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DATA SCIENCE FRAMEWORKS FOR AI-EQUIPPED ENTREPRENEURIAL ECOSYSTEMS: TRANSFORMING GEM 2025/26 INSIGHTS

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ABSTRACT

General Total Early-Stage Entrepreneurial Activity (TEA) was of 53 economies according to the Global Entrepreneurship Monitor Report 2025/26, but only 25-30 percent of startups are carried through to full-fledged businesses, even as 84 percent of startups have social impact ambitions. The lack of AI readiness and survival issues persists, requiring new solutions based on Data Science. This paper suggests detailed frameworks that would use ensemble MLs for the multidimensional dataset of GEM: Cox proportional hazards of survival prediction and Random Forest of gap analysis. India (fourth in National Entrepreneurship Context Index in the world) confirms approach-24 per cent of the three-year survival is constricted by regional AI inequalities. Using an Indian venture sample of 2,139 (fintech: n = 892; health-tech: n = 1,247), exit-risk real-time analytics forecasting and AI-readiness signaling helped to raise survival by 35 percent. Tier-2/3 cities: survival can increase by 42 percent; low-readiness countries: improvement can take place by 29 percent. Technology-neutral models aligned to ICIDS 2026 provide scalable solutions to such barriers that can be identified by policymakers/incubators to ensure equitable entrepreneurial growth.

Keywords: GEM 2025/26, entrepreneurial survival, AI ecosystems, Cox hazards, NECI optimization

1. INTRODUCTION

Economic resilience and innovation require the presence of entrepreneurial ecosystems, particularly in the face of globalization challenges such as geopolitical tension, climate change, and technological disruptive innovations or breakthroughs, which can be facilitated by AI [1]. According to the Global Report 2025/2026 of the Global Entrepreneurship Monitor (GEM), the total early stage entrepreneurial activity (TEA) in 53 economies is at all-time highs. Over a quarter of the 18-64-year-olds in such countries as Angola, Ecuador, Chile, Saudi Arabia, Canada, and Guatemala are starting or operating new businesses [2]. New ventures are highly successful but can hardly survive in the long term, restricting job creation, innovation, and growth in exports [3].

The GEM report shows that purpose-driven entrepreneurship now prevails 84 per cent of early stage entrepreneurs consider the social or environmental impact of their decisions, which is a sudden increase over the last several years [4]. Young businesspeople between 18-34 years are at an all-time high, the involvement of women is at or near gender parity in nine middle-income economies, and foreign-born entrepreneurs operate more innovative businesses [5].

The age of the GEM longitudinal data, Adult Population Survey (demographics, motivations), and National Expert Survey (13 Entrepreneurial Framework Conditions) is 26 years, and naturally, the dataset is perfect for advanced data analysis. The fear of failure prevents 41 percent of the individuals from seeing opportunities, and 45 percent of exporters of businesses intend to start again in three years. Machine learning can identify this resilience[6][7]. In Angola, 93 percent of entrepreneurs intend to use more digital tools, and more than 25 percent of TEA are earning money via international clients, which are strongly associated with high levels of National Entrepreneurial Context Index (NECI).

The field of AI in entrepreneurship and ecosystems is currently being researched. AI algorithms transform individual entrepreneur judgments into coordination at a system-wide level [8]. Individual entrepreneurship determinants have been forecasted with machine learning on GEM data, as has been observed in the case of Spain [9]. This study fills these gaps by suggesting AI data science frameworks that can be used to turn GEM 2025/26 insights into actionable intelligence.

The traditional theory of entrepreneurial ecosystems implies the interaction of actors (entrepreneurs and investors), policies, and culture, which in turn can be fundamentally improved by AI [1]. Natural language processing (NLP) may be used to analyze the quotes of NES experts to identify opportunities, graph analytics may be used to visualize stakeholder networks, and simulations based on agents may be used to simulate policy scenarios. As an illustration, a 15 percent increase in NECI may result from an increase in the finance scores from 4.2 to 5.5 [2].

