



Article

Evaluation Model for Determining the Level of E-Commerce Development in Romania Within the European Context, Using Advanced Data Mining and Artificial Intelligence (AI) Techniques

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Abstract

In recent years, the e-commerce sector has undergone continuous adaptation to both consumer needs and the economic context. This adaptation is driven by technological advances and the development of new software products. The present study aimed at achieving two primary objectives. First, it sought to assess the current state of e-commerce development in Romania within the broader European context. Second, it identified the use of AI-driven automation as a potential strategy for improving e-commerce in the country. To this end, e-commerce indicators were extracted from the questionnaire “ICT Usage and E-commerce in Enterprises,” which was conducted by National Statistical Authorities and centralized at the level of the European Commission. The questionnaire was carried out on a sample of 157,000 companies. A range of sophisticated techniques were employed to these indicators with the aim of reducing their dimensionality and classification error, with the objective of achieving a robust classification with the lowest possible error rate. We then proceeded to analyze Romania’s position in this ranking and, given the structure of e-commerce companies in the country, proposed the use of AI-driven automation as a potential strategy for enhancing activity in this sector.

Keywords: e-commerce; data analysis; Romania; automation; EDI



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1. Introduction

E-commerce has become an integral component of modern business operations and a fundamental aspect of consumers’ daily lives. Estimates indicate that e-commerce reached a valuation of 27 trillion dollars on a global scale at one point [1]. This is equivalent to one-quarter of the global GDP [2]. It is evident that global trade, encompassing both business-to-business (B2B) and business-to-consumer (B2C) transactions, is undergoing a period of significant transformation, driven by a series of evolving trends.

The initial phenomenon under consideration is the process of reglobalization, which is characterized by the transition from a single, interconnected web of trade to a multi-hub model [3,4].

Secondly, the term “servicification” is employed to denote the ongoing trend of accelerated growth in global services exports, which continue to increase at a rate that exceeds that

of goods exports. It is noteworthy that digitally delivered services constitute a substantial proportion of these exports, accounting for approximately 56% of the total worldwide services exports. However, in least developed nations, the share of digitally delivered services is less than 20% [5,6].

Finally, the substantial growth in artificial intelligence (AI) infrastructure has led to an increased demand for critical materials such as copper, aluminum, and cooling systems. This heightened demand has the potential to provide significant economic benefits, including the optimization of logistics routes for companies operating in the field.

On a global scale, the pandemic has been identified as the primary factor contributing to the accelerated growth of e-commerce. Its long-term impact is anticipated to be significant, as this transition is perceived as a fundamental step in the ongoing digital transformation of human society [7].

The global pandemic has precipitated an accelerated shift towards e-commerce, a transformation that has persisted in shaping the dynamics of business and consumer behavior within this digital economy.

1. The implications of artificial intelligence (AI) for business are extensive. Technology has profound effects at the employee level, on the supply chain [8], automation and efficiency [9], and the consumer journey, from product discovery to post-sale support [10,11].
2. Extended reality, otherwise known as augmented reality (AR), shows greater promise through smartphone and wearable integration. In contrast, virtual reality (VR) suffers from an adoption bottleneck due to hardware and mobility constraints [12].
3. Mobile is the preferred e-commerce channel, with almost 80% of shopping occurring through a phone [13].
4. Social commerce and live commerce facilitate consumer targeting and increase user engagement, transforming a once solitary ordeal into a dynamic social experience [14,15].
5. BNPL (buy now, pay later) has emerged as a prominent payment option, gaining traction both online and at physical retail locations. Research has demonstrated that BNPL has the potential to augment online spending by 6–10% and to elevate the average order value by 85% [16,17].

The United Nations has identified a significant disparity in the utilization of digital services among various global economic categories, namely developed, emerging, and least developed economies [5]. A parallel can be drawn between this observed digital discrepancy on a global scale and within the European Union members, as discussed by the authors. The European Union has implemented a series of initiatives aimed at addressing its declining share of the ICT global market, achieving Digital Sovereignty, and maintaining worldwide competitiveness. The Digital Decade Program [18] and the 2030 Digital Compass [19] underscore the pivotal function of e-commerce within the European Union, providing a framework for its advancement and integration.

A paradox can be observed in Romania. Despite the robust broadband infrastructure and the noteworthy 9.2% compound annual growth rate (CAGR) of e-commerce in the 2020–2025 period, the e-commerce adoption rate among small and medium-sized enterprises (SMEs) remains at 12% [20], which is among the lowest in the European Economic Area (EEA) [21]. A study revealed that 74.3% of Romanians had made at least one online purchase in 2025 [22]. Despite this, the B2B sector exhibits low levels of digital transformation, with minimal process automation [23]. Although some definitions exclude services, the EU survey indicates that e-commerce refers to the purchase or sale of goods or services through electronic transactions conducted via the internet [24,25].

The primary objectives of this study are multifaceted. Firstly, an examination will be conducted of the current state of e-commerce development in Romania. Secondly, the study

will propose and implement a plan for the advancement of e-commerce in the country, with a focus on the utilization of Artificial Intelligence (AI) tools.

The specific research questions to be addressed in this study are listed as follows:

RQ1. What is Romania's position in the European Union in terms of e-commerce?

RQ2. Can the level of e-commerce in Romania be improved using automation and AI-driven automation software?

The novelty of the study lies in the fact that, to the authors' knowledge, no other study has been conducted in the field of e-commerce in Romania that uses advanced data classification techniques and combines AI elements as a proposal for improving activity in this field.

This research is of significant theoretical importance, as it expands the comparative literature on e-commerce within the European Union by establishing a framework for the systematic classification of member states based on a set of relevant indicators. Rather than focusing on Romania in isolation, the study employs a multivariate comparison system with other European Union (EU) countries, thereby facilitating a more detailed understanding of digital maturity profiles and relative positioning within the Digital Single Market.

The dissemination of this research coincides with a pivotal moment in the EU's Digital Decade and the formulation of national digital action plans, which underscore the imperative for meticulous monitoring and evaluation of digital performance at the national level. Furthermore, the accelerated development of AI solutions and automation has led to a pronounced urgency in enhancing e-commerce in Romania through automation and artificial intelligence. This issue is of critical importance not only for the Romanian economy but also for the broader Central and Eastern European region.

In order to provide a comprehensive overview of the study's findings, the research paper is structured as follows: Section 2 presents a review of the existing literature on the subject. Section 3 details the materials and methods employed in conducting the study. Section 4 presents the results of the study. Section 5 offers a discussion of the results. Section 6 presents the study's conclusions, as well as the appendices and references cited.

2. Literature Review

2.1. E-Commerce in the European Union: Evolution and Determinants

Early and recent studies emphasize that e-commerce growth is inseparable from broader processes of digital transformation, innovation diffusion, and institutional development [26]. From a macroeconomic perspective, e-commerce is increasingly associated with productivity gains and structural economic change in the European Union [27].

Several empirical studies suggest a significant and sustained increase in e-commerce activities across EU member states, particularly after 2019 [28]. Multiple studies indicate that improvements in broadband infrastructure, increased internet penetration, enterprise-level digitalization, and a growing orientation toward sustainable consumption appear to have contributed significantly to this growth [29,30]. Panel data and cross-national analyses further demonstrate that the development of e-commerce is positively associated with GDP per capita, educational attainment, and digital skills, suggesting that technological availability alone is insufficient without complementary human and institutional capital [31].

Mobile commerce has become a major accelerator of e-commerce growth in the EU [28,32]. Research focusing on generational and regional patterns highlights the growing importance of mobile devices as the primary interface for online transactions, particularly in regions with high rates of mobile technology adoption [33].

The COVID-19 pandemic is widely considered a structural break in the evolution of e-commerce within the European Union. Numerous studies document a rapid and forced

shift toward online channels during lockdown periods, leading to unprecedented increases in online sales and user adoption rates [34]. Importantly, post-pandemic analyses suggest that these changes were not temporary; rather, they accelerated pre-existing trends and permanently expanded the base of online consumers and digitally active firms [28,31].

Despite the overall growth, the literature consistently points to substantial differences across EU member states. Western and Northern European countries generally show high levels of e-commerce penetration and well-developed markets, whereas Central and Eastern European economies start from lower levels but are experiencing faster growth [29]. Existing analyses show that differences in firms' levels of digital maturity, together with the institutional context, play a significant role in shaping national disparities in e-commerce development [26,33].

2.2. E-Commerce in Romania: Evolution and Systemic Constraints

Within the European context, Romania has increasingly attracted academic attention due to the rapid growth of e-commerce in recent years [35]. The COVID-19 pandemic further accelerated these dynamics, as consumers and firms in Romania adapted to mobility restrictions and heightened safety concerns [36]. Comparative analyses based on EU-level indicators consistently place Romania among the lower-performing member states in terms of effective digital use in business, despite the country's relatively strong internet infrastructure [37,38]. This apparent paradox between infrastructure quality and actual levels of use has been repeatedly highlighted in the academic literature [38,39].

Various studies identify structural barriers that constrain the development of e-commerce in Romania. These include limited digital skills, low levels of trust in online transactions, and the uneven adoption of advanced digital technologies by firms, particularly small and medium-sized enterprises [40]. The central role of trust, perceived reliability, and usability in sustaining online engagement is emphasized in some research with focus on e-commerce satisfaction and service quality [41,42].

