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Artificial Neural Networks in Forecasting the Consumer Bankruptcy Risk with Innovative Ratios

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ABSTRACT

This study aims to develop nine different consumer bankruptcy forecasting models with the help of three types of artificial neural networks and to verify the usefulness of new, innovative ratios for implementation in personal finance. A learning sample comprising 200 consumers, and a testing sample of 500 non-bankrupt and 500 bankrupt consumers from Poland are used. The author employed three research approaches to using the entry variables to the models. The unique feature of this study is the proposition of the use of newly developed ratios in household finance similar to the financial ratio analysis that is commonly used in corporate finance. The proposed ratios demonstrated high predictive abilities. The paper answers following questions – (a) Are the three commonly implemented types of neural networks useful in forecasting personal bankruptcy risk?; (b) Which forecasting technique is the most effective not only from the viewpoint of overall effectiveness, but also from the perspective of Type I and II errors?; (c) Which research approach (minimalization versus maximization) guarantees maximum effectiveness?; (d) Are the newly developed types of ratios effective in forecasting personal risk bankruptcy? The research identifies and fulfills three gaps in the literature, and also delivers practical solutions for identifying the level of consumer bankruptcy risk. It provides effective solutions for forecasting the risk in terms of usable models and also delivers highly informative ratios that combine demographic and financial indicators in the twelve ratios. It is one of the first attempts to implement ratio analyses in the usage of household finance worldwide.

KEY WORDS: consumer bankruptcy; recurrent neural networks; feedforward multilayer network; self-organizing maps; financial crisis of households.

JEL Classification: G17; G51.

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1. Introduction

The importance of prognostic research has increased considerably, especially in view of the three latest global crises that impacted the world economy. The first is the financial crisis that started in 2007; the second is the COVID-19 pandemic that began in early 2020; and the third is the current war in Ukraine that directly and indirectly affects countries across the world through, inter alia, the energy and food crisis. Available statistics confirm that the risk of consumer bankruptcy has increased significantly. For example, in Germany, the number of reported household bankruptcies increased by 93.6%, from 56,324 cases in 2020 to 109,031 in 2021. The number of consumer bankruptcies reached record levels in the United Kingdom, reportedly with 111,397 and 110,022 insolvent consumers in 2020 and 2021, respectively. Another example is Poland. In 2021, 18,207 household insolvencies were announced, over 39% those in 2020

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(13,092) and 128% more than in 2019 (7,975). Rising interest rates, inflation, and energy and food costs strongly and negatively affect the economic situation of most households globally. Thus, 2022 appears to be even worse in terms of the number of consumer bankruptcies throughout the world. Due to such a dynamic increase in the number of personal bankruptcies, the topic of forecasting the risk of households' insolvencies has become even more crucial today than it was in the past. The scale and negative economic and social consequences of consumer bankruptcies require scientific search for new and innovative ways of forecasting this type of risk.

Personal bankruptcy is not a central element of any known economic theory. Economic literature distinguishes multiple models of enterprise growth and failure. However, models forecasting the factors affecting household bankruptcy are still lacking. The majority of research available is devoted to predicting bankruptcy of enterprises, not of households. Moreover, the sparse literature devoted to predicting personal bankruptcy, in most cases, concerns the impact of macroeconomic events on the scale of bankruptcies in a country (Korol, 2021). Early identification of consumers' insolvency risk may reduce the number of bankruptcies in the economy. Such forecasting models can be used by both consumers and banks. With the popularization of effective prediction methods, consumer awareness can increase, and in banks, such models may be used as supporting tools in the decision-making process.

To fill this gap in the literature, the present research aims to program nine different consumer bankruptcy forecasting models, using three types of artificial neural networks (feedforward multilayer perceptron, recurrent networks, and self-organizing maps) and to verify the usefulness of new, innovative ratios for implementation in personal finance. The models available in the literature are based on single demographic or financial information about consumers. They lack any constructed ratios, unlike in predicting the insolvency risk of firms where financial ratios (e.g., liquidity and profitability) are used to assess financial risk (Ari et al., 2021). To conduct this study, the author used three research approaches to examine the possibility of using financial and demographic data as input variables for the models. These approaches are characterized by different states of input variables. Thus:

- the first approach uses variables in single forms; that is, the absolute values of financial and demographic information, such as monthly income, education level, and age;
- the second approach verifies the possibility of using values of newly created types of ratios that combine financial and demographic information into twelve ratios, in forecasting the bankruptcy of households;
- the last approach verifies the effectiveness of the artificial neural networks in the case of the maximization of entry data. That is, in the entry layer of networks, all information is provided, both in absolute terms and in relation to the mixture of demographic and financial data.

The paper contributes to the literature on predicting the risk of personal bankruptcies in a three-fold manner. First, it verifies the usefulness of recurrent neural networks, a feedforward multilayer perceptron, and Kohonen networks (self-organizing maps) in forecasting the insolvency risk of consumers in Poland. Second, it identifies the most effective set of entry variables (maximization versus minimization of entry variables). Third, it proposes new innovative ratios that contain a much larger load of information than the commonly used variables in the literature. Such indicators can set a completely new direction for research on the use of ratio analysis in personal finance, similar to that of financial situation of enterprises.

This paper consists of five sections. In this section—the introduction—the author justifies the topic, study objectives, and contributions and innovations of the literature. Section two describes the concept of artificial neural networks. Section three explains the study's research methodology. In the fourth section, the developed models and the results are presented. The last section concludes the paper and formulates implications for future research.

