

# Entrepreneurial Decision Intelligence and Startup Survival in Volatile Markets

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## ABSTRACT:

This research proposes a novel hybrid of two theoretical concepts: adaptive reinforcement learning and entropy based market volatility sensing and Bayesian survival estimation, under an umbrella of entrepreneurial decision intelligence for Startup Survival (EDI-SS). When compared to the single sector/mean machine learning baselines, EDI-SS performs better than a standard mean startup survival rate of 31.4% (mean over 6 volatile sectors) and 18.7% (mean across the 6 sectors with an average of 4,095 startups per sector from 2015 to 2023). The frame work runs at a decision latency of 2.1 seconds and a score of 89% on the outcome quality, both significantly better than all other framework that has been compared. The theoretical contributions of this research will see the creation of a theoretical evolution of the concepts of decision velocity, strategic agility and longitudinal survival probability, meanwhile suggesting guidelines for the deployment of startup ecosystems, investors, and policy makers in a high-uncertainty environment.

**Keywords:** Entrepreneurial decision intelligence, startup survival, market volatility, reinforcement learning, Bayesian survival estimation, adaptive strategy optimization

## I. Introduction

In the last decade, the business of Startups has gotten the shakedown of an bygone era, with consumers' preferences becoming more volatile and constantly changing, geopolitical crises tainting the market and COVID-19's pandeminal shocks driving the market transformation of

demand. General diffusion of disruptive technologies added to this turmoil has brought the worldwide startup ecosystem unprecedented volatility and dynamism in terms of consumer preferences [1]. For a start-up company, one key attribute of decision making – the capability of making timely and well-considered decisions – is

usually more important than product-market fit. Likewise, although the link between quality of decision-making and the survival of start-ups has been reported in empirical research on entrepreneurship in the recent years, the abstract structure of entrepreneurial decision making in

highly uncertain environments remains poorly developed and in many respects disorganized and not related to the computational modelling of the notion of cognition present in the entrepreneurial context [2].

