

DBERA: A Dynamic Bayesian Network Framework for Real-Time Entrepreneurial Risk Assessment

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Entrepreneurial ventures are inherently exposed to multiple risks arising from financial uncertainty, competitive dynamics, and individual decision-making behaviors. A Bayesian network-based model provides a probabilistic framework for capturing and analyzing these interdependent risk factors. Traditional methods often rely on static financial ratios, subjective judgment, or linear risk assessment models that fail to adapt to dynamic market conditions and complex interrelationships among variables. This limits their ability to provide accurate, context-aware risk evaluation for entrepreneurs. To address these limitations, the Dynamic Bayesian-Economic Risk Analyzer (DBERA) is proposed, which integrates market volatility, competitor signals, and personal investment patterns into a unified Bayesian framework. Continuously updated conditional probability distributions enable DBERA's context-aware, real-time risk assessment for entrepreneurs. Unlike static models, it adjusts to market dynamics and uncovers new causal linkages between indicators. The model was tested using simulated and real datasets using scenario-based Monte Carlo simulations. Validation measures, including sensitivity analysis, probabilistic inference consistency, and prediction accuracy, were used to assess resilience across varied situations. Scenario planning may help politicians, bankers, and business owners assess their approaches to managing uncertainty and identify success factors. DBERA considerably improves forecast accuracy and decision-making help. The prediction power increases by 83% for competition intensity, 95% for investment pattern impact, 93% for finance availability, 96.1% for operational capacity, 97.3% for innovation index contribution, and 82.5 for environmental risk exposure. These discoveries demonstrate that DBERA is a versatile tool for reducing risk and achieving entrepreneurial success.

Povzetek: Študija predstavlja dinamični bayesovski model (DBERA) za celovito in sprotno ocenjevanje podjetniških tveganj, ki z vključevanjem tržnih, finančnih in vedenjskih dejavnikov bistveno izboljša napovedno natančnost ter podporo odločanju v negotovih razmerah.

1 Introduction

Entrepreneurship is an essential contributor to innovativeness, economic development, and job creation, but is inherently uncertain and risky [1]. Entrepreneurs constantly face complex decision-making environments in which financial, market, and personal factors are interwoven, making risk evaluation difficult [2]. It is essential to understand and analyze risks, as this is crucial for improving business sustainability and implementing safeguards for risky strategic decisions [3]. The proliferation of risk assessment methods in entrepreneurship generally relies on deterministic models, financial ratio assessments, or expert subjective evaluations [4]. Each of these assessments can be useful; however, they are also limited when managing uncertainty, adapting to change, or accounting for the complexity of causal

dependencies arising from multiple factors [5]. Because of the static approach they use, entrepreneurs often find themselves with incomplete or partial risk evaluations relative to real-world conditions (e.g., market shocks, competitor strategies) [6]. To overcome the limitations noted, this study suggests an alternative: the DBERA is a model based on Bayesian network norms for assessing entrepreneurial risk considerations, bringing together three concepts — market volatility, competitor signals, and personal investment procedures—into a dynamic probabilistic model [7]. In this way, DBERA accumulates and updates conditional probabilities, offering entrepreneurs more flexible, real-time insights into changing risk conditions [8]. The proposed method identifies high-risk scenarios and illustrates the interconnections among risk factors, enabling entrepreneurs and investors to take preemptive measures [9]. The findings indicate that DBERA

enhances forecasting precision, reveals hidden dependencies, and improves decision-making [10]. The framework improves both the understanding of the theory behind entrepreneurial risk management [11] and its practical application [12]. The proposed method identifies high-risk scenarios and illustrates the interconnections among risk factors [13], enabling entrepreneurs and investors [14] to take preemptive measures.

1.1 Inspiration

The impetus for this paper stems from the pressing need to provide enterprises with reliable tools to navigate volatile business environments. Static risk models that have been around for a long time often fail to account for market changes. The proposed DBERA architecture, grounded on Bayesian networks, aims to provide entrepreneurs with adaptive, data-driven, and actionable insights to facilitate resilience and growth.

1.2 Problem statement

Traditional methods of risk assessment for entrepreneurship struggle with complex, nonlinear, and dynamic factors — such as financial, legal, and market uncertainty — that hinder accuracy, delay decision-making, and limit the efficiency of risk evaluation and control. Methods cannot be entirely accurate; thus, there is a need for intelligent, data-driven technologies (e.g., big data, deep learning, machine learning) that can leverage the reality of uncertainty to improve the assessment and control of entrepreneurial risk.