Romania's digital trajectory is also influenced by institutional and behavioral factors, there are studies focusing on digital public services and e-government adoption point to persistent gaps in institutional trust and digital inclusion, which in turn indirectly shape the adoption of e-commerce in the private sector [43,44].

2.3. E-Commerce Dynamics in B2C and B2B Segments

The advantages for both businesses and consumers have driven the ongoing development of e-commerce, particularly in recent years [45]. E-commerce plays a vital role in B2C, having established itself as the right instrument [46] to fulfill ever-increasing expectations from consumers, in both product quality and service level [47]. Despite e-commerce's low consumer adoption before the COVID-19 pandemic [48], the channel's variety and convenience subsequently drove increased interest in online purchases across diverse categories [49]. A very important aspect, from consumers' point of view, is that the e-commerce business model reduces the number of intermediary links in product sales [50], thus increasing the competitiveness of prices and offering a wide range of producers to choose from [51]. Recent studies show that digital interactive presence in e-commerce significantly enhances consumers' sense of social presence, which in turn increases their purchase intention [52]. This evolution has transformed firms' operational and sales models by reshaping traditional business–consumer relationships and enabling direct interaction through digital platforms [53].

While early research on e-commerce focused predominantly on B2C transactions, more recent literature increasingly recognizes the strategic importance of B2B e-commerce as a driver of productivity and competitiveness [54]. Several research studies at the European

Union level demonstrate that innovation activity is closely correlated with performance across the B2C, B2B, and B2G segments, thereby highlighting the systemic nature of digital commerce [26,55].

Previous studies indicate that the adoption of B2B e-commerce is significantly influenced by firm size, sectoral specialization, and digital capabilities [54,56]. Large enterprises and firms operating in knowledge-intensive sectors tend to adopt B2B solutions at a faster pace, whereas small and medium-sized enterprises face persistent barriers related to costs, interoperability, and organizational complexity [57]. Comparative analyses between countries, suggest that disparities in B2B adoption appear to account for a substantial share of the differences in overall e-commerce performance across EU member states [58–60].

In Romania, the B2B e-commerce segment remains underdeveloped relative to European standards [61–63]. Empirical evidence points to the limited use of automated procurement systems, electronic data interchange, and integrated digital supply chain solutions, particularly among small and medium-sized enterprises [64]. These limitations constrain productivity growth and reduce firms' ability to integrate into European digital value chains [65–67].

2.4. E-Commerce and Technology: Artificial Intelligence and Automation

Technological progress represents a central theme in contemporary research on e-commerce [68], with recent discussions centering on artificial intelligence [69–71], machine learning [72], and neuronal networks [73–75]. These tools are increasingly regarded as key enabling factors for efficiency, personalization, and decision support in digital commercial environments. At the macroeconomic level, studies examining the diffusion of artificial intelligence emphasize its contribution to economic growth and competitiveness, including within emerging economies of the European Union [76].

At the applied level, artificial intelligence offers multiple use cases in e-commerce, ranging from demand forecasting and customer segmentation to recommendation systems, dynamic pricing [77,78], and fraud detection [79]. Some studies suggest that machine learning and neural network-based models outperform traditional statistical methods in prediction and classification tasks, particularly when processing large volumes of firm-level data [80]. Research focused on the Romanian context suggests potential performance benefits from adopting artificial intelligence in e-commerce, while also highlighting significant implementation barriers related to skills, organizational readiness, and limited access to financial resources; the latter remains a major obstacle to technology adoption [28,81–83].

Considering the above, workflow automation technologies are increasingly discussed as practical tools for improving operational efficiency, particularly in economies dominated by small and medium-sized enterprises [84]. This approach is particularly relevant for Romania, where the economic structure, dominated by small and medium-sized enterprises, often faces constraints related to the lack of resources required for the large-scale adoption of enterprise resource management software [85–87].

2.5. Research Gap

The accelerated development of e-commerce in the European Union is reflected in the growing attention it receives in academic literature, which points not only to this increased interest but also to a persistent structural heterogeneity across member states, driven by differences in digital maturity, innovation capacity, and the institutional environment [26,31]. Romania fits into this pattern, combining a rapid growth dynamic with significant gaps compared to the EU average in terms of firm-level e-commerce adoption, especially in the B2B segment and in the use of advanced digital technologies [36].

Although many studies use EU-level indicators and econometric models to examine the determinants of e-commerce, they rely mainly on descriptive or regression-based approaches, which provide only a limited view of the multidimensional structure of e-commerce development and of Romania’s relative position within the European Union [30,31]. In addition, the literature on B2B e-commerce stresses the critical role of innovation and digital capabilities in firm performance, yet studies focused on Romania remain fragmented and only rarely make use of comparable European-level data to classify and assess structural differences [26,57].

At the same time, more recent research highlights the potential of artificial intelligence and automation in improving the efficiency and overall performance of e-commerce [76]. However, these technologies are still addressed mainly at a conceptual or microeconomic level [64–67,70]. There is limited evidence in the existing literature on the integration of advanced data analysis techniques and AI-based solutions as operational tools for assessing and improving the level of e-commerce development at the national level, particularly in SME-dominated economies such as Romania [34,58,61]. This research gap provides the motivation for the present study and underpins the proposed research objectives and questions.

3. Materials and Methods

The indicators used in the application were derived from the questionnaire conducted in 2024 on “ICT Usage and E-commerce in Enterprises,” which was developed by National Statistical Authorities and centralized at the level of the European Commission [88]. The study was conducted on a sample of 157,000 companies with over 10 employees, out of a total of 1.54 million existing in the European Union (EU). The population from which the sample was drawn has the following structure: The majority (83%) of companies have less than 50 employees, while 14% of companies fall into the medium-sized category with 50 to 250 employees. A mere 3% are classified as large, with over 250 employees [89].

According to the authors, the indicators that best characterize the subject of e-commerce are presented in Table 1. To facilitate a comparative analysis of countries, all indicators were expressed as a percentage of the total achieved at the European Union (EU) level.

Table 1. The indicators used in the application.

Code	Description
I1	Enterprises which use (EDI)-type sales
I2	Enterprises which use web sales only
I3	Enterprises which use both types of e-sales
I4	Enterprises which use EDI-type sales only
I5	Enterprises with the turnover from web sales
I6	Enterprises with the turnover from EDI-type sales
I7	Enterprises with web sales via their own websites or apps
I8	Enterprises with web sales via e-commerce marketplaces
I9	Enterprises with the turnover from own website or apps
I10	Enterprises with the turnover from marketplace
I11	Enterprises with the activity as Business to consumer (B2C)
I12	Enterprises with the activity as Business to business and business to government (B2BG)

The present work uses a methodological framework inspired from recent studies [90–93] that was adapted to the specifics of the researched domain.

To accomplish the objectives proposed in the preceding section, the authors applied the following methodology, broken down into stages (Figure 1):

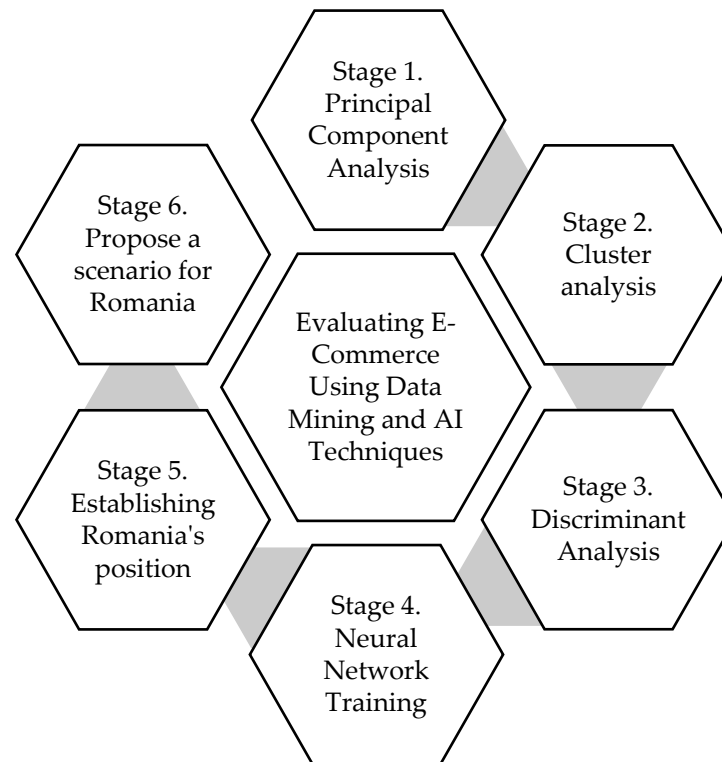


Figure 1. The research methodology applied in the study.

Stage 1. The principal component analysis (PCA) reduces the dimensionality of the indicators while preserving the maximum possible level of information. The objective of this stage is to generate synthetic indicators that will be utilized in subsequent phases of the study.

Stage 2. The second stage of the analysis involved the application of cluster analysis to the indicators resulting from the first stage. This was done in order to produce an initial classification of European Union countries in terms of the selected indicators.

Stage 3. To minimize classification error and achieve results that closely align with reality, discriminant analysis was used on the results from stage 2.

Stage 4. A classification neural network was trained with the intention of reducing the classification error resulting from stage 3 and in order to obtain a classification of EU countries based on all indicators.