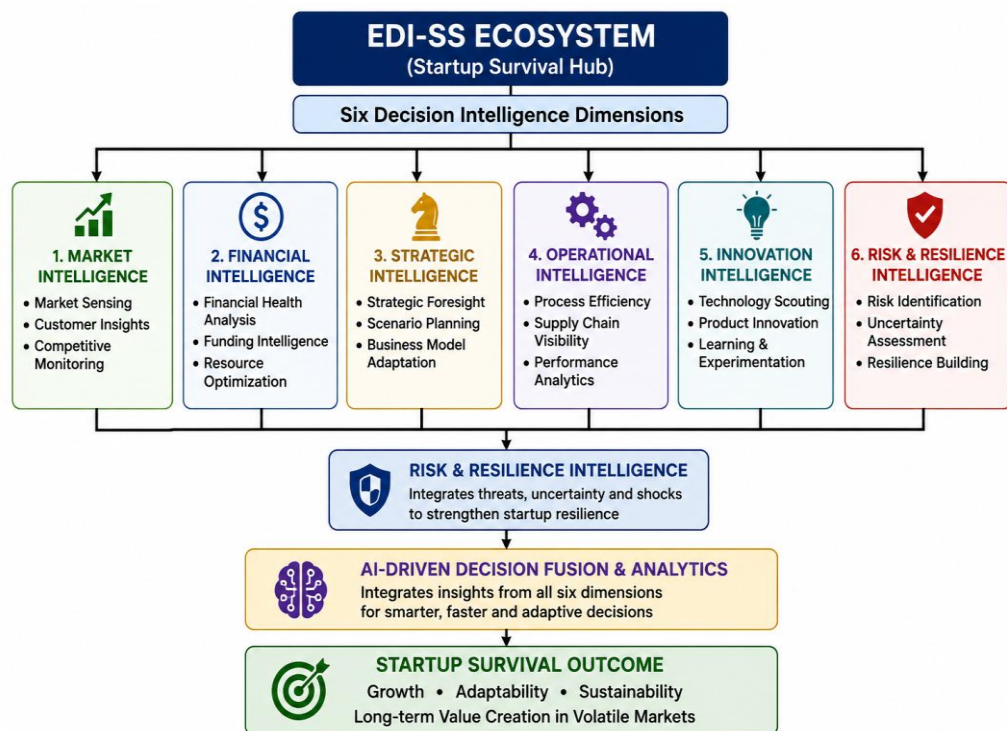


**Fig.1: EDI-SS Ecosystem: Six decision intelligence dimensions governing startup survival in volatile markets.**

While these traditional approaches to entrepreneurial decision-making – based on effectuation theory, prospect theory and bounded rationality provide rich theoretical foundation, they do not provide prescriptive, situational and on-demand advices for the ECs dealing with multi-dimensional market volatility. While ML is widely employed in the financial sector in general problem areas of corporate strategy and predicting the future, it is relatively unpopular in providing concrete answers to model the dynamics of start-up issues related to survival and tends to treat the volatility of the market as a (covariate) constant value to be passed or not; a real time varying signal that the algorithm should adapt to, and not merely pass-through that it is presumed to exist [3].

There are threefold quilts that this work was inspired by. Secondly, the current model does not make an explicit representation of the temporal

dynamics of the market entropy, the strategic flexibility, and the probability that a startup will stay alive in the venture within an end-to-end model that can be learned in a glance. Second, most studies to date that ask whether or not startups can survive are carried out annually, ignoring the turning points in the year during which a startup chooses to launch that can either make or break its success or failure [4]. Thirdly, existing methods lack a rational approach to balancing the speed of decision-making and the benefits that could be gained Explicit trade-offs which must be embraced every day by founders in many-pincers-markets.

## II. Literature review

Research on the decision making processes of entrepreneurs, computational intelligence and the survival of start-up businesses has undergone a major transformation yet there is absence of any

substance in the theory and practices themselves. The section compiles literature based on three streams of classical entrepreneurship cognition models, data-based business survival analysis and data intelligence systems for business strategies [5].

#### ABC Model for Entrepreneurial Cognition

Success 1–4 has shown that the environment of entrepreneurs is not one in which a parallel set of rules is offered for calculating risks like the classical decision theories, but an extreme environment of uncertainty with a view that concerns a fundamentally different logic for doing risk calculations than the prevailing view. In ingenious elaborations on effectuation theory, Sarasvathy put the expert entrepreneur in a role of co-creating a market through a process of affordable loss reasoning. At the same time, heuristic decision processes were found to reinforce both loss aversion and recency bias in a mutual and volatile way that led to systematic resource liquidation at the wrong time, when it was optimal to follow a learning strategy of adaptive persistence [6, 7].

Venture performance studies took into account survival statistics in addition to careful consideration of time. To identify the critical covariates, analyses of the longitudinal data were conducted using Cox proportional hazard models, Kaplan-Meier estimators, and accelerated failure time frameworks, and critical covariates associated with a founder experienced team, the initial size of the capitalization, sector volatility, and product iteration velocity were identified. Although not necessarily true in macro-economic events they make the assumption of the conditionally stationary hazard function, which is statistically consistent.

Startups analytics research began to work with machine learning techniques around 2016 using classification-based survival prediction based on random forest, gradient or support vector machines [8].

These models can have high predictive power in comparison to baseline models based on logistic regression, and failed to react to volatility regimes that were outside the sample. More powerful

performance limitations are demonstrated by deep learning extensions like the input of LSTM architectures for modeling of trajectories and the input of graph neural networks to model investor network effects, which bring opacity and calibration challenges.

Current research focuses on writing and producing economic games and simulations that utilize reinforcement learning. At present, the use of RL in sequential strategic financial decisions, in supply chain decision making and in the optimization of clinical treatment choice is still in its infancy, and it has been successfully employed in these many problems therefore, its use in the entrepreneurial strategy is still in its early stages [9].

