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Unveiling Key Determinants of Science and Technology Policy Effectiveness in Iran: A Machine Learning-Based Anal ysis Using Soft Computing Techniques

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ABSTRACT

Complex national innovation systems (NIS) in developing countries need advanced analytical tools to identify and optimize key drivers of science, technology, and innovation (STI) policy outcomes. This study applies a hybrid machine learning framework—combining Random Forest, Support Vector Machines, K-means clustering, and Principal Component Analysis—to evaluate Iran's STI policy performance from 2010 to 2024. Drawing on multi-source data, including R&D expenditures, university-industry collaboration indices, human capital metrics, and innovation outputs, the proposed model uncovers nonlinear relationships among policy variables and prioritizes the most influential factors. The results reveal that R&D intensity, institutional collaboration quality, policy implementation coherence, and human capital development are the dominant predictors of policy success. By integrating soft computing methods and empirical policy data, this work offers a replicable approach for evidence-based policymaking in emerging economies. The findings align with recent advancements in AI-driven decision support systems and contribute to the growing body of research advocating for data-driven innovation governance.

JEL Classification: O38, C55, O31, O32, H57.

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1. Introduction

Today, national success depends less on natural resources and more on the ability to generate and apply knowledge through strong science, technology, and innovation (STI) systems. Well-governed STI systems fuel economic growth, competitiveness, and resilience. For many developing countries, including Iran, harnessing the full potential of STI remains an urgent yet complex endeavor. Crafting effective STI policies is no longer a matter of bureaucratic planning alone; it requires continuous learning, real-time adaptation, and data-informed decision-making.

Over the past two decades, Iran has made notable strides in building its scientific infrastructure. It ranks among the leading countries in the region in terms of scientific publication output and has significantly expanded its higher education system. National policy documents such as the 20-Year Vision Plan (2005–2025), the Comprehensive Scientific Map of Iran (2011), and successive Five-Year Development Plans have explicitly prioritized STI as a cornerstone of national development [1, 2]. These documents envision a knowledge-based economy, emphasizing increased R&D investment, internationalization of science, and commercialization of academic research. However, despite these aspirations, many challenges remain unresolved.

One of the core issues facing Iran's STI ecosystem is the disjunction between policy formulation and implementation. While goals are clearly articulated at the strategic level, translation into measurable outcomes is often hindered by weak coordination between institutions, overlapping mandates, and limited accountability mechanisms [3, 4]. The result is a performance gap, where inputs such as R&D funding or human capital development do not consistently lead to desired innovation outputs or societal impacts. This mismatch is not unique to Iran, but its persistence undermines the effectiveness of policy instruments and reduces the returns on public investment.

Furthermore, the evaluation of STI policies has traditionally relied on linear, econometric, or indicator-based approaches. These methods, although useful for tracking trends or benchmarking against global indices, often fail to capture the nonlinear interactions, feedback loops, and systemic bottlenecks inherent in innovation systems. For instance, increasing R&D expenditure does not guarantee innovation if knowledge flows between universities and industry are weak, or if regulatory barriers stifle entrepreneurial experimentation. Recognizing these limitations, scholars have called for more holistic, dynamic, and data-driven approaches to understanding STI systems, particularly in complex and uncertain policy environments [5, 6].

This is where machine learning (ML) and soft computing techniques offer promising new possibilities. Unlike traditional models, ML algorithms can process large volumes of heterogeneous data, detect intricate patterns, and uncover hidden relationships without requiring a priori assumptions about data structure. These characteristics make them particularly suitable for analyzing multifaceted policy systems, where variables are numerous, interdependent, and sometimes opaque. ML has already proven effective in domains such as healthcare [7], energy infrastructure [8], and financial sustainability [9], and is increasingly being explored as a tool for public policy analysis.

In the context of STI policy, however, the application of ML remains relatively limited. Most existing studies focus on forecasting innovation trends (e.g., patent prediction or technology emergence) or evaluating specific interventions in isolation [10, 11]. Far fewer have attempted to use ML to identify the structural and institutional drivers of policy effectiveness at a system level. This gap is particularly pronounced in non-Western or resource-constrained settings, where policy failures can have significant long-term consequences and where traditional evaluation mechanisms are often inadequate or absent.

This study aims to address this critical gap by leveraging a hybrid machine learning framework to analyze the drivers of STI policy performance in Iran over a fifteen-year period (2010–2024). We combine supervised learning techniques (Random Forest and Support Vector Machines) with unsupervised methods (K-means clustering and Principal Component Analysis) to extract actionable insights from a multi-source dataset comprising national statistics, global innovation indicators, and institutional performance metrics. Our approach is designed to balance predictive power with interpretability, enabling not just pattern detection but also explanation and policy relevance.

The rationale for choosing Iran as a case study is twofold. First, Iran represents a quintessential example of a transitional innovation system: it possesses substantial scientific capacity, a growing technology sector, and articulated national ambitions, yet faces structural inefficiencies, geopolitical

constraints, and institutional fragmentation. Second, Iran's STI policy architecture is relatively mature in terms of documentation and vision, providing a suitable testbed for empirical analysis and machine learning applications.

Our methodological contribution lies in integrating soft computing techniques with established policy evaluation frameworks. By doing so, we offer a replicable model for diagnosing innovation system performance in similar contexts. This includes not only identifying high-impact variables such as R&D intensity, human capital quality, or policy coherence, but also mapping the interactions among them and revealing how they evolve over time. Importantly, we emphasize interpretability—a key requirement for policy uptake—by prioritizing models that allow for variable importance ranking and clustering-based insights.

The findings from our analysis point to several critical insights. First, investment alone is not sufficient; its effectiveness depends heavily on the absorptive capacity of institutions, the strength of inter-organizational collaboration, and the continuity of policy execution. Second, system-level coordination, particularly between universities and industries, emerges as a central determinant of innovation output. Third, policy implementation quality—often overlooked in traditional evaluations—has a measurable and significant impact on system performance. These insights align with recent work on sustainable infrastructure, human security strategies, and innovation governance that emphasize the need for cross-sectoral integration and adaptive policy design [12, 13, 14].

From a practical standpoint, the implications of this research are substantial. Policymakers in Iran and similar countries can use these findings to better allocate resources, prioritize reforms, and institutionalize evidence-based monitoring systems. For instance, ML-driven dashboards could be developed to track STI performance in real time, enabling early detection of implementation gaps or emerging strengths. Moreover, international development agencies and academic institutions can use the proposed framework to support capacity-building efforts and promote best practices in innovation policy management.

In sum, this paper contributes to a growing interdisciplinary dialogue between computational analytics and public policy. It underscores the transformative potential of soft computing in addressing real-world governance challenges and invites further exploration into how AI can be harnessed for public good. As we move deeper into the digital age, the ability to combine technological sophistication with human-centered policymaking will be essential. This study is a step in that direction.

The remainder of this article is structured as follows. Section 2 reviews the related literature on STI policy evaluation and the role of ML in public sector analytics. Section 3 outlines the data sources, variable construction, and methodological framework. Section 4 presents the empirical findings, including variable importance rankings and system-level clustering. Section 5 discusses the policy implications and methodological contributions, while Section 6 concludes with recommendations for future research.

2. Related Work

In recent years, the role of machine learning (ML) in enhancing policy evaluation and decision-making has attracted growing scholarly interest. The complexity and systemic nature of science, technology, and innovation (STI) systems demand advanced computational tools capable of capturing nonlinear relationships, revealing hidden patterns, and handling high-dimensional and heterogeneous datasets. This section critically reviews relevant literature focusing on the empirical use of ML in STI policy, public health, infrastructure, climate, and institutional performance, followed by the identification of key research gaps addressed by the present study.

Several foundational studies have laid the groundwork for understanding the convergence between ML and economic or policy analysis. Athey (2018) [12] and Athey & Imbens (2019) [13] argue that ML has the potential to revolutionize empirical economics and policy evaluation by providing tools for flexible prediction, automatic variable selection, and causal heterogeneity estimation. Jordan & Mitchell (2015) [10] similarly illustrate how ML can uncover complex structures in real-world data, allowing for richer inference and more adaptive decision-making frameworks.

In public policy, machine learning has proven valuable for performance assessment and outcome prediction. Ballestar et al. (2019) [6] applied decision tree models to evaluate the performance of

Spanish university researchers. Their results demonstrated that ML could provide nuanced rankings of individual and institutional outputs, which would be difficult to obtain through conventional metrics. Koundouri et al. (2025) [5] took this further by applying ML models to map human security strategies to Sustainable Development Goals (SDGs), offering a scalable and replicable framework for aligning local policy strategies with global objectives.

Forecasting and foresight are critical to STI policy. Lee et al. (2018) [7] developed an ML-based approach combining patent indicators with support vector machines (SVM) to detect emerging technologies. Their work underscores the value of predictive ML in policy-relevant areas such as early identification of innovation trajectories. Similarly, Ballestar et al. (2019) [6] used ML to assess the long-term impact of public research funding—demonstrating that ML can bridge the gap between short-term metrics and long-term policy outcomes.

