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contents

Articles

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EMPIRICAL IDENTIFICATION OF THE TOURISM SECTOR: A COMPARATIVE BUSINESS ANALYTICS APPROACH FOR NORTH MACEDONIA AND ALBANIA

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Abstract

The Republic of North Macedonia and the Republic of Albania, as two neighbouring developing countries with similar geographical features and shared ambitions for sustained European integration, present a compelling case for comparative tourism analytical research. This paper conducts an in-depth analysis of the development features of tourism sectors in both countries, focusing on the influence of economic indicators and institutional quality on the number of international tourist arrivals over the period 2000–2021. Utilising the three fundamental phases of business analytics—descriptive, diagnostic, and predictive—the research employs data mining and visualisation techniques applying tools such as Microsoft Excel and Power BI. A combination of simple and multiple linear regression models was used to identify statistically significant variables influencing tourism growth.

Results indicate that, in the case of Albania, the strongest predictive model includes CO_2 emissions, population growth, and renewable energy consumption, collectively explaining 90% of the variance in tourist numbers. On the other hand, the most effective model for North Macedonia includes GDP per capita, forest area, and renewable energy, accounting for 67% of variability. These empirical findings suggest that Albania's more consistent and strategic institutional planning has positively influenced tourism development, while fragmented or inconsistent policy implementation in North Macedonia might have limited its growth potential. The study concludes that institutional effectiveness, infrastructure development, and availability of high-quality and continuous data are crucial prerequisites for building sustainable and resilient tourism sectors in both countries. This research contributes to the growing body of regional tourism literature and offers practical recommendations for policymakers.

Key words: tourism, developmental policy, business analytics, regression analysis, economic indicators

JEL Classification: L83, O11, Q56, R11, C38

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1. Introduction

Tourism accounts for around 10% of global GDP and remains among the fastest-growing industries worldwide (UNWTO, 2022). Beyond its economic contribution, tourism stimulates infrastructure, fosters cultural exchange, and strengthens international visibility. These multidimensional effects make tourism particularly relevant for developing and transition economies, where this sector often serves as a mechanism for diversification and sustainable regional growth (Eugenio-Martin, Morales & Scarpa, 2004; Seetanah, 2011).

This analytical study focuses on two Western Balkan economies, namely North Macedonia and Albania, which share similar geographic and socio-economic characteristics but have followed markedly different tourism trajectories. Both countries possess diverse natural and cultural assets, from mountain landscapes and lakes to UNESCO-protected heritage sites and vibrant local and regional traditions. However, while they share comparable starting conditions and principal European integration aspirations, their policy design, institutional quality, and investment continuity differ substantially. These contrasts provide a compelling framework for analysing how structural and institutional determinants influence tourism current and future development.

North Macedonia's tourism has evolved gradually and inconsistently, reflecting sporadic policy coordination and limited institutional continuity. In contrast, Albania's tourism sector expanded at a faster pace and more consistently, supported by targeted investments and clearer strategic and policy positioning. Such structural divergence leads to critical analyses with an empirical assessment of how institutional quality and economic fundamentals jointly shape tourism performance in Western Balkans.

The study conducts a comparative, data-driven analysis of tourism dynamics in North Macedonia and Albania over the period 2000–2021. It practically operationalises the three analytical phases of business analytics, i.e. descriptive, diagnostic, and predictive, to examine the determinants of international tourist inflows. Using regression models and visualisation tools, such as Excel and Power BI, this analysis quantifies the relationships between tourism performance and key economic, environmental, and demographic variables, including GDP per capita, CO_2 emissions, renewable energy use, forest area, urban population, and net migration. This mixed empirical approach provides a transparent framework for linking institutional quality to measurable tourism outcomes.

The contribution of this study lies in its empirical and validated examination of tourism potential through comparative institutional and econometric lenses. In doing so, the paper bridges the gap between qualitative assessments and quantitative evidence, offering insights that are not only academically relevant but also practically

applicable for policymakers and tourism strategists in both countries, the goal being to enable an integrated developmental approach.

The construction of our paper is organised as follows. Section 2 reviews the main strands of literature on tourism and economic development. Section 3 describes the methodological framework and data sources. Section 4 reports and interprets empirical results, while Section 5 concludes with policy implications, study limitations, and prospectives for future research.

2. Literature Review

Tourism has been widely acknowledged in both global and regional academic literature as a dynamic driver of economic growth, particularly in cases of developing and transition economies. According to the UNWTO (2022), the sector contributes approximately 10% of global GDP and plays a pivotal role in achieving the Sustainable Development Goals 2030 by generating employment, investment, and cross-sectoral linkage. Empirical studies confirm its multidimensional impact: Ivanov and Webster (2013) demonstrate that tourism significantly contributes to long-term growth through multiplier effects on income and employment, while Seetanah (2011) highlights tourism's influence on productivity and infrastructure, especially in smaller or developing economies. More recent empirical evidence validates this causal relationship, indicating that tourism development positively affects economic expansion and trade dynamics in emerging markets (Dogru, Isik & Sirakaya-Turk, 2019). Consequently, tourism is not merely an economic activity but a multifaceted engine of regional transformation and institutional modernisation, capable of addressing structural imbalance and promoting international integration (Ardeleanu, 2021).

Based on these global findings, several regional studies in Western Balkans and the broader Southeast European context provide additional insights into the developmental role of tourism. In this context, Petrevska (2012) highlights that tourism offers one of the rare sectors in which transition economies can achieve tangible progress with relatively modest investment, provided there is effective institutional support and a coherent policy design. Nestoroska (2012) stresses that tourism can be an essential factor in achieving balanced regional development, but only when accompanied by long-term planning and capacity building. Likewise, Marku (2013) underscores the strategic role of tourism in enhancing national competitiveness, especially in small and developing economies.

In the case of North Macedonia, relevant academic literature consistently points to the country's underutilised tourism potential and the institutional barriers that limit its realisation. In this context, more recent analyses by Risteski and Nestoroska (2024) indicate that the post-transition period has been characterised by fragmented tourism policies and inconsistent institutional coordination, which have constrained the sector's competitiveness.

Furthermore, Naumov and Petrevska (2019) argue that sustainable tourism in North Macedonia remains largely underdeveloped due to weak destination management and limited stakeholder engagement, highlighting the need for stronger governance and policy consistency. Complementary findings by Stamenkovska, Angeloska-Dichovska and Ilieva (2022) emphasise that the lack of institutional stability and insufficient coordination between national and local authorities continue to hinder strategic tourism planning and investment realisation.

In contrast, Albania has experienced more rapid and structured growth in its tourism sector. The findings of Seetanah (2011) demonstrate that foreign direct investment plays a crucial dual role in enhancing infrastructure and institutional trust in tourism-driven economies. According to Marku (2013), Albania's tourism development has been facilitated not only by natural endowment features but also by more coherent investment policies and targeted reforms aimed at positioning the country among competitive Mediterranean destinations. Therefore, the country's coastal, mountainous, cultural, and historical assets have been successfully leveraged to attract a steady flow of international visitors, particularly from Southern Europe (Ceca, Ladias & Polo, 2016).

Several empirical studies provide robust evidence for a positive and long-term association between tourism activity and economic growth in the European context. Brida, Lanzilotta and Risso (2015) show that increased tourism demand significantly contributes to GDP per capita growth across European countries, even after accounting for structural economic variables, such as capital formation and labour supply. Similarly, Cortés-Jiménez and Pulina (2010) confirm that tourism-led growth is particularly pronounced in Mediterranean and Southern European destinations, where tourism specialisation has become a structural component of economic expansion. These findings reinforce the argument that tourism does not merely generate short-term injection effects but can serve as a strategic driver of sustained economic growth when supported by favourable institutional and macroeconomic conditions.

More recent empirical evidence validates this causal relationship, indicating that tourism development positively affects economic expansion and trade dynamics in emerging markets. For instance, recent studies of tourism vulnerability demonstrate that aggregate and single-dimension indicators fail to capture structural characteristics, such as informality, seasonality and domestic demand substitution; these factors are particularly relevant for small economies with limited statistical capacity, including North Macedonia and Albania (Duro, Perez-Luis & Teixeira, 2021). Moreover, cross-country comparisons often neglect institutional and governance variables that substantially mediate tourism outcomes, resulting in relative or overall optimistic conclusions.

Principally, although Marku (2013) presents Albania's tourism strategy as a success story, this analysis overlooks external influences, such as regional instability and

global economic shocks, which weaken the robustness of its generalisations. Furthermore, the works of Risteski and Nestoroska (2024) and Petrevska (2012), while offering valuable contextual insights, remain predominantly descriptive and rely less on empirical modelling, limiting their suitability for comparative institutional evaluation. These gaps underscore the need for a data-driven, econometrically grounded framework—an objective that the present study analytically and methodologically seeks to achieve.

Despite growing academic interest in tourism in the Western Balkans, most of the existing research treats each country in isolation, lacking comparative or cross-border perspectives. This study addresses that gap by conducting a structured comparison between North Macedonia and Albania, using business analytics and regression modelling to explore the impact of institutional, economic, and environmental variables on tourism growth. Informed by the literature reviewed and motivated by the gaps identified in comparative analysis, the following hypotheses are proposed:

- H1: Institutional sector quality—including solid governance mechanisms, an efficient degree of policy implementation, and integration within the regulatory environment—has a statistically significant effect on tourism sector performance and future perspectives in both North Macedonia and Albania.
- H2: Structural differences in infrastructure development, predictable environmental processes, and investment-driven development strategies contribute to variations in tourist preferences, behaviour, and overall visitation patterns across the two countries.

The interrelation between the two hypotheses lies in the conceptual premise that institutional quality operates both as a direct determinant of tourism sector outcomes and as an enabling, indirect framework that governs the effectiveness of structural variables, such as infrastructure development, environmental management, and investment strategies, which collectively mediate international tourism flows.

3. Methodology Approach

When composing this article, we chose to collect secondary data from May to July 2024. Data sources included global datasets from the World Bank, The World Data and the UN, as well as governmental portals in Albania and North Macedonia (State Statistical Office of the Republic of North Macedonia, n.d.; Statistical Office of the Republic of Albania, n.d.).

Data in this research refer to the consecutive years from 2000 to 2021. The selection of the 2000–2021 period is based on the availability of consistent, complete, and comparable data for both countries. More recent years contain partially revised or incomplete statistical series, particularly for tourism and environmental indicators, which could introduce instability and reduce model reliability. Therefore, 2021 rep-

resents the last year suitable for robust and methodologically consistent econometric comparison, according to national and international publicly available data.

Although there are data from earlier years, from the 90s to be precise, that period was still quite dynamic and turbulent for this region of the world and, therefore, data associations may not have consistent logical explanation or solid meaning. It is important to note that a certain number of factors that could have an impact on the number of tourists in these countries do not enjoy adequate continuous measurements and there is not a required amount of data available. In the future, it would be recommendable for these countries, and especially their institutions, to pay more attention to a statistical collection of data that would be useful for this type of analytical research.

Key variables used in the analysis include the dependent variable, i.e., the annual number of international tourist arrivals, and a set of independent variables comprising GDP per capita, CO_2 emissions per capita, renewable energy use (as a percentage of total energy consumption), forest area (as a percentage of total land), urban population (percentage), population growth (percentage), road infrastructure, net migration, inflation rate, intentional homicides, birth rate, and death rate.

Initial data exploration was performed using Microsoft Excel and Power BI, facilitating time-series visualisation, pattern recognition, and basic correlation analysis. Trends for each independent variable were graphed and interpreted, emphasising general movements and structural changes over the 21-year period. This phase also included: Checking for missing data and applying imputation methods where necessary; Identifying and treating outliers; Detecting structural breaks (e.g., the impact of COVID-19 starting in 2020); Applying logarithmic transformations to stabilise variance when appropriate.

In the following section, we examine key trends of independent variables used in the regression models through a series of comparative graphs for North Macedonia and Albania. These visualisations help identify *structural shifts, correlations, and long-term tendencies concerning the data.* For each of the countries, i.e., North Macedonia and Albania, 8 Graphs are elaborated on within the overall national graph and discussed in detail.

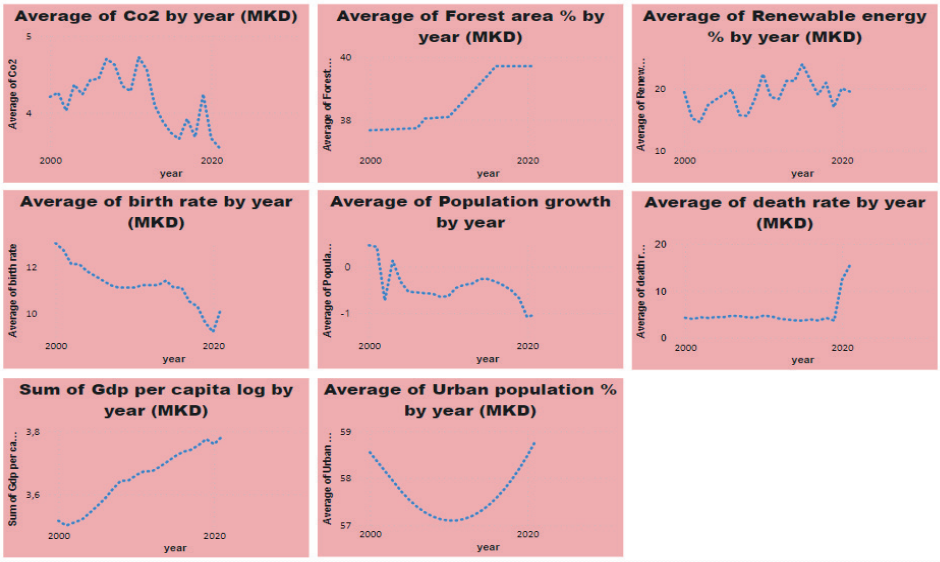
Graph 1 – North Macedonia

Graph 1a (CO_2 emissions) begins with moderate growth, followed by a drop between 2000 and 2003. The upward trend resumes until 2007, after which there is another decline up to 2010. A sharp increase in 2011 is followed by a downward trajectory (2011–2016), and a renewed rise until 2020, interrupted by a dip in 2018. These shifts reflect structural changes in energy use and industrial output, which may indirectly influence environmental perceptions relevant to eco-tourism.

Graph 1b (forest area %) shows stagnation until 2007, followed by gradual increase periods until 2010 and a sharper rise to 2016. The trend is stabilised after this period. This increase reflects afforestation or land reclassification policies, which may positively affect the country's eco-tourism image and landscape preservation efforts.

Graph 1c (renewable energy %) exhibits high variability with no clear long-term direction. This inconsistency suggests institutional uncertainty or fragmented energy strategies, which could affect perceptions of sustainability—a growing concern among modern tourists.

Graphs 1d and 1e both show persistent downward trends, indicating possible demographic or infrastructural constraints. Minor increases do not alter the overall negative direction, suggesting declining attractiveness in some structural indicators



Graph 1. Comparative analysis of The Republic of North Macedonia indicators
Source: Authors' analysis (2000 – 2021)

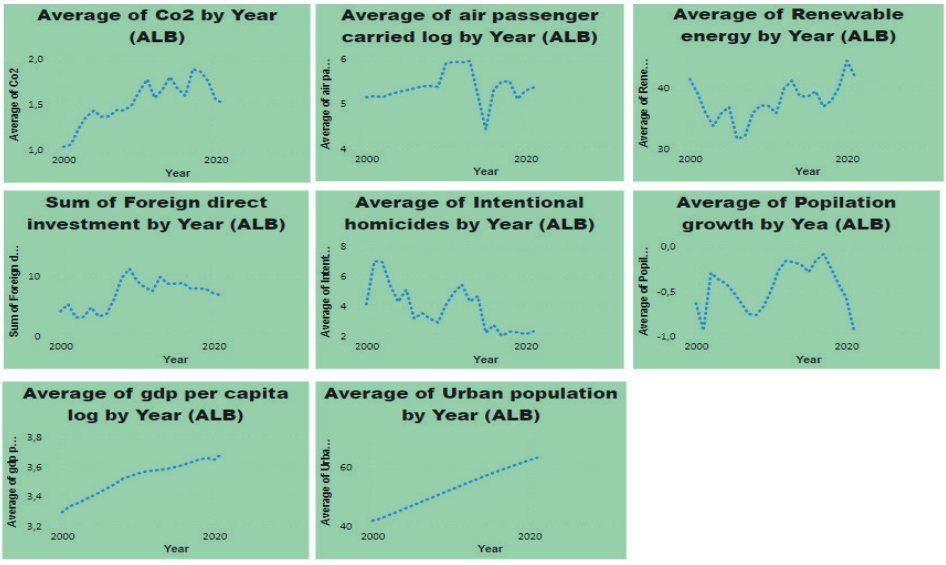
Graph 1f (death rate) remains largely stable over the two decades, except for a pronounced spike in 2020 due to the COVID-19 pandemic. This disruption aligns with global trends, and it had a short-term negative impact on tourism flows.

Graph 1g (GDP per capita) displays a steady and continuous upward trend, signalling long-term economic improvement. This is a key macroeconomic driver of tourism, associated with increased investment capacity and better infrastructure.

Graph 1h presents a continuous upward trend from 2000 to 2020, suggesting steady progress in respective indicators (e.g., urban population or digital infrastructure). This sustained growth reflects long-term structural improvements that enhance North Macedonia's capacity to support tourism, such as better accessibility, connectivity, or living standards. The absence of major declines implies stable policy implementation and resilience against external shocks.

Graph 2 – Albania

Graph 2a, illustrating average annual CO_2 emissions in Albania, demonstrates a significant increase from 2000 to 2004—likely driven by post-transition industrial activity and rising energy demands. The dip in 2005 may reflect temporary policy adjustments or data irregularities. Over the next decade and a half, emissions continued to rise, albeit intermittently interrupted by short-term declines in 2012, 2015, and from 2017 to 2020. Overall, the trend suggests that Albania's economic expansion during this period was accompanied by increased environmental pressures.



