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Article
Scenarios to Improve E-Commerce SMEs Activity Based on Their Classification: A Case Study on Romania

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Abstract: With the onset of the COVID-19 pandemic, society has increasingly relied on alternative ways to procure goods, leading to an e-commerce boom. This study analyzes the performance of small and medium-sized enterprises (SMEs) that are active in e-commerce in Romania and provides recommendations for entrepreneurs to improve their efficiency. Through unsupervised learning techniques, three classes are identified according to company performance: (1) a class of high-performing companies whose entrepreneurs took the risk of investing in the business, (2) a class of medium-performing companies that maintained their position in the market and (3) a class of financially weak companies whose managers adopted risk-averse, defensive policies. Furthermore, we present scenarios for moving companies from a lower-performing class to a higher-performing class. The research identifies the strategies that managers need to adopt in order to stimulate the activity of e-commerce companies, provides foreign investors a rubric for making investment decisions, and offers a starting point for an entrepreneurship course in academia.

Keywords: classification; data analysis; scenarios; cluster; data mining; neural network; SMEs

1. Introduction

The pandemic has made major changes globally in the way people conduct their work and practice their professions, imposing a rapid and forced adaptation to life conducted increasingly online. The pandemic has impacted multiple aspects of people’s lives [1], refocusing more attention on one another, on those in one’s proximity and on what really matters to each person. Restrictions, limited travel and a lack of interaction with friends or loved ones caused people in the pandemic to feel fear, anxiety or stress [2].

The global pandemic has created an incredibly difficult business climate, prompting organizations around the world to look for the best ways to cope with the new conditions and to identify the best ways to adapt their strategies to new customer demands [3]. However, the pandemic has had an undoubtedly beneficial impact on online businesses (e-commerce), not only for food or home delivery services [4] but also for the sale of non-perishable products.

E-commerce, according to the NTIA Office of the Assistant Secretary [5], refers to the process of selling, buying, transferring and exchanging products, services and/or information over the Internet. It encompasses various perspectives, such as communication, commerce, the business process, service, the learning process, collaboration and the community. This wide range of perspectives enables the development of an online platform where members of different communities can learn, transact and collaborate efficiently. From a communication perspective, e-commerce enables individuals and organizations to exchange information through online platforms. This includes online learning in schools,
universities and other institutions, allowing for more accessible and flexible education. From a commerce perspective, e-commerce facilitates the selling and buying of products, services and information, along with electronic payment systems. This provides businesses with the opportunity to expand their customer base and reach a global audience [6].

Furthermore, e-commerce fosters collaboration among governments, businesses, consumers and management. It aids in reducing costs within the sales chain, fulfilling the desires of these entities. This collaboration is supported through various models of e-commerce. For instance, the Business-to-Business (B2B) model involves transactions between two companies. The Business-to-Customer (B2C) model focuses on the relationship between companies and individual consumers. Additionally, the Business-to-Government (B2G) model involves interactions between businesses and government entities. In addition to B2G, there is a complementary model called Government-to-Business (G2B). These models together form an interactive, efficient and user-friendly environment for information exchange. They facilitate seamless communication between businesses and governments, which is particularly beneficial for regulatory compliance and enhanced public services.

Overall, e-commerce offers a comprehensive set of tools and platforms that enable individuals, organizations and communities to communicate, transact and collaborate effectively. It provides a framework for online learning, e-commerce transactions and collaborative efforts between various entities. The different models of e-commerce, such as B2B, B2C, B2G and G2B, facilitate specific types of interactions and enable the creation of an integrated and streamlined digital environment. The number of online shoppers in the European Union (EU) has increased by 20 percentage points in the last ten years, reaching 75%. Significant growth in online shopping was observed in Estonia, Hungary, Czechia and Romania. In 2020, Romania had 15.35 million Internet users, which accounted for over 78% of the population. Data from DataReportal [7] indicate that 78% of Romanians visited online stores’ websites, and 70% made online purchases at least once in 2020. Most Romanians used mobile phones to access the Internet (87%), and more than half of online orders were still made through laptops (54%) [8]. According to the Romanian National Institute of Statistics (NSI) [9], 66% of Internet users in Romania made at least one online order in 2021, a significant increase of 8.7 percentage points compared to 2020. Romania also outperformed Bulgaria, Turkey and Italy in terms of online shopping percentages [10,11].

This research paper aims to identify how e-commerce companies successfully met consumer demand in 2020, the first year of the pandemic, when a very large part of economic activity transitioned to the Internet.

The main objectives of this study are as follows:

Objective 1. Identify the indicators that best characterize a company’s performance.

Objective 2. Achieve the most efficient grouping of companies according to the calculated indicators to provide an overview of the performance of e-commerce companies in Romania.

Objective 3. Identify scenarios in which companies can improve their economic and financial situation in order to reach a better class of performance.

This study seeks to address a gap in the literature concerning the performance of Romanian retail companies conducting e-commerce and to identify appropriate solutions for improving the economic activity of such companies, based on their classification and the scenarios they currently face. The main research questions (RQs) we considered when developing this study are as follows:

RQ1: Can companies whose activity is focused on retail trade through order boxes or the Internet be classified according to performance indicators recorded during the pandemic period? If so, which classifications best characterize their activity?

RQ2: Can companies in a low-performing class improve their activities in order to reach another class with a high performance?

