Cultural Participation and Innovation Performance in Europe

1. Introduction

1.1 Research Context

The impact of cultural participation is notoriously difficult to measure, and its perceived importance is easily overshadowed by competing policy priorities, particularly during periods of economic crisis or fiscal constraint. Whilst substantial individual-level studies consistently demonstrate that cultural and artistic education fosters creative and divergent thinking, which are capacities fundamental to innovation and economic dynamism, the extent to which national-level cultural participation translates into measurable innovation performance remains unclear.

Resources allocated to cultural infrastructure, arts funding, and cultural programming are decreasing worldwide, and the European countries are not the exception. As public budgets face mounting pressure from competing demands, cultural funding increasingly becomes vulnerable to retrenchment. Decision-makers confront difficult questions: should limited resources be allocated to cultural investment, or would direct investment in research and development, education, or innovation infrastructure yield greater economic returns?

If there's empirical evidence linking cultural participation to measurable innovation outcomes, it can be one of the grounds that cultural policy is justified for sustained investment. Therefore, this study examines whether cultural participation correlates with and predicts innovation performance across European countries. By providing empirical evidence on this relationship, the study aims to inform more evidence-based allocation of cultural resources and to clarify whether cultural investment represents a genuine innovation strategy.

1.2 Research Questions

This study addresses two complementary research questions designed to clarify the empirical relationship between cultural participation and innovation performance:

RQ1: Is there a significant correlation between national cultural participation rates and innovation performance scores across European countries?

RQ2: Can national innovation performance be predicted using cultural participation data as a key independent variable, and with what accuracy?

2. Data and Methods

2.1 Data sources

The analysis draws on two primary data sources. Cultural participation data were sourced from Eurostat's EU-SILC (Statistics on Income and Living Conditions) database, specifically the indicator tracking participation in cultural activities among the population aged 15 and above.[1] This indicator measures the percentage of the population that participated in cultural activities within the 12 months preceding the survey. The indicator encompasses three broad categories of cultural engagement: attendance at cinema screenings, attendance at live performances (theatre, concerts, ballet), and visits to cultural sites (historical monuments, museums, art galleries or archaeological sites).

The participation rate reflects the breadth of cultural engagement, with the proportion of the population actively engaging with cultural activities. This operationalisation aligns with the hypothesis that widespread cultural

---

[1] https://ec.europa.eu/eurostat/databrowser/view/ilc_scp03$dv_550/default/table?lang=en&category=cult.cult_pcs.cult_pcs_ilc

participation reflects the availability and accessibility of cultural infrastructure and programming, which in turn may foster the creative thinking environments conducive to innovation.

Data were extracted for the year 2022, the most recent year with complete country coverage available during the study period. The data was provided for across 27 EU member states, Iceland, Norway, Switzerland, United Kingdom, Albania, Montenegro, North Macedonia, Serbia and Türkiye. Among them, the countries absent of 2022 data were excluded from the analysis.

Innovation performance metrics were obtained from the European Innovation Scoreboard (EIS), an annual benchmarking exercise conducted by the European Commission's Directorate-General for Research and Innovation.[2] The EIS constructs a composite Summary Innovation Index (SII) that aggregates performance across multiple dimensions of national innovation capacity.

The Summary Innovation Index encompasses three broad analytical domains: innovation enablers (human resources, research infrastructure, institutional quality), firm activities (innovation-friendly environment, firm-level R&D intensity, intellectual asset development), and innovation outputs (employment in knowledge-intensive sectors, international competitiveness of exports). The composite index normalises each country's performance against the average, which is set at 100. Countries scoring above 100 are classified as "innovation leaders," whilst those below are "followers" or "moderate innovators."

The decision to use the composite Summary Innovation Index rather than individual component indicators reflected the research objective of understanding overall national innovation performance. The EIS data covered the 2022-2025 period, providing a time dimension that could reveal stability or change in the relationship over successive years.

2.2 Analytical Strategy

Stage 1: Exploratory Data Analysis

The analysis began with descriptive exploration. The first analytical stage computed descriptive statistics (mean, standard deviation, minimum, maximum, and quartiles) for both cultural participation and innovation scores. These statistics characterised the central tendency, spread, and distribution of both variables across the sample, identifying potential outliers or unusual distributions that might affect subsequent analyses.