Stage 5. Romania's current position in the ranking was evaluated based on outputs from stage 4.

Stage 6. Authors propose the utilization of automation elements that are specifically designed for artificial intelligence to enhance Romania's performance in the given context.

Principal component analysis (PCA) is a dimensionality reduction technique that constructs linear combinations of the initial variables, x_i , thereby allowing the information they contain to be expressed in an identical number of other variables, z_i , which are known as principal components. These components have decreasingly distributed variance and are uncorrelated with one another. These two fundamental characteristics of principal components enable the elimination of the information redundancy that is characteristic of correlated variables. This facilitates the transition to a different space of smaller-sized variables while experiencing only negligible loss of information, a key property of principal component analysis [94], that is used in other empirical studies [87]. Accordingly, the novel

set of variables, devoid of redundancies, facilitates a more lucid depiction of each variable’s contribution to the aggregate variability.

The term of variance is generally defined as a measure of the amount of information present in a variable. Therefore, it follows that the first constructed principal component, which is the most informative, will have the highest root mean square deviation, and the last constructed principal component, which is the lowest, will have the lowest variance.

Mathematically, if we consider a vector of n original variables $(x_1, x_2, \dots, x_n)'$, PCA consists in identifying a linear variance maximizing transformation by applying which it is possible to move to a vector of p principal components $(z_1, z_2, \dots, z_p)'$ ($p < n$) which retains a satisfactorily large amount of the original variability.

The principal components can be written:

$$\begin{aligned} z_1 &= a_{11} \cdot x_1 + a_{21} \cdot x_2 + \dots + a_{n1} \cdot x_n \\ z_2 &= a_{12} \cdot x_1 + a_{22} \cdot x_2 + \dots + a_{n2} \cdot x_n \\ &\vdots \\ z_n &= a_{1n} \cdot x_1 + a_{2n} \cdot x_2 + \dots + a_{nn} \cdot x_n \end{aligned} \tag{1}$$

In matrix terms, these relationships can be translated into:

$$\begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{pmatrix} = \begin{pmatrix} a_{11} & a_{21} & \dots & a_{n1} \\ a_{12} & a_{22} & \dots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{nn} \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} \tag{2}$$

which can be summarized as:

$$z = A' \cdot x \tag{3}$$

where $z = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{pmatrix}$, $x = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}$, $A' = \begin{pmatrix} a_{11} & a_{21} & \dots & a_{n1} \\ a_{12} & a_{22} & \dots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{nn} \end{pmatrix}$, $A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix}$.

In the geometric approach, the definition of principal components aims to identify a subspace on which the points are best represented. In the algebraic approach, the identification of principal components starts from the formulation of the problem of maximizing their variance. If the covariance matrix of the initial variables is Σ , then the variance of the principal component z_i , can be written as:

$$\text{var}(z_i) = \text{var}(a^{(i)'} \cdot x) = a^{(i)'} \cdot \Sigma \cdot a^{(i)} \tag{4}$$

where $a^{(i)} = \begin{pmatrix} a_{1i} \\ a_{2i} \\ \vdots \\ a_{ni} \end{pmatrix}$ is the i -th column vector of the matrix A .

So, to build z_i , it is necessary to identify the vector $a^{(i)}$ which ensures a maximum level of variability.

- Since the multiplication of $a^{(i)}$ with a scalar would lead to a new maximum level, it is necessary to impose a condition for identifying:

$$a^{(i)'} \cdot a^{(i)} = 1 \tag{5}$$

➤ However, this does not completely solve the problem, as the main component is still not uniquely identified from a sign perspective:

$$(-a^{(i)'}) \cdot (-a^{(i)}) = a^{(i)'} \cdot a^{(i)} = 1$$

Imposing this condition actually involves taking into account vectors $a^{(i)}$ of unit length—with a norm equal to 1.

$$\|a^{(i)}\| = \sqrt{a_{1i}^2 + a_{2i}^2 + \dots + a_{ni}^2} \tag{6}$$

The maximization problem can be described as:

$$\begin{cases} [\max]_{\alpha} \text{var}(z_i) = a^{(i)'} \cdot \Sigma \cdot a^{(i)} \\ a^{(i)'} \cdot a^{(i)} = 1 \end{cases} \tag{7}$$

To solve the problem, the method of Lagrange multiplier can be applied:

$$L(a^{(i)}; \lambda_i) = a^{(i)'} \cdot \Sigma \cdot a^{(i)} - \lambda_i \cdot (a^{(i)'} \cdot a^{(i)} - 1) \tag{8}$$

In addition, the utilization of the principal components as indicators will facilitate the implementation of cluster analysis [60,95] for the preliminary classification of the countries under consideration. The number of classes will be determined by sectioning the resulting dendrogram.

The two fundamental components encompassed by the objective of discriminant analysis are as follows. Firstly, this analysis is employed for the construction of a discriminant space, and secondly, it facilitates the formulation of a distribution rule for the individuals, which can serve as a reference in subsequent applications [96]. The discriminant space is the graphical representation of the discrimination functions. The discrimination function can be conceptualized in the following manner: it can be represented as a linear combination of explanatory variables (7 principal components from previously). To determine the discrimination functions for each class Equations (9) and (10) were used.

$$Sk1_i = \sum_{j=1}^7 \lambda_j \cdot Ck1_j + ak1, \forall i = \overline{1, 27}, k = 1, 2, 3 \tag{9}$$

$$Sk0_i = \sum_{j=1}^7 \lambda_j \cdot Ck0_j + ak0, \forall i = \overline{1, 27}, k = 1, 2, 3 \tag{10}$$

where:

$Sk1_i$ represents the probability (score) of country i to be in class k ;

$Sk0_i$ represents the probability (score) of country i not to be in class k ;

λ_j represents the value of the principal component for country $i, j = 1 \dots 7$;

$Ck1_j$ represents the coefficients of the function which calculates the probability of belonging to a country in class $k (k = 1, 2, 3)$;

$Ck0_j$ represents the function coefficients which calculate the probability that a country does not belong to class $k (k = 1, 2, 3)$;

$ak1$ and $ak0$ are constants related to linear functions that calculate probabilities.

i represents the number of the country.

Machine learning is widely used to improve prediction and enhance classification accuracy in complex systems [80]. In this regard, to enhance the accuracy of classification and minimize error, a neural classification network will be trained [73–75]. The proposed

neural network will comprise three layers. The input layer will consist of seven neurons, with each neuron corresponding to a principal component. The intermediate layer will contain a number of neurons, determined empirically. The final layer will consist of three neurons, with each neuron corresponding to a single country class. The training algorithm will be incremental propagation.

Next, we will present the empirical results found after applying the methodology previously outlined.

4. Results

The objective of this study is to examine the current state of e-commerce development in the European Union (EU), identify Romania’s position in this context, and explore strategies to revitalize its e-commerce sector. The initial step in our methodology involves the implementation of PCA to reduce dimensionality and identify synthetic indicators. This will increase the calculation speed for future processing. The software utilized for the implementation of PCA on the initial data matrix is SAS Enterprise Guide, version 8.5.

Table 2 presents the correlation matrix of the indicators in the analysis and provides important information on whether to use PCA. Consequently, in instances where there is a correlation among indicators, the utilization of this technique is substantiated.

Table 2. The matrix of correlations between indicators.

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
I1	1	0.283513	0.942468	0.955666	0.380563	0.789949	0.368392	-0.56668	0.485533	-0.20513	0.172547	0.419259
I2	0.283513	1	0.415469	0.140348	0.425927	-0.06184	-0.29387	0.072533	0.239704	0.371089	0.355982	0.219228
I3	0.942468	0.415469	1	0.802251	0.443996	0.635462	0.34006	-0.55982	0.525385	-0.15698	0.304138	0.385528
I4	0.955666	0.140348	0.802251	1	0.288535	0.85097	0.358346	-0.51888	0.404302	-0.22806	0.040246	0.409137
I5	0.380563	0.425927	0.443996	0.288535	1	0.204497	0.056958	-0.15663	0.86531	0.390932	0.681994	0.815623
I6	0.789949	-0.06184	0.635462	0.85097	0.204497	1	0.345843	-0.40978	0.350853	-0.28108	-0.11818	0.44547
I7	0.368392	-0.29387	0.34006	0.358346	0.056958	0.345843	1	-0.85149	0.229682	-0.58546	0.026778	-0.01114
I8	-0.56668	0.072533	-0.55982	-0.51888	-0.15663	-0.40978	-0.85149	1	-0.30302	0.599103	0.001918	-0.11032
I9	0.485533	0.239704	0.525385	0.404302	0.86531	0.350853	0.229682	-0.30302	1	0.067854	0.713921	0.806019
I10	-0.20513	0.371089	-0.15698	-0.22806	0.390932	-0.28108	-0.58546	0.599103	0.067854	1	0.377045	0.291678
I11	0.172547	0.355982	0.304138	0.040246	0.681994	-0.11818	0.026778	0.001918	0.713921	0.377045	1	0.318838
I12	0.419259	0.219228	0.385528	0.409137	0.815623	0.44547	-0.01114	-0.11032	0.806019	0.291678	0.318838	1

Table 2 presents the following correlations: A positive correlation was observed between I1 and I3, I4, and I6, while a negative correlation was identified between I1 and I8. Furthermore, I3 demonstrated a positive association with I4, I6, and I9, as well as a negative correlation with I8. Additionally, I4 showed a positive link with I6 and a negative correlation with I8. I5 was found to be positively associated with I9, I11, and I12. On the other hand, I7 exhibited a negative relationship with I8. Finally, I8 demonstrated a positive correlation with I10. I9 was found to be positively correlated with I11 and I12. Given that there are a multitude of observed intercorrelations, it appears reasonable and justifiable to proceed with the further application of PCA and, consequently, the subsequent utilization of the resulting synthetic indicators (main components) in future analyses.