The research performed will be useful for many plans, from business to academia. Our scientific findings rooted in e-commerce data analysis will constitute a solid and relevant
foundation on which managers from Romania or abroad can base their decisions, in order to assume well-justified risks in the next financial-accounting periods.

This paper consists of the following sections: Section 2 presents a short literature review of relevant studies. Section 3 describes the methodology used in the application, Section 4 presents the main results obtained after applying the methodology, and Section 5 discusses the results from Section 4 and proposes how companies can respond to various scenarios in order to revitalize their activity. Section 6 presents the conclusions.

2. Literature Review

The COVID-19 crisis marked a turning point in history, which led to a redesign of the economic and social system, especially in terms of financial costs, economic efficiency and information quality [12]. It helped bring to light the need for the systemic acceleration of performance and sustainability, especially because the latest research indicates that Sustainable Development (SD), through digital behavioral changes, has become increasingly relevant to employers, employees and customers, as well as other stakeholders in society [13]. The shift from physical trade to e-commerce, particularly as a result of the pandemic, has opened up new opportunities to create new businesses, even in less-explored sectors, such as the rural areas. This means that people who left these areas in search of higher income areas are returning home to take advantage of these new opportunities [14].

Organizations have the potential to generate new value from digitization, particularly as they seek to recover from the post-pandemic economic crisis, and they have a leadership role to play in increasing the performance and sustainability of economies [15]. A number of managers have perceived that digitization will bring a number of strategic advantages, the most important of which being the possibility of direct contact with customers and the absolute availability of time and space. Moreover, digital implementations have been perceived as extremely advantageous, from a long-term cost perspective, thus leading to the new normal of business. The pandemic accelerated the trend toward digitization, as companies were forced to adapt to the new context [15,16]. E-commerce as an economic sector has emerged as a result of the technological revolution, and like any other sector of the economy, it has its pros and cons, especially in the labor market [17]. Thus, whether in Business-to-Business (B2B) or Business-to-Customer (B2C) contexts, companies have experienced unprecedented acceleration toward online business, and entrepreneurs have realized that it is necessary to invest heavily in digital technology and continuous training courses in order to face this new challenge [18].

Over the past decade, digitization and the shift to e-commerce have affected all major economic sectors around the world. Those that were hit the hardest have been SMEs and micro-SMEs, who have had to bear the cost of implementing all-new and sometimes not cheap technologies in their day-to-day operations in order to keep up. The biggest hurdle is the implementation of digital payment systems throughout the supply chain [19]. As part of the global response to the COVID-19 crisis, the digital technology industry, especially the financial technology (Fintech) sector, has played a key role in creating and providing services and technologies that have at least partially mitigated the effects of the pandemic on multiple aspects of people’s lives. The interest in and increased use of Fintech applications, such as digital applications related to finance, payments, banking and e-commerce, have ensured the livelihoods and businesses of people who have been and continue to be threatened by the pandemic [1].

The impact of the pandemic on business has been significant, with country restrictions and blockages leading to a considerable slowdown in economic growth. However, some types of businesses (especially in the B2C sector) have been able to create opportunities in this situation, notably by digitizing a significant part of their business [20]. In a business environment that was more digitally connected through e-commerce, SMEs found new ways to exploit business opportunities in the global economy [21]. Thus, some categories (supermarkets, e-commerce and healthcare) have exploded, whereas other categories, such
as jewellery and luxury, fashion and clothing, machinery and tools, and travel, have largely lost some ground [4].

Changing ways of thinking, organizational behaviors and large-scale digitization are now the key catalysts of the socio-economic model in the post-pandemic world. As economic and social activities become more digitized in response to constraints, both people and businesses have come to rely more on the Internet and connectivity [22]. Under these conditions, digitization becomes a business necessity, resulting in greater productivity and efficiency through the adoption of Customer Relationship Management (CRM) or Enterprise Resources Planning (ERP) solutions, optimized business processes, improved customer and employee experiences and higher earnings. The pandemic has further accelerated this process and has made organizations fully aware of the role and power of digitization, while also prompting a change in people's behavior as they are forced to use online platforms.

In the current digitized reality, the Internet, mobile technologies, nanotechnologies and learning algorithms based on artificial intelligence continue to develop and gain key positions in people’s lives. However, although these cutting-edge technologies offer significant benefits to businesses, some risks may arise as these new technologies continue to develop and inevitably become more and more difficult to control. A review of the literature on the use of artificial intelligence in commerce suggests that the increased use of artificial intelligence will require addressing certain controversial issues, such as security, the protection of personal privacy, ethical issues and employment issues [23].

Digitization has not only laid the foundation for overcoming many mental barriers, but it has also generated and continues to produce systemic changes in behavior. A strong digital strategy and the adoption of the right technologies can provide the framework and tools for innovation that is necessary for organizations now facing great challenges. Customer Experience (CE) is a new and recently theorized concept and refers to the cumulative impact of all interactions between the company and the customer, and it is defined as a multidimensional framework that focuses on the behavioral, cognitive, affective, sensory and social responses provided to customers [24]. This experience includes every element related to the promises made to the customer, such as the ease of use of services or products, trust, promptness, quality and the efficiency of customer relations before and after the purchase.

