regions and sectors, or to test new models, allowing even regional and sectoral comparability.

References

1. Hossain, M. B. – Wicaksono, T. – Nor, K. M. – Dunay, A. – Illes, C. B. (2022). E-commerce Adoption of Small and Medium-Sized Enterprises During COVID-19 Pandemic: Evidence from South Asian Countries. The Journal of Asian Finance, Economics and Business, 9(1), 291–298. https://doi.org/10.13106/JAFEB.2022.VOL9.NO1.0291
2. Sági J. – Szennay Á. (2022): A COVID-19 pandémia első évének magyar vállalkozásokra gyakorolt hatása, különös tekintettel a fenntarthatósággal kapcsolatos kérdésekre, Polgári Szemle, 18. évf. 1–3. szám, 80–97. o. https://doi.org/10.24307/psz.2022.1107
3. Központi Statisztikai Hivatal (KSH): A kiskereskedelmi forgalom kiigazítatlan volumenindexe üzlettípusok szerint, havonta, negyedévente. Elérhető: https://www.ksh.hu/stadat_files/bel/hu/bel0019.html (Hozzáférés dátuma: 2023.11.17.)
4. Központi Statisztikai Hivatal (KSH):A kiskereskedelmi üzletek száma üzlettípus szerint, Elérhető: https://www.ksh.hu/stadat_files/bel/hu/bel0002.html (Hozzáférés dátuma: 2023.11.17.)
5. Paár D. – Ambrus R. A. – Szóka K. (2021): Gazdasági elemzés a beszámolók információi alapján. Soproni Egyetem Kiadó, Sopron, 151 p. ISBN 978-963-334-402-6
6. Massey J. E. – Larsen J. P. (2006): Crisis Management in Real Time: How to Successfully Plan for and Respond to a Crisis. Journal of Promotion Management, Vol. 12(3/4), 63-97. o. https://doi.org/10.1300/j057v12n03_06

7. Charalambous C. – Martzoukos S. H. – Taoushianis Z. (2021): Estimating corporate bankruptcy forecasting models by maximizing discriminatory power. Review of Quantitative Finance and Accounting, vol 58. június, 297-328. o. https://doi.org/10.1007/s11156-021-00995-0
8. Virág M. (2004): A csődmodellek jellegzetességei és története. Vezetéstudomány, 35. évf. 10. sz. 24-32. o.
9. Bugár Gy. (2016): Piaci és hitelkockázat menedzsment. Akadémiai Kiadó, ISBN 978 963 05 9862 0, Budapest, Elérhető: https://mersz.hu/hivatkozas/dj192pehm_0_p1/#dj192pehm_0_p1, (Hozzáférés dátuma: 2023. 09. 21.)
10. Imre B. (2008): Bázel II definíciókon alapuló nemfizetés-előrejelzési modellek magyarországi vállalati mintán (2002-2006). Doktori értekezés, Miskolc, Elérhető: http://midra.uni-miskolc.hu/document/5557/1208.pdf, (Hozzáférés dátuma: 2023.09.06.)
11. Ágoston N. (2022,b): Mesterséges intelligencia és gépi tanulási módszerek a vállalati fizetésképtelenség becslésére. Statisztikai Szemle, 100. évf. 6. sz. 584-609. o. https://doi.org/10.20311/stat2022.6.hu0584
12. Kristóf T. – Virág M. (2019): A csődelőrejelzés fejlődéstörténete Magyarországon. Vezetéstudomány, 50. évf. 12. sz. 62-73. o. https://doi.org/10.14267/veztud.2019.12.06
13. Virág M. – Kristóf T. (2005): Az elsõ hazai csődmodell újraszámítása neurális hálók segítségével. Közgazdasági Szemle, 52. évf. február 144-162. o.
14. Comerford R. A. (1976): Bankruptcy as business strategy: a multivariate analysis of the financial characteristics of firms which have succeeded in Chapter XI compared to those which have failed. Doctoral dissertation, 237 o.
15. Molnár P. (2018): Önkormányzati közüzemi vállalatok vizsgálata csőd-előrejelzési modellek alkalmazásával. Új magyar közigazgatás, 11. évf. Különszám 45-59. o.
16. Ratting A. (2015): Fizetésképtelenség-előrejelzési megközelítések. Gazdaság és Társadalom, 7. évf. 3. sz. 53-73. o. https://doi.org/10.21637/gt.2015.3.04.
17. Egri-Retezi K. – Egri I. I. (2022): Csődeljárás, végelszámolás, felszámolás, kényszertörlés, vagyonrendezés. A cégmentés és a cégbezárás tudnivalói. Vezinfó Kiadó, Budapest, 233 o. ISBN: 978-615-5058-99-4