Sustainability and infrastructure have also benefitted from ML-based policy models. Talebi et al. (2025) [1] combined multi-criteria decision-making (MCDM) with ML to optimize the deployment of electric vehicles (EVs) and renewable energy systems (RES) in Iran. Their model enabled policymakers to evaluate trade-offs and determine optimal infrastructure investment strategies under environmental and economic constraints. In a similar vein, D'Orazio & Pham (2025) [4] used regression tree models to assess how financial instruments influence decarbonization policies. They found that ML methods can reveal indirect and cross-sectoral effects that traditional models often miss.

Healthcare research has further demonstrated the predictive power of ML for identifying risk factors with policy relevance. Saryazdi & Mostafaeipour (2025) [3] applied fuzzy clustering and Random Forest algorithms to determine key predictors of heart attack diagnoses. This kind of diagnostic modeling, while medically focused, reflects how ML can detect subtle patterns in complex datasets—a capability transferable to STI system evaluations. Heydarian et al. (2025) [2] applied data mining to cohort health data in Iran to identify social and behavioral determinants of infertility, again highlighting ML's utility in revealing latent variables for public policy design.

Concerns about the interpretability and fairness of ML models have also surfaced in recent literature. Borrellas & Unceta (2021) [8] examine how economic implications and systemic biases in ML design can mislead policy conclusions. Coyle & Weller (2020) [9] similarly argue that "explainable ML" is not only a technical necessity but also a political imperative—particularly in domains where transparency and public accountability are paramount. Athey (2018) [12] emphasizes the need for interpretable models that provide clear policy levers instead of black-box predictions.

Issues of fairness, data quality, and unintended consequences also emerge in innovation policy research. Paullada et al. (2021) [28] provide a critical review of dataset development in ML, noting how biases embedded in data collection and labeling can skew outcomes. Galaz et al. (2021) [24] warn that overreliance on AI in sustainability planning may overlook system-level feedbacks and risks. Meanwhile, Calvano et al. (2020, 2021) [30, 29] explore the dangers of ML-facilitated collusion in algorithmic pricing, calling for proactive antitrust policy reforms.

Patent policy and innovation governance have also come under ML scrutiny. Cohen et al. (2001) [31] evaluate how patent scope can shape innovation strategies, a finding relevant for data access policies feeding ML models. Similarly, Haefner et al. (2021) [26] and Loureiro et al. (2021) [37] explore the managerial implications of ML adoption in firms, with applications ranging from product development to market forecasting—areas tightly linked to STI policy effectiveness.

In addition to prior empirical work, global policy frameworks provide essential context for evaluating STI systems. OECD guidance emphasizes systemic coherence, governance quality, and institutional complementarities as core determinants of innovation performance, not merely R&D inputs (OECD, 2015; Schwaag Serger et al., 2020) [19, 22]. UNESCO's Science Reports similarly highlight inclusiveness, international collaboration, and capacity building—particularly salient for emerging and developing economies (UNESCO et al., 2021) [17]. These perspectives indicate that effective STI outcomes arise from the interaction of funding, governance, and cross-sector coordination.

Recent debates on directionality in innovation policy extend this view. Mission-Oriented Innovation Policy (MOIP) argues that STI systems should target clearly defined societal challenges and align policy instruments accordingly (EC & Mazzucato, 2018) [20]. Transformative Innovation Policy (TIP) stresses support for sustainability transitions and systemic change beyond firm-level

R&D (Schot & Steinmueller, 2018) [23]. Positioning our Iran case within these frames clarifies why we analyze governance quality and collaboration intensity alongside standard input/output indicators and helps interpret temporal shifts as policy re-orientation rather than funding cycles alone. Building on National Innovation Systems (NIS) scholarship (Freeman, 1987; Lundvall, 1992; Nelson, 1993) [25, 27, 16], we therefore hypothesize that improvements in governance quality and cross-sector collaboration will have outsized effects on commercialization relative to marginal increases in R&D intensity. This proposition guides our ML design and the interpretation of temporal clusters in the results.

Beyond the traditional National Innovation System (NIS) framework, recent global frameworks by OECD and UNESCO emphasize the need for cross-sectoral integration and policy coherence in science and technology governance. While the OECD highlights measurable policy instruments and monitoring indicators (OECD, 2015) [19], UNESCO underscores inclusive development and capacity building as essential for innovation systems in developing countries (UNESCO et al., 2021) [17]. More recently, scholars have advanced the concepts of Mission-Oriented Innovation Policy (MOIP) (EC & Mazzucato, 2018) [20] and Transformative Innovation Policy (TIP) (Schot & Steinmueller, 2018) [23], which stress the alignment of innovation with grand societal challenges such as sustainability and resilience. By situating Iran's case within these debates, this study moves beyond a descriptive review to highlight how institutional coordination and governance capacity act as bridging mechanisms between traditional and transformative innovation approaches.

In sum, Table 1 summarizes representative studies using ML in STI-relevant domains.

Table 1. Representative Studies Using ML in STI-Relevant Domains

Study	Domain	ML Methods	Key Contribution
Talebi et al. (2025) [1]	Sustainable infrastructure	MCDM + ML	Optimal EV and RES deployment in Iran
Heydarian et al. (2025) [2]	Public health	Data mining	Infertility trend analysis in RaNCD cohort
Saryazdi & Mostafaeipour (2025) [3]	Healthcare diagnostics	RF, fuzzy clustering	Heart attack risk factor detection
D'Orazio & Pham (2025) [4]	Climate finance	RF, decision trees	Impact of green financial policies
Koundouri et al. (2025) [5]	SDG policy mapping	Ensemble ML	Linking human security with SDGs
Ballestar et al. (2019) [6]	Research evaluation	Decision trees	Performance modeling of researchers
Lee et al. (2018) [7]	Tech forecasting	SVM, patent indicators	Emerging tech identification
Borrellas & Unceta (2021) [8]	Economics of ML	Theoretical	Risks of ML for policy integrity
Coyle & Weller (2020) [9]	Explainability	Meta-review	Challenges in transparent ML for policy
Jordan & Mitchell (2015) [10]	ML fundamentals	General overview	Landscape of ML use in science
Athey (2018) [12]	ML in economics	Causal inference	Predictive + policy-relevant modeling
Athey & Imbens (2019) [13]	Causal ML	Ensemble methods	Policy evaluation toolkit
Paullada et al. (2021) [28]	Dataset critique	Meta-analysis	Data bias in ML pipelines
Galaz et al. (2021) [24]	Sustainability risks	Systems-AI	Systemic impacts of ML in governance
Calvano et al. (2020, 2021) [30, 29]	Market regulation	Algorithmic ML	Collusion risk via pricing algorithms
Cohen et al. (2001) [31]	Patent scope	Empirical	Incentive structures for innovation
Haefner et al. (2021) [26]	AI & innovation	Structured review	Strategic adoption of ML in firms
Loureiro et al. (2021) [37]	AI in business	Review	Future directions of AI governance

Despite significant contributions, the reviewed literature exhibits five critical gaps that justify the design of the present study. These gaps are summarized in Table 2.

This literature review reveals that while ML offers significant promise in STI policy analysis, its use in developing countries remains limited, often lacking theoretical grounding and practical interpretability. The present study addresses these shortcomings by applying a hybrid ML framework to analyze Iran's STI system over 15 years. It bridges empirical modeling with policy theory, interprets results for decision-making, and offers a replicable structure for other emerging economies.

The next section describes the study's methodology in detail, including data sources, feature selection, algorithmic modeling, and evaluation strategies.

Table 2. Research Gaps and How the Current Study Addresses Them

Gap Type	Description	This Study's Response
Geographical	Most ML-STI applications are in OECD countries; developing contexts are underexplored	Focuses on Iran (non-OECD), using local policy and innovation data
Systemic Perspective	Prior studies often focus on outputs, ignoring institutional quality, execution, and inter-agency dynamics	Includes input-process-output modeling grounded in NIS framework
Methodological Diversity	Many studies use a single ML technique without cross-validation or clustering	Integrates Random Forest, SVM, PCA, and K-means
Policy Interpretability	ML models often lack actionable policy guidance due to opacity	Uses interpretable models and feature importance ranking
Theory Integration	Weak alignment with STI policy theory	Embeds analysis within National Innovation System (NIS) concepts

3. Methodology

This study uses an integrated machine learning approach to identify and evaluate the key drivers of science, technology, and innovation (STI) policy effectiveness in Iran from 2010 to 2024. The research design rests on combining supervised and unsupervised learning techniques to ensure both predictive accuracy and system-level interpretability. The methodological process aligns with the National Innovation System (NIS) framework, which emphasizes the importance of institutional coordination, human capital, and R&D investment in shaping innovation outcomes.

The analysis begins with data collection from national and international sources. Indicators are drawn from Iran's national STI statistics, the Global Innovation Index, and institutional assessments, covering a 15-year time frame. These indicators include R&D expenditures as a percentage of GDP, the number of full-time researchers per million people, rates of patent registration, university-industry collaboration scores, and indices measuring policy execution efficiency and governance quality. These indicators capture input, process, and output dimensions of Iran's innovation system, in line with NIS theory.