The most successful brands and companies build and design customer experiences to incorporate and deliver on their value propositions in every interaction between the company and the customer [25]. Not all contact points are equal in their value and importance to the customer, and what constitutes a relevant interaction channel can change significantly over time. The COVID-19 pandemic has not only forced companies to shift from offline day-to-day operations to becoming fully online, but it has also changed consumer behavior [26]. A key moment is an interaction that leaves a strong impression, regardless of whether that impression is positive or negative. For this reason, these interactions need to be planned, evaluated and monitored in order to anticipate problems and improve the quality of the customer experience [27]. According to the results of PwC’s extensive Global Consumer Insights Survey, technology facilitates, but the human factor is the key to a great relationship (human interaction is desirable for 74% of consumers, and technology should be non-intrusive or supportive of this interaction), with a focus on elements such as speed, convenience, consistency and friendliness. For consumers, these elements represent over 70% of their motivation for their purchasing decisions [28]. Fast and friendly services, ease of purchase and bouncy employees matter far more than adopting technology just to keep up with changing times.

Consumers expect technology to be flawless at all times, websites and applications to be smart and friendly, and automation. However, if speed, information and convenience are lacking, the experience instantly becomes unpleasant, and their loyalty instantly shifts [29,30]. Most customer-oriented companies use marketing, green marketing [31], service, sales and commerce over cloud software to optimize customer interactions. Digital
marketing strategies using social media are becoming increasingly important as information technology evolves, especially in recent years as a result of the pandemic. Younger generations such as millennials are embracing new technology and this new way of life [32], and they tend to like and prefer brands that use digital marketing tools (e.g., social platforms such as YouTube) [33]. Although e-commerce is a relatively new concept and research topic, it has already generated new trends, such as s-commerce. These technologically advanced platforms have led to the development of new concepts, such as collaborative commerce and sharing commerce [34]. This can provide a personalized customer experience across all touch-points, especially now when products are becoming more standardized, with the post-purchase experience being the most important factor according to which customers rate their overall experience and satisfaction [35,36]. From the first customer contact to the last, companies work to ensure that every interaction is one that delivers satisfaction, which is vital to business success [37].

The results of conducted studies [38–40] have revealed that the affective dimension has the greatest influence and highlights the importance of the sensory experience, which goes beyond even the cognitive experience [41].

Companies understand that the relationship is more important than the transaction, so they are paying maximum attention to good EC management, focusing on activities that can create long-term benefits rather than generating short-term profitability benefits [40,42]. As the pandemic continues to hit the world economy, there is a risk that those SMEs that are reluctant to adopt the latest technologies, especially e-commerce and digital marketing, will collapse [43,44]. Although the adoption of e-commerce has shown a number of benefits, especially during the recent pandemic crisis, not all companies are open to adopting these technologies [45]. For example, during the pandemic, the Brazilian economy saw a massive increase in new company registrations specializing in e-commerce. Due to restrictions imposed by the national government, online business was the only way to conduct business. However, soon after the restrictions were eliminated and people could move freely, the majority of newly created companies began disappearing [46]. On the other hand, Southeast Asian countries adopted e-commerce through open innovation strategies, minimizing the negative economic impact of the pandemic [47].

3. Materials and Methods

This study examines how Romanian retail companies fared in selling through order houses or through the Internet in the first year of the COVID-19 pandemic, and it identifies directions for improvement in order to maintain positive trends.

The methodology used in this research study has the following stages:

Step 1. Record the main indicators in the balance sheets at the end of 2020 for the set of 400 Romanian companies that reported e-commerce as their main activity by defining and calculating the rates used for the application.

Step 2. Apply cluster analysis to achieve a first classification of the selected companies in the sample. At this stage, we removed the outliers to create a homogeneous sample of data.

Step 3. Apply discriminant analysis to minimize the error resulting from the previous step. The result of this procedure was to obtain the equations of the discrimination space and to improve the classification.

Step 4. Apply unsupervised classification techniques to the results obtained from Step 3 in order to achieve a division of companies, with minimal error. Specifically, we trained a feed-forward classification neural network, with three layers of neurons. The input layer is composed of the indicators defined in step 1, the intermediate layer (hidden) has a number of neurons determined experimentally, and the final layer contains the performance classes of the companies.

Step 5. Describe scenarios for migrating a company from a class with modest results to one with better results, offering recommendations based on the results obtained from the neural network and taking into account the transfer functions.
Our proposed five-step methodology is our own design, and as far as we know, there are no other studies in the literature that use the same approach. There are, in fact, studies in various fields that use methods of one-by-one or combinations of two-by-two. The way that these methods are combined to find hidden information in data is an important element of the originality of our study.

The indicators that we consider important for capturing the economic–financial situation of each company, calculated on the basis of the data from the balance sheets, are presented in Table 1.

Table 1. Indicators used in the application.

<table>
<thead>
<tr>
<th>Crt. No.</th>
<th>Coding the Indicator</th>
<th>Name of the Indicator</th>
<th>Calculation Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I1</td>
<td>Profit Rate</td>
<td>(Gross Profit/Turnover) × 100</td>
</tr>
<tr>
<td>2</td>
<td>I2</td>
<td>Degree of Debt</td>
<td>(Total Debts/Total Assets) × 100</td>
</tr>
<tr>
<td>3</td>
<td>I3</td>
<td>Debt to Turnover Ratio</td>
<td>(Total Debt/Turnover) × 100</td>
</tr>
<tr>
<td>4</td>
<td>I4</td>
<td>Equity Solvency Rate</td>
<td>(Equity/Total Liabilities) × 100</td>
</tr>
<tr>
<td>5</td>
<td>I5</td>
<td>Receivables to Assets Ratio</td>
<td>(Receivables/Total Assets) × 100</td>
</tr>
<tr>
<td>6</td>
<td>I6</td>
<td>Inventory Rate</td>
<td>(Stocks/Total Assets) × 100</td>
</tr>
<tr>
<td>7</td>
<td>I7</td>
<td>Financial Profitability of Equity</td>
<td>(Net Profit/Equity) × 100</td>
</tr>
<tr>
<td>8</td>
<td>I8</td>
<td>Debt Collection Period</td>
<td>(Receivables/Turnover) × 365</td>
</tr>
</tbody>
</table>