2. Literature Review

As previously mentioned, most studies on bankruptcy forecasting focus on predicting the risk of failure for enterprises, not households. The available studies devoted to predicting consumers' insolvency are based on traditional credit scoring methods that help banks decide whether to grant credit to consumers who apply for them (Lyn, 2000). This study focuses on the verification of the usability of a wide variety of artificial neural networks in forecasting the risk of personal bankruptcy.

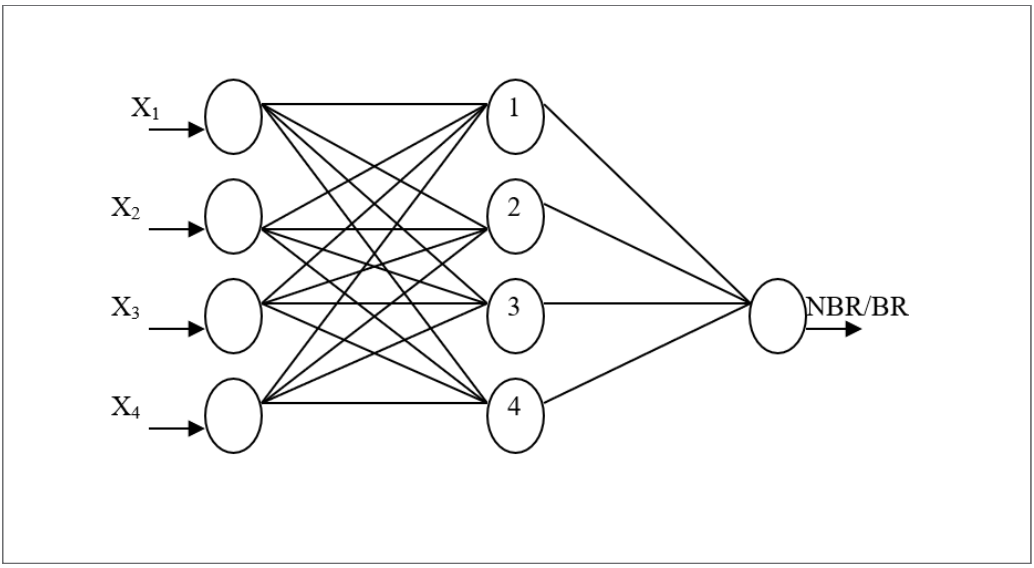
The intensive development of biological, mathematical, and information sciences has contributed to the development of artificial neural networks (ANN). The theoretical assumptions of neural networks were presented in 1943 by W. Pitts (Warren & Pitts, 1943). The first practical application of these models in finance occurred in the 1980s and 1990s. The latest examples of studies on predicting bankruptcy phenomena using artificial intelligence are as follows: Alaka et al. (2018), Barboza et al. (2017), Garcia et al. (2019), Heo et al. (2020), Hosaka (2019), Jardin (2018), Lei and Heng (2021), Marso and El Merouani (2020), and Ptak-Chmielewska (2019). These networks are algorithms, the idea of which is based on the function of human nerve cells. The concept of artificial neural networks is understood as a mathematical model composed of networks of computing nodes called neurons and their connections, which simulate the action of biological systems and can effectively solve specific problems (Chen et al., 2015; Min & Lee, 2005). In contrast to traditional forecasting models, such as multivariate discriminant analysis, the essence of neural network activity is a purely mechanical approach to the analyzed phenomenon, without the detection of internal relations and the strength of existing relationships (Akkoc, 2012).

Artificial neural networks can be divided into three main groups (Iturriaga & Sanz, 2015):

1. feedforward neural networks; that is, networks with a one-direction flow of signals:
   - monolayer, containing a single layer of output neurons, with no hidden neurons
   - multilayered, containing more than one layer of neurons, and the output layer contains at least one hidden layer (called a feedforward multilayer perceptron).
2. recurrent neural networks, in which feedback loops exist between the input, output, and hidden layers. Thus, neurons of the recurrent network can react to their own simulations in response to signals associated with previous observations.
3. clustering neural networks, in which mutual coupling between processing elements is related only

Figure 1

An Example of the Architecture of a Multilayer Perceptron



to the neighborhood.

The most common type of neural network for predicting the bankruptcy of enterprises is the feedforward multilayer perceptron (Brabazon et al., 2012; Jayanthi et al., 2011; Lin et al., 2012; Ravi & Ravi, 2007), in which the signal flow is only in one direction—from the input, where the network takes input data; through the hidden layer, where the main processing of neural signals takes place; to the output, where the network provides a solution. An example of the architecture of such a neural network is shown in Figure 1.

At the input of the neural network, independent variables are introduced, namely, information relating to the consumer, such as demographic (e.g., age and level of education) and financial data (e.g., monthly salary and mortgage expenditures). The input neurons are responsible only for sending a copy of the independent variable values to the hidden layer. Based on the data entered at the network inputs, the total activation of neuron e is usually calculated as a linear combination of inputs, which can be represented as (Zhang et al., 1999):

$$e = \sum_{i=1}^{n} w_i x_i$$

where:

x_i (i=1,2, ..., n) is a vector [n × 1] of the input signals,

w_i (i=1,2, ..., n) – is a vector [n × 1] weight, which, on the one hand, expresses the degree of validity of the information transmitted via this input and, on the other, constitutes a type of neuron memory that remembers the relationships between input signals and output signals.

The input signal of neuron y depends on its total activation (Sharda & Wilson, 1994):

$$y = \varphi(e)$$

where φ is the so-called neuron activation function.