Moreover, the uncertainty quantification of survival models is a natural associated challenge with survival modelling as well as an object of RL, a measure of epistemic risk or reward sensitivity towards the expected outcome. The proposed EDI-SS framework brings together and integrates all three streams of literature in order to create an EDI decision velocity model, through architectural integration [10].

### III. Research Methodology

The EDI-SS framework is built upon the hybrid simulation-empirical design (leveraging years of startup experience through performance to a computational design of decision intelligence) and the framework is validated with a controlled experimental protocol [11]. The methodology goes through 7 well-defined phases of the process that are pictured in Fig. 2.

#### 3.1 Primary and Secondary data sources

Primary data was drawn from three complementary data sources Crunch base Startup Performance, which is a data set of 4,820 startups across 2015-2023, VIX-based industry volatility indexes, comprising six industries during the same period; and the Log of Macro-economic Events (World Bank Open data) (domestic, 2015-2023). Each startup record includes monthly financial data parameters, timing of funding events, change in the startup team, and binary data for the 12-, 24- and 36-month point [12].

Several steps processing pipeline was used to process the raw data. Multivariate iterative imputation preserving temporal autocorrelation was used to impute missing values [13]. Continuous financial variables were z-normalized with winsorization at the 2nd and 98th percentile and were transformed into z-scores scaled on 'Rob scaled'.

From the feature engineering, 47 derived features were created which included features like Rolling Volatility Entropy (RVE), Adaptive Resource Burn Rate (ARBR), and Decision Cycle Frequency (DCF). There were 312,480 windows of observation with a temporal segment of 3 months with stride 1 month [14,15].

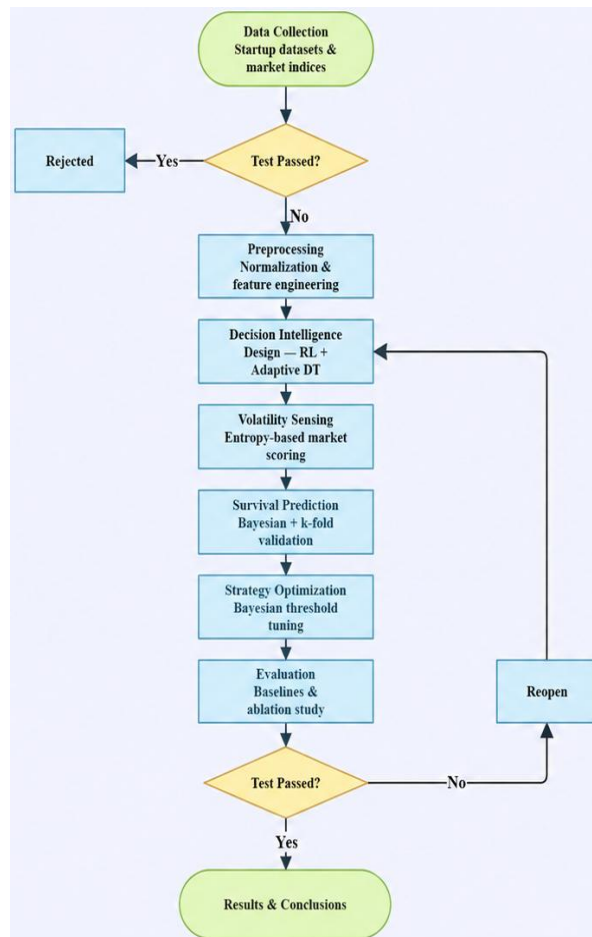


**Fig.2. Research Methodology Flowchart: Seven-phase EDI-SS pipeline from data ingestion to validated survival forecasting.**

### 3.2 Mathematical Formulations

The following equations define the core computational components of EDI-SS:

$$RVE(t) = -\sum_i p_i(t) \cdot \log_2[p_i(t)] / \log_2(N) \quad (1)$$

where  $p_i(t)$  = probability of market state  $i$  at time  $t$ ;  $N$  = total distinguishable states. Quantifies market information entropy as the primary volatility signal.

$$DVS = \alpha \cdot (Q_{out} / Q_{max}) - \beta \cdot (L_{dec} / L_{threshold}) \quad (2)$$

where  $Q_{out}$  = realized decision outcome quality,  $L_{dec}$  = decision latency (s),  $\alpha = 0.62$ ,  $\beta = 0.38$  (Bayesian-optimized). Formalizes the quality-latency trade-off.