To calculate the size of the sample of companies to be analyzed, we considered a 95% confidence level (with a corresponding value of the z-score of 1.96) and a precision level of ±5% [48]. Given the fact that, in this field of activity, a total of 18,808 SMEs operate in Romania, the sample size was determined by using the following formula [49]:

\[
 n = \frac{z^2 \cdot p(1-p)}{\epsilon^2} = 1 + \frac{1.96^2 \cdot 0.5(1-0.5)}{0.05^2 \cdot 18808} = 376.47 \tag{1}
\]

where \(N\) is the population size; \(z\) is the value of the z-score; \(\epsilon\) is the margin of error; and \(p\) is the sample proportion.

Although the result in Formula (1) is 376, we chose a sample size of 400 companies to avoid a situation in which there may be outliers from classifying algorithms. It is known that outliers must be removed from the analysis in order to not influence the results.

The algorithm used in the first classification is Ward’s hierarchical clustering method, which makes it possible to obtain classes that are as homogeneous as possible, located as far apart as possible from each other. In other words, it tries to maximize the inter-cluster distance and minimize the intra-cluster distance.

One way to minimize the error resulting from clustering is to apply the discriminant analysis method. The discrimination functions that describe the discrimination space have the following general form, presented in Equations (2) and (3):

\[
 Sk_1_i = \sum_{j=1}^{8} I_{j_i} \times Ck_{1_j} + ak1_i, \quad \forall i = 1, 330, \quad k = 1, 2, 3 \tag{2}
\]

\[
 Sk_0_i = \sum_{j=1}^{8} I_{j_i} \times Ck_{0_j} + ak0_i, \quad \forall i = 1, 330, \quad k = 1, 2, 3 \tag{3}
\]

where

- \(Sk_1_i\) represents the probability of company \(i\) being in class \(k\);
- \(Sk_0_i\) represents the probability of the company not being in class \(k\);
- \(I_{j_i}\) represents the value of indicator \(j\) for company \(i\), and \(j\) belongs to the set composed of the indicators calculated for each company;
C\textsubscript{k1} represents the coefficients of the function that calculates the probability of belonging to class k of a company (k = 1, 2, 3);
C\textsubscript{k0} represents the coefficients of the function that calculates the probability of not belonging to class k of a company (k = 1, 2, 3);
ak1 and ak0 are constants related to the linear functions that calculate the scores;
i represents the sample order number of the company.

After applying the discriminant analysis, the next step is to train a neural network that further refines the classification achieved.

The network we propose to improve the classification made with the help of discriminant analysis is a feed-forward network with three layers of neurons. No information processing is performed in the input layer; this is performed in the intermediate and output layers. At the level of each neuron, in the intermediate and final layers, there are two processing stages: the linear stage (the activation function of the neuron) and the nonlinear stage (the output function of the neuron).

The following equations are defined for a neuron j in the intermediate layer:

- The activation function when the vector is applied at the input
  \[ net^h_j = \sum_{i=0}^{8} w^h_{ji} \times I_i, \]  
  where \( \{ w^h_{ji} \}, j = 1, 2, 3, 4, 5 \) represents the set of weights related to the hidden layer;
  \( I^m = (I_1^m, I_2^m, I_3^m, I_4^m, I_5^m, I_6^m, I_7^m, I_8^m) \) is called the input vector;
  \( h \) index comes from the number of hidden layers.

- The output calculation (marked with \textsubscript{i}j) is made according to the following formula:
  \[ i_j = f^h_j \left( net^h_j \right), \]  
  \( j = 1, 2, 3, 4, 5 \), where \( f^h_j \) is a hyperbolic tangent nonlinear function \( f: \mathbb{R} \rightarrow \mathbb{R}, f(x) = \tanh(x) \).

For a certain neuron k in the output layer, the following equations are defined:

- The activation function when vector I is applied to the input layer of the network is presented in Formula (4):
  \[ net^o_k = \sum_{j=1}^{5} w^o_{kj} \times I_j, \]  
  where \( \{ w^o_{kj} \}, k = 1, 2, 3, \) \( j = 1, 2, 3 \) represents the set of weights related to the output layer.
- The output of neuron k is determined with activation \textit{net}^o_k and is expressed by Formula (5):
  \[ y^m_k = f^o_k \left( net^o_k \right), \]  
  \( k = 1, 2, 3 \), where \( f^o_k \) is the hyperbolic tangent.

The function \( f^o_k \) is the hyperbolic tangent.

The main objective of the training algorithm of the multilayer perceptron network is to minimize the error on the training sample:

\[ E = \frac{1}{K} \sum_{p=1}^{K} E_p, \] 
where \( E_p = \frac{1}{2} \sum_{k=1}^{3} \left( y^p_k - y^p(m)_k \right)^2 \) is the error caused by the driving vector \( p \).