The output values of the neurons in the last layer are the output values from the network. The characteristics of the activation function determine the type of neuron and its area of application. We can distinguish the following commonly used activation functions (Hastie et at., 2009; Rahimian & Singh, 1993):

- threshold function:

$$\varphi(e) = \begin{cases} 1 & when \quad e \geq 0 \\ 0 & when \quad e < 0 \end{cases}$$

- logistic function:

$$\varphi(e) = \frac{1}{1 + \exp(-\beta e)}$$

- hyperbolic tangent function:

$$\varphi(e) = \tanh(\beta e) = \frac{\exp(\beta e) - \exp(-\beta e)}{\exp(\beta e) + \exp(-\beta e)}$$

- signum function:

$$\varphi(e) = \begin{cases} 1 & when \quad e > 0 \\ 0 & when \quad e = 0 \\ -1 & when \quad e < 0 \end{cases}$$

- Gaussian function:

$$\varphi(e) = \exp\left(\frac{-e^2}{2}\right)$$

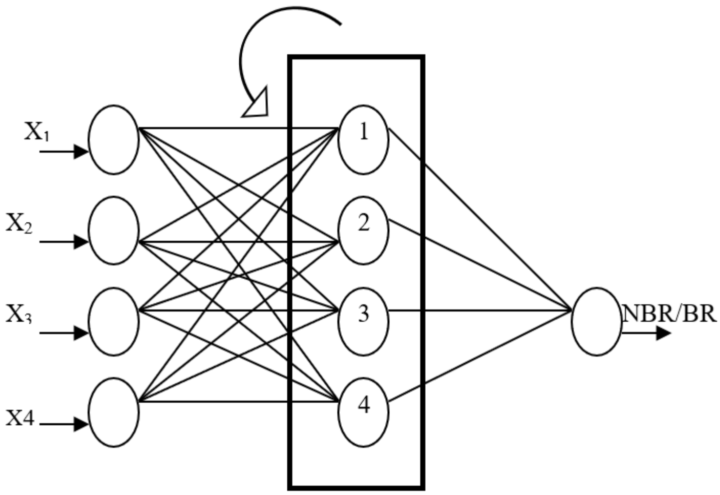
- sinus function:

$$\varphi(e) = \begin{cases} -1 & when \quad e < -\frac{\pi}{2} \\ \sin \beta_e & when \quad -\frac{\pi}{2} \leq e \leq \frac{\pi}{2} \\ 1 & when \quad e > \frac{\pi}{2} \end{cases}$$

Second, next to the multilayer perceptron, the type of neural network that can be used to predict household bankruptcy is a recurrent network. In the topology of recurrent networks, the use of reverse connections is acceptable. The output from any neuron can also pass through its input. Therefore, the neuron state is dependent not only on the value of the input signal but also on the past state of any neuron, not excluding this particular neuron. In this case, the network response to a specific input has an iterative character. Once activated, the network modifies the neuron outputs repeatedly to achieve a steady state in which they remain constant. A typical structure of such a network is illustrated in Figure 2.

The third type of neural network used in this study is the Kohonen network, a specific group of neural networks used in the process of data classification and grouping. These networks typically consist of an input layer and one layer of processing neurons. Each neuron in the processor layer is connected to all the

Figure 2
An Example of the Architecture of a Recurrent Neural Network



inputs. Self-organizing maps (SOMs) are the most widely used types of Kohonen networks. The SOM network creates a mapping of the n-dimensional space of input data in the one- or two-dimensional space of neurons. Each input vector is classified using the simple method of "nearest neighbor" (Jardin & Severin, 2011). The values of all neurons are calculated for the distance from the weight vectors. Then, a winning neuron is assigned to the one with the weakest response. SOM network learning introduces the concept of neighborhood neurons. This is understood in terms of the geometrical position of the neuron with respect to the winner. The weights of units close to the winner are modified more strongly than those of the distant neurons. This effect is realized using the neighborhood function. The following can be used as a neighborhood function (Kiang & Kumar, 2001):

$$h(c,i) = \exp\left(\frac{-r_{ic}^2}{2\sigma^2}\right)$$

where h(c,i) is the neighborhood function, r_{ic} is the distance i of this neuron from the winner, and σ is a parameter defining the width of the neighborhood.

3. Research Methods

The objective of this study is to develop nine forecasting models using three different types of artificial neural networks and three different approaches regarding the type and number of data entries. In the previous section, the author described the types of neural networks used to develop personal bankruptcy risk forecasting models: feedforward multilayer perceptron, recurrent neural network, and self-organizing maps. The distinguishing feature of this study is the proposition of new types of ratios in the science of household finance.

Most scholars have used the following variables in research devoted to evaluating consumers' risk of insolvency: age, education level, gender, income level, mortgage expenditures, mortgage length, marital status, number of dependents, employment status, credit card expenditures, number of credits, and value of assets (e.g., Aristei & Gallo, 2016; Diaz-Serrano, 2005; Ghent & Kudlyak, 2011; Guiso et al., 2013; Haughwout et al., 2009; Hira, 2012; Jackson & Kaserman, 1980; Patel et al., 2012; Worthington, 2006). The usage of such single information loads about evaluated consumers (e.g., the age of consumers) seems quite outdated. Increased global risk, as well as the changes in computing technology, force the invention of more complex ways of assessing households' risk of bankruptcy. The unique assumption of this research approach is that it proposes the use of financial ratios in household finance, similar to those used for analysis in corporate finance. In the twentieth century, financial ratio analyses have become popular managerial tools, as well as tools for determining the financial risk of firms (Korol, 2018; Sayari and Mugan, 2017). Many empirical studies highlight the importance of financial ratios in detecting early warnings of corporate financial distress (e.g., Alaka et al., 2018; Altman, 2018; Delen et al., 2013; Dong et al., 2018; Giannopoulos & Sigbjornsen, 2019; Jardin, 2009; Jardin, 2017; Jayasekera, 2018; Laitinen et al., 2014; Liang et al., 2016; Sun et al., 2014; Tian et al., 2015; Tian & Yu, 2017).