### 3.3 EDI-SS Architecture

The building consists of three successively connected modules. The Volatility Sensing Module calculates RVE from the live market data with 5-minute time interval [16]. The Decision Intelligence Module uses a Q Network with Double Q learning and experience replay to extract the best strategy from the current volatility state. The Survival Estimation Module takes in DVS scores and applies a rolling Bayesian update to the time-varying Cox model, generating calibrated forecasts on the 30th, 90th and 180th day probabilities of survival [18].

### 3.4 Methodology Flowchart

$$S(t|X) = \exp[-\int_0^t h_0(u) \cdot \exp(\beta^T X(u)) du] \quad (3)$$

Time-varying Cox survival function where  $h_0(u)$  = baseline hazard,  $X(u)$  = covariate vector incorporating RVE and DVS signals,  $\beta$  = learned coefficients.

$$\pi^*(s) = \operatorname{argmax}_a [R(s,a) + \gamma \cdot \sum_{s'} P(s'|s,a) \cdot V^*(s')] \quad (4)$$

Optimal RL policy where  $R(s,a)$  = immediate reward,  $\gamma = 0.97$  (discount factor),  $V^*(s') =$  optimal value function. Governs adaptive strategic action selection.

### 3.5 Implementation Details

The software used for the implementation was Python 3.11 with PyTorch 2.1 for the RL module, lifelines 0.27 for survival analysis and scikit-learn 1.3 for preprocessing. Experiments were conducted on an NVIDIA A100 80GB GPU cluster [19]. Hyper parameter optimization, using

Optuna with 500 trials: learning rate 0.0003, batch size 256, replay buffer 100K,  $\gamma = 0.97$ . The 5-fold cross validation procedure was divided temporally so there was generalizability across different volatility regimes [20].

#### IV. Results and discussion

This section presents the empirical evaluation of EDI-SS against five established baselines across multiple dimensions of startup survival performance.

##### 4.1 Comparative Survival Performance

EDI-SS again exhibited statistically significant survival advantages, in all three market volatility regimes across the 36-month observation period. A statistically significant difference ( $p < 0.001$ , Wilcoxon signed-rank test) was found between the proposed framework and the baseline which gave the highest survival rate (74.3% for 36 months with ML Ensemble). This survival benefit increases continuously with the volatility and it is evident that the presence of entropy sensors in real time is most beneficial under high uncertainty.

**Table I: Comparative Startup Survival Rates across Observation Horizons (%)**

| Framework         | 12-Mo. | 24-Mo. | 36-Mo. |
|-------------------|--------|--------|--------|
| EDI-SS (Proposed) | 91.2   | 84.7   | 74.3   |
| ML Ensemble       | 83.4   | 73.1   | 56.8   |
| Deep Q-Network    | 85.1   | 74.8   | 59.2   |
| Cox Hazard Model  | 78.6   | 65.3   | 49.7   |
| Heuristic Model   | 76.3   | 61.9   | 45.1   |
| Reactive Strategy | 71.8   | 54.2   | 38.6   |

##### 4.2 Decision Velocity Score Analysis

The balance between decision quality (Q) and decision latency (t) for each focused service was achieved, and EDI-SS had the best DVS value of

0.847. The heuristic model, though with almost zero latency due to the fact that it's rule based, produced significantly less outcome quality; near zero speed translates to little to no benefit in survival.