Applying the backpropagation algorithm to train the neural network involves going through several steps until the weights are adjusted so that the error is minimal. The steps of the algorithm are presented below:

Step 1. The first vector in the neural network training matrix is chosen. The vector is applied to the network input \( I^m = (I_1^m, I_2^m, \ldots, I_8^m) \), for which the ideal output vector is known: \( c^m = (c_1^m, c_2^m, c_3^m) \).

The set of weights is randomly generated, i.e.:

- The set of weights of the hidden layer: \( \{ w^h_{ji} \}, j = 1 \ldots 5, i = 1 \ldots 8 \);
- The set of weights of the output layer: \( \{ w^o_{kj} \}, j = 1 \ldots 5, k = 1, 2, 3 \).
Step 2. The activation thresholds and the outputs of the neurons in the hidden layer are calculated with the following calculation relations (6) and (7):

$$net^h_j = \sum_{i=1}^{8} w^h_{ji} f^m_i, \quad j = 1 \ldots 5$$  

$$i_j = f^h_j (net^h_j), \quad j = 1 \ldots 5$$  

Step 3. The activation thresholds and the outputs of the neurons in the output layer are calculated with the following calculation relations (8) and (9):

$$net^o_k = \sum_{j=1}^{5} w^o_{kj} i_j, \quad k = 1, 2, 3$$  

$$c^m_k = f^o_k (net^o_k), \quad k = 1, 2, 3$$

Step 4. The error terms are calculated according to the following relationships:
- For the neurons from the output layer: $$\delta^o_k = (c_k - c^m_k) \cdot f'_o k (net^o_k), \quad k = 1, 2, 3;$$
- For the neurons from the hidden layer: $$\delta^h_j = f'_h j (net^h_j) \sum_{k=1}^{3} \delta^o_k w^o_{kj}, \quad j = 1 \ldots 5.$$

Step 5. The weights for the output layer are adjusted based on the following calculation ratio, Equation (10):

$$w^o_{kj}(t+1) = w^o_{kj}(t) - \eta \frac{\partial E}{\partial w^o_{kj}}, \quad k = 1, 2, 3, \quad j = 1 \ldots 5$$  

The formula for adjusting the weights of the output layer is equivalent to the following equation: $$w^o_{kj}(t+1) = w^o_{kj}(t) - \eta \delta^o_k i_j, \quad k = 1, 2, 3, \quad j = 1 \ldots 5.$$

Step 6. The weights of the intermediate layer are adjusted accordingly to Equation (11):

$$w^h_{ji}(t+1) = w^h_{ji}(t) - \eta \frac{\partial E}{\partial w^h_{ji}}, \quad j = 1 \ldots 5, \quad i = 1 \ldots 8$$

The formula for refining the weights of the hidden layer has the following form: $$w^h_{ji}(t+1) = w^h_{ji}(t) + \eta \delta^h j x_i, \quad j = 1 \ldots 5, \quad i = 1 \ldots 8.$$

Step 7. The error due to the training vector is calculated based on Equation (12):

$$E = \frac{1}{2} \sum_{k=1}^{M} \left( c_k - c^m_k \right)^2$$

Step 8. If there are still vectors in the training set, the algorithm is applied to the new vector. Finally, the error corresponding to an epoch is calculated as the simple arithmetic mean of the errors due to each vector in the training set.

A training epoch involves implementing the algorithm for all vectors in the training set. The training algorithm of the multilayer perceptron ends after a fixed number of epochs.

4. Results

The main results obtained following the application of the methodology proposed in the previous section are as follows. The first step is to analyze the data series from the point of view of object distributions. The main indicators describing the data series are calculated in Table 2.
Table 2. Descriptive statistics of the indicators.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Bimodality</th>
</tr>
</thead>
<tbody>
<tr>
<td>I1</td>
<td>13.71</td>
<td>14.66</td>
<td>2.71</td>
<td>10.66</td>
<td>0.61</td>
</tr>
<tr>
<td>I2</td>
<td>46.75</td>
<td>26.75</td>
<td>0.30</td>
<td>0.01</td>
<td>0.36</td>
</tr>
<tr>
<td>I3</td>
<td>16.09</td>
<td>13.09</td>
<td>2.32</td>
<td>12.12</td>
<td>0.42</td>
</tr>
<tr>
<td>I4</td>
<td>52.97</td>
<td>26.68</td>
<td>-0.29</td>
<td>0.01</td>
<td>0.36</td>
</tr>
<tr>
<td>I5</td>
<td>22.44</td>
<td>17.31</td>
<td>1.11</td>
<td>1.11</td>
<td>0.54</td>
</tr>
<tr>
<td>I6</td>
<td>37.45</td>
<td>22.48</td>
<td>0.02</td>
<td>-0.85</td>
<td>0.46</td>
</tr>
<tr>
<td>I7</td>
<td>59.16</td>
<td>32.29</td>
<td>-0.16</td>
<td>-0.87</td>
<td>0.47</td>
</tr>
<tr>
<td>I8</td>
<td>28.98</td>
<td>27.25</td>
<td>1.59</td>
<td>3.15</td>
<td>0.57</td>
</tr>
</tbody>
</table>

The eight data series have a single point of maximum (bimodality less than 1) and have a distribution close to the normal distribution (skewness is in the range \([-3; 3]\)), and the flattening of the graph is different, with some series that have larger queues on the right (I1, I3) or on the left (I6, I7), but also other series that are very close to the graph of the normal distribution (I2, I4, I5, I8).