As illustrated in Table 3, the eigenvalues of the correlation matrix are calculated, thereby determining the amount of information recovered by each of them. Consequently, if the initial seven principal components are selected, the information recovered from the point cloud is 98.01% of the total. This assertion is further substantiated by the graphical representation displayed in Figure 2.

Consequently, the dimensionality will be reduced to seven principal components, which will account for 98.01% of the information contained within the point cloud. Each principal component is defined as a linear combination of the initial indicators, with the weights assigned by the coordinates of the eigenvectors corresponding to the eigenvalues of

the correlation matrix between indicators. These weights are derived from the Eigenvectors of the correlation matrix table, as detailed in Appendix A. The eigenvectors delineate the directions of the principal components, while the eigenvalues signify the magnitude of the variation in these directions.

Table 3. Eigenvalues of the correlation matrix.

Eigenvalue	Difference	Proportion	Cumulative
5.21	2.08	0.43	0.4339
3.12	1.74	0.26	0.6941
1.38	0.36	0.12	0.8091
1.02	0.53	0.08	0.8940
0.49	0.11	0.04	0.9346
0.38	0.21	0.03	0.9660
0.17	0.07	0.03	0.9801
0.10	0.03	0.01	0.9887
0.07	0.01	0.01	0.9946
0.06	0.06	0.00	1.0000
0.00	0.00	0.00	1.0000
0.00		0.00	1.0000

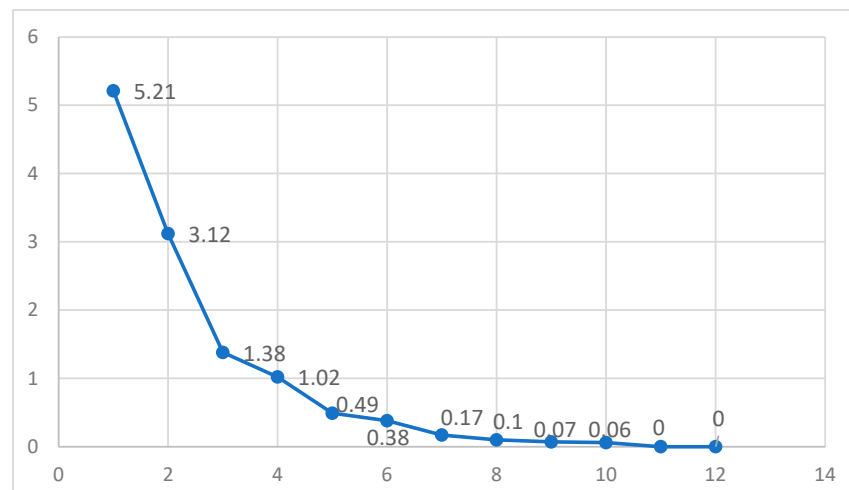


Figure 2. Scree Plot of the eigenvalues.

The initial data are projected onto the new axes represented by the principal components, thereby obtaining the principal component scores (score matrix).

Table 4 presents the values of the new synthetic indicators for each EU country. These will be integrated into subsequent processing. The next step in the methodology is to perform an initial classification of countries using cluster analysis. The implementation of this processing was executed in SAS Enterprise Guide, version 8.5, employing Ward’s classification method.

Table 4. The values of the new synthetic indicators for each EU country (score matrix).

Country	PRIN1	PRIN2	PRIN3	PRIN4	PRIN5	PRIN6	PRIN7
Austria	−0.1163	−0.19212	0.036081	−0.53727	−0.67008	−0.6695	2.017222
Belgium	1.764432	−0.11356	0.390143	1.050361	−1.03444	−0.06757	−1.20122
Bulgaria	−1.52771	−0.30002	−0.12869	0.597993	−0.61814	1.003419	−1.83334
Croatia	0.64325	0.056786	−0.10135	−0.03982	−1.20623	0.506039	−0.856
Cyprus	−0.53219	1.772927	−1.40218	−0.14749	1.049419	−1.44983	0.11811
Czechia	0.52845	0.069247	−0.73901	0.988059	0.113295	0.179976	1.194441
Denmark	1.622309	−1.47973	1.895693	−0.63604	0.860107	0.165319	0.354003

Table 4. Cont.

Country	PRIN1	PRIN2	PRIN3	PRIN4	PRIN5	PRIN6	PRIN7
Estonia	0.221274	-0.91925	-1.2811	-0.86135	-0.24976	-0.26298	-0.85754
Finland	1.451465	-0.79099	0.57486	0.266694	-0.22056	-0.36328	0.725825
France	-0.94669	-1.41987	-0.38228	-0.19376	-0.3941	0.14014	-0.34829
Germany	-0.26149	-0.22435	0.475214	0.576211	0.909016	-0.35496	0.627761
Greece	-1.36927	0.619607	-0.63149	-0.32002	-0.61251	-1.37655	0.774863
Hungary	0.138589	-0.19957	-0.65288	1.705813	-2.48195	-0.98401	0.502001
Ireland	1.664897	1.782426	-0.86554	-1.02988	0.33201	0.172377	-1.00407
Italy	-0.21498	0.290085	0.014143	0.891378	2.440933	-1.54069	0.184891
Latvia	-0.5834	-0.45174	-0.73767	-0.40402	0.539263	0.162288	-1.79511
Lithuania	-0.63977	3.311069	2.63869	-0.22964	-0.83544	0.716292	-0.42975
Malta	-0.34033	-0.24576	0.104732	-2.05255	-0.58163	0.709594	1.06748
Netherlands	0.549944	0.275258	-0.87558	-0.4494	-0.20178	-0.22822	0.22993
Poland	-1.13109	-0.13257	0.589502	1.179782	0.078744	-1.03542	0.367262
Portugal	-0.35896	-0.18113	0.664137	0.711891	1.89915	2.058094	0.828696
Romania	-0.98133	-0.49784	-0.65253	0.166839	1.081191	0.721084	-1.40792
Serbia	-1.12981	-0.66199	0.219102	-2.1252	-0.66332	0.715644	0.583492
Slovakia	-0.00679	0.284518	-0.85408	2.055851	-0.2828	2.552079	1.093633
Slovenia	-0.7218	-1.043	2.299022	0.229557	-0.14562	-1.47359	-0.98044
Spain	0.374101	0.273132	-0.46545	-1.18261	0.415901	0.443496	0.813749
Sweden	1.903185	0.118443	-0.1315	-0.21138	0.479344	-0.43925	-0.76967

The dendrogram is the result of aggregating the objects, countries in our case, into classes. The closer the cutoff is to zero, the more closely related classes will be formed. Our objective is to select those classes that are as far apart from each other as possible and contain objects that are as similar as possible, as confirmed by the calculation of Euclidean distance. In the scenario where the graph is segmented along an axis, as depicted in Figure 3, the division yields three distinct classifications of countries. The first class consists of the following countries: Belgium, Croatia, Denmark, Ireland, Lithuania, Slovenia, and Sweden. The second class comprises the following countries: Austria, Cyprus, the Czechia, Finland, Germany, Greece, Hungary, Italy, the Netherlands, Poland, Portugal, Slovakia, and Spain. The third class consists of the following countries: Bulgaria, Estonia, France, Latvia, Malta, Romania, and Serbia.

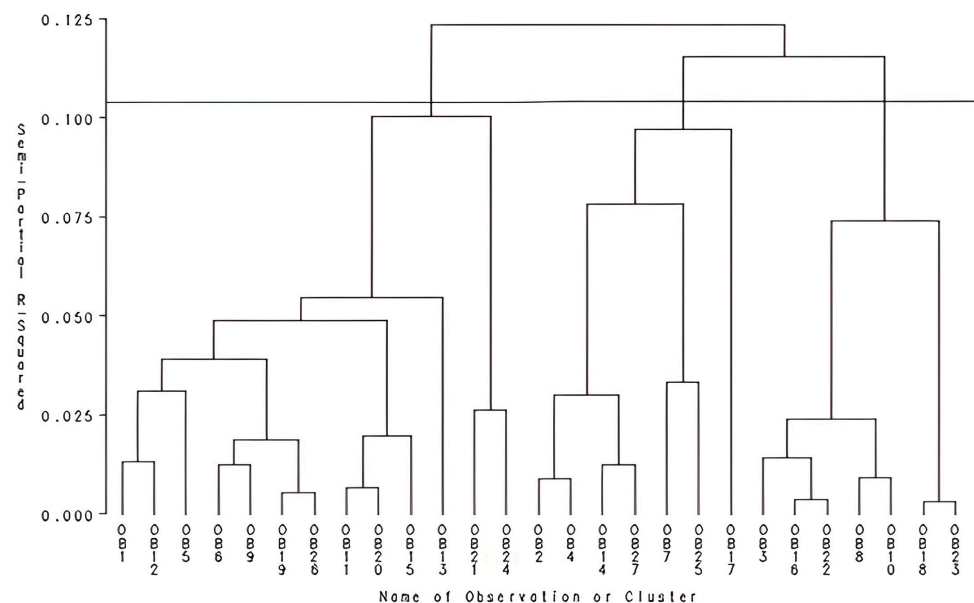


Figure 3. The classification dendrogram.