Parallel to descriptive statistics, exploratory visualisation was conducted using a scatter plot with a regression line overlay. This visualisation technique serves multiple purposes. First, it reveals the raw bivariate relationship visually. Second, it identifies the general pattern (linear, curved, random). Third, it highlights influential outliers that might disproportionately affect regression estimates. Fourth, it provides an intuitive foundation for interpreting subsequent numerical findings. The regression line is fitted using ordinary least squares (OLS) to provide a preliminary estimate of the linear relationship that formal regression analysis would examine more rigorously.

Stage 2: Correlation Analysis

Following exploratory visualisation, a formal correlation analysis was conducted. The Pearson correlation coefficient was calculated between cultural participation rates and innovation scores. This statistic quantifies the strength and direction of the linear relationship between the two variables, ranging from -1 (perfect negative correlation) to +1 (perfect positive correlation), with 0 indicating no linear relationship. The correlation analysis provided a summary statistic of effect size that addresses Research Question 1: whether a significant relationship exists between cultural participation and innovation performance.

---

[2] https://projects.research-and-innovation.ec.europa.eu/en/statistics/performance-indicators/european-innovation-scoreboard/eis#/eis

Interpretation of correlation magnitude followed conventional thresholds: $r > 0.7$ indicates strong correlation, $0.4 < r < 0.7$ indicates moderate correlation, and $r < 0.4$ indicates weak correlation. However, the analysis acknowledged that correlation does not imply causation, and that observed relationships may reflect confounding by unmeasured variables.

Stage 3: Predictive Modelling

The third analytical stage employed machine learning techniques to address Research Question 2: whether cultural participation data can predict innovation performance. Two complementary models were trained and evaluated.

Linear Regression Model: The linear regression model serves as the baseline approach, implementing the classical statistical model where innovation scores are regressed on cultural participation rates. The model was fitted using scikit-learn's LinearRegression class on the training dataset (75% of observations).

Random Forest Regression Model: A random forest regressor was employed as a more flexible, non-parametric alternative capable of capturing potential non-linear relationships. The random forest model works by constructing an ensemble of decision trees, each trained on a bootstrap sample of the training data, and averaging predictions across all trees. This ensemble approach typically reduces overfitting and provides more robust predictions than individual decision trees. The random forest model was configured with 500 trees (n_estimators=500), a standard hyperparameter choice that balances computational efficiency against predictive stability. The random state was fixed (random_state=42) to ensure reproducibility. Unlike linear regression, random forests do not assume any specific functional form of the relationship and can capture complex, non-linear patterns in the data.

Cross-Validation and Model Evaluation: Both models were evaluated using a train-test split strategy. The dataset was divided into a training set (75% of observations) and a test set (25% of observations), with random assignment controlled by a fixed random state (42) to ensure reproducibility. The training set was used to fit model parameters, whilst the test set—held entirely separate from the training process—was used to evaluate generalisation performance. Model performance was evaluated using two metrics. The coefficient of determination (R^2) measures the proportion of variance in innovation scores explained by the model, ranging from 0 to 1, with higher values indicating better fit. $R^2 = 0.6$ is conventionally considered "acceptable," $R^2 > 0.7$ is "strong," and $R^2 > 0.8$ is "excellent" in social science applications. The Root Mean Squared Error (RMSE) provides an absolute measure of prediction error in the units of the outcome variable (innovation score points). RMSE is calculated as the square root of the mean of squared differences between predicted and observed innovation scores on the test set. Lower RMSE values indicate more accurate predictions.

3. Results

3.1 Descriptive Statistics

The analytical dataset comprised 128 country-year observations from 32 European countries across the period 2022-2025. Cultural participation rates exhibited substantial variation across nations, ranging from 35.9% (Türkiye) to 88.9% (Luxembourg), with a mean of 69.3% (SD = 15%). Innovation performance, measured by the Summary Innovation Index, demonstrated comparable cross-national variation. Innovation scores ranged from 37.9 points (Albania, 2024) to 164.2 points (Switzerland, 2025), with a mean of 99.97 (SD = 35.78).