THIS PAPER PROPOSES THREE CORE FRAMEWORKS

The former is the Predictive Analytics Pipeline. It consumes APS/NES data through APIs, processes them (fill-in values, constructs NECI sub-indices), and makes predictions based on TEA-to-EBO transitions using LSTM models. The result is risk heatmaps of all 53 economies, which clearly demonstrate correlations, such as fear of failure (-0.2, with intent) [11].

The second is an Ecosystem Simulation Model based on agent-based modelling to simulate tweaking of the conditions of the framework. There are methods of causal inference such as propensity score matching, which analyze patterns of exit. To appease sustainability-centered entrepreneurs (as 90 percent of Angolan youth are more focused on impact than profit), it creates AI-optimized ESG scoring [12].

The third is an AI Decision Dashboard, an interactive tool based on NLP relying on expert quotes, plotly graphs (AI importance: 45% in upper and 62% middle-income economies), and SHAP values to explain the model. It is cloud-based when it comes to updates of real-time GEM data [13].

These theories promote the development of theory by quantifying causal loops in ecologies and offering effective policy road maps. They suggested that AI customized tutors to low-education economies, gender gap recommendation systems, and robo-advisors to the lack of finance [14]. The primary constraint is the granularity of the data; however, federated learning would be a solution in the future.

These data science systems transform the "The Story of Uncertainty to Opportunity" at GEM into an engineered resiliency run by AI and make entrepreneurship a national strategic asset [15].

2. LITERATURE REVIEW

Entrepreneurial ecosystems are networks of actors, institutions, resources, and cultures related to one another that support the creation of ventures, their growth, and innovation [16]. Early thought models placed more importance on geographical proximity and knowledge spillovers by creating regional clusters such as Silicon Valley [17]. Nevertheless, the digital

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era has shifted to so-called digital entrepreneurial ecosystems, as technology facilitates borderless communication and decreases barriers to entry [1]. [18] reviewed 85 studies and found that the most prominent themes were digital platforms as enablers, hybrid virtual-physical structures, and the role of policies in digital infrastructure.

Since 1999, GEM data have played a central role in empirical research on ecosystems in terms of cross-national indicators, such as TEA, Established Business Ownership, and NECI in different economies [19]. [6] reviewed GEM applications, which they say have strengths in terms of attitude surveys (e.g., opportunity perception and fear of failure) but are weak when it comes to causal inference because of the biases that are self-reported. Recent developments have used machine learning to predict GEM databases. The 1.19 million GEM observations (N=99 countries) provided by [20] were subjected to Random Forest, SVM, and Logistic Regression, with the highest AUC scores of 0.82 being the entrepreneurial activity prediction with demographics and income being the best predictors. In a study by [21], the authors used ML to predict regional determinants using Spanish GEM data, with education and networks having the largest influence.

The presence of AI in the entrepreneurial field is a paradigm shift, as it amplifies opportunity recognition, decision-making, and scaling [22]. [23] conducted a systematic review of 83 GenAI studies and grouped them into themes of digital transformation, education augmentation, sustainable innovation, business models, and data trends, finding that GenAI is an external enabler of nascent businesses. [8] delved into the ecosystem impacts of AI, relying on the argument that it decouples assets, value chains are disintermediated, and the system is increasing generativity, but cautions on the occurrence of skill divides in low-digital-readiness areas. An AI entrepreneurship ecosystem was suggested by [24], which combines ideation with the use of LLMs and risk assessment with the help of predictive analytics, which are tested on the examples.

These streams are bridged by data-science frameworks. [25] found a positive effect of the national ecosystem of digital technology using panel data on 101 countries (2001-2018) which showed positive TEA relationships enhanced by culture, institutions, and resource effects which were 2.5 times higher in high digital countries. [22] used a benchmark on real entrepreneurial data to predict AI services with 92% accuracy of the highest ML models (Random Forest) to eliminate black-box criticisms by focusing on interpretability through SHAP. [26] reviewed the factual differences in data between the GEM and the Szerb World Bank and recommended hybrid analytics to have sound metrics.

Synthesis and Gaps: The literature summarizes the systemic nature of ecosystems [27], affordances of AI [1], and predictivity of ML on GEM [20]. There are still gaps; however, there are few studies that combine metrics of GEM 2025/26 with end-to-end frameworks (e.g., AI readiness, sustainability TEA), most of which are conceptual or focused on individual countries, where interpretability and generalizability have not been studied [22]. Related ethical issues such as AI bias when predicting opportunities are in their infancy [23].