Applying Ward’s method on the data series, the aggregation graph of the companies was obtained (Figure 1), and following its cutting, with an assumed error, three classes were identified. The detailed components of each can be found in Appendix A.

Furthermore, according to the methodology, we applied a discriminant analysis in order to improve the classification made in the previous step. For each class, we identified functions that calculate the probability of an object belonging to that class.

The discrimination functions for the three classes are the following:

- For class 1, Equations (13) and (14):
  
  \[
  S_{10i} = -0.21 \times I_1 + 22.19 \times I_2 + 0.31 \times I_3 + 22.37 \times I_4 - 0.11 \times I_5 - 0.23 \times V_6 + 0.04 \times I_7 - 0.13 \times I_8 - 1.1 \times 10^3, \quad i = 1,330
  \]  
  \[
  S_{11i} = -0.26 \times I_1 + 22.24 \times I_2 + 0.3 \times I_3 + 22.39 \times I_4 - 0.1 \times I_5 - 0.19 \times V_6 + 0.13 \times I_7 - 0.15 \times I_8 - 1.1 \times 10^3, \quad i = 1,330
  \]
- For class 2, Equations (15) and (16):

\[ S_{20i} = -0.13 \times I_1 + 22.25 \times I_2 + 0.29 \times I_3 + 22.53 \times I_4 - 0.13 \times I_5 - 0.28 \times V_6 - 0.05 \times I_7 - 0.11 \times I_8 - 1.1 \times 10^3; i = \frac{1}{330} \]  

\[ S_{21i} = -0.08 \times I_1 + 22.34 \times I_2 + 0.26 \times I_3 + 22.73 \times I_4 - 0.15 \times I_5 - 0.3 \times V_6 - 0.09 \times I_7 - 0.1 \times I_8 - 1.12 \times 10^3; i = \frac{1}{330} \]  

- For class 3, Equations (17) and (18):

\[ S_{30i} = -0.22 \times I_1 + 22.62 \times I_2 + 0.22 \times I_3 + 23.03 \times I_4 - 0.14 \times I_5 - 0.16 \times V_6 + 0.22 \times I_7 - 0.14 \times I_8 - 1.1 \times 10^3; i = \frac{1}{330} \]  

\[ S_{31i} = -0.2 \times I_1 + 22.44 \times I_2 + 0.25 \times I_3 + 22.77 \times I_4 - 0.13 \times I_5 - 0.2 \times V_6 + 0.13 \times I_7 - 0.14 \times I_8 - 1.1 \times 10^3; i = \frac{1}{330} \]  

Following the application of the discriminant analysis on the data set, it can be seen that 46 companies migrated from one class to another, and their movements are presented in Appendix B. Due to the large number of companies that changed the initial class as a result of the discriminant analysis, we further improved classification through the use of an unsupervised learning technique, namely the training of a neural classification network.

The objective function of the neural network is to minimize the classification error by maximizing a company’s belonging to a class (maximum likelihood), having a learning rate at each iteration of 0.85. Prior to the application of the neural network backpropagation algorithm, the data sample was randomly divided into 40% network training data, 30% model validation data and 30% already trained network testing data.

Before starting the process of training the neural network, the scoring functions had the following formulas (Figure 2):

- For the hidden layer of neurons, the functions are presented in Equations (19)–(23):

\[ H_1 = 0.03 \times I_1 - 0.02 \times I_2 - 0.09 \times I_3 + 0.18 \times I_4 - 0.08 \times I_5 - 0.54 \times I_6 + 0.28 \times I_7 - 0.04 \times I_8 \]  

\[ H_2 = -0.023 \times I_1 + 0.2 \times I_2 - 0.51 \times I_3 + 0.6 \times I_4 + 0.16 \times I_5 + 0.01 \times I_6 + 0.34 \times I_7 + 0.06 \times I_8 \]  

\[ H_3 = 0.06 \times I_1 + 0.21 \times I_2 + 0.3 \times I_3 + 0.22 \times I_4 + 0.26 \times I_5 - 0.36 \times I_6 + 0.17 \times I_7 + 0.11 \times I_8 \]  

\[ H_4 = -0.49 \times I_1 + 0.52 \times I_2 - 0.4 \times I_3 - 0.39 \times I_4 - 0.55 \times I_5 + 0.13 \times I_6 - 0.39 \times I_7 + 0.65 \times I_8 \]  

\[ H_5 = -0.28 \times I_1 + 0.18 \times I_2 - 0.16 \times I_3 - 0.18 \times I_4 - 0.27 \times I_5 - 0.18 \times I_6 - 0.19 \times I_7 - 0.001 \times I_8 \]  

- For the output layer of the network, all neurons had values of 0.
- The activation thresholds for the two layers had the following values:
  - Hidden layer: \(-1.04, 0.58, -0.78, 1.62, 0.4\);
  - Output layer: \(-0.49, -0.87, -0.73\).

The process of training the neural network had 2002 iterations (Figure 3), and the error of an object belonging to a class decreased from 0.317 to 6.5 \times 10^{-4}, which was desirable.