Hence, to conduct the study objective, we implement three different approaches to using entry variables. The first two approaches (R1 and R2) are presented in Table 1. In R1, we use traditional entry variables containing single demographic and financial information about the analyzed consumers. In R2, using a combination of demographic and financial data (from V1 to V11), we propose new types of ratios (X1 to X12). The last research approach, that is, R3, assumes maximization of entry data. That is, in this approach, we support all the data of R1 and R2 in respect to the models (V1 to V11 and X1 to X12). This study is one of the first attempts, worldwide, to implement ratio analyses in the usage of household finance.

Additionally, five out of the eleven variables in the research approach R1 were quantified (Table 2). Such quantification allows us to use demographic information in the ratio analysis (approach R2) and model the influence of each ratio on the bankruptcy risk of consumers.

This study used two samples. The first was a learning sample, comprising 100 bankrupt and 100 non-bankrupt consumers. The second sample was the testing sample, a balanced sample comprising 500 solvent and 500 insolvent consumers. Both samples contained information on households that took consumption credits in Poland, and information for both was collected from 2015 to 2019. Choosing this period helps avoid the impact of a sudden, unforeseeable event, such as the COVID-19 pandemic. The use of balanced samples ensures the reliability of the received results, as all the models were tested on an equal number of solvent and insolvent cases. Detailed demographic characteristics are presented in Table 3 for 500 bankrupt consumers, and in Table 4 for 500 non-bankrupt consumers.

The first observation is the equal distribution of non-bankrupt males (48%) and females (52%) in the testing sample, whereas in the case of bankruptcy, there is a significantly higher share of males (68%) than females (32%). This can be a sign that men are characterized by riskier financial behavior than women. The majority of bankrupt females were in the age group–27–50 (67.5%). Similarly, for males, the age group of 27–50 consists of the maximum number of bankruptcies, with 202 cases, constituting 59.41% of 340 male consumers. The distribution of education levels in particular age groups is also quite interesting. From Table 3, we can see that among bankrupt females, the highest share in all three age groups (27–50, 51–60, and above 60 years) is for those holding Bachelor's degrees. There is a dominance of high-skilled and elementary education levels only in the youngest group of bankrupt females. In the case of bankrupt males (Table 3) younger than 26 years, the riskiest group had only elementary level education (47.92% cases). In the 27–50 age group, 76.74% of bankrupt males are characterized by the highest education level (Masters/Doctorate). Most male consumers in the oldest group (≥ 60 years) have a high level of education (42.86%).

As for the distribution of age and education level of non-bankrupt consumers (Table 4), the highest share of both females and males is in the group aged 27–50 years (62.31% of non-bankrupt females, 64.17% of non-bankrupt males). Both males and females younger than 26 years are characterized by an even distribution between the four types of education levels (from 21.62% to 32.43% in the case of women and from 17.24% to 34.48% in the case of men). Additionally, most of the non-bankrupt males in all three age groups (27–50, 51–60, and older than 60) have a university edu-

Table 1

Entry Variables and Created Financial Ratios for Personal Finance Evaluation

R1 = 11 variables	V1= age V2 = level of education V3 = annual income V4 = monthly income V5 = the total value of assets held V6 = the value of all loans taken V7 = credit card debts V8 = the value of monthly interest rates paid V9 = number of children V10 = marital status V11= length of employment
R2 = 12 developed financial ratios	X1=annual income (V3) / value of total assets (V5) X2=annual income (V3) / total credits (V6) X3=monthly interest rates paid (V8) / monthly income (V4) X4=credit card debts (V7) / total credits (V6) X5=value of total assets (V5)– total credits (V6)) / total credits (V6) X6=value of total assets (V5) / total credits (V6) X7=monthly income (V4) / credits card debts (V7) X8=education (V2) / age (V1) X9=education (V2) / number of children (V9) X10=marital status (V10) / length of employment (V11) X11=education (V2) / (total credits (V6) / annual income (V3)) X12=age (V1) / (total credits (V6) / annual income (V3))

cation (Bachelor, Master, or Doctorate). For non-bankrupt females across the three age groups, there is an additional share of high-skilled employees.

4. Results and Discussion

In the first stage of the study, the author gathered and calculated all variables and ratios specified in Table 2 for both research samples (learning and testing), consisting of a total of 1200 consumers. In the next stage, the author programmed nine different artificial neural network models using three techniques (feedforward multilayer perceptron, recurrent neural network, and self-organizing maps) and three different research approaches (R1, R2, and R3).