Given that the classes were determined empirically through sectioning the dendrogram with a straight line, discriminant analysis will be applied to verify the results previously obtained and to correct any errors by minimizing the classification error. Thus, for each class, the discriminant analysis algorithm will be implemented in SAS Enterprise Guide version 8.5, and the equations determining whether a country belongs to that class will be established.

For Class 1, the functions from Equations (11) and (12) are applicable:

- Belonging to the class:

$$\text{PRIN1} \times 4.76 + \text{PRIN2} \times 2.01 + \text{PRIN3} \times 4.68 - 0.66 \times \text{PRIN4} - 1.18 \times \text{PRIN5} - 0.32 \times \text{PRIN6} - 3.73 \times \text{PRIN7} - 6.03; \quad (11)$$

- Non-belonging to the class:

$$-1.67 \times \text{PRIN1} - 0.70 \times \text{PRIN2} - 1.64 \times \text{PRIN3} + \text{PRIN4} \times 0.23 + \text{PRIN5} \times 0.41 + \text{PRIN6} \times 0.11 + \text{PRIN7} \times 1.31 - 0.74; \quad (12)$$

For Class 2, the functions from Equations (13) and (14) are applicable:

- Belonging to the class:

$$-0.52 \times \text{PRIN1} + \text{PRIN2} \times 1.01 - 1.78 \times \text{PRIN3} + 3.12 \times \text{PRIN4} + 1.33 \times \text{PRIN5} - 1.51 \times \text{PRIN6} + 5.16 \times \text{PRIN7} - 3.17; \quad (13)$$

- Non-belonging to the class:

$$0.48 \times \text{PRIN1} - 0.94 \times \text{PRIN2} + 1.65 \times \text{PRIN3} - \text{PRIN4} \times 2.89 - \text{PRIN5} \times 1.23 + \text{PRIN6} \times 1.39 - \text{PRIN7} \times 4.78 - 2.73; \quad (14)$$

For Class 3, the functions from Equations (15) and (16) are applicable:

- Belonging to the class:

$$-4.32 \times \text{PRIN1} - \text{PRIN2} \times 3.67 - \text{PRIN3} \times 2.33 - 3.98 \times \text{PRIN4} - 0.72 \times \text{PRIN5} + 2.60 \times \text{PRIN6} - 3.75 \times \text{PRIN7} - 6.54; \quad (15)$$

- Non-belonging to the class:

$$1.51 \times \text{PRIN1} + 1.28 \times \text{PRIN2} + 0.82 \times \text{PRIN3} + \text{PRIN4} \times 1.39 + \text{PRIN5} \times 0.25 - \text{PRIN6} \times 0.91 + \text{PRIN7} \times 1.31 - 0.80; \quad (16)$$

As a result of applying the discriminant analysis, it can be seen (Appendix B) that Finland has moved from class 2 to class 1, and Slovenia from class 1 to class 3. The new classification of countries is as follows:

- Class 1: Belgium, Croatia, Denmark, Ireland, Lithuania, Sweden, Finland,
- Class 2: Austria, Cyprus, Czechia, Germany, Greece, Hungary, Italy, Netherlands, Poland, Portugal, Slovakia, Spain,
- Class 3: Bulgaria, Estonia, France, Latvia, Malta, Romania, Serbia, Slovenia.

Following this, a neural network classification will be trained to minimize the country grouping error. The network will have three layers: the first layer, which we designate as the input layer, will contain seven neurons, with each neuron corresponding to one of the principal components of the analysis. The second layer will contain five neurons. The third and final layer will consist of the number of country groups that were determined in a previously conducted stage of the analysis. The activation function of the neurons in the intermediate layer will be hyperbolic tangent, and the training algorithm will be incremental backpropagation. The data was divided into the following categories: 40% of the data is allocated for network training, 20% for result validation, and 40% for test data. The training of the neural network was facilitated by the SAS Enterprise Miner software, version 15.2. The activation weights of each neuron in the second layer, as well as the scoring functions, can be found in Appendix C.

The training process comprised 120 epochs (see Figure 4), and beginning with epoch 25, a constant value of training and validation errors is evident, with the classification error decreasing from 1.035 to 0.312. In the aftermath of the training of the neural network,

Serbia's classification was adjusted from Class 3 to Class 2. The revised classification of countries is as follows:

- Class 1: Belgium, Croatia, Denmark, Ireland, Lithuania, Sweden, Finland,
- Class 2: Austria, Cyprus, Czechia, Germany, Greece, Hungary, Italy, Netherlands, Poland, Portugal, Slovakia, Spain, Serbia,
- Class 3: Bulgaria, Estonia, France, Latvia, Malta, Romania, Slovenia.

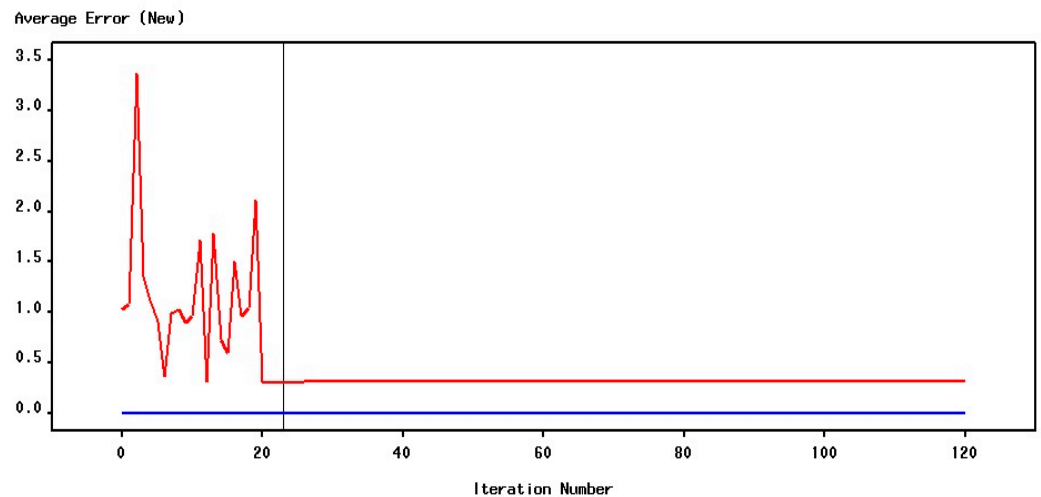


Figure 4. The evolution of training and validation errors of the neural network.

According to the established methodology, the 12 indicators have been consolidated into seven synthetic indicators. Through the implementation of cluster analysis, discriminant analysis, and neural network training, we have successfully reduced classification errors. This has culminated in a robust classification of EU countries.

This research paper presents a study based on a clear set of indicators (I1–I12) and a well-defined theoretical objective, which is articulated through the research questions. The study aims to assess Romania's position within the EU in terms of e-commerce and, depending on the national context, identify ways to enhance the sector through AI-driven automation. The stratified methodology aims to reduce dimensionality by combining indicators (PCA) and then refine the classification of countries based on the new synthetic indicators resulting from cluster analysis, discriminant analysis, and neural networks. This approach differs from constructing a bottom-up theory based on open-ended observations.

The study does not start with qualitative data, and following their analysis, new indicators cannot be constructed or profiles of groups of countries cannot be created. Furthermore, we do not conduct impact studies on the use of AI-driven automation software in a group of countries, so we cannot claim that the study is inductive. In summary, the study is primarily deductive in its approach, starting from a theoretical framework of e-commerce indicators, reducing their dimensionality, and statistically classifying the variables within the EU context. Based on the findings, it identifies Romania's position and proposes directions for enhancement through the application of AI-driven automation.

The methodology employed is a combination of multivariate, incremental, and hybrid approaches, integrating classical statistics with machine-learning techniques. This methodological framework is well-suited for a comparative, deductive study that incorporates numerous indicators and necessitates the achievement of the most precise possible position for Romania.

If alternative methods had been selected, such as regression or clustering alone, the capability to reduce dimensionality and eliminate redundancy (PCA) would have been

lost, as would the capacity to adjust and optimize the resulting classification (discriminant analysis and neural networks).

In the next section of our research, we will examine Romania's current standing in this ranking and propose strategies for enhancing the e-commerce sector, incorporating elements of artificial intelligence.

5. Discussion

In the initial stage of the study, PCA was employed to reduce dimensionality and thereby minimize the time and effort required for data processing. The 12 indicators were reduced to seven synthetic ones, while maintaining 98.01% of the information present in the scatter plot. According to Benzecri's criterion, which stipulates that the informational value used must exceed 70% to ensure the validity of the results [94,95], it can be extrapolated to the entire sample. In our case, with an information loss of only 1.99%, the classification results are valid even if the synthetic indicators are abandoned and the initial indicators are used (see Table 5).

Table 5. The average of each indicator calculated at the level of each class.