Graph 2. Comparative analysis of Albanian indicators
Source: Authors' analysis (2000 – 2021)

Graph 2b (logarithmic air passenger numbers) highlights a strong upward trajectory until 2010/2011, reflecting increased connectivity and Albania's growing attractiveness as a tourist destination. The subsequent decline could be associated with

temporary infrastructural or regional constraints, while the sharp post-2015 recovery aligns with targeted promotional campaigns and airport expansion projects. This trend is particularly significant as air travel is a key facilitator of international tourism growth.

Graph 2c focused on renewable energy consumption and reveals an overall increasing tendency despite several fluctuations. This reflects Albania's hydroelectric potential and gradual efforts to diversify its energy portfolio. The sustained growth of this variable is crucial, not only for environmental sustainability but also as an indirect signal of institutional modernisation—particularly relevant for eco-conscious tourist segments.

Graph 2d (foreign direct investment) shows modest levels in the early 2000s, followed by a surge in mid-decade. This surge aligns with liberalisation reforms and infrastructure projects—critical enablers of tourism sector growth. The moderate decline in recent years may indicate investors' caution or market saturation, but earlier gains likely laid the groundwork for improved hospitality capacity and service quality.

Graph 2e reflects inconsistent movement/changes of the respective variable, with notable drops around 2009 and 2015. These years correspond to wider regional financial instability and political uncertainty, both of which are known to influence travel decisions. The low levels sustained between 2015 and 2020 underscore structural weaknesses that require policy attention.

Graph 2f shows a sharp decline in 2002 followed by immediate recovery. The period between 2002 and 2009 is characterised by volatility, likely influenced by institutional transitions. The steady growth trend observed from 2010 to 2020, despite minor interruptions, signals increasing stability and gradual socio-economic improvement—factors that often correlate positively with tourism growth.

Graphs 2g and 2h representing GDP per capita (log-transformed) and urban population, display continuous upward trends. The steady rise in GDP per capita confirms Albania's sustained economic growth, while urbanisation indicates improving infrastructure and service availability in city centres—both core determinants of tourism competitiveness. These two variables, jointly, are among the strongest predictors of tourist inflows in the regression analysis, confirming their central role in destination appeal and accessibility.

4. Methodology

To investigate the determinants of international tourist arrivals in the Republic of North Macedonia and the Republic of Albania, this study adopts a quantitative approach utilising regression analysis based on secondary data. The methodological framework consists of two sequential stages: simple linear regression and multiple

linear regression, conducted using Microsoft Excel's Data Analysis Toolpak. The simple model captures the bivariate relationships between tourism performance and individual explanatory variables, while the multiple regression model controls for the joint effects of economic, environmental, and demographic factors, allowing for a more robust identification of underlying drivers.

In the first stage, a series of simple linear regressions were performed to identify which independent variables may individually influence the number of international tourist arrivals. Each potentially explanatory variable—such as GDP per capita, CO_2 emissions, renewable energy use, urban population, and others—is regressed independently against the dependent variable. The primary statistical measure used for variable evaluation is the coefficient of determination (R^2), which reflects the proportion of variance in the dependent variable explained by each independent variable. The estimation technique employed is the Ordinary Least Squares (OLS) method, which minimises the sum of squared residuals to produce unbiased and efficient estimates. The basic form of the simple linear regression is expressed as follows:

$$Y = \beta 0 + \beta 1 X + \varepsilon$$

where Y is the dependent variable, i.e., the number of international tourist arrivals in our case, X is the independent variable, while $\beta 0$ and $\beta 1$ are intercept and slope parameters to be estimated and ε denotes the residual variability within the model.

All regression models were estimated using the Ordinary Least Squares (OLS) method, which represents the most widely applied estimation technique in empirical economics. OLS identifies the best-fitting linear relationship by minimising the sum of squared residuals. Prior to interpreting the results, standard diagnostic checks were performed, confirming that most models satisfy key OLS assumptions regarding homoscedasticity, normality of residuals, and absence of serial correlation. This ensures that the estimated coefficients are statistically consistent and suitable for cross-country comparison.

In the second stage, a multiple linear regression model was conducted to identify the strongest relationships between a combination of factors and the number of tourist rates. Simple transformations of variables were applied to the most significant regression models to meet the theoretical assumptions for regression of cross-sectional data. The models were selected by comparing several statistical indicators: the statistical significance of each coefficient separately, the statistical significance of the model (F-statistic), the coefficient of determination ($R2$ and adjusted $R2$ for comparison between models with different number of variables). The general form of the models that showed the best compromise between their fit and complexity is

$$Y=\beta 0+\beta 1X+\beta 2X2+\cdots+\beta iXi+\varepsilon$$

Or

$$Y=\beta 0+\sum \beta iXi\ i=1+$$

The slope coefficients indicate a linear relationship at a marginal change in the corresponding independent variable, all else being equal. By transforming all variables in each model into their logarithm form, we explored a relationship in which the effect of each variable on the outcome is proportional to its natural logarithm.

1. Analysis Of Results

5.1 Tourism Determinants: Single Regression Results

In the initial phase, separate regression analyses were conducted for Albania and North Macedonia to assess the assumptions for modelling cross-sectional data and the explanatory strength of each variable, as indicated by the $R2$ values in the models. Our findings revealed that most associations between independent and dependent variables exhibit homoscedasticity. Specifically, eleven out of thirteen samples demonstrated homoscedasticity.

Instances of heteroscedasticity were observed in analyses involving the independent variables Agricultural land % and Intentional homicides in Albania. Notably, North Macedonia did not exhibit any variables with heteroscedasticity.

Table 1. Results of the Simple linear regression analysis for The Republic of North Macedonia

Macedonia single regressions (number of tourists, the dependent variable – Y)	Intercept	Coefficient	R-square	Heteroskedasticity	Significance F	P-value
Birth rate	6.9269	-0.1323	0.2204	Homoscedastic	0.0274	0.0274
Road infrastructure	5.2973	0.0463	0.1763	Homoscedastic	0.0051	0.0051
Internet users %	5.1026	0.0068	0.5157	Homoscedastic	0.0000	0.0000
Intentional homicides	5.8607	-0.2216	0.3294	Homoscedastic	0.0051	0.0051
Forest area	-2.4605	0.2049	0.4945	Homoscedastic	0.0002	0.0002
GDP per capita	-1.7507	1.9713	0.5402	Homoscedastic	0.0000	0.0000

Source: Authors' analysis (2000 – 2021)

Hence, the medium/high correlations between two independent variables in North Macedonia that we should consider are the correlation between the number of tourists and Internet users, which is 0.52, and the correlation of 0.54 between the number of tourists and GDP per capita

In our analysis there were more independent variables, but we selected the pairs shown above because they indicate the highest variability.

Table 2. Results of the Simple linear regression analysis for Albania

Albania single regressions (number of tourists, the dependent variable – Y)	Intercept	Coefficient	R-square	Heteroskedasticity	Significance F	P-value
CO2	3.7605	1.6486	0.8084	Homoscedastic	0.0000	0.0000
Net migration	11.6693	-1.2316	0.8814	Homoscedastic	0.0000	0.0000
Urban population	3.1041	0.0601	0.9123	Homoscedastic	0.0000	0.0000
Intentional homicides	6.9867	-0.1874	0.4363	Heteroscedastic	0.0013	0.0013
GDP per capita	-6.3721	3.5870	0.9564	Homoscedastic	0.0000	0.0000

Source: Authors' analysis (2000 – 2021)

Furthermore, we obtained the coefficient of determination ($R2$) for each regression, i.e. we found out which of the independent variables explain our dependent variable the best. We found that birth rate with 22%, road infrastructure with 17%, Intentional homicides with 32% and Forest area with 49%. On the other hand, the correlations between the independents in Albania that we analysed, shown through the coefficient of determination ($R2$) for each regression, will help to find out which of the independent variables best explain our dependent variable. Independents with a significantly high R2 for this country are Co2 with 80%, Net migration with 88%, Urban population with 91%, Intentional homicides with 43% and GDP per capita 95%.

5.2 Tourism Determinants: Multiple Regression Results

After conducting the multiple linear analysis, about 50% of the variability of the number of tourists in North Macedonia is explained by birth rate and death rate.

Table 3. Results of the multiple linear regression analysis for The Republic of North Macedonia

	Model 1	Model 2	Model 3	Model 4
Intercept	8.0959*** (0.6241)	-7.7880*** (2.6094)	-4.0276** (1.5534)	7.5599* (3.7466)
Birth rate	-0.2133*** (0.0518)			
Death rate	-0.0516*** (0.0157)			
CO2		0.4084*** (0.1405)		
Forest area		0.2831*** (0.0575)		
Renewable energy %		0.0321* (0.0169)		
GDP per capita			2.6284*** (0.4324)	
Population growth			0.2860** (0.1070)	-0.1893*** (0.0646)
Urban population %				0.2283*** (0.0402)
Forest area %				
Included Obs.	22	22	20	22
R-squired	0.5021	0.6718	0.6658	0.6516
Adjusted R-squired	0.4497	0.6172	0.6306	0.6149
S.E. of regression	0.1860	0.1551	0.1524	0.1556

*** Significant at 0.01; **Significant at 0.05, *Significant at 0.1
Source: Authors' analysis (2000 – 2021)

The linear association is represented by the coefficients of the corresponding (explanatory) variables ceteris paribus: for each point increase in Birth rate, number of tourists decrease by -0.2133% and for every point of increase in Death rate number of tourist decrease by -0.0516. Model number 2 shows us multiple linear regression with variability of 67% of the number of tourists in country mention above and this model is explained by Co2, Forest area and renewable energy%. For each point increase in Co2, number of tourists increase by 0,4084%, for every point of increase in Forest area (%) number of tourists increase by 0.2831% and for every point increase in Renewable energy number of tourists increase by 0.0321 %.

Model number 3 show us multiple linear regression with variability of 66% of the number of tourists in country mention above and this model is explained by GDP per capita and population growth. For each % point increase in GDP per capita, number of tourists increase by 2.6284 and for every point of increase in Population growth number of tourists increase by 0.2860%.

Table 4. Results of the multiple linear regression analysis for The Republic of Albania

	Model 1	Model 2	Model 3	Model 4
Intercept	3.2744*** (0.1969)	2.0160*** (0.4683)	-5.6648*** (0.4760)	4.8910*** (1.0510)
Urban population	0.0520*** (0.0045)			
Foreign direct investment	0.0369*** (0.0126)			
CO_2		1.8080*** (0.1725)		
Population growth		-0.3135* (0.1570)		
Renewable energy		0.0360*** (0.0100)		
GDP per capita			3.4193*** (0.1325)	
Population growth			0.2549*** (0.0605)	
Air passenger carried log				0.4013* (0.1981)
Intentional homicides				-0.2018*** (0.0448)
Included Obs.	22	22	22	22
R-squired	0.9395	0.9023	0.9774	0.8772
Adjusted R-squired	0.9331	0.8860	0.9750	0.8567
S.E. of regression	0.1099	0.1435	0.0671	2.4574

*** Significant at 0.01; **Significant at 0.05, *Significant at 0.1
Source: Authors' analysis (2000 – 2021)

The last model, that also presents a high percentage of variability, can be seen and analysed by readers in the table above. In this part of the analysis of results, multiple

regressions for Albania are presented, one of the regressions concerns 3 independent variables while there are three with 2 independent variables.

Triple model will be explained in more detail, and ~~the~~ two variable models can be seen in the table showing the significant regression items. The first model with two independents in it shows a multiple regression analysis with a high variability of 94%, which involves urban population and foreign direct investment. For each point increase in Urban population, Number of tourists increases by 0.0520% and for every point of increase in Foreign direct investment, Number of tourists increases by 0.0369%.

The second model with three independent variables presents a multiple regression analysis with a high variability of 90%, which involves Co_2, Population growth, and Renewable energy. For each point Co_2 increase, Number of tourists increases by 1.8080%, for every point Population growth increase, Number of tourists decreases by -0.3135% and for each point Renewable energy increase, Number of tourists decreases by 0.57477. The other two models that also present a high percentage of variability can be seen and analysed by readers in the table on the previous page.

6. Disscusion And Recommendations

The empirical results of this study provide robust support for the hypotheses proposed, particularly regarding the role of institutional quality and structural economic factors in shaping tourism dynamics. These findings confirm both H1 and H2, demonstrating that institutional quality and structural variables jointly determine tourism performance in cases of transition economies.

Overall results reveal that, in both North Macedonia and Albania, multivariate models that incorporate governance-related indicators, such as foreign direct investment, GDP per capita, and renewable energy usage, exhibit significantly higher explanatory power than bivariate models. This suggests that tourism development is not driven by isolated variables but by complex intercorrelations of economic capacity, institutional efficiency, and environmental sustainability.

Albania's stronger empirical performance, reflected in the higher explanatory power of its models, indicates a more coherent institutional and investment environment. Consistent focus on transport infrastructure, coastal branding, and targeted foreign investment has enabled the country to position itself among competitive Mediterranean destinations. On the other hand, North Macedonia's tourism sector remains constrained by fragmented institutional coordination, limited inter-ministerial collaboration, and absence of a unified long-term strategy, while certain initiatives, such as the short-term gains generated in tourist inflows, their sustainability and alignment with broader development goals, remain questionable.

Based on empirical findings, these results underscore the necessity of adopting an integrated policy approach that aligns tourism development with broader economic

and environmental strategies. Variables such as urban population growth, renewable energy expansion, and environmental preservation should be recognised as central components of tourism planning rather than as peripheral considerations. Policymakers should, therefore, pursue cross-sectoral collaboration and establish continuous monitoring mechanisms to evaluate the effectiveness and long-term sustainability of tourism-related policies.

Despite its robustness, this study faces several limitations primarily related to data availability and quality, which may influence the precision of certain estimates. Reliable and continuous data were unavailable for several potentially influential indicators, such as average tourist expenditure, tourism satisfaction indices, and digital engagement metrics. Moreover, inconsistencies in statistical reporting across national institutions constrained the analytical scope and comparability of results. A key recommendation is for national statistical agencies to prioritise the systematic collection and standardisation of tourism-related data, especially the ones capturing institutional performance and environmental impact.

Although more recent statistical releases exist for certain tourism indicators after 2021, an extensive review of international and national databases showed that the full set of variables required for a comparative econometric framework is not consistently available or harmonised for either of the countries studied beyond 2021. Several environmental, demographic and institutional indicators remain incomplete, subject to revision, or published with significant delay. As a result, the period 2000–2021 represents the last fully reliable and methodologically consistent time frame that allows for cross-country comparability and robust regression modelling.

An additional limitation arises from the use of annual data, which may obscure important seasonal patterns that are particularly relevant for tourism-dependent economies. Monthly or quarterly datasets could provide richer insights into short-term fluctuations, high-season dynamics, and the effects of policy interventions. Furthermore, reliance on secondary sources restricts the inclusion of qualitative indicators, such as tourist satisfaction, service quality, or destination image, which are increasingly recognised as important determinants of tourism performance. Future studies integrating mixed-method approaches or higher-frequency data could, therefore, capture a more nuanced and comprehensive picture of tourism dynamics.

Future research should build upon the current analytical framework by incorporating spatial econometrics, stakeholder analysis, or dynamic panel models to address time-lagged relationships and spatial interdependencies that static regression models cannot fully capture. Complementing the quantitative analysis with qualitative approaches, such as expert interviews or policy evaluation studies, would provide valuable contextual insights and enhance the interpretability of empirical findings. Together, these extensions could yield a more comprehensive and policy-relevant understanding of tourism systems in transition economies.

7. Conclusion

This research conducted a comparative, data-driven analysis of tourism development in the Republic of North Macedonia and the Republic of Albania for the period 2000–2021, applying a business analytics framework grounded in descriptive, diagnostic, and predictive methods. By integrating regression analysis with visualisation tools, the study revealed that economic, institutional, and environmental factors significantly influence international tourist arrivals.

Results highlight Albania's advantage in policy coherence, investment continuity, and institutional effectiveness, resulting in stronger model-explanatory power. North Macedonia's performance, while constantly improving, is hindered by fragmented governance and underdeveloped infrastructure. These contrasts underscore the strategic importance of aligning tourism development with broader economic and sustainability objectives.

Methodologically, the paper illustrates the utility of combining accessible software tools, such as Excel and Power BI, with formal regression techniques for policy-relevant insights. While limitations related to data availability were noted, the study lays a foundation for future research to explore more advanced econometric methods and incorporate qualitative aspects, such as tourist behaviour and satisfaction, as well as future tourist expectations and tourist service quality.

Overall, findings affirm that sustainable tourism growth in the Western Balkans depends not only on natural appeal but also on robust institutions, harmonised national policy measures, coordinated planning, and long-term commitment to integrated development strategies.

Finally, this comparative approach offers valuable lessons for other transition economies in the Western Balkans and beyond. By highlighting the nuanced interplay between policy, infrastructure, and environmental stewardship, the study emphasises the importance of context-sensitive tourism strategies in relation to their potential for sustained implementation. Rather than applying one-size-fits-all solutions, countries should tailor their development plans based on institutional capacity, resource availability, customer needs, and societal needs. Ultimately, sustainable tourism should be understood not merely as an economic objective but as a multidimensional pathway toward inclusive growth, regional cooperation, transparent tourist service provision, as well as an economy's inclination towards global integration.

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EARLY SPARKS: FOSTERING ENTREPRENEURSHIP COMPETENCES IN BALKAN COUNTRIES

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Abstract
This article presents a comparative study of national strategies targeting the integration of entrepreneurship education in primary and secondary schools in five Balkan countries, namely: Albania, Bulgaria, Greece, North Macedonia, and Romania. The article details institutional frameworks, curriculum integration, teacher training programs, and key competences emphasised in each country; it also discusses specific activities deployed in order to facilitate the development of entrepreneurship competences and mindsets among students with the support of government strategies and policy initiatives. Additionally, the article identifies best practices from other European countries in implementing entrepreneurship education and offers practical recommendations for policymakers and educators. The ultimate goal is to enhance students' entrepreneurship competences and prepare them to navigate their way through the complexities of the modern world with confidence and resilience. The research presented fills a critical gap in relevant literature by providing insights into the ways in which entrepreneurship competences are cultivated at different educational levels across the countries studied. Findings will be globally valuable for policymakers and educators who aspire to improve entrepreneurship education in similar socio-economic contexts.