We used the correlation matrix to choose the best predictors for the entry layer in the networks in the case of the first two approaches, which assume the use of a wide spectrum of demographic and financial variables (V1 to V11) in R1 and calculation of the proposed ratios (X1 to X12) in R2. We selected only five of the eleven variables in the first approach (R1); similarly, we chose five of the twelve ratios created in the second approach (R2) that were weakly correlated with themselves and strongly correlated with the grouping variable, representing the status of the risk of bankruptcy or lack thereof for the given households. Figure 3 presents the architecture of the multilayer perceptron in research approaches R1 and R2. Both models have the same hidden layer of five neurons and one neuron at the exit of the network, representing the risk of bankruptcy for the analyzed households. Although the entry layers of both networks consist of the same

Table 2
Quantification of Selected Demographic Variables

Variable	Quantification of variable
V1 – age	1 – from 27 to 50 years old
	2 – from 51 to 60 years old
	3 – younger than 26 or older than 60 years old
V2 – level of education	1 – elementary school
	2 – high skilled worker
	3 – bachelor's degree
	4 – master's or doctorate degree
V9 – number of children	1 – from 0 to 2 children
	2 – from 3 to 4 children
	3 – more than 4 children
V10 – marital status	1 – married
	2 – single, widowed
V11 – length of employment	1 – up to 5 years of job experience
	2 – from 6 to 10 years of work experience
	3 – more than 11 years of work experience

number of neurons, in the first approach, variables V1, V2, V4, V5, and V6 are implemented in the model. In the second approach, the ratios X2, X5, X11, and X12 are entered into the network.

In the third research approach (R3), the author developed a feed-forward multilayer perceptron with the assumption of maximizing entry indicators. Thus, there are twenty-three entry neurons, 11 with demographic and financial variables (from V1 to V11) and 12 developed ratios (from X1 to X12). Such maximization of information requires a more complex hidden layer. In this model, there were two hidden layers. The first hidden layer consisted of 12 neurons and the second had six neurons. The model is shown in Figure. 4.

The second type of artificial intelligence model is the recurrent neural network. For this type, the author used the same type of entry indicators as in the case of multilayer perceptron for all three research approaches. Figure 5 shows the architecture of the models for the R1 and R2 approaches. The only difference between multilayer perceptron and recurrent network is the existence of reverse connections in the hidden layer. This ensures better calculation ability of the models. Accordingly, in the third research approach, assuming maximization of entry data (twenty-three entry neurons), the recurrent neural network consists of only one hidden layer with 12 neurons (Figure 6). Owing to the better processing of the calculations, there is no need to create two hidden layers, as in the case of the previous type of neural network.

The third type of neural network is the self-organizing map. When developing this model, the following entry indicators were used: V1, V2, V4, V5, and V6 in R1; X2, X3, X5, X11, and X12 in R2; and all twenty-three in R3. Owing to the limited size of the paper and the poor effectiveness of the models in research R1 and R3, only the map of the self-organizing network for R2 is presented in Figure 7. This model consists of a map of eight neurons (row) × eight neurons (column). On the map, there is a boundary between the area of bankruptcy risk for consumers and the zone of no risk.

In the last stage of this study, the author evaluated the effectiveness of all nine programmed models. Three formulas, widely recommended in the literature on bankruptcy forecasting, are used

Table 3

Distribution of Bankrupt Households' Gender, Age, and Education Level in the Testing Sample

Testing sample – 500 bankrupt entities					
Gender	**Distribution**	**Age**	**Distribution**	**Education**	**Distribution**
Female	160 (32%)	<26	17 (10.62%)	Elementary	5 (29.41%)
				High-skilled	8 (47.05%)
				bachelor	3 (17.64%)
				Master or doctorate	1 (5.88%)
		27-50	108 (67.5%)	Elementary	14 (12.96%)
				High-skilled	12 (11.11%)
				bachelor	49 (45.37%)
				Master or doctorate	33 (30.55%)
		51-60	32 (20%)	Elementary	3 (9.37%)
				High-skilled	7 (21.87%)
				bachelor	12 (37.5%)
				Master or doctorate	10 (21.25%)
		>60	3 (1.88%)	Elementary	1 (33.33%)
				High-skilled	0 (0%)
				bachelor	2 (67.67%)
				Master or doctorate	0 (0%)
Male	340 (68%)	<26	48 (14.11%)	Elementary	23 (47.92%)
				High-skilled	13 (27.08%)
				bachelor	8 (16.66%)
				Master or doctorate	4 (8.34%)
		27-50	202 (59.41%)	Elementary	18 (8.91%)
				High-skilled	21 (10.39%)
				bachelor	8 (3.96%)
				Master or doctorate	155 (76.74%)
		51-60	69 (20.29%)	Elementary	12 (17.39%)
				High-skilled	17 (24.64%)
				bachelor	21 (30.43%)
				Master or doctorate	19 (27.54%)
		>60	21 (6.18%)	Elementary	3 (14.29%)
				High-skilled	9 (42.86%)
				bachelor	3 (14.29%)
				Master or doctorate	6 (28.57%)

(Korol, 2020):

- overall effectiveness of model - S = {1 - [(D1 + D2) / (BR + NBR)]} × 100%,
- type I error - E1 = D1 / BR • 100%,
- type II error - E2 = D2 / NBR • 100%.

where D1 is the number of bankrupt consumers classified by the model as non-bankrupt, D2 is the number of non-bankrupt entities classified as consumers at risk of bankruptcy, BR is the number of bankrupt consumers in the sample, and NBR is the number of non-bankrupt consumers in the sample.

Table 5 presents the results of the model run on the test sample.