Indicator	Class 1	Class 2	Class 3
I1	11.27	5.11	5.07
I2	25.33	19.23	16.84
I3	5.43	2.34	2.82
I4	5.83	2.78	2.25
I5	10.27	7.88	5.65
I6	14.42	9.89	7.15
I7	85.66	86.26	87.2
I8	36.15	47.95	39.26
I9	8.7	6.92	4.78
I10	1.57	1.35	0.93
I11	4.28	3.97	2.81
I12	6	4.28	2.9

Class 1 encompasses nations that have amassed sizable, high-performing enterprises within the domain of e-commerce. These enterprises demonstrate a pronounced inclination toward integrated e-sales [97], a strategic focus on conventional EDI methodologies [98], and the utilization of their own proprietary websites [99]. Consequently, the class exhibits high values for most of the indicators (I1, I2, I3, I4, I5, I6, I9, I10, I11, I12), while demonstrating the lowest values for I7 and I8. The companies operating within these countries have established themselves as leaders in the domains of combined EDI and web-based sales, with the highest percentages of sales recorded in I1 (11.27%, utilizing EDI), I2 (25.33%, web-only), I3 (5.43%, both), I4 (5.83%, EDI only), and I5/I6 (10.27%/14.42%, web/EDI turnover). The predominant activity of these companies is oriented towards business-to-business (B2B) and business-to-government (B2G) interactions, as indicated by the I12 indicator, which registered a value of 6%, the highest among the three classification categories. The companies predominantly conduct their operations through their own websites (I2 = 25.33%, the highest value) and to a limited extent through marketplaces (I8 = 36.15%, the lowest value). Consequently, it can be asserted that the B2C segment within these companies is notably well-developed, as evidenced by the highest average value for indicator I11, which stands at 4.28%.

Class 2 constitutes countries with medium-sized companies in terms of e-commerce performance, dependent on external marketplace platforms, with moderate adoption of EDI (I3/I4 (2.3%/2.78%). Consequently, it demonstrates intermediate values or values

converging towards Class 3 for certain indicators (I1 = 5.11%, I7 = 86.26%, I10 = 1.35%), yet higher values for others. The average value of indicator I8 = 47.95% shows a high degree of dependence on marketplace platforms, which is the highest value among the three classes.

Class 3 encompasses countries with companies demonstrating substandard performance in the sphere of e-commerce, exhibiting minimal adoption of EDI (I1 = 5.07%, I4 = 2.25%, and I6 = 7.15%), prioritizing the conduct of business primarily through their individual websites (I7 = 87.2%, the highest value among the three classes), with modest values for the remaining indicators. The limited implementation of EDI has repercussions for sectors such as B2B/B2G (I12 = 2.9%, the lowest value) and B2C (I11 = 2.81%, the lowest value).

Romania has a lower rate of sales using EDI (I1 = 3.95%, compared to the class average of 5.07%) and web exclusive channels (I2 = 10.79%, compared to the class average of 16.84%), but exceeds the class average for marketplace sales (I8 = 47.18%, compared to 39.26%). The number of companies that recorded marketplace turnover was higher than the Class 3 average (I10 = 1.36% compared to 0.93%). Web sales turnover is slightly higher in Romania than the Class 3 average (5.75% in Romania compared to 5.65% for Class 3), with a predominant focus on the B2C segment (3.42% in Romania compared to a 2.81% class average). These values suggest that Romanian companies are oriented towards external platforms and individual consumers, unlike the Class 3 average. The B2B segment is also weaker in Romania (I12 = 2.78%) than the Class 3 average (I12 = 2.9%).

The differences in e-commerce indicators in Romania between 2013 and 2024 (Figure 5) are due to interactions between economic and social problems, market growth, and changes in behavior. These interactions form a complete economic cycle that includes the following stages: stagnation, growth, correction, and market stabilization.

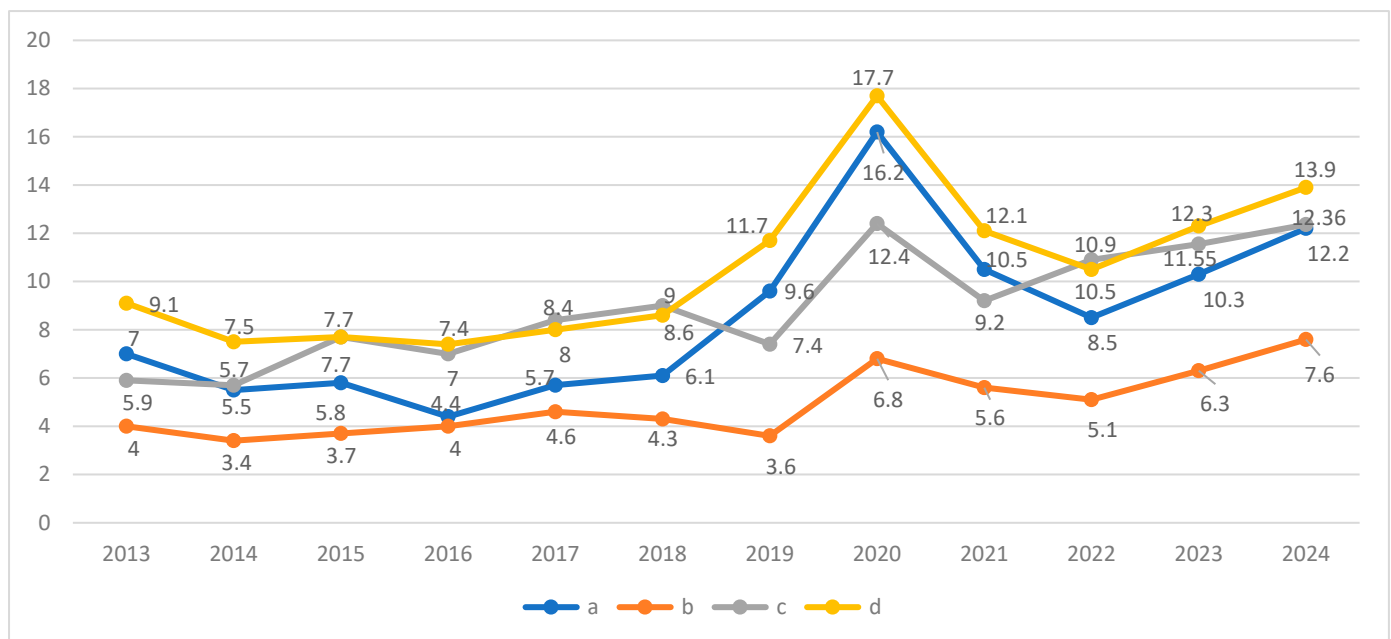


Figure 5. The main indicators of e-commerce in Romania between 2013 and 2024. Data source: Statista [13]. Legend: a—Share of enterprises that make B2C e-commerce sales via a website; b—Share of enterprises that make B2B and B2G e-commerce sales via a website; c—Share of e-commerce as a proportion of total turnover of enterprises; d—Share of enterprises that sell online.

Indicator a, the share of enterprises that make B2C e-commerce sales via a website, demonstrates a substantial increase in 2019 (9.6%) and 2020 (16.2%), reflecting the rapid growth in online sales during the pandemic period, due to the health restrictions related to

the SARS-CoV-2 virus. After returning to normalcy, marked by the reopening of malls and a return to pre-pandemic life, this indicator recorded a decline (10.5% in 2021). Thereafter, it evidenced a stable recovery in 2023 (10.3%). The business-to-consumer (B2C) segment is particularly influenced by consumer behavior.

Indicator b, the share of enterprises that make B2B and B2G e-commerce sales via a website, displays a more stable evolution, with moderate increases, its jump being spectacular in 2020 (6.8%) due to accelerated digitization in the B2B and B2G sectors. This indicator demonstrates sensitivity to economic cycles, as evidenced by the declines observed in 2019 (3.6%) and 2021 (5.6%), with a projected return to growth anticipated in 2023 (6.3%) and 2024 (7.6%).

Indicator c, the share of e-commerce as a proportion of total turnover of enterprises, it is evident that the year 2020 (12.4%) witnessed a significant disruption to its growth trajectory, driven by the surge in online sales that served as a compensatory mechanism for the restrictive measures imposed in response to the pandemic. Subsequently, starting in 2021 (9.2%), the increases in this indicator (10.9% in 2022, 11.55% in 2023, and 12.36% in 2024) showcases how e-commerce has become an integral and permanent part of the business component.

Indicator d, the share of enterprises that sell online exhibits a similar trend, with the adoption of online sales by the business environment reaching its highest rate in 2020 (17.7%). Consequently, following cyclical adjustments that exhibited an upward trajectory, this indicator stabilizes in 2023 at 12.3% and in 2024 at 13.9%.

Subsequently, analysis of the shares of Romanian firms engaging in e-commerce sales from 2013–2024, segmented by company size (Figure 6), confirms the patterns observed in the primary e-commerce indicators shown in Figure 5.