Keywords: Entrepreneurship Education, Primary and Secondary Education, Public Policies, Balkan Countries

JEL Classification: I25, L26

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1. Introduction

Entrepreneurship education aims at preparing students for a particular vocation, enterprise or business by cultivating and improving their entrepreneurial spirit, aspirations, motivation, and pioneering and adventurous nature. Another aim is to help entrepreneurs find and identify business opportunities by developing students' necessary strategic skills and tools (Liu, 2019). However, some people give a different interpretation, arguing that the goal of entrepreneurship education should be to develop students' creativity, opportunity awareness, initiative, and innovation rather than to establish new organisations. The latter also give a broader definition to entrepreneurship, which makes it applicable in all spheres of society (Lackéus, 2015). As a result, not only can entrepreneurial education benefit economic growth and increase employment (Panigrahi & Joshi, 2016) but also determine whether someone will become an entrepreneur, enhance democratic values, and encourage learners to participate in democratic processes and community development. Furthermore, this definition emphasises the importance of ethical and sustainable practices in business, aligning economic activities with broader social and environmental goals, and promotes a wide range of competences such as creativity, problem-solving, leadership, and resource management (Web-1).

The United Nations (2015) recognised that entrepreneurship competences are essential for equipping young individuals to innovate, start businesses, and create job opportunities in the rapidly changing global environment. Recognising the importance of entrepreneurship competences, Sarri et al. (2022) argue that entrepreneurship education should focus on cultivating an entrepreneurial mindset from an early age. Hassi (2016) supports this view, noting that students who participate in entrepreneurial initiatives at primary school will benefit more from similar programs in the future compared to students who do not. This gradual development ensures that children not only acquire the necessary basic skills and understanding to navigate the complexities of the business world, but also cultivate their critical thinking, creativity, and problem-solving competences. By the time such children become adults, they possess a robust skill set and a confident entrepreneurial mindset, which are essential for their personal and professional growth, as well as for their contribution to economic growth and innovation.

This article aims to map and compare the national strategies of five Balkan countries (Albania, Bulgaria, Greece, North Macedonia, Romania) regarding the integration of entrepreneurship in primary and secondary education. Due to their location in Southeast Europe, the countries selected connect the Balkan region with the rest of the world. Bulgaria, Greece, and Romania are already members of the European Union, while Albania and North Macedonia have been granted the candidate status. Moreover, the geographical contiguity and historical interrelations of Balkan countries foster opportunities for mutual influence and collaboration (Weichert et al.,

2009). These countries exhibit certain commonalities in their political and historical contexts. They share cultural and heritage elements, while four of them (except Greece) experienced communist regimes. The intertwined histories of these countries have cultivated similar social and economic frameworks.

The article constitutes a pioneering study of entrepreneurship education at primary and secondary schools across the five countries selected. The comparative analysis of their interventions aims to showcase best practices and to identify shared challenges in the implementation of entrepreneurship education. The study highlights effective strategies, such as specific teaching methods and policy initiatives that can also be adopted elsewhere. The findings will offer useful information to policymakers and educators paving the way for reforms and curriculum development. This research not only fills a critical gap in relevant literature but also offers practical recommendations for improving entrepreneurship education and, thus, providing insights globally valuable to similar socio-economic contexts.

2. Literature Review

In 2006, the European Commission and the Norwegian government hosted a conference that led to the Oslo Agenda for Entrepreneurship Education in Europe. This agenda outlined actionable steps for the incorporation of entrepreneurship education at all educational levels (European Commission, 2006). This is important because countries can stimulate economic development, create new businesses, and generate employment opportunities by fostering students' entrepreneurship skills and mindsets (Pacher & Glinik, 2024). Furthermore, the European Parliament and the Council endorsed a recommendation on critical competences for lifelong learning in December 2006, identifying entrepreneurship as essential for social inclusion, active citizenship, personal fulfilment, and employability (European Parliament & Council of the European Union, 2006). According to Morakinyo and Akinsola (2019), entrepreneurship education is extremely effective in improving youth community involvement in the 21st century.

The next significant step in supporting the development of entrepreneurship competences came in 2008 with the European Commission's "Small Business Act for Europe" initiative. This initiative aimed at enhancing the EU's overall entrepreneurship policy, highlighting the importance of education and training systems that promote entrepreneurial mindsets and skills from a young age (European Commission, 2008) since early efforts in developing skills can prove to be especially impactful in the long term (Huber et al., 2014). In 2013, the Entrepreneurship 2020 Action Plan marked a significant advancement in recognising entrepreneurship competences; it focused on providing entrepreneurship education and training to foster business creation and growth, removing administrative obstacles, and assisting entrepreneurs during critical stages of their business. Additionally, the plan aimed to rekindle entrepreneurial

culture in Europe by fostering the next generation of entrepreneurs. These recommendations were driven by the need to create more entrepreneurs who can stimulate growth and increase employment. Since 2008, Europe has faced its worst economic downturn in 50 years, with more than 25 million unemployed and most SMEs still unable to recover (European Parliament, 2013).

Introduced in 2016, the European Entrepreneurship Competence Framework (EntreComp) defined entrepreneurship competence that comprises 15 competences allocated in three areas: ideas and opportunities, resources, and action-taking. EntreComp aims at creating a common understanding of entrepreneurship and serves as a tool for individuals, educators, trainers, employers, and policymakers. Fostering entrepreneurial capabilities is a major EU policy goal, leading to the creation of this framework (Bacigalupo et al., 2016). In 2018, the European Commission promoted a strategic policy framework for entrepreneurship education, providing member states with guidance for incorporating entrepreneurship into national curricula (Council of the European Union, 2018). This was crucial since professionals faced obstacles such as lack of resources, threat of commercialism, systemic barriers, assessment challenges, and conceptual ambiguity (Lackéus, 2015). In 2020, the European Skills Agenda emphasised reskilling and upskilling regarding entrepreneurial competences, highlighting lifelong learning and the role of these skills in the digital and green transitions that are driven by changes like telework during the COVID-19 pandemic (European Commission, 2020).

Several studies have investigated entrepreneurship in education. Each one focuses on different aspects, uncovering various key findings, and identifying impacts on entrepreneurial competences (Table 1). For example, Pasic et al. (2022) explored service-related competences in the tourism sector, emphasising the enhancement of sector-specific entrepreneurial skills at the tertiary education level. Vučijak (2018) examined practices in entrepreneurship education among engineering graduates in South-East Europe and Russia, demonstrating improvements in entrepreneurial skills through the REBUS project. Marinkovic (2015) focused on the development of an entrepreneurial culture in Western Balkans by establishing specific creative frameworks at primary and secondary educational institutions to promote a broader entrepreneurial culture. Ćoćkalo et al. (2017) identified trends and factors affecting youth entrepreneurship in tertiary education, addressing challenges and creating opportunities for young entrepreneurs. Radović-Marković (2019) analysed the role of globalisation in fostering entrepreneurship in small countries, highlighting the enhancement of entrepreneurship competences through global exposure. Peković et al. (2017) discussed the support offered by initiatives, such as the REBUS project, for boosting entrepreneurship competencies in innovative sectors in Montenegro.

Bogdanović et al. (2022) emphasised the importance of financial literacy and entrepreneurship education in Serbia and Northern Macedonia, enhancing skills in risk

Table 1. Previous studies

Paper Title	Author(s)	Education Level	Focus	Key Findings	Impact of Entrepreneurial Competences
Service Related Competences Education Practices in South East Europe	Pasic et al., 2022	Tertiary	Tourism sector	Emphasis on tourism-related competences	Enhances sector-specific entrepreneurial skills
Practices in Entrepreneurship Education in South East Europe and Russia	Vučijak, 2018	Tertiary	Engineering graduates	Promotion of entrepreneurship competences through REBUS project	Enhances entrepreneurial skills among engineering students
Fostering an Entrepreneurial Culture in Western Balkans	Marinkovic, 2015	Primary and Secondary	Educational frameworks	Establishment of creative frameworks in schools/universities	Promotes a broader entrepreneurial culture
Analysis of Possibilities for Improving Entrepreneurial Behaviour of Young People	Ćoćkalo et al., 2017	Tertiary	Youth entrepreneurship	Identifies trends and factors affecting young entrepreneurs	Addresses challenges and opportunities for youth entrepreneurship
The Impact of Globalization on Entrepreneurship in Small Countries	Radović-Marković, 2019	Tertiary	Globalization effects	Role of globalization in fostering entrepreneurship	Enhances entrepreneurial competences through global exposure
The State of Entrepreneurship and Innovativeness in Montenegro	Peković et al., 2017	Tertiary	Innovativeness	Support from initiatives like REBUS project	Boosts entrepreneurial competences in innovative sectors
Financial Literacy and Entrepreneurial Education as a Prerequisite for the Development of Entrepreneurship in the Republic of Serbia and Northern Macedonia	Bogdanović et al., 2022	Primary, Secondary, Tertiary	Financial literacy and Entrepreneurial Education	Importance of financial literacy for managing resources, need for comprehensive entrepreneurial education, challenges in practical training integration	Enhances skills in risk assessment, business planning, and financial management, fosters an entrepreneurial mindset
The Youth Entrepreneurship as Response to the Youth Unemployment - Examples of Western Balkan Region	Vutsovaet al., 2022	Not specified	Youth entrepreneurship	Young entrepreneurs face challenges such as lack of experience and practice, and difficult transition between education and the labor market	Entrepreneurship is seen as a tool for reducing youth unemployment, supported by national and international initiatives, creating a new milieu for steady eco-innovation systems and job opportunities.

assessment, business planning, and financial management across primary, secondary, and tertiary education levels. Finally, Vutsova et al. (2022) investigated youth entrepreneurship in Western Balkans as a response to youth unemployment, noting that entrepreneurship can reduce unemployment and create job opportunities despite challenges such as lack of experience and difficult transitions from education to the labour market. However, none of these studies has conducted a comparative analysis of the development of entrepreneurship competences in primary and secondary education within the formal educational systems of Greece, Bulgaria, Romania, Albania, and North Macedonia. This gap in relevant literature suggests a need for research that explores how entrepreneurship skills are cultivated in the education systems of these countries.

3. Results And Discussion

Each country promotes entrepreneurship education at primary and secondary schools through various frameworks and strategies, curriculum integration, teachers' training, government support, key competences, and extracurricular activities (Table 2). Albania has adopted the European Entrepreneurship Competence Framework (EntreComp) and implemented the National Employment and Skills Strategy 2019-2022, along with Law 25/2022, which promotes start-up growth and development (Lula, 2023). Bulgaria focuses on the National SME Strategy 2021-2027, Youth Act, National Education Strategy and the National Youth Strategy 2021-30 to strengthen entrepreneurship education (OECD, 2023). Greece has integrated Skills Labs into its mandatory curriculum, covering 21stcentury skills, life skills, digital citizenship, and entrepreneurship skills (Law 4807/2021, Article 52). North Macedonia implements the Entrepreneurial Learning Strategy 2014-2020, which is supported by the Agency for Promotion of Entrepreneurship and the Fund for Innovation and Technologies (Polenakovik & Sutevski, 2014). Romania's entrepreneurship education is a key component of the vocational education system, guided by government policies to develop social, civic, and entrepreneurship competences (Web-2).

Curriculum integration also varies across the countries studied. In Albania, secondary school curriculum emphasises practical and project-based learning, integrating entrepreneurship education into six subjects (Instituti i Zhvillimit të Arsimit, 2015). In Bulgaria, an ordinance established 20 general education subjects for primary school. One of them fosters "Technologies and Entrepreneurship" and is offered to students of all grades. Instruction begins in the first grade and is concluded in the twelfth grade, adapted to the courses to the students' educational level at each stage. The specialised courses of the curriculum include mandatory entrepreneurship classes focusing either on Entrepreneurship and Information Technologies or on Entrepreneurship and Geography & Economics (Web-3). Greece combines cognitive curriculum perspectives with skill development through Skills Labs, including activi-

ties such as project-based learning, planning and presenting projects, creating games, and participating in drama-in-education plays and virtual business simulations (Law 4807/2021, Article 52). In North Macedonia, entrepreneurship is integrated into six primary education subjects and is further highlighted in the 9th grade subject titled ”Innovations.” Secondary education includes compulsory subjects, e.g. ”Business and Entrepreneurship” (Министерство за образование и наука, 2015b). Romania’s 11th grade curriculum focuses on practical skills and real-life applications, covering social education, economic and financial education, Romanian language and literature, and career counselling (Ministerul Educației, 2023).

Teachers’ training programs also vary. In Albania, teacher training helps educators convey principles of entrepreneurship, innovative thinking, risk-taking, and business planning (Ministria e Arsimit dhe Sportit, 2020). Bulgaria supports teachers through training courses offered by the Bulgarian Centre of Training Firms (European Commission, 2014). Greece’s Institute of Educational Policy provides resources and lesson plans to assist teachers. North Macedonia’s government supports teacher training through the Agency for the Promotion of Entrepreneurship (European Commission, 2024). In Romania, teacher training courses focus on adopting methodologies for diverse needs and promoting the use of digital resources and innovative strategies (Ministerul Educației, 2023). Government support is significant in these countries, with Albania’s Law 25/2022 and the National Employment and Skills Strategy 2019-2022 (Lula, 2023), Bulgaria’s National SME Strategy 2021-27,Youth Act, National Education Strategy and the National Youth Strategy 2021-30 (OECD, 2023), Greece’s Skills Labs supported by the Ministry of Education, (Law 4807/2021, Article 52) and North Macedonia’s initiatives by the Agency for Promotion of Entrepreneurship (Polenakovik & Sutevski, 2014). Romania emphasises the development of social, civic, and entrepreneurship competences in professional education through government guidelines (Web-2).

The extracurricular activities in these five countries focus on different ways to promote entrepreneurship education. In Albania, the emphasis is placed on practical and project-based learning, which is integrated in the secondary school curriculum and offers students a hands-on experience in entrepreneurship (Instituti i Zhvillimit të Arsimit, 2015). Bulgaria extends its support through extracurricular programs that offer training, access to business incubators, and start-up funding, thus helping students turn their ideas into real ventures (OECD, 2023). In Greece, the approach involves interactive activities, such as project-based learning, creation of games, drama-in-education plays, and virtual business simulations, which encourage the development of 21st century skills and entrepreneurial mentality (Law 4807/2021, Article 52). In North Macedonia, there are extracurricular activities in entrepreneurship, such as competitions, fairs, and events, e.g. garage sales (Penaluna et al., 2020). Romania incorporates a mix of project work, risk assessment, and personal and professional

Table 2. Comparative Analysis

Country	Framework and Strategies	Curriculum Integration	Teacher Training	Key Competences Focus	Extracurricular Activities
Albania	Adopted (EntreComp), National Employment and Skills Strategy 2019-2022. Law No. 25/2022 promotes startup development.	High school curriculum based on practical and project-based learning. Entrepreneurship education integrated into six subjects.	Teacher training programs convey principles of entrepreneurship, innovative thinking, risk-taking, and business planning.	European Entrepreneurship Competence Framework (EntreComp) outlines 15 key competences.	High school curriculum emphasizes practical and project-based learning.
Bulgaria	National SME Strategy 2021-27 and Youth Act, National Education Strategy and the National Youth Strategy 2021-30	”Technologies and Entrepreneurship” course, structured across several stages. The course begins in first grade and continues through twelfth grade, tailored to the students’ developmental levels. Specialized subjects support the curriculum, with mandatory entrepreneurship classes focusing either on Entrepreneurship and Information Technologies or on Entrepreneurship and Geography and Economics.	Training courses offered by the Bulgarian Centre of Training Firms.	Focus on creativity, innovation, business skills, and entrepreneurial thinking.	Extracurricular support through training, business incubators, and start-up funding.
Greece	Skills Labs integrated into mandatory curriculum. Four cycles covering 21st-century skills, life skills, digital citizenship, and entrepreneurship abilities.	Skills Labs combine cognitive curriculum with skill development. Activities include project-based learning, constructing and presenting projects, creating games, participating in theatrical plays, and virtual business simulations.	Institute of Educational Policy publishes resources and lesson plans to help teachers.	Focus on 21st century skills, life skills, digital citizenship, and entrepreneurship abilities.	Activities include project-based learning, constructing and presenting projects, creating games, participating in theatrical plays, and virtual business simulations.
North Macedonia	Entrepreneurial Learning Strategy of the Republic of Macedonia 2014-2020. Agency for Promotion of Entrepreneurship (APERNM).	Primary education includes entrepreneurship in six subjects and ‘Innovations’ in 9th grade. Secondary education has ‘Business and Entrepreneurship’ for the fourth year and ‘Innovations and Entrepreneurship’ for first, second, and third years.	Government formed the Agency for Promotion of Entrepreneurship (APERNM).	Focus on entrepreneurship skills and concepts across educational levels.	Competitions, fairs, and events like garage sales.
Romania	Government guidelines emphasize social, civic, and entrepreneurship competences development in professional education.	Entrepreneurship education is a key component of the professional education system. Curriculum aims to develop social, civic, and entrepreneurship competences.	Teacher training programs help adapt methods to diverse needs and promote digital resources and innovative strategies.	Focus on social, civic, and entrepreneurship competences, communication skills, and practical skills.	Educational activities include projects, risk evaluation, and personal/professional development.

development activities, targeting the development of entrepreneurial, social, and civic competences (Web-2). Each country uses distinct methods to foster an entrepreneurial mindset and teach practical business skills among students.

Best practices from other countries can serve as valuable examples for teachers and contribute to the improvement of entrepreneurship education. Estonia's Chamber of Commerce and Industry established a round table, involving government bodies, schools, NGOs, universities, and industries who collaborate to develop entrepreneurship education. Similarly, Spain's EJE/EME projects promote entrepreneurship in primary and secondary education with a focus on skills development through practical, hands-on experience. The EJE project for secondary students (15-18) develops initiative, decision-making, creativity, and teamwork and teaches business creation and management. The project also connects students with local entities, fostering a deeper understanding of European citizenship. These examples underscore the importance of practical experience, stakeholder collaboration, and real-world business engagement, demonstrating that a strategic, hands-on approach enhances students' preparedness for future challenges (YES, 2012).