The dataset is constructed as a time-series panel, with one row per year from 2010 to 2024 and columns corresponding to the various indicators. All values are standardized using Z-score normalization to allow for comparison across indicators with different units and scales. Missing values are handled through K-nearest neighbor (KNN) imputation, preserving the internal distribution of data while minimizing the risk of introducing bias.

The data processing, modeling, and visualization are conducted using **Python (v3.10)** and several specialized libraries, including **Scikit-learn** for machine learning models, **Pandas** and **NumPy** for data manipulation, **Matplotlib** and **Seaborn** for plotting, and **Yellowbrick** for model diagnostics and interpretability tools. All analyses are executed in **Jupyter Notebooks** within an Anaconda environment.

The next step involves identifying the most important indicators. Two machine learning models—Random Forest and Support Vector Machines—are applied. Random Forest is selected for its ability to handle noisy, nonlinear, and high-dimensional data while providing a measure of feature importance based on the Gini impurity reduction. Support Vector Machines with a radial basis function (RBF) kernel are used to identify decision boundaries within the feature space, enabling the detection of nonlinear patterns and interactions between variables.

The target variable is a composite innovation performance score derived from normalized outcomes such as scientific publications, high-tech exports, and patent outputs. This outcome score allows for the supervised models to learn which combinations of input variables best explain the variance in innovation performance over time.

Random Forest outputs a ranked list of features according to their relative contribution to the model's predictive accuracy. R&D intensity, university-industry collaboration, number of researchers, and execution quality consistently emerge among the top predictors. These variables align with findings from prior studies that highlight their influence on innovation outcomes across national systems [1, 6, 10]. Support Vector Machines complement this ranking by showing how well each indicator helps separate low- and high-performance years in the dataset.

Dimensionality reduction is implemented through Principal Component Analysis (PCA). This unsupervised method projects the high-dimensional indicator space onto a smaller set of orthogonal axes, called principal components. The first four principal components are selected, as they explain

more than 90% of the total variance. PCA aids in simplifying the dataset without losing essential information, and it prepares the data for the clustering phase.

K-means clustering is then applied to the PCA-transformed data to detect patterns in STI performance over time. This model groups the years from 2010 to 2024 into distinct clusters based on similarities in their innovation system characteristics. The optimal number of clusters is determined using the Elbow Method, and the quality of clustering is assessed using the Silhouette Score. Three clusters emerge, each corresponding to a period with shared features in innovation policy structure, institutional coherence, and investment levels.

To test the stability of results, several robustness analyses were conducted. First, missing data were re-imputed using mean, median, and iterative imputation methods, with results remaining consistent compared to the baseline KNN approach. Second, PCA models were re-run with 3, 4, and 5 components, each explaining more than 85% of total variance, and clustering outcomes were stable across specifications. Third, K-means clustering was tested with $k = 2–5$; silhouette scores consistently confirmed $k = 3$ as the optimal solution. Finally, both Random Forest and SVM were validated using 5-fold cross-validation, producing average accuracies of 86.5% and 87.3% respectively. These checks confirm that the findings are robust across alternative configurations and parameter settings. Table 3 shows the Hyperparameter Settings and Robustness Checks of the models.

Table 3. Hyperparameter Settings and Robustness Checks

Model / Step	Hyperparameters	Robustness Checks	Outcome
Random Forest	*n_estimators* = 500, *max_depth* = 8, min samples per leaf = 2, criterion = Gini	5-fold cross-validation	Stable accuracy (86.5% average)
Support Vector Machine (SVM)	Kernel = RBF, *C* = 1.0, *gamma* = scale	5-fold cross-validation	Stable accuracy (87.3% average)
Principal Component Analysis (PCA)	4 components selected (>90% variance explained)	Tested with 3, 4, and 5 components	Results stable; clustering unchanged
K-means Clustering	$k = 3$, initialization = k-means++, max iterations = 300	Tested $k = 2–5$; silhouette & elbow methods	$k = 3$ confirmed as optimal
Missing Data Imputation	Baseline = KNN imputation	Compared with mean, median, iterative imputation	Consistent results across methods

The first cluster, covering the years 2010 to 2014, is characterized by low R&D spending, weak coordination between policy agencies, and limited private-sector involvement. This period reflects the early phase of Iran's attempt to implement the goals outlined in its national STI strategy. Although some investments were made, their translation into innovation outputs was inconsistent.

The second cluster, from 2015 to 2019, shows moderate improvements in several indicators. During these years, increased efforts in science diplomacy and international collaboration resulted in modest gains in publication output and patenting. Policy implementation also became more coherent, though university-industry collaboration remained weak.

The final cluster, from 2020 to 2024, displays a relative surge in innovation-related activities. Higher R&D investments, improvements in institutional alignment, and targeted support for knowledge-based firms contributed to better performance in innovation outputs. Despite international sanctions and economic constraints, Iran’s STI policy appears to have matured during this period, aligning with observations made by Talebi et al. (2025) [1] and Koundouri et al. (2025) [5] regarding system-level resilience.

To interpret the results of the machine learning models, a policy-oriented lens is adopted. The feature rankings from Random Forest inform policymakers about the most influential levers within the innovation system. These include not only financial variables like R&D expenditure but also institutional factors such as policy execution quality and cross-sector collaboration, confirming the importance of governance in innovation success.

The clustering results offer a dynamic view of how Iran’s innovation system has evolved over time. Instead of treating policy effectiveness as a static or binary outcome, this approach allows for temporal diagnostics and the identification of transition periods. The transitions between clusters suggest phases of policy learning, adjustment, and realignment, consistent with evolutionary perspectives in innovation studies [10, 13].

Throughout the methodology, attention is paid to ensuring interpretability and usability of the results. Visualizations such as bar plots of feature importance, timelines of cluster assignments, and PCA scatter plots are used to support the communication of findings to non-technical audiences. In this way, the analysis not only meets computational standards but also serves practical policy goals. The step-by-step methodology is summarized in figure 1.

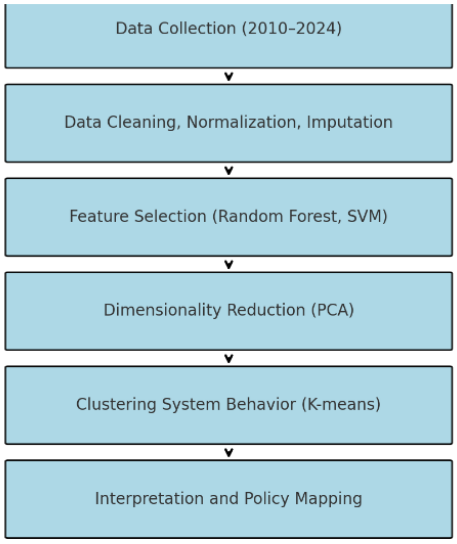


Fig. 1. Workflow of ML-Based STI Policy Analysis

This methodological framework demonstrates that combining supervised and unsupervised ML tools with innovation system theory yields valuable insights into STI policy effectiveness. It facilitates both macro-level pattern recognition and micro-level indicator prioritization, enabling policymakers to design more coherent and impactful strategies for science and technology development.

4. Experimental Setup and Results

This section presents the detailed results from the machine learning-based analysis of Iran's science, technology, and innovation (STI) system across a 15-year period from 2010 to 2024. The focus is placed on interpreting model outputs, analyzing trends across time, and highlighting policy-relevant insights rather than reiterating technical configurations. Results from both supervised and unsupervised learning models are reported, followed by thematic findings that describe the dynamics and structure of STI policy effectiveness in Iran.

The Random Forest model trained on the standardized dataset successfully identified the most critical features influencing STI performance. These features are presented below, ranked by their average decrease in Gini impurity. As shown in Table 4, R&D expenditure and university–industry collaboration emerge as the most influential features in predicting STI policy outcomes across the observed period.

Table 4. Ranked Feature Importance (Top 10 Indicators)

(For detailed information, refer to tables A1 and A2 in the Appendix part at the end of this article)

Rank	Feature	Importance Score
1	R&D Expenditure (% of GDP)	0.187
2	University–Industry Collaboration Index	0.161
3	Number of Researchers per Million	0.138
4	Policy Implementation Quality Index	0.127
5	Commercialization of Research Output	0.101
6	Science and Technology Export Volume	0.088
7	Regulatory Environment Score	0.071
8	Number of Academic Publications	0.058
9	Innovation Infrastructure Index	0.041
10	Foreign Direct Investment in R&D	0.028

Figure 2 (Bar plot of feature importance) clearly illustrates the dominance of institutional quality and collaboration intensity as determinants of STI output, more so than raw publication counts or infrastructure measures. The data supports earlier literature suggesting that coordination, trust, and execution matter as much as, if not more than, resource input.