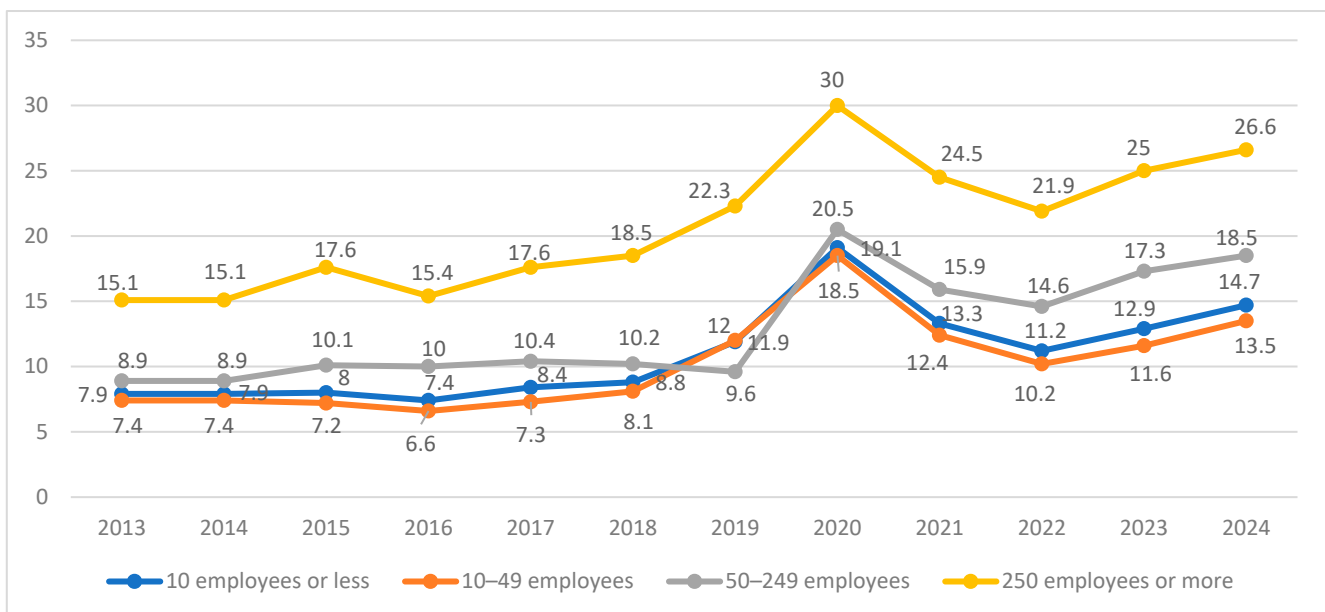


Figure 6. Evolution of the share of enterprises with e-commerce sales in Romania between 2013 and 2024. Data source: Statista [13].

Companies with fewer than 10 employees exhibited a stable trajectory, at approximately 8% until 2008, rising to 11.9% in 2019, surging to 19.1% in 2020, then declining to 11.2% in 2022, then ascending again to 14.7% in 2024.

Companies that had between 10 and 49 employees, classified as small companies, exhibited a trend analogous to that of micro-enterprises. However, this trend manifested at a slightly lower level, reaching a minimum of 6.6% in 2016. During the pandemic in 2020,

the figure increased to 18.5%, and subsequently, it stabilized at a modest growth rate of 13.5% in 2024.

Medium-sized companies (50–250 employees), have shown consistent growth, rising from 8.9% in 2013 to 9.6% in 2019. A notable surge was observed in 2020, with an increase to 20.5%, followed by a value of 18.5% in 2024.

Large companies, defined as those with over 250 employees, have exhibited consistently high values since the beginning (15.1%), followed by moderate fluctuations up to a maximum of 30% in 2020, with a post-pandemic 2022 where they recorded a decline at 21.9%, and 2024 projections at 26.6%.

In Romania, for companies whose primary activity is e-commerce, the National Tax Administration Agency (NTAA) has reported that there are three companies with over 250 employees, 22 medium-sized companies with between 50 and 250 employees, while remaining 22,201 companies are small, with fewer than 50 employees [100]. Given the prevalence of small companies, the procurement of Enterprise Resources Planning (ERP) or Customer Relationship Management (CRM) solutions often results in exorbitant and unsustainable costs. A more affordable yet highly effective solution is the utilization of a platform that integrates multiple applications, including AI, and automates nearly all existing processes.

This structural constraint is compounded by a broader pattern of low artificial intelligence and EDI technology adoption in Romanian enterprises. Recent data published by Eurostat indicate that, as of 2024, only approximately 3.1% of Romanian enterprises with 10 or more employees reported using AI technologies, compared to an EU average of 13.5%. This places Romania among the lowest-ranked EU member states in terms of AI adoption, alongside Poland and Bulgaria. By contrast, several countries belonging to class 1 according to the present study's e-commerce ranking—namely Denmark, Finland, and Sweden—are also identified by Eurostat as leaders in AI adoption, with usage rates substantially exceeding the EU average [101].

Although the present study's classification does not incorporate AI adoption indicators directly, the coincidence of low e-commerce performance and low AI and EDI technology usage in Romania is noteworthy. A recent study conducted by the AI Chamber found that approximately 81% of Romanian SMEs report some form of AI usage, but that this usage is predominantly limited to isolated applications (e.g., marketing automation, chatbots) rather than end-to-end process automation [102].

In this context, given the structure of e-commerce companies in Romania, the authors propose, as an alternative to using ERP and CRM software, the adoption of automation technology that incorporates artificial intelligence. One such example is the n8n application. The n8n platform, version 2.1, facilitates the automation of e-commerce processes by establishing connections between online stores (WooCommerce, Shopify, Magento, and others) and a suite of business software such as: CRM, email marketing, invoicing, delivery platforms, specialized accounting, and internal communication [103].

N8n therefore allows for automation and total control [104] over the main e-commerce processes, without the need for human intervention [105] from the moment an order is received from the customer until post-order services. When a customer places an order on an online store platform, the stock is checked, the invoice is created (by integrating one of the programs: SmartBill, FGO, or Facturare), the data is sent to the company's preferred courier (Fan Courier, Sameday, DPD), and finally, an order confirmation email is sent to the customer. If the customer adds a product to the cart but does not complete the order, an automation can be performed whereby the system waits between 1 and 24 h, sends a reminder email to the customer and, possibly, a discount coupon; if the value is high enough, a sales agent can be assigned to the customer for guidance along the sales

funnel. After the order is completed, the stocks in the online store are updated with the actual stocks, products with zero stocks are deactivated from the online store, and at the same time, an internal alert can be sent to initiate new supply/production orders through post-order services. Once the order has been completed, post-sale emails can be sent to the customer to measure order and product satisfaction. In the case that a customer chooses to return a product, the n8n system is programmed to initiate the process by automatically generating an internal ticket, notifying the warehouse, generating a return AWB, updating the order, and sending an email to the customer with the return confirmation and next steps to follow. Reports can be generated automatically [106] at specified intervals, such as daily, weekly, monthly, or quarterly, on a variety of metrics, including sales, best-selling products, the value of returns, the number of returned products, and the percentage of failed sales out of total orders [107].

6. Conclusions

The primary objectives of this research paper were twofold: first, to assess the degree of e-commerce development in Romania within the global context of the European Union, and second, to propose enhancements to this development through the integration of artificial intelligence components. From the authors' perspective, these objectives were achieved by addressing the research questions.

In response to the initial research question (RQ1), which focused on Romania's position in the EU concerning e-commerce, our research findings indicated that the level of e-commerce remains underdeveloped. Consequently, by implementing sophisticated data analysis techniques (PCA, cluster analysis, discriminant analysis, and neural network classification) sequentially, a classification of countries according to the fundamental indicators that characterize e-commerce was obtained. Romania was positioned in the third class, which corresponds to the group with the smallest values of the aggregate indicators. Accordingly, the response to the first question was found.

The response to the second research question (RQ2), which posited the question of whether the level of e-commerce in Romania can be enhanced through the integration of AI-driven automation software, has been determined to be affirmative. Considering the business population structure in Romania, which is predominantly composed of small companies, the implementation of alternative solutions such as ERP or CRM has proven to be financially unsustainable. In response to these challenges, a potential solution has been proposed by the authors: the utilization of AI-driven software for process automation, specifically the n8n platform, version 2.1.

In accordance with existing literature on the digital maturity of enterprises, digital convergence, and the impact of emerging technologies on e-commerce, we create an integrated conceptual model that addresses three levels. Firstly, we propose the collection and percentage-based reporting of 12 e-commerce indicators for each EU country. Secondly, we suggest dimension reduction and country grouping using PCA and cluster analysis, followed by classification refinement through discriminant analysis and a classification neural network. Finally, we identify Romania's position within the EU and formulate development pathways based on the implementation of automation and AI-driven elements in e-commerce business processes.

The present study adopts an applied-theoretical approach, employing statistical data and a rigorous methodological framework to generate two primary contributions. First, it offers an empirical positioning of Romania, and second, it presents a set of theoretical hypotheses regarding the role of automation and artificial intelligence in bridging digital divides within the EU. This approach contributes to the advancement of scientific knowledge in the domain of e-commerce and digital transformation. The paper presents a classification

methodology that can be extended to other digital economy indicators and an analytical framework for future comparative research in the EU.

From a practitioner's perspective, the study offers Romanian businesses a comprehensive understanding of their position within the European Union concerning e-commerce. Additionally, it provides guidance on enhancing performance through automation and artificial intelligence (AI)-driven solutions. The results of this study support the prioritization of investments in digital infrastructure, training, and the development of an environment conducive to e-commerce by policymakers. This will permit Romania to narrow the gaps with more advanced member states and converge toward a medium-to-high level of digital maturity within the EU.