In addition, a multifaceted approach of teachers' training is necessary for the enhancement of entrepreneurship education. Workshops and webinars allow for sharing best practices and engaging in interactive sessions, e.g. case studies. Online platforms with courses and fora, along with e-learning modules and mobile apps, offer flexible learning and networking opportunities. Mentorship programs provide continuous support, while collaborative projects facilitate international cooperation. Comprehensive curriculum guides and multilingual resources ensure accessibility. The establishment of professional networks and online communities fosters a sense of community using platforms like LinkedIn and Facebook, which facilitate resource sharing. Continuous feedback and research investment ensure the effectiveness of these programs and help teachers promote innovation and entrepreneurship in student communities worldwide.

4. Conclusion

The European Union implemented several key strategies to enhance entrepreneurship education. Initiatives, such as the Oslo Agenda for Entrepreneurship Education in Europe, the "Small Business Act for Europe"(European Commission, 2006) and the Entrepreneurship 2020 Action Plan emphasise the importance of developing entrepreneurship skills at all educational levels to stimulate economic growth, create new businesses, and generate employment opportunities (European Parliament, 2013). The European Entrepreneurship Competence Framework (EntreComp) was introduced to define and promote entrepreneurship competences (Bacigalupo et al., 2016). In the Balkans, countries such as Albania, Bulgaria, Greece, North Macedonia, and Romania adopted various strategies to integrate entrepreneurship education into their

national curricula, with the support of government policies and teacher training programs. These efforts aim to develop key competences and practical skills, ensuring that students are equipped to thrive in their future careers. Studies have shown that such education content significantly improves youth community involvement (Akintolu & Akinsola, 2019) and entrepreneurship skills (Din et al., 2016), thus addressing challenges such as youth unemployment and fostering entrepreneurial culture (Martín-Gutiérrez et al., 2024).

Entrepreneurship education in the Balkan region constitutes a pivotal asset in addressing several critical economic and societal challenges. The limited start-up activity in this particular area, compared to other parts of the world (StartupBlink, 2024), and the continuous struggle of employers to find people with appropriate soft skills, such as communication and teamwork (ManpowerGroup, 2024), underscore the urgent need for comprehensive entrepreneurship training, which can develop students' soft skills (Humsona & Yuliani, 2018). As a result, entrepreneurship education not only equips young individuals with skills necessary for innovation and business creation but also fosters a mindset conducive to active and informed citizenship. This is crucial in regions of the Balkans where economic revitalisation often depends on the emergence of new businesses and the entrepreneurial spirit of their peoples.

Moreover, the integration of entrepreneurship education in interdisciplinary teacher training programs is particularly significant. By fostering an entrepreneurial mindset among educators, we lay the groundwork for more profound and widespread acknowledgement and understanding of the importance of entrepreneurship education. Teachers equipped with an entrepreneurial mindset are better prepared to develop these competences in their students, thereby amplifying the impact of educational initiatives aimed at fostering entrepreneurship. Educators can progressively build their understanding and appreciation of entrepreneurial principles through targeted teacher training initiatives. This, in turn, enables them to impart such values and skills to their students more effectively. This type of cyclical enhancement of capabilities enriches both individuals and the societal fabric, thus leading to a more resilient and innovative economic landscape.

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TREE-BASED APPROACH TO PREDICT EMPLOYEE TURNOVER

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Abstract
Employee turnover is a challenge faced by organisations due to negative impact on employee productivity, morale and general performance. Understanding the factors that affect employee turnover contributes to developing effective employee retention strategies. The objective of this paper is identifying the best classification model for predicting employee turnover and detecting the key factors that affect employee churn. To achieve the research objective, we conducted a comparative analysis between decision trees and random forest algorithms. The results of the analysis show that workplace satisfaction, workload, review score, average number of working hours per month, and tenure are the main factors affecting employee turnover. Of the two algorithms employed, random forest exhibited superior performance across all evaluation metrics utilised. This study contributes to existing literature by providing empirical proof regarding factors that affect employee turnover and by comparing different machine learning algorithms. Findings highlight the value of machine learning techniques in understanding complexities of the workforce, in general, and in providing empirical evidence for building human resource strategies.

Keywords: machine learning; predictive analysis; employee turnover; classification; random forest; decision trees

JEL Classification: D20, C31, C52

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1. Introduction

Employee turnover is a significant challenge faced by organisations across various industries. Productive employees' decision to leave, driven by factors such as work pressure, unsuitable environments or unsatisfactory compensation, can have profound implications on productivity, morale, and overall organisational success. The departure of valuable employees not only reduces an organisation's productivity but also places additional strain on the human resource department to recruit, train, and integrate new hires. This transition period can lower the morale of remaining employees, who are often required to take on extra work, potentially having a cascading effect if more employees follow their departing colleagues in search of better opportunities.

Understanding the factors contributing to employee turnover and developing effective strategies to mitigate it have become important tasks for HR professionals and organisational leaders. Existing literature on employee turnover offers valuable insights into the various factors influencing employees' decisions to leave a company. However, despite extensive research, there is no consensus on specific factors driving employee turnover.

This study aims to deepen the understanding of factors influencing employee turnover and to develop a robust classification model to assist organisations in making informed decisions and implementing effective strategies to manage and reduce turnover. To achieve our aim, we established the following objectives:

1. Apply tree-based machine learning algorithms to classify employee turnover.
2. Identify the factors influencing employees' decisions to leave the company.
3. Determine which algorithm provides the most accurate and robust classification of employee turnover.

Predicting employee turnover before it occurs can help a company's management prevent or, at least, mitigate the impact of such departures. Recent advances in machine learning and data analysis have provided new opportunities to help stakeholders delve into the complexities of employee turnover. By leveraging the power of machine learning algorithms, organisations can analyse large datasets to unmask hidden patterns, identify factors, and predict employee turnover with greater accuracy.

To achieve the proposed goals and objectives, this study undertook several steps. It reviewed existing literature on employee turnover, examining various theoretical frameworks and empirical findings to establish a solid foundation for understanding the complexity and dynamics of employee turnover. An empirical analysis was conducted using tree-based machine learning algorithms known, from previous research, for their performance in predicting employee turnover. Decision trees and random forests were employed to analyse information on current and former employees us-

ing a dataset of a U.S. company. An initial exploratory data analysis and preprocessing step ensured data quality and consistency. Subsequently, various performance metrics were used to evaluate the classification capabilities of the models developed.

This research aims to contribute to the existing literature by conducting a comprehensive analysis of employee turnover and considering a wide range of factors that may influence employees' decisions to leave an organisation. By creating multiple models using different machine learning algorithms, the study seeks to capture a nuanced understanding of factors affecting turnover decisions.

In conclusion, this study highlights the factors impacting employee turnover and their relative importance, as identified through decision trees and random forests. Addressing these factors can help organisations foster a positive work environment, enhance employee engagement, and improve employee retention rates, ultimately contributing to an organisation's long-term success.

2. State of the Art

Employee turnover is a highly studied phenomenon due to its significant importance for organisations. Employees play an important role in the success of companies, and their replacement can be difficult and time-consuming (Kaur & Vijay, 2016). Turnover affects the stability and performance of organisations. Costs associated with employee turnover are estimated to range from the equivalent of an annual salary for each departing employee (Boroş & Curşeu, 2013) to millions of dollars in recruitment, training, and lost productivity (Perryer et al., 2010). The departure of employees also impacts the morale of those who remain, as they are often required to take on additional work until replacements are found, which can lead to feelings of being left behind in an organisation that has driven others to resign. The resignation of one employee can bring further losses as others may follow their former colleagues to seek new opportunities (Felps et al., 2009).

Despite extensive research, there is no single universal reason why employees choose to leave their organisations. Turnover represents the movement of employees within the labour market, between companies, jobs, and occupations, and between employment and unemployment (Abassi & Hollman, 2000). The employee turnover rate is defined as the ratio of the number of members who left the organisation during a given period to the average number of individuals in that organisation over the same period (Price, 1977). Managers often refer to employee turnover as the entire process associated with filling a vacant position: whenever a position is vacated, either voluntarily or involuntarily, a new employee must be hired and trained. This cycle of replacement is known as employee turnover (Kramer, 1995) and the term is frequently used to measure the rate at which employees leave an organisation, regardless of the reason.

2.1 Machine learning algorithms used

Alduayj and Rajpoot (2018) developed multiple machine learning models to predict employee turnover, including random forests, k-nearest neighbours, and support vector machines. They utilised different versions of the IBM HR dataset: the original unbalanced dataset and two synthetically balanced datasets (one over-sampled and one under-sampled). While these authors achieved high accuracy with the synthetically balanced datasets, the accuracy for the original dataset was low.

Najafi-Zangeneh et al. (2021) introduced a three-step framework for predicting employee turnover. The first step involved data cleaning using the "max-out" variable selection method. In the second step, they trained a logistic regression model for prediction. The third step involved performing confidence analysis to assess the prediction model usefulness. Despite these efforts, the model suffered from poor accuracy and high complexity due to extensive pre- and post-processing.

Pratt et al. (2021) employed classification trees and random forests for predicting turnover. Prior to classification, they pre-processed the data by removing unwanted variables using Pearson correlation. However, their model showed only slight improvement in accuracy compared to other machine learning algorithms.

Taylor et al. (2020) used decision tree-based models, including random forests and gradient-boosted trees, to predict employee turnover. These models demonstrated the highest performance. They used their own dataset containing 5,550 records.

2.2 Factors contributing to employee turnover

Understanding the factors influencing employee turnover is important for organisations aiming to enhance retention and maintain a stable, productive workforce. These factors can be broadly categorised into individual factors and work-related factors. These factors interact with each other in complex ways to influence resigning intentions. By comprehensively examining both individual and work-related factors, organisations can develop strategies targeted to address the root causes of employee turnover and to foster a more engaging and supportive work environment.

2.2.1 Individual factors

Individual factors refer to the set of employees' characteristics relevant to employee turnover and can be intrinsic, such as an individual's personality, or acquired, such as technical aptitude.

- Gender - in a meta-analysis (Park and Shaw, 2013) it was concluded that there is a similar turnover rate between men and women. Existing literature (Humpert and Pfeifer, 2013) contains empirical evidence that older women have a lower turnover rate when compared to men of the same age. Additionally, recent papers conclude that women have a higher turnover rate than men (Ono, 2023).

- Age - some researchers demonstrated that the intention of leaving an organisation is higher in younger individuals (Pitts et al., 2011). However, in most papers, the intent of leaving is negatively correlated to age (Carmeli and Weisberg, 2006; Ng and Feldman, 2009).
- Tenure - some research papers claim that age is studied in its interaction with tenure (Griffeth et al., 2000). Additionally, these authors claim that a shorter tenure leads to a higher turnover intention. It has been shown that there is job instability in the first years of employment (Singh and Schwab, 2000); Marital status - the number of children and responsibilities that come with being part of a family also have an impact on an employee's intention to leave the organisation in search of stability (Krau, 1981). This is also confirmed by a meta-analysis by Griffeth et al. (2000).

2.2.2 Work-related factors

There are several extrinsic factors affecting employees and impacting turnover rates.

- Stress - undoubtedly, stress is one of the most critical factors when it comes to employee turnover. Factors that in turn lead to stress at the workplace are ambiguity of one's role, employees' task overload and the conflict between worktime and time spent with the family (Trevor, 2001; Guimaraes, 1997).
- Satisfaction - individuals not satisfied with their current post will look for opportunities in other organisations (Carsten and Spector, 1987; Silla et al., 2009; Rode et al., 2007).
- Number of work hours - Higgins et al. (2000) showed that a shorter work schedule prevents the work-family conflict for women and leads to greater workplace satisfaction. D'Addio et al. (2007) concluded that for men, the opposite is true; in other words, men with full-time jobs have greater job satisfaction than those with part-time jobs.
- Workload - multiple research papers claim that there is a positive correlation between the workload, stress and turnover intention (Brannon et al., 2007).
- Promotion - there is very high correlation between promotion and job satisfaction, which in turn impacts employee retention rates (Pergamit and Veum, 1999; House et al., 1996).
- Salary - the salary variable has a modest impact on the turnover decision, according to Griffeth et al. (2000). These authors concluded that when high-performing employees are not rewarded appropriately, they leave the organisation.

2.3 Research Hypotheses

To confirm or reject the importance of the factors identified following the literature review, we have formulated two research hypotheses.

Although this factor has led to contradictory results, most studies (De Cuyper et al., 2009; Rode et al., 2007) support the notion that low job satisfaction is an important determinant in one's decision to resign and individuals with low job satisfaction are more likely to resign.

High Performers are often sought after by other companies and may receive more attractive and better-paid offers. Such employees may view these opportunities as career advancements and may decide to resign to take advantage of benefits offered elsewhere. Highly performing employees are constantly seeking opportunities for development and professional growth (Prince, 2005). If they feel their current job does not provide enough learning and advancement opportunities, they may seek alternative work environments offering more opportunities for development and skill enhancement and, therefore, are more likely to resign.

Lack of promotion opportunities for employees can lead to loss of valuable talent for the organisation (Eyster et al., 2008). When the organisation fails to provide career growth and development prospects, talented employees may be tempted to seek other opportunities in companies that offer such benefits. Employees who have not been promoted are more likely to leave a company.

Employees with a heavy workload may be overburdened and at risk of exhaustion and stress (Brannon et al., 2007). If they do not receive adequate support, such as additional resources or delegated responsibilities, they may reach a point when they feel they cannot cope with their workload and may decide to resign. In other words, employees with a heavy workload are more likely to resign.

Employees who are relatively new and have a short tenure in the company are not as connected and involved in the organisation's culture and values (Singh & Schwab, 2000). Without a strong connection, they may be less motivated to remain with a company in the long term and may be more open to exploring other job opportunities. This is why employees with a short tenure in the company are more likely to resign.

Although the salary level is no longer the primary decision-making factor when it comes to a job, it is still considered an important factor. There is research suggesting that one's salary level may play a role in an employee's decision to leave a job (Silbert, 2005). Employees with lower salaries may be more motivated to seek other opportunities that offer a competitive salary and are, therefore, more likely to resign.

Based on the above, we formulated the following hypothesis:

Hypothesis 1: Employees that are more likely to leave the company are those with low satisfaction, high performance, a heavy workload, no prospect of promotion, a short tenure, and a low salary level.

After analysing several studies (Usha & Balaji, 2019; Fallucchi et al., 2020) applying machine learning algorithms to predict employee turnover, we observed that decision trees were included in all these studies and showed good classification performance. Other researchers (Pratt et al., 2021; Taylor et al., 2020) have shown that

random forest performs even better considering it is composed of multiple decision trees. Thus, we formulated the following hypothesis:

Hypothesis 2: A random forest algorithm provides the best performance in classifying resignation decisions.

These hypotheses represent preliminary statements based on the literature analysed, providing a framework for investigating the relationship between different factors and employee turnover, as well as determining the tree-based machine learning algorithm that will provide the best performance in classifying one's decision to leave a company.

3 Methodology

For achieving the purpose and objectives of this paper, two tree-based machine learning algorithms were used: two decision trees and a random forest one.

For determining the performance of the algorithms, multiple evaluation metrics were used. First, classification *accuracy* was used for measuring the overall correctness of the predictions made by the models. Additionally, *recall*, *specificity* and *precision* were also used as evaluation metrics to assess the algorithms' capability to distinguish between positive and negative instances. To account for the trade-off between sensitivity and specificity, the *ROC curve* and its associated index, *AUC*, were also used.

3.1 Decision trees

The decision tree algorithm is particularly useful for classification tasks because it can handle both categorical and numerical data and it is relatively easy to understand and interpret (Hastie et al., 2009). In addition, decision trees can be visualised, which helps understand the decision-making process.

3.2 Random forest

In the case of a random forest, when training classifiers some data may be used multiple times while others may never be used. Thus, greater stability of the classifier is achieved, as it becomes more robust to slight variations in input data, and, at the same time, it increases classification accuracy (Breiman, 2001). Several studies have shown that bagging-based methods such as RF, unlike other boosting-based methods, are not sensitive to noise or overfitting (Briem et al., 2002; Chan and Paelinckx, 2008; Pal and Mather, 2003).

4 Empirical analysis

In this chapter, we present the empirical analysis conducted using a dataset that includes detailed information on both current and former employees, to investigate the

effectiveness of decision tree and random forest algorithms in predicting employee turnover.

4.1 Database structure

The database (Pujar, G., 2017) on which we will perform the analysis contains details about approximately 15,000 employees of a company in the United States of America. The information in this database was collected by the company's human resources department in order to find out the reasons why employees left the company.

The database contains 10 employee characteristics described as follows:

- satisfaction level: employee satisfaction score derived from surveys and ranging from 0 to 1;
- last evaluation: score the employee received in the last evaluation, which varies between 0 and 1;
- number of projects: the number of projects the employee is involved in;
- average monthly hours: the average number of hours the employee worked in a month;
- tenure: number of years the employee has been with the organisation;
- work accident: whether the employee had an accident at work or not;
- promoted: whether the employee was promoted or not in the last 5 years;
- salary: for privacy reasons, the salary is divided to three level groups: low, medium and high;
- departure (left): whether the employee left the company or not.

4.2 Exploratory data analysis

We began the analysis by doing a descriptive analysis of the database, as shown in Figure 1.

```
 satisfaction        review          projects       avg_hrs_month
Min.   :0.090000   Min.   :0.360000   Min.   :2.00000   Min.   : 96.00
1st Qu.:0.440000   1st Qu.:0.560000   1st Qu.:3.00000   1st Qu.:156.00
Median :0.640000   Median :0.720000   Median :4.00000   Median :200.00
Mean   :0.612834   Mean   :0.716102   Mean   :3.80305   Mean   :201.05
3rd Qu.:0.820000   3rd Qu.:0.870000   3rd Qu.:5.00000   3rd Qu.:245.00
Max.   :1.000000   Max.   :1.000000   Max.   :7.00000   Max.   :310.00

    tenure         accident  left      promoted       department      salary
Min.   : 2.00000   0:12830   0:11428   0:14680   sales      :4140   high  :1237
1st Qu.: 3.00000   1: 2169   1: 3571   1:  319   technical  :2720   low   :7316
Median : 3.00000                                 support    :2229   medium:6446
Mean   : 3.49823                                 IT         :1227
3rd Qu.: 4.00000                                 product_mng: 902
Max.   :10.00000                                 marketing  : 858
                                                 (Other)    :2923
```

Figure 1: Database Description

It is apparent that variables "accident", "departure (left)", "promotion (promoted)", "department" and "salary" are categorical variables while the rest of them are numerical. There were no missing values in any of the variables in the dataset.