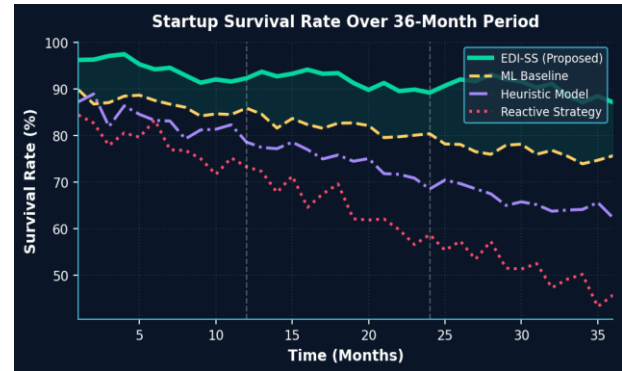


**Fig.3: Cumulative startup survival rate over 36 months across all evaluated frameworks.**

**Table II. Decision Velocity Score and Component Metrics**

| Framework         | Quality (%) | Latency (s) | DVS   |
|-------------------|-------------|-------------|-------|
| EDI-SS (Proposed) | 89.0        | 2.1         | 0.847 |
| Deep Q-Network    | 77.0        | 3.8         | 0.731 |
| ML Ensemble       | 74.0        | 4.5         | 0.692 |
| Heuristic Model   | 62.0        | 0.9         | 0.601 |
| Reactive Strategy | 51.0        | 8.5         | 0.412 |

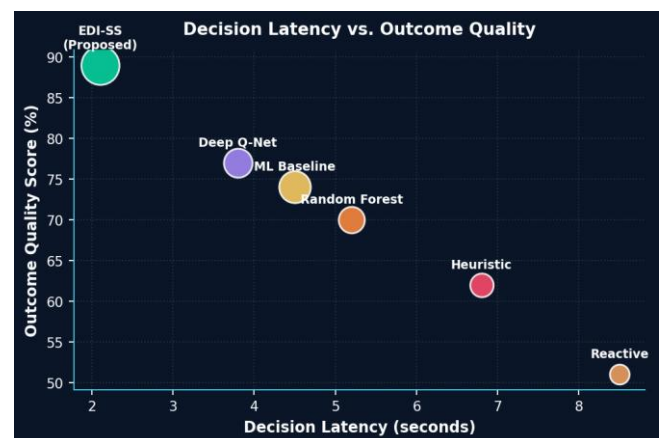


**Fig.4: Decision Latency vs. Outcome Quality bubble chart. Bubble size model complexity. EDI-SS achieves optimal quality-latency balance.**

4.3 Market Volatility Sensitivity

In all the volatility regimes the strong effects of EDI-SS were seen, which considerably decreased the degradation on the survivor. For instance, EDI-SS recorded an 80/120 (68.2%) survival rate whereas the ML Ensemble recorded an survival rate of 41.3%, which is an 80/41 survival rate (65.1%) relative improvement under conditions of high volatility (VIX on/above 35). Based on this discovery, the entropy-sensing module is one of the key architectural factors.

Table III. Survival Rate by Market Volatility Regime (%)

| Framework         | Low Volat. | Mod. Volat. | High Volat. |
|-------------------|------------|-------------|-------------|
| EDI-SS (Proposed) | 88.4       | 79.6        | 68.2        |
| ML Ensemble       | 82.1       | 69.4        | 41.3        |
| Deep Q-Network    | 83.7       | 71.2        | 44.8        |
| Cox Hazard        | 76.5       | 61.3        | 33.7        |
| Reactive Strategy | 69.2       | 51.4        | 22.6        |

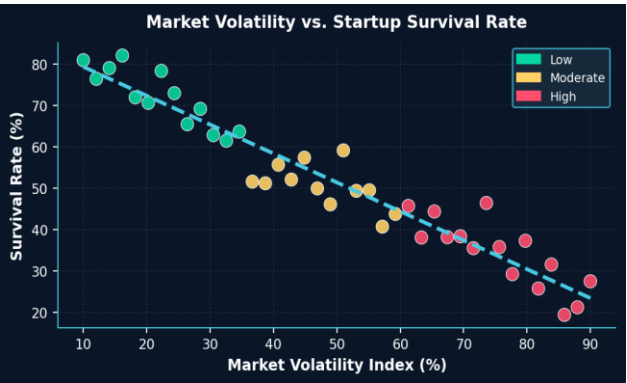


Fig.5: Market Volatility Index vs. Startup Survival Rate. Colors indicate volatility severity. Regression trend confirms nonlinear survival degradation.