After the training process of the neural network had been successfully completed, the scoring functions, for a future use of the already trained neural network, had the following form (Figure 4):

- For the hidden layer, the functions can be seen in Equations (24)–(28):

\[ H_1 = 1.32 \times I_1 - 0.2 \times I_2 - 0.02 \times I_3 + 0.56 \times I_4 + 0.65 \times I_5 - 0.78 \times I_6 + 0.57 \times I_7 + 0.58 \times I_8 \]  

\[ H_2 = -0.36 \times I_1 - 0.33 \times I_2 - 1.39 \times I_3 + 1.45 \times I_4 - 0.7 \times I_5 + 1.99 \times I_6 + 6.25 \times I_7 + 0.41 \times I_8 \]
\[ H_3 = 0.03 \times I_1 + 0.19 \times I_2 + 0.12 \times I_3 + 0.14 \times I_4 + 0.15 \times I_5 + 0.15 \times I_6 + 0.36 \times I_7 - 0.08 \times I_8 \] (26)

\[ H_4 = -2.57 \times I_1 + 1.65 \times I_2 - 1.16 \times I_3 - 4.34 \times I_4 - 0.06 \times I_5 + 1.5 \times I_6 + 5.7 \times I_7 - 0.28 \times I_8 \] (27)

\[ H_5 = -2.38 \times I_1 + 2.35 \times I_2 + 1.04 \times I_3 - 3.71 \times I_4 + 0.12 \times I_5 - 0.86 \times I_6 - 0.64 \times I_7 - 0.24 \times I_8 \] (28)

Figure 2. Neural network before training.

Figure 3. Evolution of the average error of training and validation of the neural network.
- For the output layer, Equations (29)–(31):

\[
P_{\text{Class 1}} = -0.98 \times H1 + 7.39 \times H2 + 2.96 \times H3 + 6.74 \times H4 + 0.53 \times H5 \tag{29}
\]

\[
P_{\text{Class 2}} = 2.55 \times H1 + 1.38 \times H2 + 1.46 \times H3 - 7.56 \times H4 - 5.3 \times H5 \tag{30}
\]

\[
P_{\text{Class 3}} = 0.82 \times H1 - 7.64 \times H2 + 1.91 \times H3 + 0.61 \times H4 + 5.37 \times H5 \tag{31}
\]

- The activation thresholds for the two layers had the following values:
  - Hidden layer: \(-1.98, 1.7, -2.02, 2.2, 1.38\);
  - Output layer: \(-4.82, -2.86, -3.31\).

![Neural network after the training process.](image-url)

**Figure 4.** Neural network after the training process.
5. Discussion

After the neural network was successfully trained, the classification resulting from the discriminant analysis was improved so that, from the test sample of 98 companies (30% of all companies, representing the test set), 3 of them changed. Atu IT SRL migrated from class 1 to class 3, Expres Colet SRL moved from class 3 to class 1, and Baros Trading Solutions SRL migrated from class 3 to class 2.

The first class of companies is composed of small companies in size, mainly with the number of employees up to 11, an average turnover of 11.4 million RON, revenues of 11.7 million RON, average expenses of 9.5 million RON, average share capital of 34,611 RON, average debts up to 1 million RON, an average advance income of 8845 RON and average advance expenses of 15,254 RON.

Class 2 mainly contains medium-sized companies, with an average of 12 employees, an average turnover of 17 million RON, revenues of 17.1 million RON, average expenses of 15.1 million RON, average share capital of 126,447 RON, average debts of 2.4 million RON, an average advance income of 35,628 RON and average advance expenditure of 20,986 RON.

Class 3 is composed of large companies with over 27 employees on average, an average turnover of 23.4 million RON, revenues of 23.6 million RON, average expenses of 23.9 million RON, average share capital of 832,118 RON, average debts of 6.2 million RON, an average advance income of 86,825 RON and average advance expenditure of 416,519 RON.

Next, we analyze Cadeo Trade SRL as a case study, identifying three courses of action ("scenarios") by which the firm can improve its activity (Table 3) to pass it from the class where it was initially classified (class 1) to a higher class (class 2).

Table 3. Scenarios for streamlining the activity for the company Cadeo Trade SRL.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Initial Data</th>
<th>Final Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>I1 = 3.99%; I7 = 38.42%</td>
<td>I1 = 5%; I7 = 47%</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>I4 = 71.07%</td>
<td>I4 = 40%</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>I5 = 5.69%; I8 = 2.35%; I7 = 38.42%</td>
<td>I5 = 0%; I8 = 0%; I7 = 45%</td>
</tr>
</tbody>
</table>

Scenario 1 involves increasing the rate of return (I1) from 3.99% to 5% and the financial return on equity from 38.42% to 47%. In this scenario, the main indicator in the balance sheet that needs to be changed in a positive way is only the profit. Given that profit is the difference between income and expenses, there are several possible actions that the firm can take: keeping expenses at the same level and increasing income, or decreasing expenses and keeping income at the same level. Such actions would require the company’s management to revise policies of the commercial, transport and logistics departments. For example, the following measures can be taken: the reorganization of human resources in the logistics department, the adoption of strategies that involve outsourcing transport and logistics flows by taking over services from an independent integrator, and forecasting logistics flows so that storage space can be adapted and used as efficiently as possible. Especially in light of the current digital transformation, companies cannot neglect the adoption of software such as Customer Relationship Management (CRM), which allows for remote work, automates logistics flows and provides forecast reports with minimal errors.

Scenario 2 focuses on lowering the financial solvency ratio (I4) from 71.07% to 40%. The financial solvency ratio expresses the degree of coverage of the medium- and long-term payment obligations, including the obligations to pay shareholders from their own capital, consisting of paid-in capital and other constituted funds. For a company, the optimal value of this indicator is between 40% and 60%, any deviation from this interval is an imbalance.