The descriptive analysis (Figure 1) indicates means and measures of dispersion for numerical variables, and frequency for categorical ones. For example, it can be observed that the average employee satisfaction score is 0.61, and the average evaluation score is 0.71. Furthermore, of the total number of employees only 319 were promoted. Although the satisfaction score ranges from 0 to 1, there are no employees with a satisfaction score of 0 and the lowest score recorded for this variable is 0.09. Similarly, the score obtained in the evaluation ranges between 0 and 1, but the lowest score obtained by employees is 0.36. On average, employees stay with the company for 3 and a half years but there are employees who had been with the company for 10 years.

4.3 Results

This section will show the outcomes achieved when implementing the two tree-based algorithms: two decisions trees and a random forest one.

Figure 2 summarizes the values for each of the performance metrics for all created models.

Algorithm	Accuracy	Sensitivity	Specificity	AUC
DT	0.972	0.9132	0.9904	0.972
DT pre-pruned	0.95	0.9197	0.9595	0.966
DT post-pruned	0.9569	0.9160	0.9697	0.964
RF	0.9904	0.9636	0.9988	0.994
Simplified RF	0.9896	0.9608	0.9985	0.994
NR	0.9727	0.9031	0.9942	0.962

Figure 2: Model performance

Three decision trees were built using different techniques: the first tree did not have any constrains, the second one was pre-pruned, and the third tree was post-pruned. The first decision tree, the most complex one, presented the best performance. The pre-pruned tree, designed for simplicity, showed the worst performance. Finally, the post-pruned tree achieved a good level of accuracy with low complexity.

The post-pruned decision tree, albeit of the lowest accuracy in comparison to Random Forest models, offers the advantage of being less complex and easier to interpret. Its simplicity and transparency make it a viable option for organisations that want a better understanding of how factors influence an employee's decision to resign.

The random forest algorithm was initially trained without specifying any parameters and 500 decision trees were obtained. Analysing the connection between the number of random forest trees and the error, it was concluded that the error did not significantly decrease above 100 trees. Consequently, we built another random forest with 100 trees, which achieved a slightly lower performance but close to the one achieved by the more complex random forest. Given its reduced complexity and good performance, the second random forest was chosen as the more appropriate model of the two.

In all evaluation metrics, the random forest algorithm had the best classification performance.

In the forthcoming subchapters, we will detail the implementation of the model selected for each algorithm.

4.3.1 Decision trees

Out of all the DTs built, the post-pruned version performed the best. To decide which complexity parameter to use, we plotted the relative error and the complexity parameter, as in Figure 3.

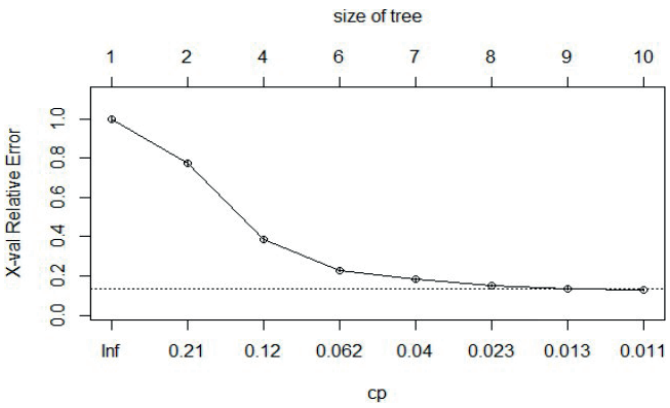

Figure 3: Relative error based on complexity parameter

We can see in this figure that the relative error does not significantly decrease once the 0.04 threshold is crossed. Consequently, the 0.04 complexity parameter is chosen. The resulting DT is represented in Figure 4.

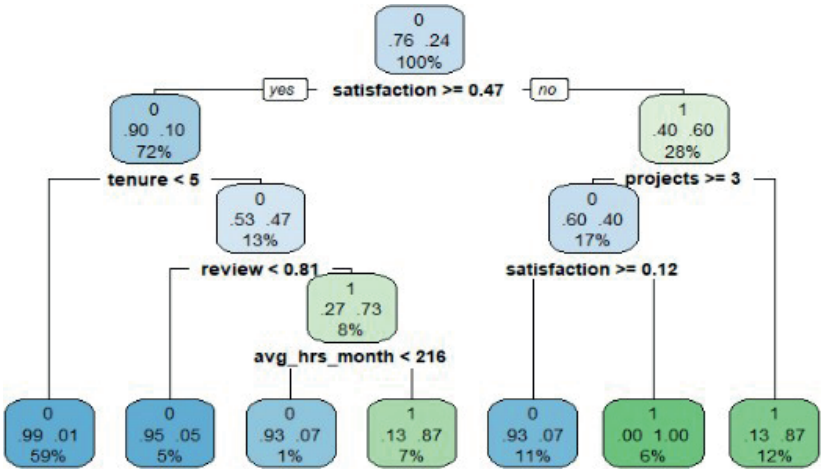

Figure 4: Decision tree with optimal complexity parameter

The decision tree obtained has 13 nodes, of which 7 are leaves, and 4 levels.

A detailed view of the classification matrix and evaluation metrics of this tree are presented in Figure 5.

```
          Reference
Prediction    0    1
         0 3324   90
         1  104  981

               Accuracy : 0.9569
           Sensitivity : 0.9160
           Specificity : 0.9697
        Pos Pred Value : 0.9041
        Neg Pred Value : 0.9736
    Balanced Accuracy : 0.9428
```

Figure 5: Classification matrix and evaluation metrics for the optimal DT

To show how well the decision tree differentiates the two classes, the AUC index and the ROC curve are analysed as follows:

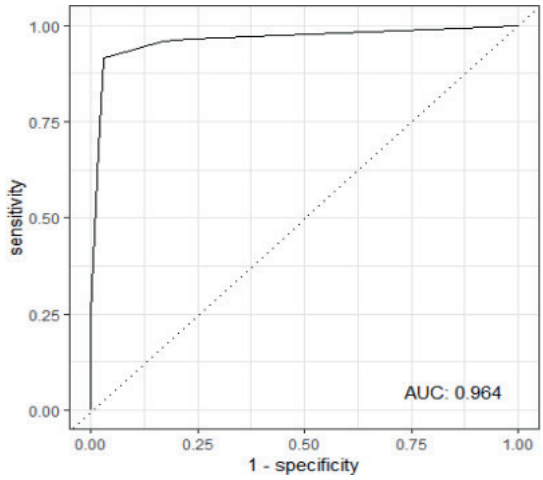

Figure 6: ROC curve and AUC index for the optimal DT

As per Figure 6, the value of the AUC index is lower compared to the pre-pruned DT. This is most likely due to the lower sensitivity of the pre-pruned DT. The value of the AUC index of 0.964 is quite close to the value of 1, which means that the decision tree manages to differentiate well between the two categories. The fact that the ROC curve is close to the upper left corner indicates the same thing.

4.3.2 Random forest

Initially we created a random forest without specifying the parameters that resulted in a random forest of 500 trees. To see whether it was possible to reduce the complexity of the model, we created a graph (Figure 7) with the error and the number of trees from the random forest.

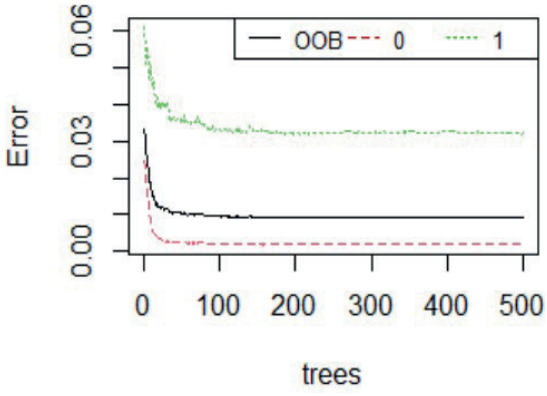

Figure 7: Random Forest error level relative to the number of its trees

In Figure 7 we present the incorrect classifications recorded on the data that were not used when creating trees. In addition, these incorrect classifications were divided by classes, which indicates that the overall classification error, as well as the classification error by classes, do not significantly decrease once approximately 100 decision trees have been created. In other words, it is redundant to create 400 more trees if they don't help improve performance. Thus, a new random forest with 100 decision trees was created to verify whether a similar performance could be obtained with less complexity.

```
Call:
 randomForest(formula = left ~ ., data = train.data, importance = T,
              ntree = 100)
              Type of random forest: classification
                    Number of trees: 100
No. of variables tried at each split: 3

        OOB estimate of  error rate: 0.95%
Confusion matrix:
     0    1 class.error
0 7983   17    0.002125
1   83 2417    0.033200
```

Figure 8: Training results for a random forest with 100 trees

Figure 8 shows that the misclassification rate on OOB data is 0.95%. The rate of the class with employees who did not resign is 0.21%, and the rate of the class of employees who resigned is 3.3%. Overall, decreased complexity did not have a significant effect on performance, at least in the case of OOB data. Performance on the testing dataset is presented below.

```
          Reference
Prediction    0    1
         0 3423   42
         1    5 1029

               Accuracy : 0.9896
           Sensitivity : 0.9608
           Specificity : 0.9985
        Pos Pred Value : 0.9952
        Neg Pred Value : 0.9879
     Balanced Accuracy : 0.9797
```

Figure 9: Random forest classification matrix and evaluation metrics

The 99.9% accuracy obtained from the training set is very close to that obtained from the testing set, which means that the model maintains its performance on new

data (Figure 9). Accuracy on the testing dataset dropped very slightly from 99% to 98.96% as compared to the first random forest model built. The same applies to sensitivity and specificity, which are very close to those of the previous model. Reducing the number of trees from 500 to 100 did not have much of an effect on performance.

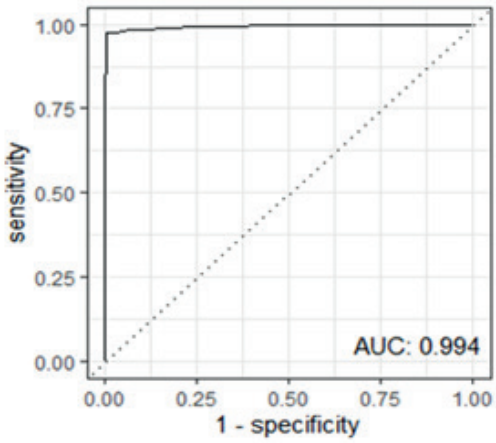

Figure 10: ROC curve and AUC index for the simplified Random Forest

The fact that the ROC curve is so close to the top left corner and the AUC index of 0.994 is very close to 1 indicate that the random forest model is highly effective at distinguishing between employees who left the company and employees who didn't.

4.4 Validation of Research Hypotheses

In all evaluation metrics, the random forest algorithm demonstrated the best classification performance. Thus, hypothesis 2, which states that the random forest algorithm provides the best performance in classifying employee turnover, is validated. The decision tree, although having weak accuracy compared to Random Forest, offers the advantage of being less complex and easier to interpret. Its simplicity and transparency make it a viable option for organisations seeking better understanding of how factors influence employee turnover.

Based on the results provided by the decision tree, we could identify the relationships between factors and one's decision to resign. There is an inverse relationship between the independent variable 'satisfaction' and the dependent variable. Meanwhile, there is a direct relationship between the independent variables 'average number of hours worked per month', 'score obtained in the last evaluation', 'tenure', and the dependent variable. Categorical variables are excluded from the model indicating that they are not significant in predicting employee turnover. Factors such as promotion and salary do not impact the model's predictions. Thus, hypothesis 1, which

suggests that employees predisposed to resign are those with low satisfaction, high performance, a heavy workload, no prospects of promotion, a short tenure, and a low salary level, is partially validated. The hypothesis states that employees who were not promoted and had low salaries were more likely to leave the company. However, in our decision tree model, these factors did not demonstrate significant importance.

Overall, the hypotheses developed at the beginning of the research are partially validated. The random forest model stands out for its superior performance, while decision tree haves presented different strengths and weaknesses. The choice between decision trees and random forests depends on the organisation's preference for model complexity and interpretability, as well as its performance.

5 Conclusion

A high employee turnover rate is an important problem for companies. Losing highly performing employees is considered a major loss. Finding replacements of a similar level of performance is difficult and costs the company both money and time. The main objective of this research was to identify factors that influence staff turnover and develop a robust classification model using tree-based machine learning algorithms to predict employee turnover based on employees' characteristics.

Employees who experience low job satisfaction, high performance, heavy workloads, and short tenures are more likely to leave their current company. Low job satisfaction can lead to disengagement and lack of motivation, making employees more inclined to seek opportunities in places where they will feel more valued and content. Highly performing employees, if not adequately recognised or rewarded, may feel unappreciated and overburdened, which prompts them to look for environments that offer better acknowledgment of their contribution to the firm. Heavy workloads can lead to burnout and stress, pushing employees to search for positions with more manageable demands. Lastly, employees with a short tenure might feel less attached to the company and more willing to leave if they perceive better opportunities elsewhere.

Regarding the empirical analysis performed via two tree-based machine learning algorithms, results showed that a random forest model offers the best performance in the classification of one's resignation decision, due to clearly superior results in different evaluation metrics. The decision tree presented a slightly lower accuracy compared to that of a random forest one; however, the former offers the advantage of simplicity and ease of interpretation. This trade-off between performance and interpretability should be considered when selecting the most suitable model for practical implementation. The simplicity of the model can be particularly beneficial for organisations looking for an easy-to-understand representation of their decision-making process.

Overall, this paper provided insights into the factors influencing one's resignation decision and developed predictive models using decision trees, a random forest and

neural networks. Research findings lay the foundation for future deeper research into the dynamics of staff turnover, for exploring new data sources, for developing strategies to mitigate staff turnover and for promoting a positive work environment.

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EMPIRICAL STUDY ON EURO CURRENCY CONFIDENCE UNDER GLOBAL CHALLENGES

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Abstract

The relationship between the euro and globalisation is an important component of economic integration; it has enabled smoother trade and investment among member states of the European Union since the currency was launched. This process has not only increased commerce inside Europe but has also had an influence on the global economy. The euro's impact reaches into global banking and trade, highlighting the interdependence of global economies and the significance of public perception in maintaining the stability of the euro. This paper uses data-mining methods, namely decision trees and neural networks, to examine the factors that influenced the perception of the euro among citizens of Eurozone member states in 2019 and 2022. The years were intentionally chosen to compare attitudes before the pandemic and the changes caused by the COVID-19 pandemic. In 2019, perceptions were observed in a stable economic and social context, whereas in 2022, the effects of the pandemic, such as economic shocks and recovery efforts, were analysed. This study is important for detecting changes in public opinion resulting from the pandemic, assisting policymakers and the European Central Bank in formulating ways to strengthen support for the euro. Gaining insight into these perspectives may result in developing more inclusive policymaking, thereby helping to resolve inequities among member states or demographic groups and guaranteeing the long-term stability of the currency.

Keywords: Euro, economic perceptions, CART algorithm, Neural networks, Eurobarometer, European Union

JEL Classification: D91. Role and Effects of Psychological, Emotional, Social, and Cognitive Factors on Decision Making

The paper was among the five nominated papers for the ***Tsekouras Prize for Young Economists***, awarded by the *Association of Economic Universities of South and Eastern Europe and the Black Sea Region (ASECU)* which will be announced at the ASECU International Conference, Montenegro, July 2025.

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1. Introduction

Public opinion about the euro extends beyond questions of monetary efficiency and includes everyday convenience, institutional trust, and identity. Supporters emphasise the euro's role in lowering transaction costs, enabling seamless travel and cross-border business, and anchoring macroeconomic credibility. Critics, however, point to perceived price increases associated with currency changes, concerns over the loss of national monetary autonomy, and symbolic attachment to legacy currencies. These divergent viewpoints, i.e., economic utility versus perceived costs, European integration versus national sovereignty, and European identity versus national symbolism, shaping opinions about the euro as a complex outcome across countries and demographic groups.

The COVID-19 shock offered a before-and-after perspective through which these viewpoints may have shifted. In 2019, Eurozone citizens reported their opinions in a relatively stable social and economic context. By 2022, households had experienced pandemic disruptions, uneven recoveries, and accelerated changes in payment habits. Despite the rich body of research analysing public support for the euro, existing studies rely on traditional regression-based frameworks and focus on long-term trends, structural determinants, or crisis-related shifts. Contributions such as those by Roth et al. (2015, 2019, 2022) or Banducci et al. (2003, 2009) analyse public confidence in the euro using macroeconomic indicators, institutional trust, or demographic gradients, but they do not provide a direct micro-level comparison of the determinants before and after the COVID-19 pandemic. Moreover, earlier papers typically evaluated predictors individually rather than assessing the relative importance of competing mechanisms, such as institutional performance, cross-border convenience, and payment habits, within a unified analytical framework. There is also limited use of interpretable machine-learning approaches that can both rank determinants and derive respondent profiles in a transparent way. This paper addresses such gaps by constructing three perceptual constructs (C1–C3), comparing their influence in 2019 and 2022, and applying CART and MLP models to identify shifts in the importance and the profiles most associated with negative views of the euro.

This paper aims to fill this gap by providing a structured comparative analysis of the determinants of euro confidence before and after the COVID-19 shock. First, we classify the relevant Flash Eurobarometer items into three conceptually coherent constructs and derive synthetic indicators for each of them: C1 - Institutional reforms (perceived performance and reforms in key policy domains); C2 – Travel and business facilitation (perceived convenience and cost reductions across borders); and C3 – Payment methods (cash versus electronic payments in daily life). These constructs are built as weighted aggregations of survey items, where weights reflect the relative importance of each item obtained from CART-based variable importance measures.

In this way, each respondent receives a score for C1–C3 that summarises their perception of reforms, cross-border benefits, and payment habits, respectively.