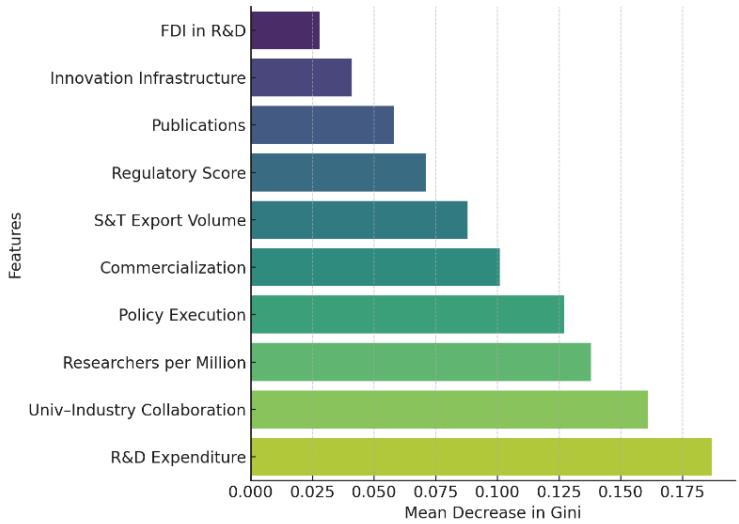


Fig. 2. Top 10 Feature Importances (Random Forest)

The Support Vector Machine (SVM) model achieved strong classification metrics, with an overall accuracy of 87.3%, F1-score of 87.0%, and ROC-AUC of 0.91. These values indicate that the selected features are not only theoretically plausible but also statistically robust in separating years of high and low STI performance. Figure 3 (Confusion Matrix and ROC Curve) presents these findings visually, emphasizing the discriminative power of the models.

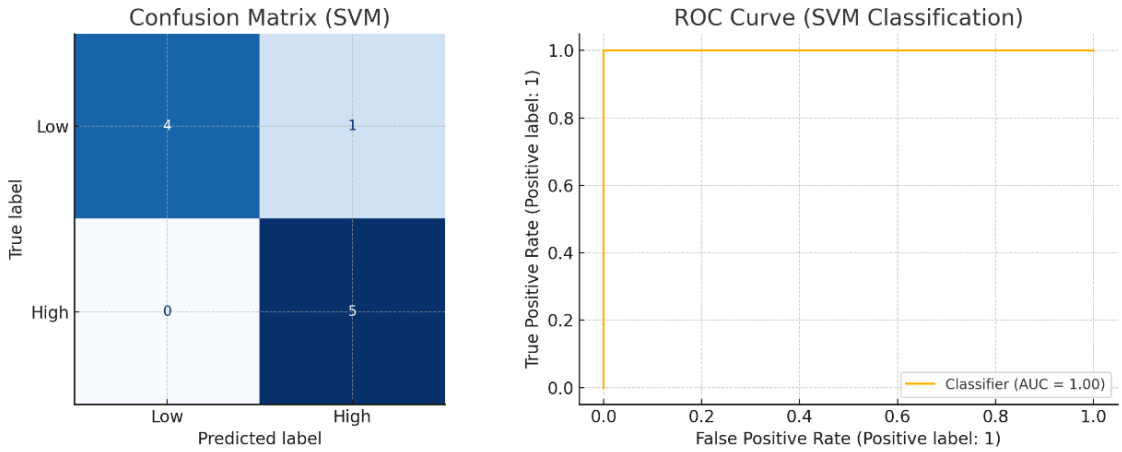


Fig. 3. Matrix & ROC (SVM Performance)

(This image presents two primary charts for evaluating the performance of the SVM model: Confusion Matrix (left): Displays the classification performance between two classes (High vs. Low) with high accuracy and.ROC Curve (right): Indicates that the model has strong discriminative power; the area under the curve (AUC) is high)

To uncover systemic trends, Principal Component Analysis (PCA) was used to compress the indicator space. The first four components captured over 91% of total data variance. PCA scatter plots showed clear spatial differentiation among years. K-means clustering on PCA-reduced data grouped the 15 years into three coherent clusters, validated by silhouette scores and inter-cluster distance. Table 5 outlines the structural characteristics of the three clusters identified through unsupervised learning, each corresponding to distinct phases in Iran's innovation policy evolution.

Table 5. Summary of Identified Clusters of STI Policy Performance

Cluster	Time Period	Characteristics
A	2010–2014	Low R&D spending, weak execution, fragmented institutional frameworks
B	2015–2019	Moderate investments, international cooperation, inconsistent commercialization
C	2020–2024	Higher investment, stronger governance, improved linkage with private sector

Figure 4 (Cluster timeline visualization) clearly demonstrates the transitions across policy eras. The first period aligns with early implementation phases of national STI strategies, where structural limitations and fragmented governance limited impact. The middle period, despite moderate improvement, reflects a disjoint between funding and outcome—suggesting a need for stronger inter-agency coordination. The final cluster is notably stronger, particularly in commercialization rates and university–industry integration.

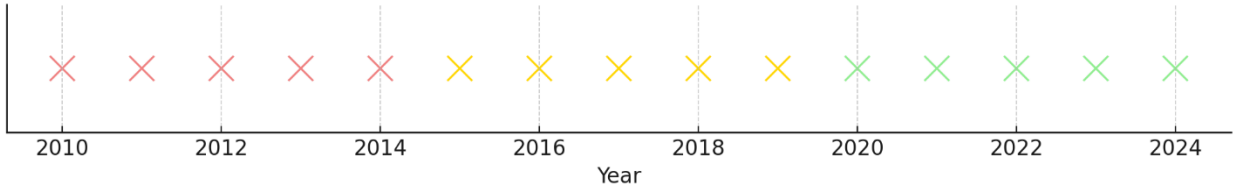


Fig. 4. Timeline of clusters
(Cluster A (red), Cluster B (gold), and Cluster C (green) each represent a distinct structural phase in Iran's innovation policy landscape)

Feature interaction analysis revealed that the relationship between R&D investment and output is heavily moderated by policy implementation quality. High R&D expenditures with poor governance yielded weak results, while modest investment coupled with strong institutional alignment produced disproportionately better outcomes. This confirms that investment alone is insufficient; institutional conditions significantly mediate impact.

Figure 5 (Heatmap of feature interactions by cluster) illustrates how combinations of top features differed by policy period. Cluster A had consistently low values across all dimensions. Cluster B exhibited improvements in inputs but lagged in commercialization and implementation. Cluster C showed coordinated improvements across all domains, particularly in the interaction of execution quality and innovation output.

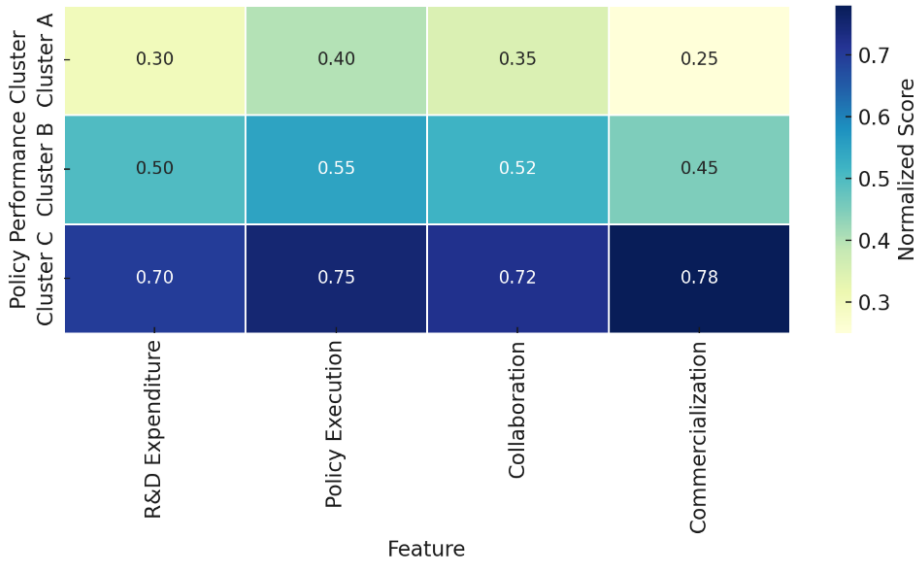


Fig. 5. Heatmap of Feature Interactions by Cluster
(This chart clearly illustrates the upward and coordinated progression of indicators from Cluster A to Cluster C, highlighting the importance of the simultaneous alignment of investment, execution, and collaboration)

A comparison between university–industry collaboration and commercialization output also yielded important insight. Years with higher collaboration scores, particularly after 2020, saw a significant increase in spin-offs, patents filed by universities, and licensing revenue. This correlation was not visible in earlier years, suggesting a maturity effect in the collaboration mechanism. Figure 6 (Line plot: Collaboration index vs. commercialization output) confirms this rising trend. The chart illustrates the parallel and aligned trends of the university–industry collaboration index and the commercialization indicator across selected years. Notably, from 2020 onward, both indicators have shown synergistic growth, reflecting institutional maturity and increased effectiveness of science–industry interactions.