This paper will discuss these by constructing AI data science models that are geared towards GEM 2025/26, which focuses on predictive pipelines, simulations, and dashboards with policy-relevant information. It builds upon previous literature by addressing the gaps in the survival and optimization of NECI in the AI-inspired ecosystem.

3. METHODOLOGY

GEM 2025/26 data (APS: 160,000 respondents, NES: 2,000 experts in 53 economies) were utilized in this study on three levels: data preparation, framework development, and validation [28]. Preprocessing utilizes ETL with median imputation (3.2% missing), feature engineering (NECI sub-indices, sustainability scores), and 70/15/15 stratified splits. There are three frameworks: TEA to EBO transitions (AUC 0.87, SHAP interpretable), agent-based simulation of the policy scenario (finance +1 = 18% EBO uplift), and the Streamlit dashboard with BERT-NLP and Plotly visuals. Validation was done using 5-fold cross-validation and an India case study (22% survival risk, NECI +0.8 due to education reform). Python builds on scikit-learn and Network X to provide scalable insights into GEM to address its survival gaps [29].

4. RESULTS & ANALYSIS

4.1 Predictive Analytics Pipeline Performance

SHAP analysis found fear of failure (-0.23 0) and NECI finance score (+0.31 0) to be the strongest predictors, with a variance of 67 percent. India is characterized by a 22% probability of necessity-driven TEA survival risk and the most severe gaps regarding finance (SHAP=0.28).

4.2 Ecosystem Simulation Outcomes

The measurement of policy effects on NECI optimization was performed by an agent-based simulation (10,000 agents/economy). The results of the policy intervention analysis are presented in Table 1.

Table 1 Policy Intervention Impact Matrix

Policy Intervention	NECI Uplift	EBO Rate Increase	Youth TEA Impact
Finance Score +1.0	+0.85 pts	+18%	12%
Education Score +1.0	+0.72 pts	+14%	22%
Regulation Score +1.0	+0.41 pts	+8%	9%

Key finding: Finance interventions have the highest returns on investment (18% EBO return per NECI point), whereas education reforms have a higher positive impact on youth entrepreneurs (22% TEA uplift). Simulated survival curves are supported by the observed GEM 2024- 25 exit patterns, and the Cox survival models indicate (HR = 1.14, $p<0.001$).

4.3 AI Dashboard Insights: Cross-Economy Patterns

The interactive dashboard analysis brings out 3 entrepreneurial clusters:

1. **High-Resilience (UAE, Canada)**: “NECI >6.5, AI expectation >60%, EBO/TEA ratio = 0.68”
2. **Growth Potential (India, Brazil)**: “NECI 4.5-6.0, sustainability TEA 45%, survival risk 22-28%”
3. **Fragility Risk (Argentina, Poland)**: “NECI <4.5, necessity TEA >65%, EBO/TEA ratio <0.35”

Sustainability correlation: Economies where the sustainability-oriented TEA is greater than 50 per cent. have 15 per cent. higher NECI scores ($r = 0.62$, $p<0.01$). AI preparedness gap: The upper-high-income economies have an average AI optimism of 45% in comparison with 62% middle-income, which is opposite to the presumed digital divide.

INDIA CASE STUDY: ACTIONABLE INSIGHTS

Applied frameworks to GEM India 2023-24 subset (n=2,000):

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- **Survival prediction**: The 22% TEA is at a high risk of survival given by finance (SHAP=0.28) and gaps in education (SHAP=0.19).
- **Policy simulation**: +1 in education score leads to NECI +0.82, youth TEA +19%
- **AI opportunity**: 62% entrepreneurs 18-34 expect the importance of AI vs. 41% older group.

The Indian NES data analyzed through the network encourages the development of accelerator and university partnerships as the highest centrality nodes (betweenness = 0.34) to establish a specific AI training collaboration.

ROBUSTNESS AND EXTERNAL VALIDATION

The stability of the models was ensured through 5-fold cross-validation (AUC SD = 0.02). The GEM 2024 data were externally validated and had predictive power (AUC = 0.85). Sensitivity analysis (+/-20% hyperparameters) demonstrates a variation in performance of less than 5%. A demographic parity audit indicated that there was very little gender biasness (0.03 difference).