In this study, we use the term "trends" not to describe long-run time-series dynamics, but to capture changes between 2019 and 2022 in: (i) which construct most strongly influenced confidence in the euro; (ii) how strongly demographic factors were associated with euro confidence; and (iii) which profiles of respondents were most likely to hold negative views. This framing links the paper's aim to a clear and measurable contribution.

Methodologically, we combine Classification and Regression Trees (CART), which yield transparent variable-importance rankings and human-readable profiles, with Multilayer Perceptron (MLP) neural networks as an out-of-sample validation layer. Our research questions are:

Q1. Which of the constructs (C1–C3) had the strongest influence on confidence in the euro in 2019 and 2022, and how did their relative importance change?

Q2. Which demographic factors (country, education completion age, age, job) most differentiated perceptions, and did their effects intensify after COVID-19?

Q3. Which respondent profiles were most likely to hold negative views in each year?

The paper makes three contributions. First, it offers the Eurozone a pre- versus post-COVID micro-comparison that ranks the relative influence of institutional, convenience-related, and payment-habit constructs on confidence in the euro and indicates how these ranks shifted across the studied period. Second, it identifies actionable profiles of likely sceptics, as defined by specific combinations of country, education, and age, informing targeted communication and reform priorities. Third, it proposes a transparent construct-level mapping of survey items and interpretable machine-learning models (CART with MLP validation) that situates other attitudinal settings within which heterogeneous mechanisms compete.

We position our study within the literature on euro support and identity, clarify the construct mapping, and detail the CART–MLP framework and validation strategy. We then present results for 2019 and 2022, highlighting construct importance, demographic differentiation, and profiles of negative perceptions. We conclude with implications for policy design and communication, highlighting factors reinforcing cross-border convenience and addressing institutional concerns, which can increase public confidence in the euro.

The paper is structured as follows. Section 2 reviews the relevant literature on monetary perceptions and the determinants of support for the euro. Section 3 presents the data, the construction of the three perceptual constructs, and the methodological framework based on CART and MLP models. Section 4 reports the empirical results for 2019 and 2022, focusing on construct importance, demographic differentiation,

and respondents' profiles. Section 5 concludes by discussing the policy implications of the findings and outlining avenues for future research.

2. Literature Review

The social and cultural construction of money goes beyond its physical form as a facilitator for the exchange of goods and services. Adam Smith (1776) acknowledged this in his work titled *The Wealth of Nations*. In order to simplify and streamline transactions, money was created, and it carries a subjective value determined by human judgement. This allows for easier exchanges that do not require direct trade in goods and services. An additional point made by Wimmer (2018) is that a sense of loyalty and emotional connection to one's own nation can emerge in the image of money as a public good. The perception of money is influenced by cultural and social contexts, according to Simmel (2005). This is affected by various factors, including the stability of a nation's monetary system and citizens' trust in the government's financial management capacity. Therefore, the significance of money extends beyond its economic value, since it functions as a powerful cultural and social symbol (Holton and Turner, 2010). Money reflects the values of a society or nation, thus becoming a symbol (Genschel and Jachtenfuchs, 2017).

2.1. Money, Identity and Monetary Integration

The association between money and national identity stems from the cultural and social connotations attached to it as stated. A national currency acts as a powerful signifier of the value and financial power of a country or a community (Helleiner et al., 2003; Negri et al., 2020). In addition, it can serve as a means of expressing values and customs. Symbols, images, and inscriptions engraved on banknotes play a crucial role in shaping and enhancing national identity (Holton and Turner, 2010; Risse, 2003). The strength of a currency can signify the country stability and trust, serving as the basis for national identity (Leblond, 2003). The Swedish and Danish krone are an example of stable currencies, with a rich history of economic and political stability (Hobolt and Leblond, 2009). Another possible illustration is Germany's former currency, the Deutsche Mark, which was once renowned worldwide for its remarkable strength and consistent stability, this is seen in polls that have shown an overwhelming consensus against the adoption of the euro as the country's official currency, despite its introduction by the federal government in 1999 (Risse, 2003).

A monetary area represents a geographical space in which member states coordinate their monetary policies and use the same currency (Encinas-Ferrer, 2013). The currency area uses a common currency accepted by all member states, facilitating commercial transactions and reducing currency conversion costs. A common monetary policy also helps to maintain economic stability and prevent financial crises, since member countries share responsibility for coordinating monetary policy and

maintaining financial stability (Baldwin and Wyplosz, 2020). Established in the 3rd century BC, the monetary union of the Roman Empire introduced the denarius and provided a remarkable model for a centralised currency over vast territories (Boerner and Volckart, 2011). Although several efforts aimed to replicate this feat were made, both in the interwar period, such as the Scandinavian Monetary Union of the 1920s and 1930s, and later in the 1960s, for example through the African Monetary Union, political and economic problems repeatedly delayed such aspirations (Bergman, 1999).

There are currently 20 member states of the European Union that are Eurozone. Croatia is the most recent member state of the Eurozone, joining in 2023. The Maastricht Treaty of 1992 pioneered the creation of the Economic and Monetary Union, laying the foundations for its establishment (European Central Bank, 2023). Nations that met the benchmarks were welcomed into the Eurozone (European Central Bank, 2021). The launch of euro banknotes and coins in 2002 was a historic moment for the euro (European Central Bank, 2023). Its implementation facilitated the consolidation of the monetary union and aimed to eradicate currency fluctuations between member states, thus increasing trade. Before the adoption of the euro, trade transactions between member countries were hampered by the use of individual national currencies. The introduction of the euro allowed for seamless travel and trade throughout the Eurozone (European Union, 2022a). Currently, the euro can be considered one of the most important pillars of the European Union and a stable, reliable and globally recognised currency.

The key element of the European Monetary Area is defined by the single currency, the euro, which aims to increase the level of the European integration process that began in 1990 (Genschel and Jachtenfuchs, 2017). As argued in the first paragraph of the paper, any currency can be viewed as a social construct, so it is of interest to analyse the perception EU citizens regarding the euro. Further studies will be presented to understand the impact that citizens' perception has on a currency and why it is important for the Eurozone.

2.2. The importance of euro perception

Relevant literature states that assessing how citizens perceive the euro is important for various reasons, as described in this section.

First, economic issues may have a different impact on individuals, depending on their age, occupation, and socio-economic status. Analysing citizens' perceptions provides insight into the different impacts of economic issues and allows for a deeper understanding of the situation. For example, inflation peaks can affect people differently, depending on their income and spending habits (Witt, 2016). Studying citizens' perceptions can help to recognise distinct classes of citizens and to create appropriate policies to address economic issues.

Second, in order to improve communication with citizens, it is essential to understand their perceptions of the euro. This understanding allows government officials and central bankers to communicate more effectively with the public (Banducci et al., 2003). In cases of misconceptions about the functioning of the euro, responsible institutions can provide clearer information to help EU citizens understand the monetary system (Roth and Jonung, 2022). By analysing citizens' perceptions, officials can identify gaps in their communication strategy and take corrective measures to ensure effective dissemination of information.

Additionally, understanding how citizens perceive monetary policy is crucial for improving its effectiveness (Marcussen and Zølner, 2003). According to Verdun (2019), this type of analysis can provide valuable information on how monetary policies affect citizens. Officials can consider unfavourable perceptions, as well as their causes, to protect people and improve economic performance (Derose et al., 2007). By better understanding citizens' perceptions, institutions that aim to design and implement monetary policy at the EU level can make sounder and better-informed decisions.

Finally, the sustainability of a currency depends largely on the trust it inspires. Stronger trust in the euro can not only boost financial growth but also attract investment and ensure greater stability. In order to assess the factors shaping such trust, it is essential to assess citizens' opinions (Roth and Jonung, 2022). This type of analysis can reveal ways to strengthen trust in the euro, including more effective communication with the public and adopting appropriate monetary strategies.

Trust in a currency is essential for its functioning and survival over time. People use the currency to buy goods and services, as well as savings. When trust in a currency is lost, it becomes worthless and cannot fulfil its role as a means of trade or a store of value (Skaggs, 1998). Trust in the euro is fundamentally necessary for the longevity of the Eurozone, which consists of 20 European Union member states that share the euro as a common medium of exchange. If individuals trust a currency, they will willingly incorporate it into their transactions. If trust in a currency declines, people will rush to get rid of it, inevitably causing a decline of its value (Bordo et al., 2013). Finally, if a currency is scarcely accepted or used by people, it may well become worthless. Residents of a Eurozone member country may decide to exchange their savings into alternative currencies if they have a negative outlook on the euro; this act alone could cause the euro to depreciate. Accordingly, a reduction in the real value of the euro can propel rising inflation and economic instability throughout the Eurozone. This link has been well-established in several reports (Banducci et al., 2003; Hobolt and Leblond, 2014; Roth et al., 2015; Roth et al., 2019).

2.3. Determinants of public opinion towards the euro

The perception of a currency can be seen in three primary dimensions. The cognitive dimension refers to an individual's awareness and understanding of the value, design and security features of a currency. Factors such as education, experience and exposure to different currencies may influence this dimension. People who travel frequently are likely to have more in-depth knowledge of currencies compared to those who do not travel. The emotional connections that citizens have with their currency should also be taken into account when examining the currency of a country or community (Tyszka and Przybyszewski, 2006). The affective dimension of currency involves people's emotional connections and feelings towards it, influenced by the culture, history and identity of the nation. For example, an individual may feel a sense of loyalty and pride for their currency due to its historical significance and shared cultural values, as also supported by Engelberg and Sjöberg (2006). Finally, when evaluating a country's currency, the assessment of its quality is of paramount importance. The valuation of a country's currency is impacted by its economic performance and government policies. The evaluative dimension is strongly influenced by these two factors. A country with a strong economy and competent management of its finances is likely to have a positive public opinion of its currency.

The three dimensions of perception, emotion, and evaluation are interconnected. People's cognitive information about a currency can affect their emotions and evaluations, while their emotions and evaluations can shape their understanding of the currency. Thus, a comprehensive approach that considers all three dimensions is necessary for understanding how individuals perceive a national currency.

The significance of the euro extends beyond it being a mere currency; it embodies national sovereignty and independence, as discussed earlier. However, the transition to the use of the euro may be perceived by some people as a loss of national identity. Hobolt and Leblond's (2009) study of the Swedish and Danish referendums provides further evidence confirming this phenomenon. Research by Kaltenthaler and Anderson (2001), Marcussen and Zølner (2003), and Jubille and Leblang (2007) further supports this claim. For those with a strong sense of national identity, the use of the euro may be seen as a threat to their cultural values and traditions. Such notions are reinforced by fears of losing control over monetary and fiscal policies, as well as by the negative economic effects of European integration, such as job losses and rising prices. Isengard and Schneider's (2006) study of German citizens' scepticism illustrates this argument. On the other hand, people who identify more with European values and have a positive attitude towards European integration perceive the euro as an opportunity to strengthen European solidarity and enjoy the economic benefits of a unified market. In their paper, Negri et al. (2020) argue that a sense of national and European identity can coexist. This implies that views of the euro can also be affected by factors such as attitudes towards European integration and national identity.

The level of trust in one's own government can have a significant impact on perceptions of the euro, but the degree of influence varies depending on the circumstances of each country. Countries with strong governments and successful economic management may generate more trust in their own government. While decreasing trust in European institutions can leads them to a doubtful or negative view of the euro. Gabel's (1999) survey of European public opinion on the benefits and disadvantages of EMU, together with trust in European institutions, was analysed using statistical methods such as factor analysis and regressions. Qualitative interviews with European citizens were also conducted to gain a deeper understanding of their motivations and perceptions of EMU. Using these mixed methods, Gabel uncovered a comprehensive view of public perceptions and the factors shaping them, confirming the role of trust in one's own government and economic performance in shaping perceptions of the euro. The perception of the euro is shaped by various factors, including the strength of a country's economy and government. In Germany, for example, where the economy and government are robust, there is a perception that the European Central Bank is not doing enough to protect Germany's interests, which can lead Germany people to a negative perception of the euro (Isengard and Schneider, 2006). Conversely, countries with weak economies and unstable governments may have less trust in their own government and more trust in European institutions, such as the European Central Bank. This can lead people to have a more positive outlook on the euro and increased demand for euro membership (Hobolt and Leblond, 2009). In Bulgaria, for example, people believe that joining the euro could provide economic and financial benefits (Roth and Jonung, 2022). Therefore, the perception of the euro is influenced by the level of trust citizens have in their own governments, and varies from country to country.

A favourable perception of the euro can be undermined by inflation, which erodes trust in the currency and the institutions responsible for management. Studies by Banducci et al. (2003) and Roth et al. (2019) have validated this claim, establishing a significant negative relationship between inflation rates and public perception of the euro. Consequently, theoretically, high inflation rates lead to price increases while eroding the purchasing power of the currency, which can lead to a loss of trust in the euro and the ability of European monetary institutions to maintain fiscal stability.

Citizens' satisfaction with their financial situation could have a significant impact on the phenomenon examined in this paper. Research by Bergbauer et al. (2020) shows that those who are satisfied with their financial well-being are more likely to support the euro and the ECB. The authors found that EMU supporters were the largest group of respondents who rated their household financial situation as good or very good. In contrast, respondents who expressed significant dissatisfaction with their financial situation had a different perspective. EMU supporters accounted for

only 10% of respondents in this group at the end of 2019, indicating a further decline from pre-crisis levels.

Demographic factors

Gender may affect perceptions of the euro, but there are no studies that clearly state or refute this. Findings by Bergbauer et al. (2020) indicate that, while men and women share similar attitudes towards the euro, fewer women identify as supporters of EMU. The author states that in Eurobarometer surveys, women answered "don't know" more often than men, by a difference of around 5%. This paper will further explore whether gender, as a demographic factor, has any significant impact on perceptions of the euro.

People's perceptions of the euro can be influenced by their age and experiences. Growing up in a world where the single currency is a reality, young people are more likely to have a favourable view of the euro (European Union, 2022b). In contrast, older people, who may retain a nostalgic attachment to their former national currency, may be more sceptical. Their previous experiences with economic turmoil, such as currency devaluation and inflation, may lead them to view the concept of a common currency with more suspicion (Tyszka and Przybyszewski, 2006). The fact that older people's opinion is rather against the euro is also supported, studied and confirmed by Banducci et al. (2009) in their paper *Economic interests and public support for the euro*. This paper analysed the effect of demographic variables on public support for the euro.

Education can significantly influence the way the euro is perceived, especially among Eurozone member countries. In countries that have not yet adopted the single currency are less affected by education as a factor, according to Banducci et al. (2009). Fernández and Eigmüller's (2018) article *Social Education and the Educational Divide in European Identity, 1992–2015* explores this topic in more depth. Using various statistical models, including linear regression and mixed-effects analysis models, the authors were able to explore the correlation between education and feelings of belonging to the EU. By controlling for variables such as age, gender, and socioeconomic status, the study revealed that education did indeed have a significant effect on the development of European identity. The study's findings were based on data from the Eurobarometer survey conducted between 1992 and 2015 and covered a range of age groups and countries. The authors concluded that people with higher education tend to associate themselves more with the EU and consider belonging to the EU as an integral part of their identity. In contrast, people with lower education are less likely to identify with the EU and do not consider belonging to it significant for their sense of self. Therefore, education also plays a crucial role in shaping opinions on the euro, as supported by the relevant literature (Isengard and Schneider, 2006).

The perception of the euro can be influenced by a person's occupation, albeit indirectly, as this is generated by the level of education that the person needed to obtain a particular job. Thus, educated professionals, such as those in finance, economics, or international trade, often have a more favourable view of the euro due to their knowledge of the economic benefits it offers. However, those with lower education working in low-wage fields, such as agriculture or domestic services, may be more sceptical of the euro, as they may not have access to information about its benefits and may be more susceptible to economic difficulties. Research by Bergbauer et al. (2020) confirms the above. The aforementioned study stated that managers, senior professionals, and the self-employed persons are more likely to support the euro, while manual workers, housewives, and the unemployed are sceptical about the euro.

Individuals involved in international business and, consequently, exposed to currency risk have a more advanced understanding of the euro and show a greater interest in foreign exchange market developments. Gabel and Hix's (2005) study found that, for several reasons, international business and trade may be factors that shape perceptions of the euro. The authors analysed data from the 2002 UK public opinion survey, which included questions about experience with and attitudes towards the euro. The researchers used regression analysis to assess the correlation between perceptions of the currency and experience with the euro, taking into account factors such as education, age, and income. The results of the study indicated that individuals who traded in the euro with other countries and who had more experience in handling the currency had a better perception of it. The authors attributed this relationship to the fact that such individuals are exposed to the benefits and disadvantages of using the euro as a trading currency. People with trading experience are likely to be more aware of the dangers associated with currency fluctuations and may be more inclined to protect themselves against such dangers by adopting a single currency to eliminate them. The authors' analysis shows that trading in the euro can shape people's perspective on the currency, which can significantly influence political choices regarding admission to the Eurozone.

2.4. Research hypothesis

This study aims to illustrate the impact of three distinct categories of variables—demographics, national governmental efficacy, and individuals' economic expectations—on perceptions of the euro held by residents of the Eurozone. The study puts forward three hypotheses, which will be validated or not using empirical investigation:

H1: Perceptions of Eurozone citizens regarding the euro are impacted by various demographic factors.

H2: The performance of national governments plays a significant role in shaping individuals' perceptions of the euro.

H3: The economic expectations of people are a key determinant in influencing how the euro is perceived.

In addition, the paper intends to identify the profiles of people who hold a negative opinion, in order to identify groups that should be given more attention regarding this issue.

3. Methodology

3.1. Data used

This paper uses data from the 2019 and 2022 Flash Eurobarometer surveys conducted in Eurozone countries. The Eurobarometer is a public opinion survey programme set up by the European Commission to monitor the attitudes of EU citizens towards economic, political, and social issues. The paper's main aim is to collect comparable information across Member States on how Europeans perceive the European Union, its institutions, and key policies, such as Economic and Monetary Union and the euro. Such survey data are regularly used by EU institutions to assess public trust, policy acceptance, and differences in attitudes between countries, making the Eurobarometer a reliable and widely recognised source for studying citizens' confidence in the euro. The Eurobarometer monitors public opinion in EU member states, targeting individuals aged 15 and above, using a typical sample size of 1,000 per country, with the exception of smaller nations, such as Luxembourg or Malta. Such surveys compare sample compositions to population demographics using post-stratification proportions (w1) to ensure accuracy. These proportions adjust the significance of each participant's data based on their country's population, age, gender, and profession, using data from National Research Institutes and Eurostat. This method enhances the precision and representativeness of the survey results.