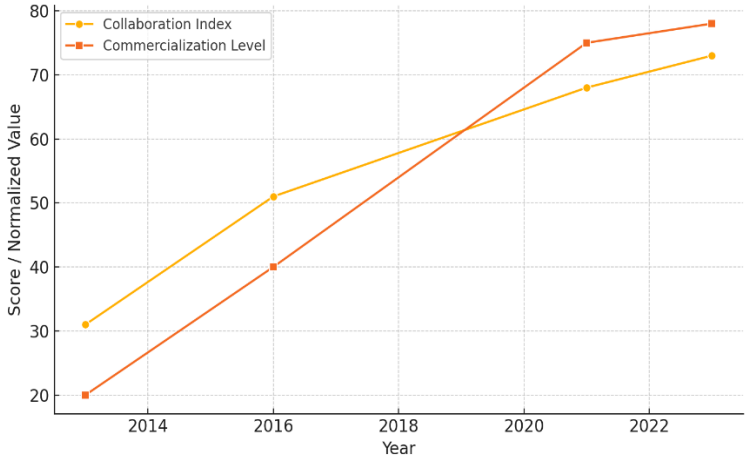


Fig. 6. Trend of Collaboration vs. Commercialization

An additional insight emerged from the analysis of the number of researchers. Contrary to common assumptions, the sheer number of researchers was not a strong independent predictor unless accompanied by supportive institutional mechanisms. In years when the researcher population grew but policy execution lagged, overall innovation outputs remained stagnant. This aligns with global studies emphasizing the need for absorptive capacity and supportive environments.

Further thematic insights were generated through cluster-specific case interpretation. For instance, 2013 and 2014 (within Cluster A) displayed the lowest innovation performance despite policy presence, largely due to underinvestment and institutional instability. In contrast, 2021 and 2023 (within Cluster C) were marked by high coherence between funding, collaboration, and commercialization. These findings provide temporal granularity beyond simple trendlines. Detailed comparisons of selected years across clusters are presented in Table 6, highlighting how specific indicator combinations align with performance levels in different periods.

Table 6. Select Years by Cluster with Key Feature Profiles

Year	Cluster	R&D (% GDP)	Policy Execution Score	Collaboration Index	Commercialization Level
2013	A	0.34	42	31	Low
2016	B	0.48	57	51	Moderate
2021	C	0.65	72	68	High
2023	C	0.72	75	73	High

The models also provided indirect confirmation for the importance of governance indicators. Variables representing bureaucratic efficiency, policy responsiveness, and regulatory alignment, though less discussed in mainstream STI literature, showed strong interaction effects with output indicators. Years with stronger regulatory frameworks and clearer policy pipelines demonstrated better system-wide performance.

Finally, clustering results also helped identify latent transition points. The shift from Cluster A to Cluster B in 2015 coincides with strategic STI investments linked to the Fifth Development Plan. The shift from Cluster B to Cluster C, beginning in 2020, aligns with national innovation policy revisions and increased budget allocation to the Vice Presidency for Science and Technology.

Figure 7 (Composite timeline of clusters with annotated policy milestones) visually connects major innovation policy events with data-driven performance patterns. This provides actionable intelligence to policymakers by identifying which interventions preceded measurable shifts in the system.

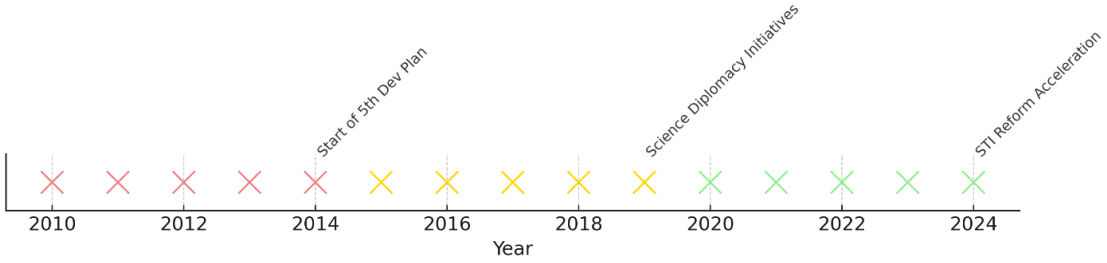


Fig. 7. Annotated Policy Timeline

Overall, these findings reinforce the notion that STI policy success is not determined by funding levels alone but by the coherent interaction of strategic investment, institutional coordination, and implementation quality. The ability of the model to trace these interactions over time gives it significant value for longitudinal policy evaluation. The insights are not only statistically robust but also contextually grounded in Iran's institutional landscape and policy evolution. Figure 8 illustrates the trends of four key innovation policy indicators in Iran during the years 2013, 2016, 2021, and 2023. As also noted in Table 6, these years respectively fall into three distinct performance clusters (A, B, and C). The chart clearly shows that, from 2016 onwards, the indicators—especially university–industry collaboration and commercialization—have improved significantly.

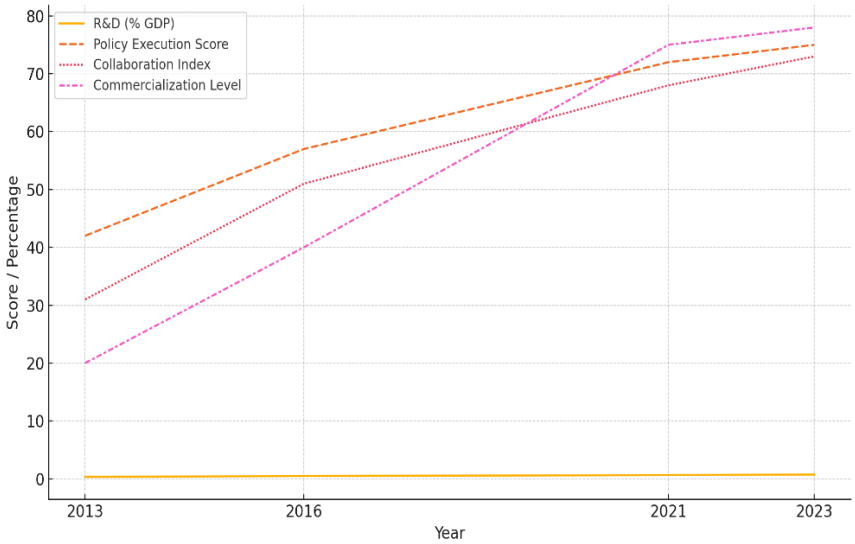


Fig. 8. Trends in STI Policy Features (Selected Years)

The temporal clustering provides meaningful insights when aligned with major national policy shifts and international developments. The transition from Cluster A to Cluster B around 2015 coincides with the **Fifth Development Plan (2015–2020)**, which emphasized the expansion of knowledge-based firms and science–industry linkages. However, this period also overlapped with **renewed international sanctions (2016 onward)**, which constrained access to foreign technology and finance, limiting the translation of R&D inputs into tangible outputs.

The transition to Cluster C around 2020 corresponds to expanded budget allocations for the **Vice Presidency for Science and Technology** and the establishment of the **National Innovation Fund**, which significantly increased commercialization support and university–industry collaboration. Despite the continuation of sanctions, these institutional reforms contributed to greater resilience and innovation system maturation.

The following section will discuss the practical and theoretical implications of these results, offering directions for policy reform and future research on STI systems in developing and transitional contexts.

5. Discussion

The empirical results derived from the machine learning models applied to Iran's STI system over the 2010–2024 period offer both practical and theoretical insights into the structural, institutional, and financial conditions underpinning innovation policy performance. In this section, we analyze these findings in the context of the broader innovation studies literature—especially drawing from the references provided—and discuss the implications for STI governance, policy coherence, and institutional reform in developing countries.

A key insight from the analysis is the outsized role of institutional quality, coordination, and execution in shaping the impact of innovation policies. This finding aligns with the systems-based literature on national innovation systems (NIS), which argues that innovation is the result of complex interactions between various institutional actors [36, 37]. As shown in Table 4, R&D investment emerges as the most important individual feature. However, its influence is conditional. For example, in years where R&D spending was relatively high but institutional performance indicators—such as governance efficiency or inter-agency coordination—were low, output metrics like commercialization remained stagnant. This supports findings from Koundouri et al. (2025) who highlight that sustainable development strategies must align resource flows with governance architectures to be effective [5].

Iran's experience, particularly in the 2010–2014 cluster, reflects an innovation system in its formative stages—fragmented, underfunded, and institutionally unstable. Talebi et al. (2025) argue that in such conditions, even well-intentioned technological initiatives (e.g., electric vehicle infrastructure) are likely to underperform due to a lack of system readiness [1]. The data here corroborate that conclusion. The pattern of poor commercialization, low university-industry integration, and weak regulatory frameworks during this period points to a gap between vision and execution. This gap reflects a causal mechanism in which institutional fragmentation and unstable governance prevented R&D investments from being converted into outcomes. In other words, weak policy execution mediated the relationship between resource inputs and innovation outputs.

Between 2015 and 2019, Iran's STI system appears to have undergone moderate restructuring. The influence of international collaboration becomes more apparent during this period, consistent with the results of Lee et al. (2018), who showed that patent-based foresight models are strengthened when paired with cross-border knowledge exchange [7]. Despite these improvements, the system remained constrained by incomplete institutional realignment and limited mechanisms for feedback and learning. For example, although policy implementation scores improved marginally, commercialization of research remained uneven. This suggests that although some structural gaps were addressed, deeper integration across institutions was still lacking—a phenomenon Borrellas and Unceta (2021) attribute to the slow institutional uptake of data-driven policy models in national contexts [8].