The research is not without its limitations. Firstly, the questionnaire from which the data for processing was taken reflects the reality of 2024 at the level of EU companies. Secondly, another limitation is that the data is collected only at the European Union level, not globally.

In terms of future research, the authors have the following proposals: to study e-commerce in Romania in detail by conducting their own questionnaires, to apply more sophisticated data mining methods for processing, and to consider the possibility of using other automation platforms with a more user-friendly interface than n8n.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
EU	European Union
EDI	Electronic Data Interchange
B2B	Business to Business
B2C	Business to Customer
B2G	Business to Government
PCA	Principal Component Analysis
SAS	Statistical Analysis System
NTAA	National Tax Administration Agency
ERP	Enterprise Resources Planning
CRM	Customer Relationship Management

Appendix A. Eigenvectors of the Correlation Matrix

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12
PRIN1	0.174965	0.055578	0.170216	0.162525	0.127756	0.14131	0.088738	-0.11972	0.14834	-0.02785	0.075261	0.126568
PRIN2	-0.06078	0.170916	-0.02402	-0.08738	0.206056	-0.10886	-0.19451	0.181397	0.13673	0.265691	0.204568	0.151541
PRIN3	0.22751	0.241164	0.159465	0.26583	-0.182	0.257502	-0.39337	0.264293	-0.26929	0.16368	-0.30775	-0.01958
PRIN4	-0.11107	-0.60122	-0.29279	0.059543	0.096864	0.349936	-0.09077	0.205917	0.160781	0.059339	-0.26528	0.487157
PRIN5	0.231688	-0.67818	0.153863	0.278225	-0.28547	0.203635	-0.03186	0.435586	0.029969	0.238779	0.851594	-0.58049
PRIN6	0.040293	-0.15234	-0.07411	0.137233	0.181648	-0.02619	0.682593	-0.41978	-0.59643	1.239511	-0.18998	-0.01042
PRIN7	-0.50032	1.042677	-0.89832	-0.10222	-0.0321	1.422027	1.017837	0.69862	0.038901	-0.12166	0.32146	-0.29839
PRIN8	-0.23454	-0.31823	1.940859	-2.12837	-0.03975	0.941728	0.277985	0.367805	-0.1628	0.203218	-0.23975	0.106609
PRIN9	0.239404	0.431019	0.316039	0.149157	-2.70018	-0.987	1.201333	0.769173	0.933951	0.491241	0.048064	1.560919
PRIN10	0.607023	-0.24367	0.593819	0.560982	1.580362	-1.36247	1.562061	2.440836	-0.42702	-0.71852	-0.91937	-0.22241
PRIN11	-0.06342	0.093602	0.213424	-0.30124	-0.78049	0.093422	-0.12332	-0.44794	84.627	32.19757	-52.9117	-60.1449
PRIN12	0	0	0	0	0	0	0	0	0	0	0	0

Appendix B. Resubstitution and Cross Validation Results

Country	Resubstitution Results			Cross Validation Results		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
Austria	4.34×10^{-7} 4.34×10^{-7}	1	1.78×10^{-6}	3.01×10^{-7}	1	2.86×10^{-6}
Belgium	1	7.37×10^{-6}	1.91×10^{-7}	1	2.14×10^{-5}	1.10×10^{-7}
Bulgaria	0.000562	1.2710^{-8}	1	0.004894	1.09×10^{-9}	1
Croatia	0.988033	9.00×10^{-7}	0.125051	0.959039	1.38×10^{-6}	0.419223
Cyprus	6.39×10^{-7}	1	2.43×10^{-6}	3.00×10^{-7}	1	4.50×10^{-6}
Czechia	1.33×10^{-6}	1	2.15×10^{-8}	1.67×10^{-6}	1	9.43×10^{-9}
Denmark	0.99997	4.41×10^{-5}	3.87×10^{-6}	0.999596	0.000518	9.70×10^{-6}
Estonia	0.000144	8.73×10^{-6}	0.999947	0.000363	1.90×10^{-5}	0.999853
Finland	0.89451	0.980469	1.19×10^{-8}	0.999511	0.884115	3.16×10^{-9}
France	2.65×10^{-7}	0.000907	0.999992	2.09×10^{-7}	0.002534	0.999984
Germany	7.09×10^{-5}	0.99998	2.26×10^{-6}	0.000124	0.999964	3.75×10^{-6}
Greece	9.83×10^{-9}	0.999996	0.005069	4.64×10^{-10}	0.999992	0.047258
Hungary	0.000163	0.999998	8.96×10^{-8}	0.002838	0.999994	9.23×10^{-9}
Ireland	0.999961	1.04×10^{-5}	2.37×10^{-5}	0.999567	4.74×10^{-5}	0.000133
Italy	2.13×10^{-5}	1	3.46×10^{-9}	7.58×10^{-5}	1	1.26×10^{-11}
Latvia	0.001576	2.31×10^{-8}	0.999999	0.006437	8.30×10^{-9}	0.999997
Lithuania	1	4.84×10^{-6}	2.10×10^{-9}	1	0.001044	8.52×10^{-30}
Malta	3.03×10^{-5}	0.001971	0.997025	8.27×10^{-5}	0.024733	0.916366
Netherlands	0.001036	0.907428	0.001005	0.001581	0.80024	0.001519
Poland	7.66×10^{-6}	0.999996	4.78×10^{-6}	1.32×10^{-5}	0.999991	9.24×10^{-6}
Portugal	3.27×10^{-6}	0.999832	0.000567	4.02×10^{-6}	0.995669	0.021397
Romania	5.21×10^{-6}	2.70×10^{-5}	0.999995	8.40×10^{-6}	8.27×10^{-5}	0.999986
Serbia	1.75×10^{-6}	5.43×10^{-6}	1	1.73×10^{-6}	1.55×10^{-5}	1
Slovakia	1.60×10^{-8}	1	7.97×10^{-6}	3.77×10^{-12}	1	5.4×10^{-5}
Slovenia	0.999363	7.58×10^{-7}	0.007303	0.91357	8.49×10^{-7}	0.755399
Spain	0.000126	0.887634	0.011906	0.000251	0.532855	0.032766
Sweden	0.999951	0.000312	8.48×10^{-7}	0.99986	0.001203	1.13×10^{-6}

Appendix C

The activation weights of each neuron in the intermediate and final layers and the scoring functions of the classification neural network.

Table A1. The weights from the input to the second layer of the neural network.

	H1	H2	H3	H4	H5
PRIN1	-0.0162	0.2993	0.0119	0.2350	-0.5207
PRIN2	-0.0378	0.2163	0.3643	-0.3896	-0.4206
PRIN3	-0.0920	0.0664	0.2286	0.1854	0.1385
PRIN4	-0.0840	-0.5456	0.1149	0.5567	-0.4217
PRIN5	0.0278	0.1697	0.3222	0.6964	0.1912

Table A1. Cont.

	H1	H2	H3	H4	H5
PRIN6	0.1887	−0.2435	0.2752	−0.4274	−0.0131
PRIN7	−0.5750	0.6422	0.0686	−0.5883	−0.1717

Table A2. The scoring functions for the intermediate layer.

Neuron	Scoring Function
H1	$-6.98^* \times \text{PRIN1} - 2.13 \times \text{PRIN2} - 2.52 \times \text{PRIN3} - 1.29 \times \text{PRIN4} + 0.88 \times \text{PRIN5} - 0.24 \times \text{PRIN6} + 1.09 \times \text{PRIN7}$
H2	$9.92 \times \text{PRIN1} + 3.73 \times \text{PRIN2} + 1.01 \times \text{PRIN3} - 6.49 \times \text{PRIN4} + 0.20 \times \text{PRIN5} + 0.33 \times \text{PRIN6} - 6.38 \times \text{PRIN7}$
H3	$-5.42 \times \text{PRIN1} + 3.21 \times \text{PRIN2} - 3.39 \times \text{PRIN3} + 0.16 \times \text{PRIN4} + 1.02 \times \text{PRIN5} - 1.98 \times \text{PRIN6} + 5.82 \times \text{PRIN7}$
H4	$-3.62 \times \text{PRIN1} - 0.76 \times \text{PRIN2} - 1.82 \times \text{PRIN3} - 4.07 \times \text{PRIN4} + 0.33 \times \text{PRIN5} + 1.55 \times \text{PRIN6} + 8.91 \times \text{PRIN7}$
H5	$-0.63 \times \text{PRIN1} + 3.84 \times \text{PRIN2} + 0.75 \times \text{PRIN3} + 1.93 \times \text{PRIN4} + 0.44 \times \text{PRIN5} - 0.27 \times \text{PRIN6} + 1.55 \times \text{PRIN7}$

Table A3. The scoring functions for the final layer.

Neuron	Scoring Function
Class 1	$-6.53^* \times \text{H1} + 0.41 \times \text{H2} - 3.81 \times \text{H3} - 1.04 \times \text{H4} + 2.59 \times \text{H5}$
Class 2	$2.81 \times \text{H1} - 3.14 \times \text{H2} + 3.22 \times \text{H3} + 4.11 \times \text{H4} + 4.91 \times \text{H5}$
Class 3	$4.31 \times \text{H1} + 0.46 \times \text{H2} - 1.56 \times \text{H3} - 0.10 \times \text{H4} - 6.03 \times \text{H5}$

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