Analyzing the results, we should answer the fol-

Table 4
Distribution of Nonbankrupt Households' Gender, Age, and Education Level in the Testing Sample

Testing sample – 500 bankrupt entities					
Gender	**Distribution**	**Age**	**Distribution**	**Education**	**Distribution**
Female	160 (32%)	<26	37 (14.23%)	Elementary	8 (21.62%)
				High-skilled	12 (32.43%)
				bachelor	8 (21.62%)
				Master or doctorate	9 (24.32%)
		27-50	162 (62.31%)	Elementary	10 (6.17%)
				High-skilled	21 (12.96%)
				bachelor	38 (23.45%)
				Master or doctorate	93 (57.41%)
		51-60	36 (13.85%)	Elementary	5 (13.89%)
				High-skilled	7 (19.44%)
				bachelor	6 (16.67%)
				Master or doctorate	18 (50%)
		>60	25 (9.61%)	Elementary	4 (16%)
				High-skilled	5 (20%)
				bachelor	5 (20%)
				Master or doctorate	11 (44%)
Male	340 (68%)	<26	29 (12.08%)	Elementary	5 (17.24%)
				High-skilled	6 (20.69%)
				bachelor	8 (27.59%)
				Master or doctorate	10 (34.48%)
		27-50	154 (64.17%)	Elementary	12 (7.79%)
				High-skilled	19 (12.34%)
				bachelor	40 (25.97%)
				Master or doctorate	83 (53.90%)
		51-60	38 (15.83%)	Elementary	6 (15.79%)
				High-skilled	3 (7.89%)
				bachelor	11 (28.95%)
				Master or doctorate	18 (47.37%)
		>60	19 (7.92%)	Elementary	2 (10.53%)
				High-skilled	3 (15.79%)
				bachelor	7 (36.84%)
				Master or doctorate	7 (36.84%)

Figure 3

An Architecture of Feedforward Multilayer Perceptron in Research Approach R1 and R2

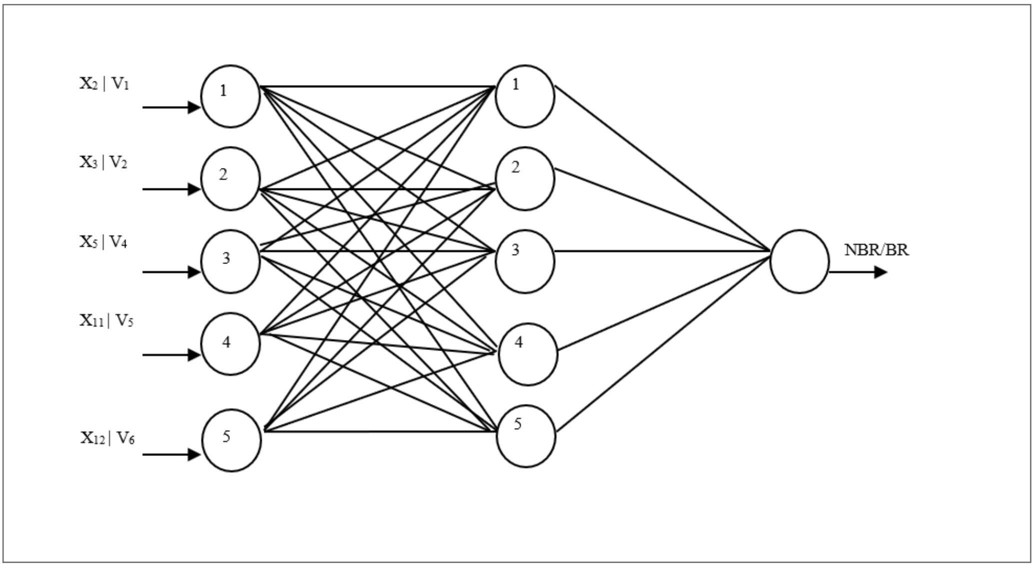
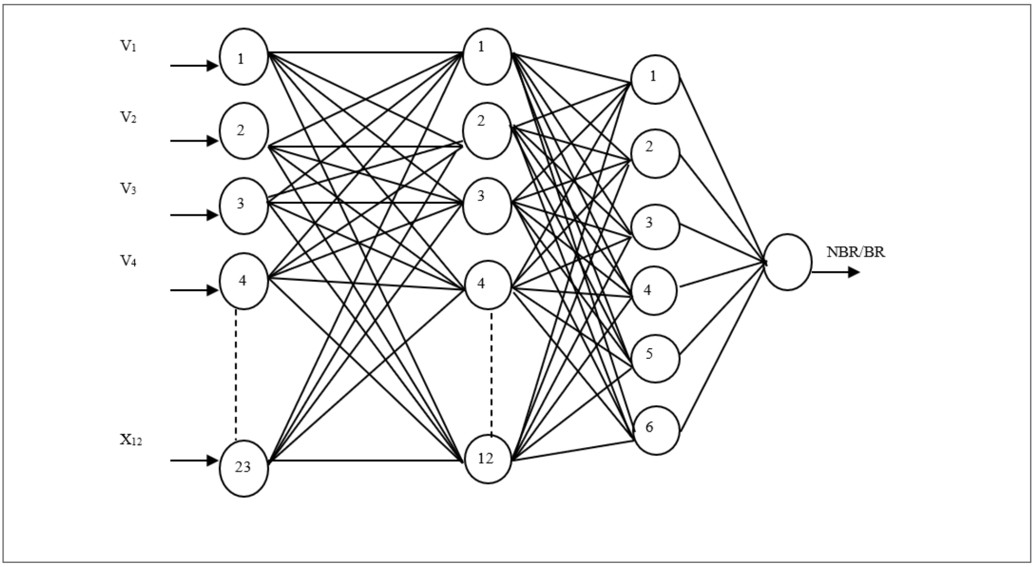


Figure 4

An Architecture of Feedforward Multilayer Perceptron in Research Approach R3



lowing four questions:

1. Are the implemented three common types of neural networks useful in forecasting personal bankruptcy risk?

2. Which forecasting technique is the most effective not only in terms of overall effectiveness, but also from the perspective of Type I and II errors?