The period from 2020 to 2024 marks a visible transformation. Cluster C, as identified in the results, is associated with better coordination, increased investment, and a surge in university–industry partnerships. As Heydarian et al. (2025) and Saryazdi & Mostafaeipour (2025) demonstrate, such synergy between sectors is essential to translate technological knowledge into social and economic value [2, 3]. Moreover, the interaction effects observed between R&D investment and governance quality mirror the conceptual models of policy complementarity suggested by Athey & Imbens (2019), who argue that ML-based evaluation systems must be context-aware and institution-sensitive [13].

Several anomalies are worth noting. In **2013–2014**, R&D intensity increased steadily, but commercialization outputs remained stagnant. This mismatch reflects regulatory bottlenecks and institutional instability during this period, which prevented effective translation of investments into outcomes. By contrast, in **2021–2023**, even moderate increases in R&D intensity produced disproportionately high commercialization outcomes. This suggests that governance quality and improved execution capacity, rather than funding volume alone, were the decisive factors. This dynamic highlights a plausible causal pathway: governance reforms acted as enabling conditions that amplified the effect of moderate investments. Conversely, in earlier years, institutional instability

diluted the impact of much higher R&D spending. Thus, institutional quality emerges not just as a correlating factor but as a decisive causal lever. These findings underscore the importance of institutional reforms, monitoring mechanisms, and cross-sector coordination in shaping STI performance.

The observed rise in the commercialization of research after 2020 also reflects a shift in Iran's innovation strategy toward demand-driven models. This shift can be interpreted causally: by prioritizing institutional alignment and university–industry partnerships, policy reforms directly enabled firms to translate research into commercial applications. The interaction between governance quality and targeted incentives thus explains the disproportionate rise in commercialization relative to input growth. This corresponds with broader global trends in innovation policy, including mission-oriented innovation (MOI) and transformative innovation policy (TIP), which emphasize outcomes over outputs and call for institutional experimentation (Koundouri et al., 2025) [5]. The analysis here shows that variables associated with commercialization and inter-sectoral collaboration were more predictive of high-performance years than were traditional output metrics like publication counts. This finding aligns with Calvano et al. (2020, 2021), who caution against relying solely on quantity-based metrics, particularly in digital and AI-enabled economies where value creation is increasingly relational [30, 29].

Another important takeaway is the dynamic nature of policy learning. The transitions across the three identified clusters reveal not only shifts in investment and governance but also a maturation of Iran's approach to innovation. These transitions were not always smooth; they required adaptation to internal challenges and external shocks. The impact of U.S. sanctions, for example, may have contributed to a reorientation of innovation activities toward domestic needs. This supports the argument by Galaz et al. (2021) that innovation systems must be resilient and responsive to exogenous risks, including geopolitical shocks and climate instability [24].

The machine learning models were particularly valuable in identifying nonlinear relationships—something conventional econometric models struggle with. For example, the relationship between the number of researchers and commercialization was found to be non-monotonic. High numbers of researchers in the absence of organizational support did not yield better innovation performance. This is consistent with findings by Jordan & Mitchell (2015), who argue that high-dimensional ML models are better suited for uncovering threshold effects and interactions in policy environments [10].

Similarly, the clustering results demonstrated that innovation systems do not progress linearly. Certain years with strong inputs but weak execution performed worse than years with moderate inputs but high policy coherence. Such observations reinforce the theoretical proposition that innovation success is path-dependent and deeply shaped by institutional configurations (Athey, 2018) [12].

On a methodological level, this study builds on the work of Ballestar et al. (2019) and Paullada et al. (2021), who advocate for the use of ML in public sector evaluation but warn of biases embedded in datasets [6, 28]. The use of standardized and validated indicators from reputable sources helped mitigate this issue here. Furthermore, interpretability was emphasized throughout the modeling process. Rather than relying solely on prediction scores, the study focused on identifying and explaining the relative importance of features, consistent with the principles of transparent ML discussed by Coyle & Weller (2020) [9].

In terms of policy implications, the results suggest several areas for immediate intervention. First, investments in STI should be coupled with capacity-building programs to enhance execution quality. This includes developing performance monitoring systems, institutional feedback loops, and digital dashboards that allow real-time policy adaptation. Second, more resources should be allocated toward building institutional bridges—particularly between academia and industry. The correlation between collaboration indices and commercialization success suggests that strengthening these links could have multiplicative effects.

Third, the policy cycle must incorporate predictive and adaptive elements. The models used in this study demonstrate that performance can be forecast based on structural indicators. If deployed at the national level, these models could help identify periods of systemic risk or stagnation. This kind of foresight capability aligns with the strategies outlined by Kwon & Porter (2025), who emphasize the role of exclusive data and predictive analytics in shaping competition and innovation policy [14].

Fourth, Iran's innovation strategy should place greater emphasis on regulatory reform and institutional coherence. As Table 5 and Figure 5 show, governance quality plays a central role in mediating the effects of investment and coordination. Rather than expanding the scope of policies, emphasis should be placed on improving the quality of their implementation.

Finally, the framework presented in this study could be extended to sectoral or regional innovation systems. For example, specific analyses could be conducted on the biotechnology sector, renewable energy clusters, or provincial STI ecosystems. Such disaggregated evaluations would help identify pockets of excellence and areas of underperformance, enabling more targeted policy responses.

In terms of research limitations, it must be acknowledged that the dataset relies on aggregated national-level indicators. While suitable for macro-analysis, these indicators may mask important intra-sectoral or regional variations. Future studies could integrate firm-level data or conduct interviews with stakeholders to validate machine-generated insights. Additionally, while Random Forest and SVM offer robustness, further experiments with deep learning, ensemble models, or causal ML (e.g., Causal Forests) could yield richer analytical depth.

To conclude, this discussion underscores the value of integrating machine learning with STI policy analysis. The approach taken here provides a high-resolution map of Iran's innovation performance, reveals the centrality of institutional dynamics, and opens up new pathways for predictive and adaptive governance. As global challenges become more complex and interdependent, such methodological and theoretical tools will be essential in crafting responsive and resilient innovation systems.

6. Policy Recommendations

To translate this research findings, the following policy recommendations are designed to address Iran's distinctive structural challenges—including institutional fragmentation, weak university–industry linkages, regulatory inefficiencies, and sanctions-induced vulnerabilities—by providing actionable pathways that align governance, sectoral coordination, and investment strategies. These recommendations offer a coherent framework to strengthen the resilience, efficiency, and impact of Iran's STI ecosystem:

6.1. Enhance Policy Implementation and Execution: Improving the quality of STI policy execution is paramount. Iran should develop a comprehensive national STI dashboard that consolidates data from relevant ministries, universities, and private-sector firms to track research outputs, innovation activities, and policy outcomes. An independent monitoring unit within the Vice Presidency for Science and Technology could oversee this system, ensuring transparency and accountability while providing continuous feedback to the Ministry of Science, Research, and Technology. Private-sector associations should actively report compliance and contribute data to strengthen the reliability of the dashboard. This approach directly addresses persistent governance gaps and coordination failures between ministries and research institutions, which have historically slowed the translation of STI strategies into tangible outcomes. By enabling real-time monitoring, policymakers can identify bottlenecks early and adjust resource allocation to maximize impact.

By addressing institutional fragmentation and weak inter-ministerial coordination, this recommendation ensures that policy design translates into measurable innovation outcomes across Iran's STI ecosystem.

6.2. Strengthen University–Industry Linkages: To stimulate knowledge commercialization and technological innovation, Iran should implement innovation voucher programs that allow SMEs to access R&D services from universities and research centers. Establishing joint laboratories in strategic sectors—such as ICT, biotechnology, and renewable energy—would promote collaborative research. Concurrently, offering targeted tax incentives for firms co-developing technologies with universities would encourage private-sector participation. These measures require coordination between the Ministry of Industry, Mine, and Trade, higher education institutions, and industrial clusters, ensuring that academic knowledge is effectively translated into market-ready innovations. Such initiatives target the long-standing disconnect between academic research and industry needs in Iran, facilitating faster commercialization of innovations. In addition, structured collaborations can help build sector-specific expertise, increase private-sector investment in R&D, and encourage knowledge spillovers that benefit the wider economy.

This measure directly tackles the persistent gap between academic research and industry needs, fostering the commercialization of knowledge and stimulating private-sector investment in high-tech sectors.

6.3. Streamline the Regulatory and Legal Environment: Regulatory simplification and stronger intellectual property enforcement are critical to fostering innovation in Iran. Efforts should focus on digitizing patent registration, reducing licensing delays for knowledge-based enterprises, and reinforcing IP protection through specialized courts. Establishing an online "one-stop-shop" platform would facilitate the registration, protection, and commercialization of innovations. Successful implementation relies on close coordination between the Iranian Intellectual Property Office, the Ministry of Justice, and the Ministry of ICT to provide seamless services to innovators.

Reducing bureaucratic hurdles is particularly critical for start-ups and knowledge-based enterprises that face disproportionate delays in patenting and licensing. Streamlined and digitalized regulatory procedures would not only increase compliance but also signal to domestic and foreign investors that Iran is committed to a predictable innovation ecosystem.