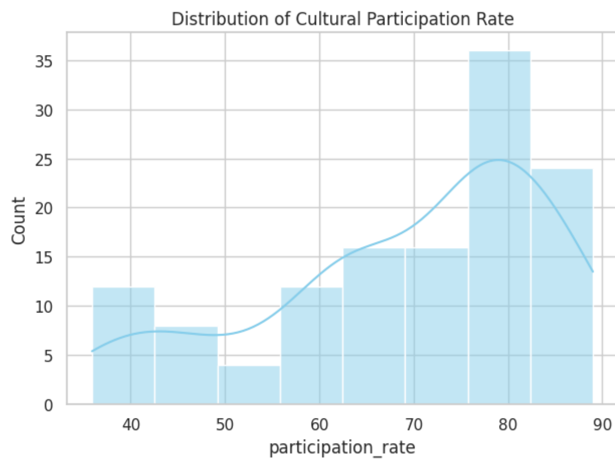
3.2 Exploratory Visualisation

Distribution of Cultural Participation Rate

The distribution of the cultural participation rate across the sampled European countries exhibits a negative (left-skewed) distribution. This indicates that a majority of the observed nations report high levels of cultural engagement, with a significant concentration of data points falling between the 75% and 85% range. The primary peak (mode) occurs near the 80% mark, suggesting a high standard for cultural participation within the region.

However, a long tail extends toward the lower end of the scale (35%–50%), representing a minority of countries with significantly lower participation levels.

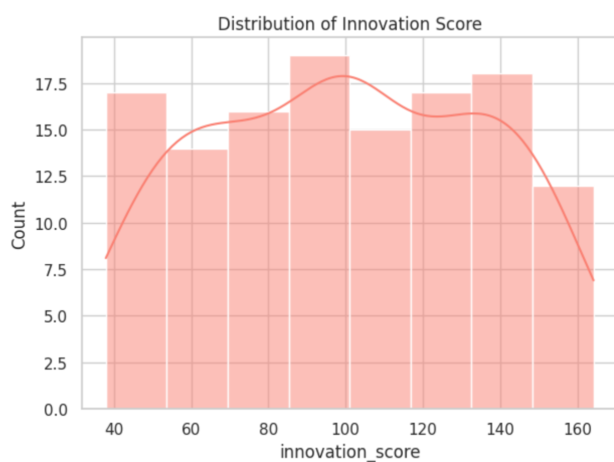
Figure 1. Distribution of Cultural Participation Rate



Distribution of Innovation Score

The innovation performance score presents a more flattened and dispersed distribution compared to the participation rate. The scores are spread widely across a range from approximately 40 to 160, reflecting a high degree of heterogeneity in innovation capabilities across Europe. Unlike the participation rate, the innovation scores are more evenly distributed across the spectrum. There is a slight concentration of countries around the 100-score mark, which serves as the approximate European average.