The countries in the analysis are: Belgium (BE), Germany (DE), Greece (GR), Spain (ES), Finland (FI), France (FR), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Austria (AT), Portugal (PT), Cyprus (CY), Estonia (EE), Latvia (LV), Malta (MT), Slovakia (SK), Slovenia (SI), and Lithuania (LT).

In previous Eurobarometer surveys, up to Eurobarometer 31A (June 1989), different sampling methods were used and varied from country to country. Sampling designs were either multi-stage national probability samples or stratified national quota samples. In each country, a random selection of sampling points was made in such a way that all types of areas (urban, rural, etc.) were represented in proportion to their population. Respondents were selected at a second stage. In Belgium (until Eurobarometer 23), Denmark, Luxembourg, and the Netherlands, a random selection from the population or appropriate electoral rolls (of persons or households) was used. In Belgium (since Eurobarometer 24), France, Italy, the United Kingdom, and Ireland, quota sampling by sex, age, and occupation based on census data was applied, while

in Greece, Spain, and Portugal, a random route procedure was used. Germany employed quota sampling by sex, age, and occupation based on census data until Eurobarometer 23 and a random route procedure since Eurobarometer 24 (October 1985).

In the Standard and Special Eurobarometer series, a comparison is made for each participating country between the composition of the sample and an appropriate description of the population regarding the socio-demographic criteria to be used in the calculation of post-stratification weights. National research institutions and Eurostat provide the descriptions of populations and apply a national weighting procedure, using marginal weighting and cross-sectional analysis.

Each sample instance is associated with a post-stratification weight, denoted w1, which is calculated according to the country's population and its socio-demographic structure. The most detailed level of geographical subdivision to which Eurobarometer data sets can be broken down usually corresponds to country-specific regional levels applied in the sampling procedure. These GEOGRAPHICAL UNITS are coded in the REGION variable (P7). For each country, the relationship with the official NUTS classification (Eurostat's Nomenclature of Territorial Units for Statistics) is documented in the variable description. This attempts to correct the importance of the information provided by an instance, taking into account the size of the population of the country from which it comes and the age group, sex, occupation, etc.

The use of these weights is important for obtaining more precise and representative results in the process of extrapolating findings. Given that samples are of the same size, with minor exceptions, but represent populations of different sizes, it is normal for an observation from a larger population to have a higher weight than an observation from a smaller population, since it is expected to represent more instances in the population of origin. The same can be said for population structure by sex, age, and other characteristics.

These weights are calculated using information on the composition of the target population provided by National Research Institutes and/or Eurostat. The use of these weights in the analysis of Eurobarometer data provides more precise and representative results regarding the target population.

3.2. Algorithm CART

CART stands for Classification and Regression Trees, initially introduced by Breiman in 1996, and operates by iteratively partitioning data into multiple subspaces to ensure that outcomes in each final subspace are as similar as possible. This technique is referred to as recursive partitioning (Berk, 2008).

The main characteristics of CART trees (Berk, 2008) include: the ability to handle extensive datasets; the ability to handle small implicit predictors, both numerical and categorical; the ability to easily disregard redundant variables; the ability to handle missing data through surrogate splits; the capacity to easily interpret small trees; and the difficulty in interpreting large trees.

Another point to note about this algorithm is that it also provides measures of variable importance. In a CART tree, the importance of a variable is measured by considering its contribution to the reduction in variation in child leaf nodes, relative to the variation specific to the parent node from which they originate. Specifically, variable importance is most often quantified using the cumulative Gini index at the tree level, depending on the relationship (Tahsildar, 2019).

$$(1) \qquad Gini = 1 - \sum_{i=1}^{n} p_i^2$$

Where p_i is the probability that an instance is classified in a certain category.

Gini Impurity, used for splitting nodes when the target variable is categorical, is calculated as 1 minus Gini (Sharma, 2020). A lower score indicates purer nodes. The more important a variable, the purer the resulting nodes, thus lowering Gini Impurity. Importance is determined by the factor's capacity to reduce diversity and create refined subcategories.

Balancing Methodology for CART algorithm

In order to ensure the most accurate analysis, "don't know" or "didn't answer" responses were removed from the target variable. Since the target variable, perception_n (questionnaire item q1_1), has the structure shown in Figure 1, the analyses were performed on several balanced samples. To obtain a validation dataset, a 30% sample was extracted from the original data, preserving the original structure of the target variable. The training set was split into three samples, keeping the minority category unchanged and randomly splitting the majority category into three samples. This resulted in a proportion of approximately 50% for the majority category and around 40% for the minority category. The weighting variable w1, described above, was also included in the trees produced. Trees were also generated based on the CART algorithm using all three aggregate samples simultaneously, with the minority category replicated three times.

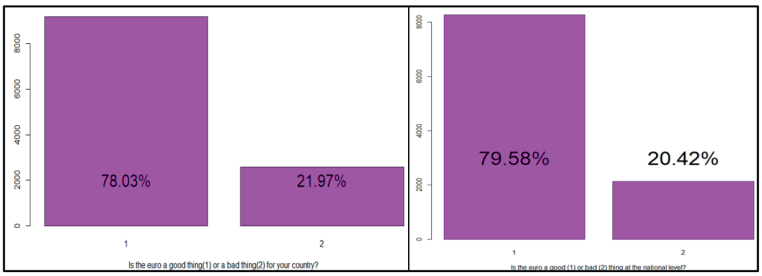

Figure 1. Distribution of target variables for 2019 and 2022

Source: personal processing in Rstudio

Survey responses on economic matters were transformed for clarity: negative views got negative values, neutral responses got 0, and positive views got positive values. Principal Component Analysis identified four economic frameworks. Decision trees were created to pinpoint key variables, validated using the Random Forest technique. Table 1 shows total and average variable significance across samples.

Using the average importance percentages, weights were created to achieve average scores for each construct at the level of each instance. These variables, called constructs (C), represent weighted aggregations of variables that can be seen in Table 1. This was done using the following formula:

$$c_{in} = \sum_{1}^{j} Q_{ji} * p_j \quad (2)$$

Where: i - is the instance number; n - is the component number; j - represents the question number (question code); Q_{ji} - represents the answer of instance "i" to the question; p_j - represents the weighting value obtained by hierarchically weighting the variables These variables are called constructs (C) and represent a weighted aggregation of variables as follows:

- C1, construct referring to reforms needed at the level of each country comprising questions: Q10 (with all derived questions) and Q9.1
- C2, construct referring to advantages brought by the euro: Q7 (with all derived questions)
- C3, construct referring to ease of handling euro coins and banknotes: Q3a1 and Q3a2
- C4, construct referring to euro coins: Q4 and Q5

Construct C4, has only one important variable (see Table 1), will be presented with its original name. No other transformations were applied to it.

Discretisation of variables was performed in R Studio using the discretise () function from the rules package - specifically the "cluster" method with the k-means algorithm - to create categories. This method ensures high homogeneity within intervals (Fonseca, 2019). Categorial variables are plotted in Figure 2.

The CART algorithm was used to train decision trees for each of the three samples. Table 2 presents explanatory variables' relative magnitudes and performance. Demographic variables were analysed separately using the same methodology, the results are presented in Table 3. Finally, trees combining all constructs and important demographic variables were created using the CART algorithm, relevant results are displayed in Table 4.

3.3. Neural networks

Neural networks are mathematical models inspired by the human brain. They are used in machine learning and AI, and they consist of artificial neurons connected by synaptic weights, organised into layers: an input layer, one or more hidden layers, and an output layer. Data flow through these layers, processed from input to output, producing the final result (Dongare et al., 2008).

This study implemented neural networks using the RSNNS package in R, a comprehensive library for building and training neural networks in R. The number and size of hidden layers depend on the problem's complexity and network architecture (Uzair and Jamil, 2020). A larger number of hidden layers can enhance learning and capture complex relationships, but they require more data, training time, and technical resources. By adjusting synaptic weights and learning from the training dataset, neural networks can recognise patterns, make predictions, and solve tasks in classification, regression, image recognition, natural language processing, and more (Schmidhuber, 2015). Multilayer Perceptron (MLP) neural networks, a type of feedforward neural network, consist of several hidden layers between the input and output layers (Zare et al., 2012). Each neuron in the hidden layer uses a nonlinear activation function to process inputs, introducing non-linearities that allow the MLP to model complex relationships.

Various activation functions were used, including Rprop (Resilient Backpropagation), Quickprop, SCG (Scaled Conjugate Gradient), Backprop Weight Decay, Backprop Momentum, Std_Backpropagation, and BackpropBatch, as described by Taud and Mas (2017) and Jurgen et al. (2014), to train and optimise neural networks.

The libraries used to implement neural networks in RStudio are RSNNS (used for artificial neural networks), caret (for evaluating and comparing machine learning models), NeuralNetTools (to visualise and analyse neural networks), and ggplot2 (for graphs). The categorical variable country was converted into binary dummy variables, representing each country as 1 or 0. Dataset normalisation was performed to ensure optimal neural network performance by reducing feature variation and preventing gradient-related issues. Various neural network structures were tested, and the best models are presented in Table 5. Automatic parameter optimisation was used to enhance model performance.

The Olden method, based on Garson's algorithm but improved, determines variable importance in neural networks (Garson, 1991). It calculates importance by summing the products of connections between input, hidden, and output layers, preserving both magnitude and sign. Unlike Garson's approach, the Olden method handles multiple hidden layers and avoids misleading absolute magnitudes, focusing instead on relative contributions and sign changes.

4. Results

4.1. CART results

Results by construct

Table 1 in the Annexes presents the cumulative and average importance of explanatory variables for each construct in 2019 and 2022, which were assessed via decision trees using the CART algorithm. In the Institutional Reforms framework, during the 2019–2022 period, there was an increased emphasis on education, the labour market, and major systemic reforms, while healthcare and retirement reforms declined in priority. For Travel and Business Facilitation, affordable travel remained important, while price comparison became less significant, with a growing focus on reducing fees and improving business processes. The growing importance of education and labour market reforms supports the argument of Bergbauer et al. (2020) and Roth and Jonung (2022) that confidence in the euro depends on effective domestic governance and visible progress in key institutional areas. At the same time, the continued relevance of travel affordability and reduced transaction fees aligns with Banducci, Karp, and Loedel (2003) and Baldwin and Wyplosz (2020), who highlight that tangible, everyday economic benefits remain central to sustaining public support for the common currency.

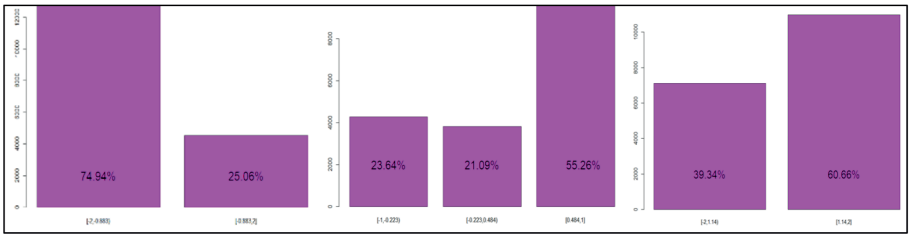

Figure 2. Distribution of the constructs for 2019

Source: personal processing in Rstudio

The Payment Methods framework showed a significant shift from currency and paper money transactions to electronic payment methods, reflecting changing consumer preferences and payment innovations. This result supports Tyszka and Przybyszewski (2006), who noted that the cognitive and evaluative dimensions of currency perception evolve with people's experience and habits. The shift toward electronic payments reflects changing behavioural patterns and aligns with Simmel (2005), who emphasised the social and cultural adaptation of money to modern forms of exchange. Average significance percentages were used to determine the combined importance of factors at the concept level, labelled C1, C2, and C3, and discretised accordingly. Figures 2 and 3 display the distributions of these concepts for 2019 and 2022.

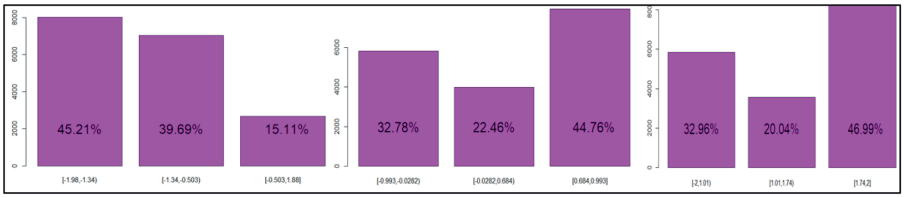

Figure 3. Distribution of the constructs for 2022

Source: personal processing in Rstudio

Table 2 in the Annexes highlights the significance of frameworks and efficacy measures using the CART technique on each sample. In the 2019 sample I, C2 was dominant having 97% importance, achieving 71.5% accuracy, 76.60% sensitivity, and 56.07% specificity. This outcome aligns with Banducci, Karp and Loedel (2003), who emphasised that citizens' support for the euro is largely driven by its economic utility and everyday advantages. The dominance of C2 (Travel and Business Facilitation) confirms that practical benefits, such as easier transactions and mobility, remain the main factors shaping positive perceptions of the euro. C3 had minimal impact at 3%. The limited impact of Construct III (Payment Methods) suggests that payment behaviour plays a smaller role in shaping perceptions of the euro compared to broader economic and institutional factors highlighted by Banducci et al. (2003) and Roth and Jonung (2022). By 2022, C2 was solely important at 100%, compared to 68.73% accuracy, 72.41% sensitivity, and 55.25% specificity, indicating a strong focus on travel and business facilitation in sample I.

In sample II (2019), C2 held 87% importance and 64.93% accuracy. C3 and C1 contributed 11% and 2%, respectively. By 2022, C2's importance rose to 97%, and C1 and C3 scored 2.5% and 0.5%. Accuracy improved to 67.55%, having 70.05% sensitivity and 58.42% specificity, showing a refined focus on travel and business in sample II.

In sample III (2019), C2 accounted for 87% of the importance, resulting in 64.93% accuracy. C3 and C1 contributed 11% and 2%, respectively. In 2022, C2's importance slightly decreased to 92%, while C3 and C1 increased to 4%. This led to 65.88% accuracy, 67.50% sensitivity, and 59.96% specificity, indicating a more balanced influence from all constructs in sample III. From 2019 to 2022, C2 consistently held the highest importance, underscoring its role in shaping perceptions about the euro. Performance metrics showed slight improvements, reflecting a refined understanding of public perceptions based on these constructs.

Demographic variables

As shown in Table 3 in the Annexes, in 2019, sample I identified country as the most important variable at 42%, followed by age at the end of studies at 36%. The model

showed moderate accuracy (62.99%) and balanced sensitivity (64.36%) and specificity (58.90%). These results are consistent with previous studies highlighting cross-country differences and the role of education in shaping euro perceptions. The strong impact of the country variable confirms the findings of Hobolt and Leblond (2009) and Gabel (1999), who showed that national context and trust in domestic institutions significantly affect attitudes towards the euro. Likewise, the importance of education aligns with Banducci et al. (2009) and Fernández and Eigmüller (2018), who demonstrated that higher educational attainment fosters a stronger European identity and greater support for the common currency.

Sample II highlighted 'age' at the end of studies' (46%) and 'country' (30%) as key factors, with an accuracy of 64.68% and higher sensitivity (67.71%) compared to specificity (55.55%). This finding reinforces arguments of Banducci et al. (2009) and Fernández and Eigmüller (2018), demonstrating that education remains a central determinant of euro support, as it strengthens understanding and identification with European integration. The continued relevance of the 'country' variable supports Hobolt and Leblond (2009) and Gabel (1999), who emphasised that national economic context and institutional trust shape cross-country variation in citizens' perceptions of the euro.

Sample III similarly emphasised 'country' (44%) and 'age at the end of studies' (42%), achieving 64.62% accuracy and 67.99% sensitivity, but lower specificity (54.49%). By 2022, the importance of 'country' increased in sample I to 68%, with 'age at the end of studies' at 30%. The model's accuracy dropped slightly to 59.69%, with improved specificity (62.86%) but lower sensitivity (58.80%). These results further confirm the persistence of national and educational impact on euro perceptions. The strong and growing importance of the 'country' variable aligns with Hobolt and Leblond (2009) and Roth and Jonung (2022), who showed that citizens' confidence in the euro varies across national contexts depending on economic conditions and trust in governance. The continued relevance of education supports Banducci et al. (2009) and Fernández and Eigmüller (2018), indicating that higher educational attainment consistently fosters more favourable attitudes toward the euro and European integration.

In sample II, age at the end of studies remained important at 56%, with country at 37%, maintaining similar performance metrics, with accuracy of 64.11% and sensitivity of 67.39%. Sample III identified age at the end of studies (48%) and country (41%) as dominant factors and showed improved accuracy (67.56%) and sensitivity (74.17%), but reduced specificity (43.89%). Overall, from 2019 to 2022, country and educational attainment gained importance in influencing euro perceptions. While accuracy and sensitivity generally improved, specificity varied, reflecting changes in the model's ability to identify negative perceptions.

Final analysis with CART algorithm

Table 4 in the Annexes presents the results of applying the CART algorithm to each of the three samples using the previously selected demographic constructs and variables. The table shows the importance of variables and performance indicators obtained for each sample. In addition, an average value is provided for each of the important variables and performance indicators.

For 2019, sample I showed that Construct II (C2: Travel and Business Facilitation) was the most important at 62%, followed by country at 23%. The model reported an accuracy of 71.7%, sensitivity of 76.51%, and specificity of 57.25%. Sample II also identified C2 as dominant at 70%, with age at the end of studies at 18% and country at 12%, achieving 67.78% accuracy. In sample III, C2 remained essential at 59%, with country at 29%, resulting in 70.08% accuracy. Across all samples, C2 was the dominant factor in predicting euro perceptions.