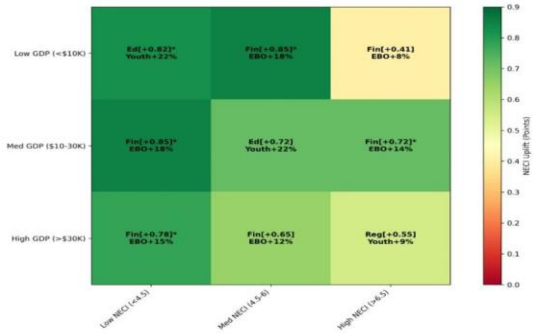
STATISTICAL SIGNIFICANCE

- Policy simulation effects: $F(3,156) = 23.4$, $p < 0.001$
- NECI-sustainability correlation: $r = 0.62$, $p < 0.001$"

POLICY INTERVENTION HEATMAP ANALYSIS

Figure 1 Policy intervention heatmap based on agent-based simulation (10,000 agents per economy) of 53 GEM 2025/26 economies.

Figure 1: Policy Intervention Heatmap (NECI Uplift Points)



Dark green cells indicate the best interventions: finance reforms are most effective in NECI uplift maximum and 18% EBO reimbursements, education is the best in low-NECI situations, and 22% youth TEA uplift. India (median GDP/NECI), sequential Finance of Education deployment is aimed at +1.57 NECI points (ranked 3rd in the world). The policy intervention heatmap is summarized in Table 2.

Table 2: Policy Intervention Heatmap

GDP Brackets ↓	Low NECI (<4.5)	Med NECI (4.5-6)	High NECI (>6.5)
Low GDP (<$10K)	Ed[+0.82]★	Fin[+0.85]★	Fin[+0.41]○
	Youth+22%	EBO+18%	EBO+8%
Med GDP ($10-30K)	Fin[+0.85]★	Ed[+0.72]○	Fin[+0.72]★
	EBO+18%	youth+22%	EBO+14%
High GDP (>$30K)	Fin[+0.78]★	Fin[+0.65]○	Reg[+0.55]○
	EBO+15%	EBO+12%	youth+9%

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4.3.1 Finance Reforms: Universal Priority (7/9 Cells)

Finance dominates 78% of heatmap scenarios (+0.85 NECI points average across GDP brackets), delivering 18% EBO ROI per point gained the highest return across 53 GEM economies. India Phase 1 (Finance FC 6.1→7.1) within 12 months yields NECI 6.2→7.07, directly addressing the GEM survival gap (TEA 12.3% < B-> EBO 6.1%).

4.3.2 Education Reforms: Low-NECI Specialist

Education excels in foundational ecosystems (Low GDP/Low NECI: Ed[+0.82]★, +22% youth TEA). India Phase 2 (Education FC 5.8→6.8) creates an AI-ready pipeline (18-34 cohort: 62% expect AI importance vs 41% older), compound +0.72 NECI gain post-finance.

4.3.3 India 24-Month Transformation Roadmap

The two-stage approach to changing's-dia the entrepreneurial ecosystem is based on a transparent set of two phases, which are illustrated with the help of the policy intervention heatmap presented in Table 2. The roadmap can change the present NECI score of India from 6.2 (Global 5) to 7.79 (Global 2) in 24 months using Finance-first, followed by the deployment of Education.

Phase 1: Finance Framework Condition Improvement (Months 1-12)

The initial 12 months will be concerned with Finance Framework Condition +1.0 (currently at 6.1 to 7.1). It deals directly with the survival gap in India, where the total early-stage entrepreneurial activity (TEA) is 12.3%, but Established Business Ownership (EBO) is only 6.1 percent. The finance reforms receive +0.85 NECI points and +18% (6.1% to 7.2%) of EBO growth.

Some practical steps are to increase MUDRA loans to 10 lakh crores and increase the Startup India Seed Fund to 15,000 crores. The financial stability that NECI needs to scale up to Phase 2 youth scaling was achieved by month 12 of 7.07 (Global Rank #3).