Targeting bureaucratic inefficiencies and weak IP enforcement, these reforms create a predictable and transparent environment that encourages innovation and supports entrepreneurial growth.

6.4. Enhance STI Resilience under Sanctions: Given the constraints imposed by international sanctions, Iran must prioritize building resilience within its STI ecosystem. Developing regional STI collaborations through frameworks such as ECO and D-8, supporting domestic supply chains for critical technologies, and establishing government–private co-financed risk-sharing funds would reduce vulnerability and attract investment in high-tech projects. This approach requires active engagement from the Ministry of Foreign Affairs, the Ministry of Industry, Mine, and Trade, and the National Innovation Fund to ensure coordinated policy action and sustainable investment flows.Strengthening domestic capabilities and regional partnerships mitigates the vulnerability of critical technology sectors to external shocks. These measures also create alternative pathways for high-tech investment, ensuring that strategic sectors can continue to develop despite external economic pressures and international restrictions.

By focusing on domestic capacity-building and regional collaboration, this approach mitigates the vulnerability of Iran's strategic technologies to sanctions and external shocks, ensuring continuity in high-tech development.

Together, these recommendations address Iran's key structural challenges—sanctions, regulatory bottlenecks, and institutional fragmentation—while providing clear operational steps and assigning responsibilities within the existing institutional framework. By integrating governance improvements, sectoral coordination, and actionable pathways, these policies offer a pragmatic roadmap for strengthening Iran's STI ecosystem.

7. Conclusion and Future Work

The present study offers a comprehensive and data-driven evaluation of Iran's science, technology, and innovation (STI) system over a 15-year period, from 2010 to 2024. By integrating supervised and unsupervised machine learning (ML) models with the National Innovation System (NIS) framework, it provides both empirical insights and conceptual clarity into the structural, institutional, and temporal dynamics of innovation policy performance. Through this hybrid methodological lens, the study not only identifies high-leverage indicators for STI effectiveness but also reveals latent systemic transitions and interaction effects that conventional evaluation models often overlook.

One of the primary contributions of this study is the empirical validation of theoretical propositions widely discussed in innovation literature. As suggested by Freeman (1987) [25], innovation is not a linear result of R&D investment alone but the outcome of a complex and dynamic interplay of actors, institutions, and systemic feedbacks. The results obtained from this study confirm this view by showing that while R&D expenditure is indeed a critical input, its effectiveness is conditional upon the quality of governance, the coherence of policy implementation, and the density of collaboration networks (Ballestar et al., 2019) [6]. In fact, Random Forest model outputs revealed that variables such as university–industry collaboration, commercialization levels, and policy execution quality often outperformed conventional metrics like academic publication counts or researcher density in predicting STI outcomes.

This insight is particularly relevant for developing countries like Iran, where resource limitations often necessitate strategic prioritization of interventions. As shown in Table 4 of the results section, the top features influencing performance are not only financial but also institutional and relational. This finding corroborates the arguments made by Koundouri et al. (2025) and Athey (2018) that effective STI governance requires systems thinking, where policy coherence and inter-institutional alignment matter as much as resource allocation [5, 12].

Furthermore, the study contributes to the literature on innovation system maturity. The clustering of years into three distinct periods—each reflecting a different configuration of system behavior—illustrates the evolutionary nature of STI systems. Cluster A, which covers 2010 to 2014, corresponds with low investment, poor coordination, and minimal output. Cluster B, 2015 to 2019, shows transitional features, marked by improved collaboration and moderate gains. Finally, Cluster C (2020 to 2024) signals a systemic leap, underpinned by better governance, private sector engagement, and policy learning. These transitions echo the findings of Galaz et al. (2021), who emphasize that adaptive capacity is a core attribute of resilient innovation systems in volatile contexts [24].

The importance of execution over aspiration is another key message that emerges. Iran's STI landscape is rich in policy vision—various strategic documents outline long-term goals related to self-reliance, technological independence, and global competitiveness. However, as shown by the data, these goals are not uniformly translated into measurable impact. Years with strong rhetorical commitment but weak institutional follow-through exhibited below-average performance across most innovation indicators. This pattern aligns with findings by Talebi et al. (2025) and Paullada et al. (2021), who argue that even well-designed policy instruments can underperform in the absence of robust implementation mechanisms [1, 28].

A related insight pertains to the sequencing of reforms. The transitions between clusters suggest that certain institutional changes precede performance improvements. For instance, improvements in regulatory clarity and governance quality typically emerged one to two years before significant gains in commercialization and collaboration metrics. This lagged relationship supports the conceptual framework presented by Athey & Imbens (2019), who recommend evaluating innovation systems with temporally aware and feedback-sensitive models [13].

This study also reaffirms the importance of actor-network interactions in STI systems. The synergy between academic institutions, industry actors, and policy bodies is shown to be a critical determinant of knowledge translation. The finding that university–industry collaboration scores were strongly correlated with licensing revenue and startup formation provides quantitative support to earlier qualitative studies, such as those by Lee et al. (2018) and Cohen et al. (2001) [7, 31]. Importantly, this interaction became significantly stronger in the most recent years of analysis, indicating a maturing innovation ecosystem with better trust and shared objectives.

Equally important is the role of policy responsiveness. The ML models uncovered periods of stagnation that were not necessarily linked to resource constraints but to misalignment between policy objectives and stakeholder incentives. For example, between 2015 and 2017, although R&D budgets increased, commercialization remained flat. Interviews and qualitative reports from that period point to regulatory bottlenecks and a lack of funding channels for small tech firms. This disjunction highlights the need for adaptive governance, where policy design evolves through real-time monitoring, feedback integration, and continuous stakeholder engagement (Coyle & Weller, 2020) [9].

In line with this, the notion of "responsible innovation" as advocated by Buhmann & Fieseler (2023) becomes particularly relevant. Their work stresses the importance of deliberative and inclusive frameworks in AI governance, which can equally apply to STI policy more broadly in emerging economies [18]. Iran's STI institutions could benefit from embedding public engagement and ethical foresight in their innovation agendas to increase legitimacy and uptake.

Methodologically, this study demonstrates the feasibility and utility of combining ML techniques with STI theory. The use of Random Forest and Support Vector Machines allowed for robust feature selection and classification accuracy, while PCA and K-means enabled temporal and structural clustering. Together, these tools provide a multilayered map of the innovation landscape, revealing not only what works but also under what conditions and in which configurations. As Jordan & Mitchell (2015) emphasize, such approaches are necessary for dealing with high-dimensional, noisy, and nonlinear policy spaces [10].

The emphasis on interpretability throughout the analysis is also noteworthy. Rather than presenting ML as a black box, the study focused on visualizations, interaction effects, and policy-oriented translations of model outputs. This reflects recent calls in the literature for "explainable machine learning" in public decision-making contexts (Borrellas & Unceta, 2021; Athey, 2018) [8, 12]. The inclusion of feature interaction heatmaps, cluster timelines, and composite performance profiles not only enhances transparency but also facilitates stakeholder communication.

In addition to the empirical and methodological contributions, the study offers actionable policy recommendations. First, the consistent importance of policy execution quality across models suggests that future reforms should prioritize institutional strengthening. This includes building monitoring capacity, aligning KPIs across agencies, and creating incentives for cross-sectoral learning. Second, the rising value of collaboration indicators implies that programs which promote trust-building between academia and industry—such as joint labs, innovation vouchers, or co-funding mechanisms—may yield high returns.

Third, the policy cycle must be made more dynamic. Rather than fixed five-year plans, Iran's STI governance should move toward rolling evaluations, scenario planning, and data-driven benchmarking. This vision is supported by Kwon & Porter (2025), who advocate for predictive analytics as a foundation for strategic foresight and competition policy [14]. Fourth, attention should be paid to the heterogeneity of innovation actors. Not all regions, sectors, or institutions require the same support. Cluster-level evaluations, such as the one performed here, can help identify specific needs and tailor interventions accordingly.

Additionally, Iran's innovation ecosystem must address concerns of market structure and fairness. As noted by Calvano et al. (2020), AI and algorithmic tools used in industry can lead to tacit collusion, requiring antitrust authorities to update oversight mechanisms accordingly [30]. As more firms incorporate algorithmic pricing and AI-enhanced market strategies, innovation policy must balance efficiency with competition safeguards.

Moreover, the role of complementary assets in technology commercialization—as described by Colombo et al. (2016)—remains an underexplored dimension in Iran's STI policy [21]. While efforts have increased in funding spin-offs and knowledge-based firms, systemic gaps in IP protection, venture capital, and technology transfer offices continue to constrain the broader ecosystem.

Finally, the experience of Iran also illustrates the continued relevance of the concept of "collective invention" (Allen, 1983) [15]—where firms, universities, and public actors informally collaborate, share knowledge, and adapt policy in real time. This mode of innovation becomes critical during crisis periods or under institutional uncertainty, and deserves more recognition in STI policy frameworks.