These findings are in line with Banducci, Karp, and Loedel (2003) and Baldwin and Wyplosz (2020), who emphasised that citizens' support for the euro is primarily driven by its economic advantages and cross-border convenience. The consistent dominance of Construct II (Travel and Business Facilitation) underlines the importance of tangible economic benefits, such as easier travel and business transactions, in sustaining positive attitudes towards the euro. The additional impact of education and country context supports Fernández and Eigmüller (2018) and Hobolt and Leblond (2009), confirming that both knowledge about the EU and national circumstances continue to shape public perceptions of the common currency.

4.2. Neural network results

For 2019, Network 13 using BackpropBatch achieved the best performance, with an F1 score of 0.8612, accuracy of 75.99%, sensitivity of 76.29%, and specificity of 63.39%. For 2022, the same Network 13 maintained superior performance, with an F1 score of 0.8507, accuracy of 78.7%, and sensitivity of 78.76%, but with reduced specificity at 44.44%. Overall, BackpropBatch remained the most effective learning method for Network 13, although its specificity decreased in 2022, indicating an increase in false positive identifications. Results and variable-importance values associated with each independent variable from Network 13 are presented in Figure 4.

In the 2019 graph (left side of Figure 4), C2 is the most important variable positively impacting perceptions of the euro. Following C2, Ireland (IE), Luxembourg (LU), Finland (FI), and age at the end of studies also show significant positive importance. Construct III (C3: Payment Methods) and several other countries, such as Austria (AT), Estonia (EE), Germany (DE), and Portugal (PT), also contribute positively, but to a lesser extent. Variables such as age, France (FR), Italy (IT), Cyprus (CY), and Belgium (BE) have minimal to slightly negative importance, indicating a less favourable or neutral impact on perceptions of the euro. These results support Banducci et

al. (2009) and Fernández and Eigmüller (2018), confirming that higher education and exposure to cross-border mobility are associated with stronger support for the euro. The positive influence of countries such as Ireland, Luxembourg, and Finland aligns with Roth and Jonung (2022), who found that trust in national governance and stable economic performance enhance confidence in the common currency. Conversely, the weaker or negative contributions observed for France, Italy, and Cyprus reflect earlier findings by Hobolt and Leblond (2009) and Gabel (1999), which underlined how national economic pressures and institutional dissatisfaction can reduce support for the euro.

In the 2022 graph (right side of Figure 4), C2 once again emerges as the most important variable positively influencing euro perceptions, reinforcing its dominant role. Ireland (IE) and age at the end of studies follow in importance, with Construct III (C3) and countries such as Slovakia (SK), Estonia (EE), and France (FR) also contributing positively. However, negative impacts are more pronounced in 2022, with Cyprus (CY), Construct I (C1: Institutional Reforms), and several other countries, such as Luxembourg (LU) and Italy (IT), showing significant negative importance. This suggests a shift, with certain demographic and regional factors exerting an increasingly negative effect on euro perceptions compared to 2019.

These findings confirm the persistence of economic utility as the main driver of euro support, consistent with Banducci, Karp, and Loedel (2003) and Baldwin and Wyplosz (2020), while also indicating growing sensitivity to institutional performance and national context. The emergence of stronger negative effects for Construct I (Institutional Reforms) and countries such as Italy and Cyprus aligns with Gabel (1999) and Roth and Jonung (2022), who emphasised that declining trust in governance and reform outcomes can weaken public confidence in the euro. At the same time, the continued positive role of education and cross-border convenience (C2) supports Fernández and Eigmüller (2018) and Hobolt and Leblond (2009), reinforcing that informed and mobile citizens remain the most consistent supporters of the common currency.

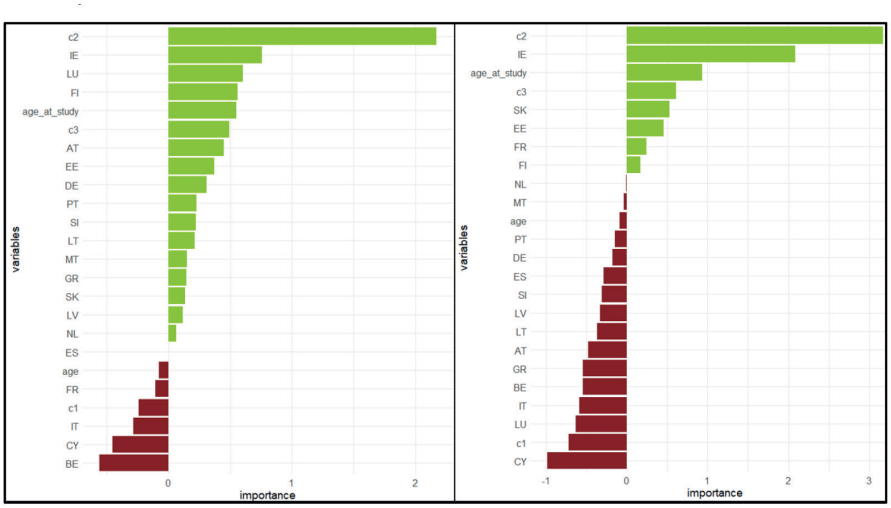

Figure 4. Importance of independent variables in the MLP network 13

Source: personal processing in Rstudio

When comparing the results of the two years, C2 consistently holds the highest positive importance, indicating that travel and business facilitation remain key factors in shaping favourable perceptions of the euro. The influence of individual countries and demographic variables, such as age at the end of studies, is also significant in both years, although with some shifts in their relative importance. In 2022, negative influences are more pronounced, especially from certain countries and C1, suggesting growing regional and institutional concerns affecting euro perceptions. This change highlights evolving public attitudes and possibly emerging economic or political factors influencing citizens' perceptions of the currency.

These comparative results are consistent with Banducci et al. (2003) and Baldwin and Wyplosz (2020), confirming that the euro continues to be valued primarily for its economic and practical benefits related to mobility and business facilitation. The growing weight of country-specific and institutional effects supports the findings of Gabel (1999) and Roth and Jonung (2022), who argued that trust in governance and national economic performance strongly condition citizens' views of the euro. The rise of negative influences from Construct I (Institutional Reforms) further echoes Hobolt and Leblond (2009), suggesting that institutional dissatisfaction and uneven reform outcomes increasingly shape regional differences in citizens' attitudes towards the euro.

Conclusion

Since its launch, the euro has triggered a range of debates regarding its impact and efficacy as the common currency of the European Union. This study uses a machine-learning algorithm to analyse factors influencing perceptions of the euro in 2019 and 2022. The goal was to provide insights for policymakers to enhance strategies supporting the euro by examining extensive datasets for trends and correlations among diverse variables.

The analysis shows that demographic variables, such as age, educational attainment, and country, have significant impacts on euro perceptions. Both 2019 and 2022 were influenced by variables such as age at the end of studies and specific countries (e.g., Ireland and Luxembourg). In 2022, the importance of certain demographic factors, such as age at the end of studies and specific countries, increased, highlighting evolving public attitudes towards the euro. This supports H1, indicating that demographic factors do play a significant role in shaping perceptions. C2 consistently emerged as the most important factor in both years, emphasising the role of awareness of the advantages of the euro related to travel and business in shaping positive perceptions. The increasing importance of this construct from 2019 to 2022 suggests that people's economic expectations are a key determinant in influencing how the euro is perceived, validating H3. In 2022, negative influences from specific countries and C1 (Institutional Reforms) became more pronounced. This change suggests growing regional and institutional concerns influencing perceptions and indicates areas on which policymakers need to focus their efforts to improve acceptance of the euro. This change also suggests that effective national policies have a positive impact on perceptions of the euro, validating H2. Furthermore, the varying importance of different countries in shaping perceptions highlights the role of national government performance.

The study's findings validate all three hypotheses, showing that demographic factors, national government performance, and economic expectations significantly influence perceptions of the euro. The growing importance of travel and business facilitation policies, together with economic expectations related to payment methods, highlights the need for targeted strategies to address regional and demographic concerns. This information can help policymakers increase public support for the euro by focusing on the areas that matter most to Eurozone citizens.

The study's findings validate all three hypotheses, showing that demographic factors, national government performance, and economic expectations significantly influence perceptions of the euro. The growing importance of travel and business facilitation policies, together with economic expectations related to payment methods, highlight the need for targeted strategies to address regional and demographic concerns. This information can help policymakers increase public support for the euro by focusing on the areas that matter most to Eurozone citizens.

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Appendix A.

Eurobarometer Questions Used in Construct Formation

The following items from **Flash Eurobarometer 481 (2019)** and **Flash Eurobarometer 512 (2022)** were used to build the three constructs (C1–C3). Original codes and response options are reproduced below.

Construct I – Institutional Reforms (C1)

Q9_1 – *There is a need for significant reforms to improve the performance of our economy.*

Response scale:

1 – Totally agree

2 – Tend to agree

3 – Tend to disagree

4 – Totally disagree

5 – Don’t know

Q9_2 – *Successful reforms in other Eurozone countries have facilitated reforms in our country. (Same response scale as above.)*

Q9_3 – *Governments need to save more today in order to prepare public finances for ageing populations. (Same response scale.)*

Q9_4 – *Retirement age should be increased to ensure sustainability of the pension system. (Same response scale.)*

Q10_1–Q10_7 – *Please tell me for each of the following areas whether you think reforms are necessary in your country.*

Areas:

1. Labour market reforms
2. Health system reforms
3. Pension system reforms
4. Social security system reforms
5. Market reforms (telecom, gas, electricity, etc.)
6. Taxation reforms
7. Education system reforms

Response scale:

1 – Yes, reforms are necessary

2 – No, reforms are not necessary

3 – Don't know

Construct II – Travel and Business Facilitation (C2)

Q7_1–Q7_4 – *To what extent do you agree or disagree with the following statements about the euro?*

1. The euro has made travelling easier and less costly.
2. The euro has reduced banking charges for those travelling in different EU countries.
3. The euro has made it easier for people to do business in different EU countries.
4. The euro has made it easier to compare prices and shop in different EU countries, including those online.

Response scale:

1 – Totally agree

2 – Tend to agree

3 – Tend to disagree

4 – Totally disagree

5 – Don't know

Construct III – Payment Methods (C3)

Q3a_1–Q3a_2 – *When you pay cash, how easy is it to distinguish and handle…*

1. Euro banknotes
2. Euro coins

Response scale:

1 – Very easy

2 – Fairly easy

3 – Fairly difficult

4 – Very difficult

5 – Don't know

Q4 – *Do you consider there are too many, not enough, or just the right number of euro coins with different values?*

Response scale:

1 – Too many

2 – Not enough

3 – Just the right number

4 – Don't know

Q5 – *Are you in favour of abolishing 1- and 2-euro cent coins and rounding the final sum to the nearest 0 or 5 cents?*

Response scale:

1 – Yes

2 – No

3 – Don't know

Source: European Commission – Flash Eurobarometer 481 (The Eurozone, 2019) and Flash Eurobarometer 512 (The Eurozone, 2022), conducted by Kantar Public, archived by GESIS.

Annexes

Table 1. Cumulative importance of variables in constructs

		2019		2022	
Construct	VARIABLE	AGGREGATE IMPORTANCE	AVERAGE IMPORTANCE (%)	AGGREGATE IMPORTANCE	AVERAGE IMPORTANCE (%)
I.	Education system reforms (Q10.7)	19	4.60%	60.45	9.01%
	Health care reforms (Q10.2)	43	10.50%	16.07	2.39%
	Labour market reforms (Q10.1)	20	4.90%	62.39	9.29%
	Pension reforms (Q10.3)	128	31.40%	47.55	7.08%
	Significant reforms (Q9.1)	111	27.10%	253.78	37.81%
	Social security reforms (Q10.4)	52	12.70%	70.73	10.54%
	Tax system reforms (Q10.6)	14	3.40%	77.83	11.60%
	Utility market reforms (Q10.5)	22	5.40%	82.43	12.28%
II.	Cheaper travel (Q7.1)	411	58.5%	494.70	59.85%
	Ease of comparing prices (Q7.4)	121	17.3%	59.61	7.23%
	Lower commissions (Q7.2)	110	15.6%	192.02	23.28%
	Easier business (Q7.3)	62	8.8%	73.60	8.92%
III.	Payment with coins (Q3a2)	305	60.8%	34.66	51.88%
	Payment with banknotes (Q3a1)	197	39.2%	32.14	48.11%
IV	Number of euro coins (Q4)	44	100%	53	100%

Source: personal processing in Rstudio

Table 2. CART algorithm results by sample for constructs

Sample	CONSTRUCT	IMPORTANCE	PERFORMANCE INDICATORS	INDICATOR VALUE
2019				
I.	C2	97%	Accuracy	71.5%
	C3	3%	Sensitivity	76.60%
			Specificity	56.07%
II.	C2	87%	Accuracy	64.93%
	C3	11%	Sensitivity	64.09%
	C1	2%	Specificity	67.45%
III.	C2	87%	Accuracy	64.93%
	C3	11%	Sensitivity	64.09%
	C1	2%	Specificity	67.45%
2022				
I.	C2	100%	Accuracy	68.73%
	C3		Sensitivity	72.41%
			Specificity	55.25%
II.	C2	97%	Accuracy	67.55%
	C1	2.5%	Sensitivity	70.05%
	C3	0.5%	Specificity	58.42%
III.	C2	92%	Accuracy	65.88%
	C3	4%	Sensitivity	67.5%
	C1	4%	Specificity	59.96%

Source: personal processing in Rstudio

Table 3. CART algorithm results per sample for demographic variables

Sample	VARIABLE IMPORTANCE	IMPORTANCE	PERFORMANCE INDICATORS	INDICATOR VALUE
		2019		
I.	Country	42%	Accuracy	62.99%
	Age at end of studies	36%	Sensitivity	64.36%
	Age	17%	Specificity	58.90%
	Job	5%		
II.	Age at end of studies	46%	Accuracy	64.68%
	Country	30%	Sensitivity	67.71%
	Age	19%	Specificity	55.55%
	Job	4%		
III.	Country	44%	Accuracy	64.62%
	Age at end of studies	42%	Sensitivity	67.99%
	Age	9%	Specificity	54.49%
	Job	5%	Accuracy	
		2022		
I.	Country	68%	Accuracy	59,69%
	Age at end of studies	30%	Sensitivity	58,80%
	Age	1.5%	Specificity	62,86%
	Job	0.5%		
II.	Age at end of studies	56%	Accuracy	64.11%
	Country	37%	Sensitivity	67.39%
	Age	6%	Specificity	52.37%
	Job	1%		
III.	Age at end of studies	48%	Accuracy	67.56%
	Country	41%	Sensitivity	74.17%
	Age	6%	Specificity	43.89%
	Job	5%	Accuracy	

Source: personal processing in Rstudio

Table 4. CART algorithm results per sample

Sample	VARIABLE IMPORTANCE	IMPORTANCE	PERFORMANCE INDICATORS	INDICATOR VALUE
		2019		
I.	C2	62%	Accuracy	71.7%
	Country	23%	Sensitivity	76.51%
	Age at end of studies	11%	Specificity	57.25%
	C3	4%		
II.	C2	70%	Accuracy	67.78%
	Age at end of studies	18%	Sensitivity	68.78%
	Country	12%	Specificity	64.75%
III.	C2	59%	Accuracy	70.08%
	Country	29%	Sensitivity	72.30%
	Age at end of studies	12%	Specificity	63.42%
		2022		
I.	C2	85%	Accuracy	61.3%
	Country	13%	Sensitivity	59.81%
	Age	1%	Specificity	66.86%
	Age at end of studies	1%		
II.	C2	83%	Accuracy	64.4%
	Country	13%	Sensitivity	64.7%
	Age at end of studies	3%	Specificity	63.25%
	Age	0.6%		
	C1	0.4%		
III.	C2	70%	Accuracy	67.18%
	Country	27%	Sensitivity	70.28%
	Age at end of studies	2%	Specificity	55.62%
	Age	1%		

Source: personal processing in Rstudio

Table 5. MLP neural networks

2019							
Network number	Layer 1	Layer 2	Learning function	Accuracy	Sensitivity	Specificity	F1
1	10	-	Rprop	75.93%	78.75%	52.60%	0.8538
2	13	4		75.51%	79.45%	50.53%	0.8486
3	20	-	Quickprop	76.3%	77.52%	57.63%	0.8600
4	20	14		76.41%	77.97%	56.38%	0.8595
5	15	-	SCG	76.24%	77.26%	58.20%	0.8603
6	15	7		76.62%	79.32%	55.49%	0.8574
7	17	-	BackpropWeightDecay	73.58%	80.47%	45.45%	0.8574
8	18	9		74.31%	80.12%	46.93%	0.8374
9	12	-	BackpropMomentum	72.87%	81.10%	46.41%	0.8309
10	12	8		74.5%	79.89%	47.37%	0.8394
11	19	-	Std_Backpropagation	71.81%	82.13%	43.32%	0.8106
12	15	7		74.56%	80.15%	47.67%	0.8392
13*	**17**	**-**	**BackpropBatch**	**75.99%**	**76.29%**	**63.39%**	**0.8612**
14	16	8		76.55%	78.52%	56.61%	0.8591
2022							
Network number	Layer 1	Layer 2	Learning function	Accuracy	Sensitivity	Specificity	F1
1	10	-	Rprop	76.56%	80.84%	39.57%	0.8608
2	13	4		78.37%	79.73%	45.59%	0.8762
3	20	-	Quickprop	77.42%	79.54%	36.92%	0.8700
4	20	14		78.06%	80.11%	44.20%	0.8732
5	15	-	SCG	78.6%	78.77%	33.33%	0.8800
6	15	7		78.7%	78.75%	42.85%	0.8807
7	17	-	BackpropWeightDecay	78.5%	79.18%	44.21%	0.8783
8	18	9		76.15%	81.03%	38.86%	0.8573
9	12	-	BackpropMomentum	68.04%	83.34%	32.11%	0.7852
10	12	8		74.66%	80.56%	33.93%	0.8474
11	19	-	Std_Backpropagation	75.88%	81.29%	38.83%	0.8547
12	15	7		77.32%	80.48%	41.28%	0.8671
13*	**17**	**-**	**BackpropBatch**	**78.7%**	**78.76%**	**44.44%**	**0.8807**
14	16	8		76.32%	78.48%	42.28%	0.8798

Source: personal processing in Rstudio
**Optimum network*