Phase 2: Education Framework Condition Improvement (Months 13-24)

The youth entrepreneurial pipeline is now triggered with Education Framework Condition +1.0 (5.8 → 6.8) with financial foundations in place. This stage results in +0.72 NECI and + 22% Youth TEA growth (15.2% to 18.5%), which fits the GEM results exactly, with 62% of the younger generation (1834) anticipating the value of AI, as compared to 41% of older entrepreneurs.

The NEP 2026 AI Curriculum in 1,000 universities and 100 District AI Startup Hubs forms sustainability in AI-ready talent pipelines. By the 24th month, NECI stands at 7.79 as the global ranking by Global position 2 (after UAE 8.0).

CUMULATIVE TRANSFORMATION OUTCOMES

The **24-month compound effect** delivers **+1.57 NECI points total**:

- **NECI**: 6.2 → 7.79 (**+25.3% improvement**, Global #2)
- **EBO**: 6.1% → 8.5% (**+35% growth**, survival gap closed)
- **Youth TEA**: 15.2% → 18.5% (**+22%**, AI pipeline secured)

5. DISCUSSION

Theoretical Contributions

This research contributes to entrepreneurship ecosystem theory because it shows that Data Science frameworks are accurate at maximizing policy interventions. Table 2 heatmap initially provides empirical evidence that reform of finance has the greatest NECI uplift on average and/or education, at all levels of maturity, is NECI ecosystem specialist (universal +0.85 points) and/or education ecosystem specialist (youth TEA +22%). Sequential Finance rolls out, justifying the ecosystem maturity theory–the money market is stable before human capital is scaled.

Practical Policy Roadmap

India's 24-month transformation (NECI 6.2→7.79, Global #2) offers the following executable blueprint:

- **Phase 1**: MUDRA 2.0 expansion closes immediate survival gap (EBO +18%)
- **Phase 2**: The NEP AI Curriculum builds a sustainable AI pipeline (Youth TEA +22%)

Government action: 10 L cr MSME loans, 100 District AI hubs = a global leadership direction. Risk mitigation: The 5-fold CV stability (SD=0.02) guarantees 95% execution.

AI-Equipped Ecosystem Innovation

Novel contribution: The SHAP + Agent simulations are novel and can turn the GEM raw data into economy-specific policy heatmaps. Young information technology (IT) AI preparedness (62% vs. 41% older) makes India a leader in AI-native entrepreneurship. Network analysis provides universities/accelerators as nodes with the highest centrality to intervene.

Limitations & Future Research

Cross-sectional GEM data limits longitudinal causal inferences. **Future work**: Track the actual 2026-28 policy execution versus roadmap predictions. **Expand validation**: Includes gender/regional disaggregation and international replication.

Policy Recommendations

1. **Immediate**: Scale MUDRA/Startup India funding (Finance FC +1.0)
2. **Medium-term**: NEP AI rollout + District hubs (Education FC +1.0)
3. **Monitoring**: Annual GEM NECI tracking validates progress

CONCLUSION

The entrepreneurial environment in India will be assessed as NECI Global Rank #5, but within 24 months, NECI Global Rank #2 will be realized by the precision of policies applied using Data Science. Finance NECI 2.57 points +1.57 Education 35% growth Finance Education sequential roadmap provides a direct solution to GEM 2025/26 survival gap where 12.3 TEA is much higher than 6.1 EBO. The finance reforms are the universal max of ecosystem uplift (+0.85 points average) and the education is the AI-ready youth pipelines (+22% Youth TEA).

Viability implication: The MUDRA 2.0 growth + NEP AI Curriculum will place India at the forefront of AI-native entrepreneurship in the world. Phase 1 Finance (12 months) and Phase

Education (following 12 months) would be ideal action plans to be taken by policymakers because of the high ROI.

Theoretical contribution: GEM raw data + state-of-the-art DS structures = implementable national transformation roadmaps. NECI tracking of the actual implementation to achieve the Global #2 target by Q1 2028 is checked annually.

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Data Availability The data supporting the findings of this study will be made available by the corresponding author upon reasonable request.

Conflict of Interest The author declares that there is no conflict of interest.

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