Figure 2. Distribution of Innovation Score

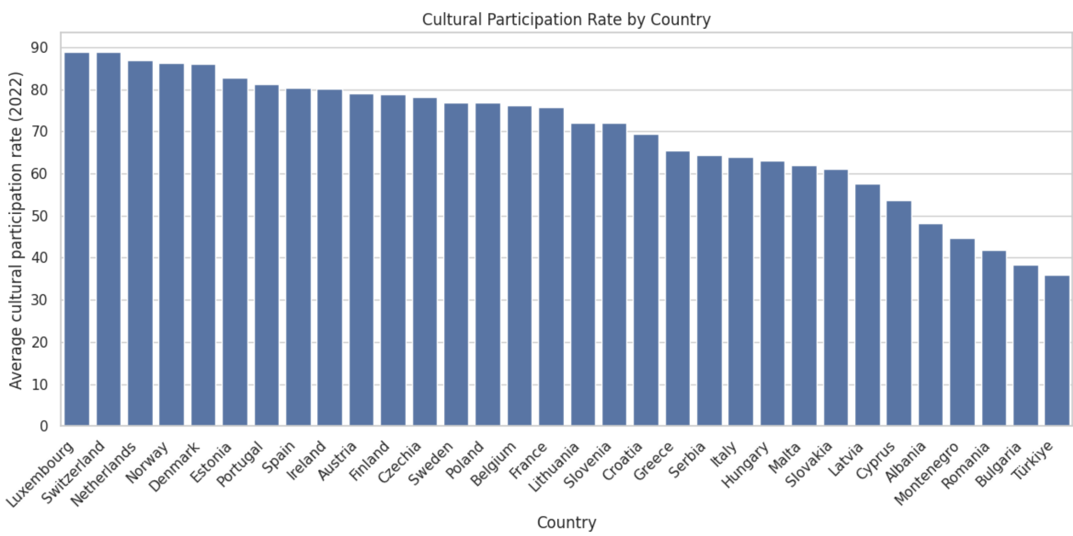


Cultural Participation Rate by Country

The bar chart sorted by descending participation rate reveals clear geographic hierarchies. Northern European countries (Luxembourg 89.0%, Norway 86.4%, Denmark 86.1%, Estonia 82.7%) dominate the highest tier with participation rates. Western European countries (Switzerland, Netherlands, Spain, Ireland, Portugal) cluster in the 79-88% range. Central European countries (Austria, Czechia, Poland, Slovenia) occupy around 72-82%. Southern European countries (Greece, Italy, Cyprus) fall to around 53-66%. Balkan and Eastern European countries (Romania

41.9%, Montenegro 44.7%, Albania 48.3%, Türkiye 35.9%) occupy the lowest tier. This geographic stratification reflects development patterns, cultural infrastructure investment, and leisure time availability correlated with economic development.

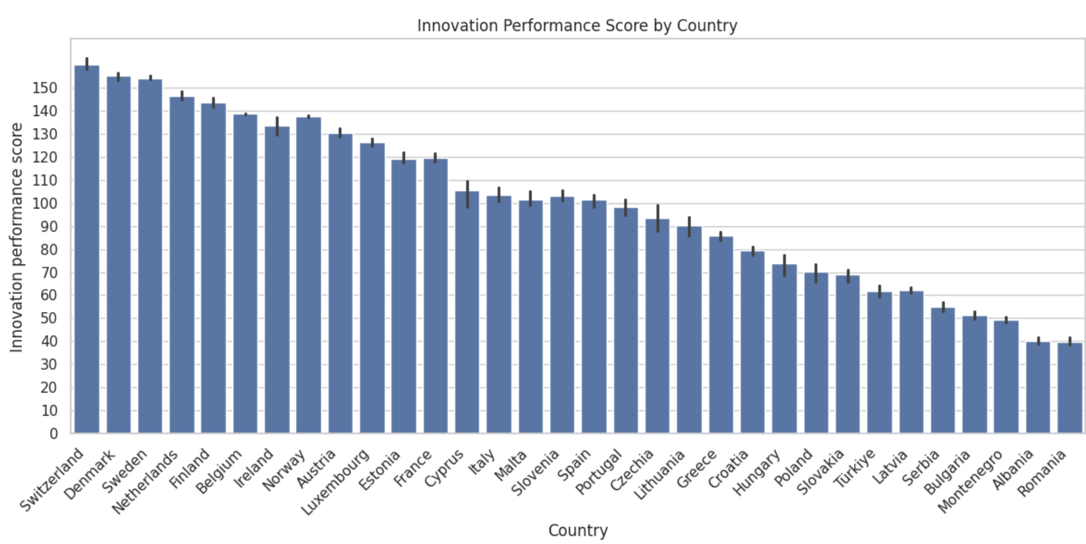
Figure 3. Cultural Participation Rate by Country



Innovation Performance Score by Country

The bar chart sorted by descending innovation score reveals similarly sharp geographic differentiation. Northern European countries (Switzerland, Denmark, Finland, Sweden) lead substantially above 140. Western European countries (Belgium, Netherlands, Luxembourg, France) score around 120-150. Southern and Balkan nations cluster below 100, with Romania, Albania, Montenegro, Bulgaria, and Serbia trailing substantially. The rank ordering shows remarkable consistency with the participation rate rankings, suggesting strong coordination between cultural engagement and innovation capacity.