3. Which research approach (minimalization versus maximization) guarantees the highest effectiveness?

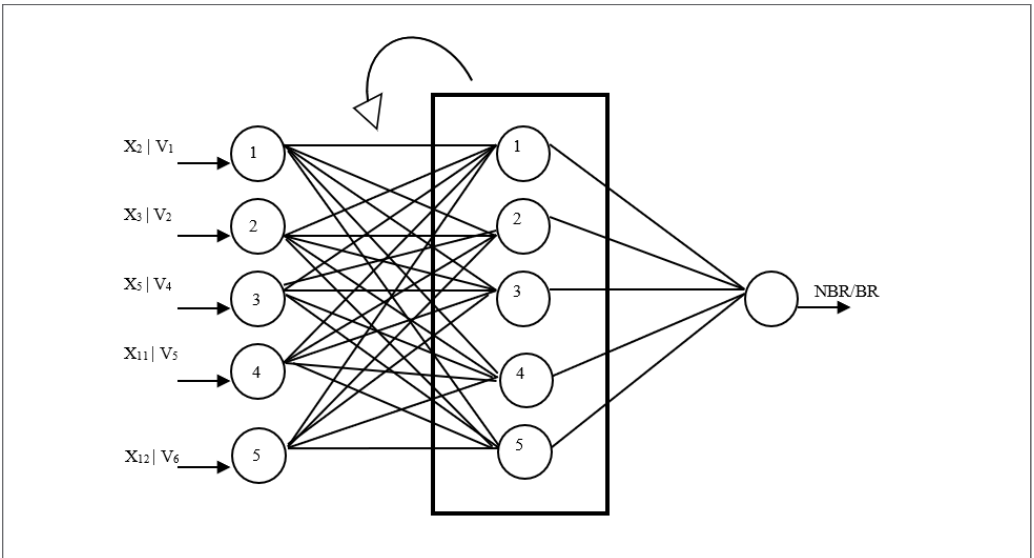
4. Are the developed, new types of ratios effective in forecasting personal risk bankruptcy?

The obtained results clearly prove that all three types of neural networks have sufficient predictive abilities to be used in forecasting such risks in a very dynamic and uncertain environment. The results show that six out of the nine developed models generated an overall effectiveness higher than 80% (Table 5). Moreover, all three types of neural networks can perform at such a high level of effectiveness. The cause of the results below 80% does not lie in the type of neural network, but in the type of input variables used in the model. The variables used in the form of individual demographic and financial information of customers (V1-V11) in research approach R1 show they are not effective in predicting the insolvency risk for households. Additionally, the implementation of such variables in the models caused all three neural networks to generate a very high level of Type I error (above 20%). For example, the self-organizing map generated this error at 30.80%, implying that practically every third future bankrupt consumer was wrongly classified as a future non-bankrupt consumer. Additionally, Type I errors are costlier than Type II errors, from the perspective of financial institutions. Type II errors consist of classifying future non-bankrupt customers as customers threatened by insolvency, meaning that institutions such as banks will refuse to grant a loan. Such a decision will only result in the bank losing potential profit, not loss, as in the case of Type I errors.

As for the second research question, it is evident from Table 5 that recurrent neural networks are the most effective for forecasting bankruptcy risk of households in Poland. They are characterized by the highest overall effectiveness (S) in research approaches R2 (93.10% correct classifications) and R3 (88.90% correct predictions). Additionally, the recurrent network generated the smallest Type I errors in both study approaches, which were 6.20% in R2 and 12.40% in R3; conversely, in other models,

Figure 5

An Architecture of Recurrent Neural Networks in Research Approach R1 and R2



DOI: 10.5709/ce.1897-9254.545

Figure 6
An Architecture of Recurrent Neural Network in Research Approach R3

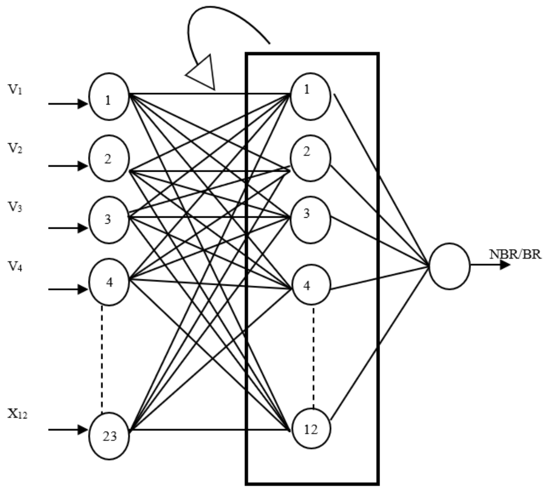


Figure 7
Map of Self-organizing Network with the Classification of Bankruptcy Risk of Consumers in Research Approach R2

BAN	BAN	NON	NON	NON	NON	NON	NON
BAN	BAN	BAN	NON	NON	NON	NON	NON
BAN	BAN	BAN	NON	NON	NON	NON	NON
BAN	BAN	BAN	NON	NON	NON	NON	NON
BAN	BAN	BAN	NON	NON	NON	NON	NON
BAN	BAN	BAN	BAN	BAN	NON	NON	NON
BAN	BAN	BAN	BAN	BAN	BAN	BAN	NON
BAN	BAN	BAN	BAN	BAN	BAN	BAN	BAN

the level obtained of these mistakes ranged from 9.20% (self-organizing map in R2) to as high as 22.40% (self-organizing map in R3). Furthermore, in the R2 approach, in the case of a recurrent network, these errors were smaller than Type II errors (7.60%). Considering these three arguments, we can identify recurrent neural networks as the best forecasting technique.