Scenario 3 proposes the elimination of debt in order to nullify the indicators regarding the debt rate (I5) and the debt recovery period (I8) and to increase the financial profitability of its own capital (I7) from 38.42% to 45%. Indicators I5 and I8 can have a value of zero.
only if the value of the receivables is zero, so the company must collect all blocked financial resources from third parties. It is recommended to recover the claims amicably because, if lawsuits are used in court, they involve additional costs, which affect the other indicators in the balance sheet. Immediate recovery of receivables leads in the short term to an increase in profit, thus implicitly increasing the value of indicator I7.

The above scenarios represent just some of the possible courses of action that a firm can pursue, based on the results of the previously trained neural network. Of course, at the theoretical level, there can be many other possible strategies, but companies must take care to choose the best options based on the economic reality that they face, the needs of the company at a given time and the assumed mission of the company.

In order to revitalize the activity of some companies and increase their performance in the global economy, managers can also recruit qualified staff from other countries, which has direct consequences in the medium and long term. Such recruitment efforts may impact the labor market and employment rate, resulting in higher costs for economic agents who recruit staff, which are passed on to the consumer and create conditions for inflationary growth. There are studies that present whether the jobs created by the development of e-commerce exceed the jobs lost as a result of the adoption of technologies, by studying the process in 28 European countries during two crises: the financial crisis of 2008 and the pandemic of 2020 [17,50]. Other comprehensive research covers a period of 17 years, from 2003 to 2020, and analyzes the use of e-commerce and its impact on GDP within the EU Member States [51]. On the other hand, a more global strategy could benefit other countries because foreign economic agents can enter into partnerships with economic agents from companies classified as high-performing in order to sell their products on the Romanian markets, thus generating positive changes in the economy of the countries where the sellers come from.

This study has implications for the academic field as well, as it can be a starting point for courses dedicated to e-business decision making and for courses involving the use of data mining techniques for extracting hidden information from data. This study can also help forge a partnership between educational institutions that seek to sell courses, books or other promotional materials online with companies that are already in the market, as this study provides an overview of the situation of e-commerce companies in Romania.

6. Conclusions

During the COVID-19 pandemic, the demand for consumer goods and products was met mainly through e-commerce [52]. Companies adapted quickly to the new economic conditions by redesigning internal flows and optimizing them for a new economic approach that emphasizes online presence [53]. As the business world moves toward a more digital approach (digital marketing, digital advertising and e-commerce), it is only natural that the labor market follows the same trend. Employees, therefore, need to develop new skills to make themselves more attractive to future employers [54].

In summary, all objectives and research questions have been addressed. From the balance sheets, we selected and calculated the indicators that characterize the activity of a company working in e-commerce. Based on these indicators, we performed an efficient classification of the companies using advanced data mining techniques, and we identified three clusters, as follows: Class 1 comprises companies that adopted an investment policy that allowed them both to survive and to meet their customers’ needs efficiently. Companies in Classes 2 and 3 manifest high levels of risk aversion, along with a conservative attitude toward business. These companies require fundamental restructuring and reconfiguration of their business model to be in line with the changes brought on by internal and external factors of their organization. Further, based on the classification, we created three scenarios in which a company in our sample can transition from a low-performance class to a high-performance one.

This study does have some limitations, however; not all indicators that would characterize the situation of a company as a whole are taken into account, but only the one
considered by the authors to be important. There are also other classification methods, such as the k-means algorithm, multiple regression or evolutionary algorithms, that may offer a different perspective on the classification of firms, but these can be considered for future research. A possible improvement of this study is to refine the classification achieved through the neural network by applying genetic algorithms, with the main goal of minimizing further error.


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**Conflicts of Interest:** The authors declare no conflict of interest.

**Appendix A. The Classification of Companies Resulting from Cluster Analysis**

<table>
<thead>
<tr>
<th>Class</th>
<th>Company</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>Company</td>
</tr>
<tr>
<td>-------</td>
<td>---------</td>
</tr>
</tbody>
</table>
Appendix B. Migration of Companies following the Application of Discriminant Analysis

<table>
<thead>
<tr>
<th>Company</th>
<th>From Class</th>
<th>To Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Olx Online Services SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Mobiu Distribution SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>SpyShop SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Euro Unelte Trading SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Promerco Import Export SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>24 Evoness SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Komoder Interactive SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Dasha Online SRL</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Librarie.net SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Globus Transport SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Expres Colet SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Atu IT SRL</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Zaniat Com SRL</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Agromir Store SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Conti SRL</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Flip Technologies SRL</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Fire Logistics SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Shopper Kingdom SRL</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Andonet Total SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Ishtar Internet Group SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Doctor Swiss SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Mr AMZ SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Evora Blue SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Rufy Roof Engineering SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Z-Online International Marketing SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Optgroup SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>I Conceptual Media SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Stuparul Punct Ro SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Direct Home Services Distribution SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>La Domiciliu Best Shopping SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>RD Oils Distribution SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Martin Corturi Evenimente SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Zoom Digital SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Mebelissimo SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>M&amp;K Outsourcing International SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Securo Slim SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>United Gold and Art Distribution SRL</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>Krasscom Trading SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Hidrostyle SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Cupon Link SRL</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>Gringo Shop SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Gardenium House Design SRL</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Corner Solutions SRL</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Mobigarden SRL</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>PRO GSM SRL</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>Aer Express Technology SRL</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

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