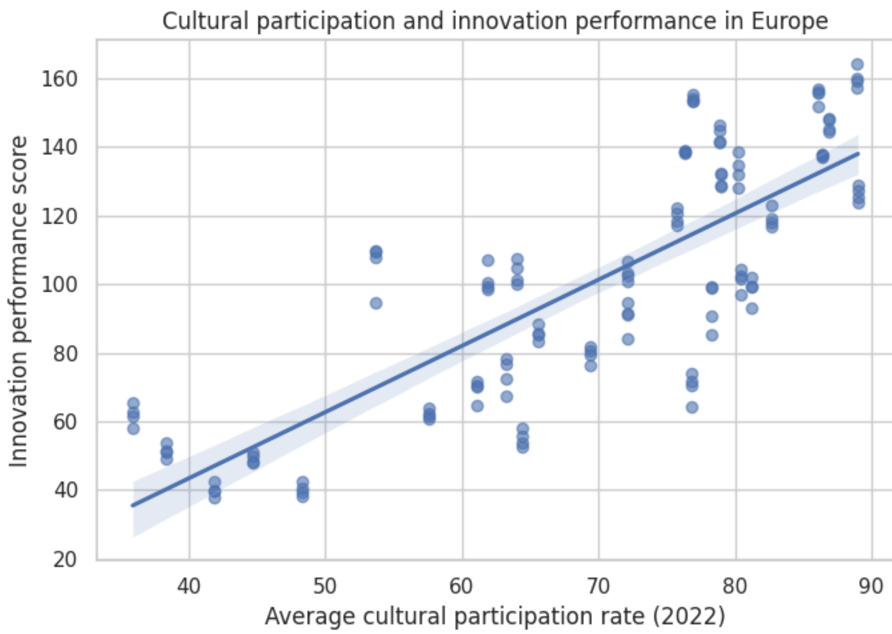
Figure 4. Innovation Performance Score by Country



Correlation between Culture and Innovation

The regression analysis reveals a strong, positive linear relationship between the cultural participation rate and the innovation performance score. The upward slope of the regression line) indicates that countries with higher levels of cultural engagement tend to achieve significantly higher innovation outcomes. While the correlation is clear, the scatter plot also highlights several outliers. For instance, some countries with participation rates near 80% show a wide variance in innovation scores (ranging from 70 to 150). This suggests that while cultural participation may be a strong predictor or catalyst for innovation, it is likely mediated by other factors.

Figure 5. Cultural participation and innovation performance in Europe



3.3 Correlation Analysis

The Pearson correlation coefficient between cultural participation and innovation scores was $r = 0.811$, indicating a statistically significant strong positive relationship. The magnitude falls into the “strong” correlation range ($r > 0.70$), providing a strong statistical foundation for the hypothesis that a culturally active population is a key characteristic of highly innovative societies in Europe.

3.4 Predictive Modeling

To further explore this relationship, two predictive models were developed to determine how accurately cultural participation can predict a country's innovation score.

Linear Regression Analysis: The Linear Regression model yielded an R^2 (R-squared) value of 0.75, meaning that cultural participation alone explains approximately 75% of the variance in innovation performance. The RMSE of 17.97 suggests that, on average, the linear model’s predictions deviate from the actual innovation scores by about 18 points. This indicates a robust linear baseline, though it suggests some complexity in the data that a straight line cannot fully capture.

Random Forest Regression Analysis: The Random Forest model significantly outperformed the linear approach, achieving an exceptionally high R^2 of 0.98. This implies that the model can account for 98% of the variance in the data. Furthermore, the RMSE dropped drastically to 5.09, indicating a much higher level of precision in its predictions.

Comparison and Key Findings: The disparity in performance between the two models is significant. The superior performance of the Random Forest model suggests that the relationship between culture and innovation is likely non-linear, implying that there are specific thresholds or interaction effects where increases in participation lead to exponential gains in innovation. The random forest model explains 98% of variance in innovation scores with prediction errors of only ±5.09 points at the mean, indicating that cultural participation combined with underlying national characteristics provides strong predictive power for innovation performance across European countries.