By answering the first research question, we rejected the type of variables used in study approach R1. Therefore, to determine whether to minimize or maximize the input data to receive better quality forecasts, we compare the results between study approaches R2 and R3. By introducing all the available information into the models, we obtained unsatisfactory results. The overall effectiveness of the feedforward multilayer perceptron decreased from 91.50% to 84.70%. The level of correct classification of recurrent neural networks decreased from 93.10% to 88.90%, and in the case of self-organizing maps, it decreased from 88.90% to 81.20%. This clearly demonstrates the superiority of data minimization.

The last research question concerns the use of new types of ratios to forecast the insolvency risk of households. In research approach R2, two of the three developed models are characterized by an effectiveness higher than 90%. Additionally, using such ratios, the forecasting model was able to achieve the highest effectiveness of 93.10% among all other research approaches. The last observation is that we could obtain Type I errors smaller than Type II errors only by using these ratios; these errors were the smallest in all three study approaches. This is strong evidence that the new types of ratios created are considerably effective and can be used in personal finance.

5. Conclusions

Due to growing uncertainty in financial markets, increasing costs of household functioning and the rising costs of servicing consumer loans, bankruptcy risk forecasting is becoming increasingly important. Today, we are faced with the question of not whether to forecast the risk of consumer insolvency, but what methods and new indicators should be used to increase the quality and credibility of the forecast in the third decade of the twenty-first century.

Table 5
Effectiveness of Nine Artificial Neural Network Models – Testing Sample

Testing sample		Results		
		Research approach		
		R1	R2	R3
Feedforward	E1	26.20% (131)	9.60% (48)	19.80% (99)
multilayer	E2	15.60% (78)	7.40% (37)	10.80% (54)
perceptron	S	79.10%	91.50%	84.70%
Recurrent	E1	27.80% (139)	6.20% (31)	12.40% (62)
neural network	E2	15.80% (79)	7.60% (38)	9.80% (49)
	S	78.20%	93.10%	88.90%
Self-organizing	E1	30.80% (154)	9.20% (46)	22.40% (112)
map	E2	22.40% (112)	13.00% (65)	15.20% (76)
	S	73.40%	88.90%	81.20%

Although the phenomenon of consumer bankruptcies is important in economic life from the perspective of stakeholders (banks, financial analysts, households themselves, financial institutions, and even government), related literature lacks both theoretical and methodological discussions. This research adds a threefold approach to the gaps in the literature and provides practical solutions for identifying the level of risk.

First, this study verifies the prediction capabilities of three different types of neural networks, using three different research approaches. The unique feature of this study is the proposition of using newly developed ratios in household finance, similar to the financial ratio analysis used in corporate finance. The proposed ratios were proven to demonstrate high predictive ability. All models using such ratios were characterized by the best quality of the forecast in terms of both overall effectiveness and the structure of Type I and II errors. Another advantage of these ratios is their versatility. None of the 12 created ratios are denominated in monetary value or strictly in demographic units (e.g., age) that would limit their usage to only one country. Such versatility means that they can be widely used in other countries globally. Thus, this study presents an effective solution for predicting the phenomenon of personal bankruptcies in terms of usable forecasting techniques and highly informative ratios that combine the demographic, economic, and financial properties of analyzed households.

Second, the empirical study reveals that among the artificial neural networks used, recurrent network models are the most effective for forecasting the insolvency risk of consumers in Poland. Furthermore, it was proved that the minimization of entry indicators leads to better results for all three types of artificial intelligence models—feedforward multilayer perceptron, self-organizing maps, and recurrent neural networks.

Another important aspect of this study is the popularization of the results of these studies, which can also increase overall consumer awareness of bankruptcy risk. Additionally, this research can be used in several aspects:

- From the perspective of assessing consumers' solvency (for example, households using forecasting models can make predictions, along with identifying factors that are likely to increase their risk of bankruptcy);
- From the perspective of credit risk assessment by financial institutions (for example, banks) as a tool to support credit decisions;
- Macroeconomic policies.

In addition, the author would like to highlight once again the possibility of using the newly developed financial ratios to assess the economic situation of households. Thanks to the fact that these ratios are versatile and simple to calculate, there is a wide range of possibilities for their use. They can be implemented not only by financial institutions but also by consumers themselves to assess their financial situation. Moreover, the author hopes that this research will initiate a discussion on proposing more new financial ratios for personal finance. Similar to the ratio analysis used in corporate finance, which began to develop in the first half of the 20th century with more than a hundred ratios nowadays, consumer ratio analysis may begin to develop today.

The main limitation of this study is the difficulty in collecting reliable data. Moreover, this is a very time-consuming process, as information about each consumer was collected individually. The author will continue research on the use of macroeconomic variables (such as exchange rates, GDP growth, and unemployment rate) to develop a multifactor early warning system for predicting consumer bankruptcy risk.

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