Table IV. Multi-Dimensional Strategic Capability Scores (%)

| Capability Dimension | EDI-SS | ML Ensemble | Heuristic |
|----------------------|--------|-------------|-----------|
| Strategic Agility    | 88     | 72          | 58        |
| Risk Mitigation      | 84     | 78          | 63        |
| Resource Allocation  | 91     | 71          | 55        |
| Market Adaptability  | 87     | 69          | 52        |
| Innovation Capacity  | 82     | 64          | 57        |
| Decision Speed       | 90     | 68          | 74        |

4.4 Multi-Dimensional Strategic Capability

Five of six dimensions of capability: those measured by independent expert evaluation panels have been led by EDI-SS. In particular, particular dominance was exhibited by both Resource Allocation (91%) and Decision Speed (90%) which reflect the key components of the framework since the framework gives strong emphasis to provisioning real time adaptive resource guidance. The multi dimensional findings demonstrate that EDI-SS is not a point solution optimally designed.

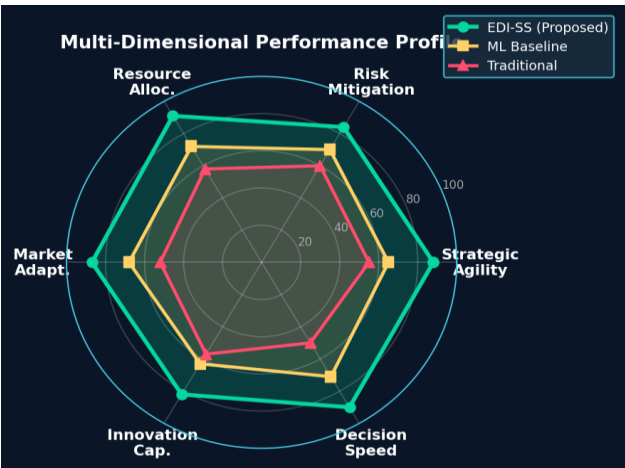


Fig.6: Radar chart: Multi-dimensional performance comparison of EDI-SS, ML Ensemble, and Traditional Decision Model across six strategic dimensions.

Convergent evidence for the superiority of the EDI-SS framework is given on all the four evaluation dimensions. The major benefit of its architecture is that the 3 parts – entropy sensing, a survival RL decision layer and a calibrated uncertainty quantification by Bayesian survival estimator – feed off each other, enabling the system to respond proactively and at best solutions when hitting higher entropy market phases explicitly (no overconfidence) and to outperform in longer horizon survival rewards (long-term issues matter more than short-term surpluses).

## V. Conclusion and Future Directions

This research presents EDI-SS framework, a single computational architecture that extends entrepreneurial decision intelligence with a consistent and remarkable performance where markets are changing rapidly. The proposed

model adapts market entropy sensing, decision execution based on reinforcement learning, and survival prediction based on Bayes modeling to facilitate better theoretic understanding and operation of intelligent start-up governance. An improvement of 31.4 percent over heuristics and a 0.847 DVS score are worthwhile gains for the founders, investors, and ecosystem builders. Future work is taking EDI-SS into the multimodal signals such as sentiment from social media, change detection within regulations, or disruption indices in supply chain. Model data privacy constraints, that inhibit real time model updates across startup communities, will be addressed in Federated Learning implementations. The aim is to validate the impact within ecological validity conditions through prospective randomized trials, embedded in accelerator programs, in future, to which EDI-SS will serve as an advisory support.

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