4. Policy Implications and Discussion

From a policy perspective, the results suggest that cultural participation should not be viewed solely as a consumption good or a social policy objective. Instead, it may represent a complementary input into national innovation capacity. Policies aimed at broadening access to cultural activities, supporting local cultural infrastructure, and reducing participation barriers may yield indirect innovation benefits. Integrating cultural participation into innovation policy frameworks could therefore enhance the coherence and inclusiveness of innovation strategies.

4.1 Cultural Investment and Innovation Competitiveness

Traditionally, cultural policy has been justified on intrinsic grounds that culture is inherently valuable for human flourishing, social cohesion, and quality of life. This analysis adds an instrumental dimension that cultural participation appears functionally integrated with innovation capacity at the national level. This reframing may strengthen political coalitions supporting cultural funding by connecting cultural policy to economic competitiveness and innovation agendas that command broader political support. This reframes cultural policy as a strategic investment integral to innovation capacity and economic competitiveness, demonstrating importance of sustained cultural funding.

4.2 Non-linear Policy Design and Regional Differentiation

The random forest model's performance superiority indicates non-linear relationship structure, suggesting that policy effectiveness depends critically on baseline participation levels. Countries already achieving high cultural participation may experience diminishing marginal returns from further participation increases. Conversely, countries with low participation (35-60%) may face threshold effects requiring substantial capital investment in cultural infrastructure, access subsidy programmes, and workforce development to cross participation thresholds where innovation spillovers emerge. Differentiated regional strategies accounting for these non-linear dynamics would enhance policy cost-effectiveness.

4.3 Integration of Cultural and Innovation Policy

Considering the strong correlation between cultural participation and innovation performance, cultural participation metrics can be incorporated into innovation monitoring systems. The European Innovation Scoreboard, which currently focuses on research, technology, and commercialisation indicators, could be extended to include cultural participation and cultural innovation measures, making explicit the role of cultural dimensions within national innovation systems. Conversely, cultural policy evaluation frameworks may incorporate innovation outcomes alongside traditional cultural objectives. Furthermore, stronger integration between cultural and innovation policy could involve joint funding mechanisms targeting cultural-innovation intersections and coordinated strategic planning.

4.4 Limitations and Future Research Recommendations

This analysis clearly demonstrates correlation between two variables but cannot establish whether cultural participation causes innovation or whether both reflect confounding by unmeasured variables. Policymakers must recognise this causal ambiguity when designing interventions. The relationship likely reflects confounding by underlying factors such as GDP, education, and governance. Therefore, empirical policy evaluation is required to assess whether increasing cultural participation in specific regions generates innovation gains for further policy design and implementation. Multivariate regression models controlling variables such as education, R&D spending, and governance would isolate cultural participation's independent contribution.

5. Conclusion

This study examined the relationship between cultural participation and innovation performance across European nations using integrated cultural data in 2022 and innovation performance metrics spanning 2022-2025. The analysis revealed a statistically significant strong positive correlation between national cultural participation rates and innovation performance scores. Predictive modelling demonstrated that non-linear machine learning approaches significantly outperformed linear regression models, indicating that the relationship between cultural participation and innovation incorporates complex threshold effects and regional interaction patterns. This non-linear structure suggests that policy effectiveness may depend on baseline participation levels and geographic context. Geographic analysis revealed pronounced clustering, with Northern and Western European nations consistently demonstrating high values on both cultural participation and innovation dimensions, whilst Balkan and Eastern nations exhibited lower values.

This analysis result provides grounds for reframing cultural policy as strategic investment integral to national innovation capacity. However, the correlational nature of this analysis requires caution regarding causal interpretation. The strong relationship likely reflects confounding by unmeasured variables such as economic development, education quality, and governance rather than direct causal effects of cultural participation on innovation. Future research employing causal inference designs is essential for establishing whether increasing cultural participation in specific regions generates genuine innovation gains. Despite these limitations, the robust evidence on correlation supports policy integration of cultural and innovation domain with sustained investment on culture and differentiated regional strategies accounting for non-linear relationship dynamics.