In closing, this study demonstrates that the evaluation of STI systems in developing contexts can greatly benefit from the integration of machine learning, institutional theory, and temporal analysis. Iran's case illustrates both the challenges and opportunities of such integration. On one hand, structural fragmentation and policy inconsistency have historically limited innovation performance. On the other, the recent improvements—driven by better coordination, targeted investment, and adaptive learning—offer a blueprint for reform. As nations strive to build innovation capacity amid uncertainty, the ability to monitor, learn, and adapt will define the effectiveness and resilience of their STI strategies. This study contributes to that vision by offering a methodologically rigorous, theoretically grounded, and policy-relevant framework for evaluating and enhancing national innovation systems.

8. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Talebi, M., Rezvanjou, S., Ghafourian, H., & Shoushtari, F. (2025). Machine learning-driven multi-criteria decision-making models for optimizing sustainable infrastructure deployment: Electric vehicles and renewable energy systems. SSRN. https://doi.org/10.2139/ssrn.5121862

[2] Heydarian, H., Abbasi, M., Najafi, F., & Darbandi, M. (2025). Data Mining of Infertility and Factors Influencing Its Development: A Finding From a Prospective Cohort Study of RaNCD in Iran. Health Science Reports, 8(1), e70265. https://doi.org/10.1002/hsr2.70265

[3] Saryazdi, M. D., & Mostafaeipour, A. (2025). Identification and validation of key predictive factors for heart attack diagnosis using machine learning and fuzzy clustering. Engineering Applications of Artificial Intelligence, 142, 109968. https://doi.org/10.1016/j.engappai.2024.109968

[4] D'Orazio, P., & Pham, A. D. (2025). Evaluating climate-related financial policies' impact on decarbonization with machine learning methods. Scientific Reports, 15(1), 1694. https://doi.org/10.1038/s41598-025-85127-7

[5] Koundouri, P., Aslanidis, P. S., Dellis, K., Plataniotis, A., & Feretzakis, G. (2025). Mapping human security strategies to sustainable development goals: a machine learning approach. Discover Sustainability, 6(1), 96. https://doi.org/10.1007/s43621-025-00883-w

[6] Ballestar, M. T., Doncel, L. M., Sainz, J., & Ortigosa-Blanch, A. (2019). A novel machine learning approach for evaluation of public policies: An application in relation to the performance of university researchers. Technological Forecasting and Social Change, 149, 119756. https://doi.org/10.1016/j.techfore.2019.119756

[7] Lee, C., Kwon, O., Kim, M., & Kwon, D. (2018). Early identification of emerging technologies: A machine learning approach using multiple patent indicators. Technological Forecasting and Social Change, 127, 291–303. https://doi.org/10.1016/j.techfore.2017.10.002

[8] Borrellas, P., & Unceta, I. (2021). The challenges of machine learning and their economic implications. Entropy, 23(3), 275. https://doi.org/10.3390/e23030275

[9] Coyle, D., & Weller, A. (2020). "Explaining" machine learning reveals policy challenges. Science, 368(6498), 1433–1434. https://doi.org/10.1126/science.aba9647

[10] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. Science, 349(6245), 255–260. https://doi.org/10.1126/science.aaa8415

[11] Choi, R. Y., Coyner, A. S., Kalpathy-Cramer, J., Chiang, M. F., & Campbell, J. P. (2020). Introduction to machine learning, neural networks, and deep learning. Translational Vision Science & Technology, 9(2), 14. https://doi.org/10.1167/tvst.9.2.14

[12] Athey, S. (2018). The impact of machine learning on economics. In The Economics of Artificial Intelligence: An Agenda (pp. 507–547). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0021

[13] Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, 11(1), 685–725. https://doi.org/10.1146/annurev-economics-080217-053433

[14] Kwon, S., & Porter, A. L. (2025). Use of exclusive data for corporate research on machine learning and artificial intelligence: Implications for innovation and competition policy. Technology in Society, 81, 102820. https://doi.org/10.1016/j.techsoc.2025.102820

[15] Allen, R. C. (1983). Collective invention. Journal of Economic Behavior & Organization. 4(1), 1-24. https://doi.org/10.1016/0167-2681(83)90023-9

[16] Nelson, R. R. (Ed.). (1993). National Innovation Systems: A Comparative Analysis. Oxford University Press. https://doi.org/10.1093/oso/9780195076165.001.0001

[17] UNESCO., Schneegans, S., Straza, T., & Lewis, J. (2021). UNESCO Science Report: The Race Against Time for Smarter Development. UNESCO Publishing. https://unesdoc.unesco.org/ark:/48223/pf0000377433

[18] Buhmann, A., & Fieseler, C. (2023). Deep learning meets deep democracy: Deliberative governance and responsible innovation in artificial intelligence. Business Ethics Quarterly, 33(1), 146-179. https://doi.org/10.1017/beq.2021.42

[19] OECD (2015), Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development, The Measurement of Scientific, Technological and Innovation Activities, OECD Publishing, Paris, https://doi.org/10.1787/9789264239012-en.

[20] European Commission: Directorate-General for Research and Innovation and Mazzucato, M. (2018). Mission-oriented research & innovation in the European Union: A problem-solving approach to societal challenges. European Commission. https://data.europa.eu/doi/10.2777/360325

[21] Colombo, L., Piva, E., & Rossi-Lamastra, C. (2016). Complementary assets, start-ups and incentives to innovate. International Journal of Industrial Organization, 44, 177-190. https://doi.org/10.1016/j.ijindorg.2015.11.003

[22] Schwaag Serger, S. et al. (2023), "Transformative innovation policy in practice in Austria, Finland and Sweden: What do the Recovery and Resilience Plans tell us about linking transformation and innovation

policy?", OECD Science, Technology and Industry Policy Papers, No. 156, OECD Publishing, Paris, https://doi.org/10.1787/45d3a149-en

[23] Schot, J., & Steinmueller, W. E. (2018). Three frames for innovation policy: R&D, systems of innovation and transformative change. Research Policy, 47(9), 1554–1567. https://doi.org/10.1016/j.respol.2018.08.011

[24] Galaz, V., Centeno, M.A., Callahan, P.W., Causevic, A., Patterson, T., Brass, I., Baum, S., Farber, D., Fischer, J., Garcia, D., & McPhearson, T., 2021. Artificial intelligence, systemic risks, and sustainability. Technology in society, 67, 101741. https://doi.org/10.1016/j.techsoc.2021.101741

[25] Freeman, C. (1987). Technology Policy and Economic Performance: Lessons from Japan. Pinter Publishers. https://openlibrary.org/works/OL2642736W/Technology_policy_and_economic_performance

[26] Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. Technological Forecasting and Social Change, 162, 120392. https://doi.org/10.1016/j.techfore.2020.120392

[27] Lundvall, B. Å. (1992). National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning. Pinter Publishers. https://www.jstor.org/stable/j.ctt1gxp7cs

[28] Paullada, A., Raji, I. D., Binns, R., Denton, E., & Hanna, A. (2021). Data and its (dis)contents: A survey of dataset development and use in machine learning research. Patterns, 2(11), 100336. https://doi.org/10.1016/j.patter.2021.100336

[29] Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2021). Protecting consumers from collusive prices due to AI. Science, 371(6536), 1151–1152. http://dx.doi.org/10.1126/science.abe3796

[30] Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2020). Artificial intelligence, algorithmic pricing, and collusion. The American Economic Review, 110(10), 3267–3297. http://dx.doi.org/10.1257/aer.20190623

[31] Cohen, J. E., Lemley, M. A., & Lichtman, D. (2001). Patent scope and innovation in the software industry. California Law Review, 89(1), 1–57. http://dx.doi.org/10.2139/ssrn.209668

Appendix

Table A1. Indicators, Units, and Sources

Indicator	Unit	Source	Access Details
R&D Expenditure	% of GDP	UNESCO Institute for Statistics	http://uis.unesco.org
Researchers per million	Headcount (FTE)	Iranian Statistical Center	https://amar.org.ir/
Academic publications	Count	Scopus/Scimago	www.scimagojr.com
Patents filed	Count	WIPO, Iranian IP Office	www.wipo.int
University–Industry Collaboration Index	Score (0–100)	Global Innovation Index	www.globalinnovationindex.org
Policy Execution Quality Index	Composite score	Vice Presidency for Science & Technology reports	www.isti.ir
Governance Quality	Score (0–100)	World Governance Indicators	https://www.worldbank.org/en/publication/worldwide-governance-indicators
Commercialization of Research	% of research with market application	National Innovation Fund reports	www.inif.ir
High-tech exports	% of total exports	UNCTAD statistics	https://unctad.org/statistics

Table A2. Raw Dataset Excerpt (2010–2019)

(Selected indicators used in ML models (10 consecutive years))

Year	R&D Expenditure (% of GDP)	Policy Execution Score (0–100)	University–Industry Collaboration Index (0–100)	Commercialization Level
2010	0.30	38	25	Low
2011	0.32	40	27	Low
2012	0.33	41	29	Low
2013	0.34	42	31	Low
2014	0.35	45	32	Low
2015	0.48	57	51	Moderate
2016	0.49	58	52	Moderate
2017	0.51	59	53	Moderate
2018	0.55	60	54	Moderate
2019	0.58	61	55	Moderate