1.3 Contributions

The suggested study makes three important contributions.

- First, it introduces the Dynamic Bayesian-Economic Risk Analyzer (DBERA), a novel Bayesian network-based framework that assesses entrepreneurial risk by integrating market volatility, competitor signals, and individual investment behaviors.
- Second, the system uses a dynamic probabilistic methodology that updates to capture evolving uncertainty and reveal causal linkages that static or deterministic models miss.
- Finally, the suggested technique has high predictive accuracy, reveals hidden interdependencies among risk factors, and helps entrepreneurs, investors, and policymakers make proactive, evidence-based decisions for sustainable business growth.

1.4 Research objectives

In contrast to more conventional static machine learning and deterministic models, this research aims to determine whether a Dynamic Bayesian Network (DBN) framework (DBERA) can improve the accuracy, flexibility, and interpretability of risk assessment for entrepreneurs. “Can a dynamic Bayesian network significantly improve the classification accuracy and causal interpretability of entrepreneurial risk outcomes under volatile market conditions?”

To address this, we hypothesize that:

- When predicting the degree of risk entrepreneurs face, DBERA will outperform static ML models such as GA-PSO, SMOTE, and PLS-SEM.
- Improved model flexibility to real-time input alterations is a result of DBERA's dynamic probabilistic updating method.
- Causal interpretability will be enhanced by the framework's revelation of hidden interdependencies among behavioral, financial, and market factors.

Monte Carlo simulations and scenario-based assessments should confirm the decision-support capacity, and the simulations should lead to quantifiable gains in prediction accuracy and resilience under uncertainty.

2 Literature review

Entrepreneurial risk assessment is an important area of research because startups face financial, legal, operational, and strategic uncertainties that threaten operational continuity. New technologies, such as big data, deep learning, data mining, and machine learning, offer innovative methods for assessing and mitigating risks. These intelligent methods enhance accuracy, efficiency, and forecasting capabilities, enabling entrepreneurs to make informed, data-driven decisions.

2.1 Big data analysis

The GA-PSO algorithm is used to design the SME risk financing risk control scheme, and it completes the SME risk financing risk assessment and risk control. The experimental results indicate that the algorithm's risk-optimization control efficiency exceeds 70%, the risk assessment accuracy for SMEs surpasses 95%, and the runtime is under 80 ms. This demonstrates effective convergence in both risk assessment and control, robust risk-optimization control capability, and precise evaluation outcomes, as reported by Li, J. et al. [15]. Starting a business as a college student is a complicated and ever-changing process. The hazards that entrepreneurial businesses confront are also

varied and interactive. The changes in risk assessment for supply chain entrepreneurship are likewise dynamic and nonlinear. They are impacted by various variables, which make the risk assessment process for supply chain entrepreneurship rather challenging, as noted by Lee, I. et al. [16]. Big data analysis technology is a new product that emerged from advancements in cloud computing and the Internet. It has the following features: it can handle large volumes of data, support different data types, and deliver significant value. It also provides researchers with more technical support for assessing risks in college student entrepreneurship.

2.2 Deep learning models

As businesses become more popular, entrepreneurs are increasingly worried about legal risks. Legal risk is the most significant hidden peril for entrepreneurs starting a business. Preventing and avoiding legal risks is a lengthy and complex process, and not all hazards can be found and prevented in time. Deep learning has made significant breakthroughs in voice recognition, image recognition, and natural language processing. The jobs in these areas only require single-mode input, whereas newer applications require multi-mode intelligence, as noted by Li, T. et al. [17]. This paper uses social cognitive theory to examine the predictive role of individual attributes, familial context, and social environment on technological entrepreneurship. The XGBoost algorithm together with the Synthetic Minority Over-sampling Technique (SMOTE) method. To find the best prediction model for technological entrepreneurship and assess feature significance, compare the results of multiple algorithms by Chen, C. et al [18]. The multimodal deep learning research on legal risks has identified several legal challenges in the growth of entrepreneurial firms, including contract, trade secret, trademark, and copyright infringement disputes.

2.3 Data mining

To help businesses better manage financial risks, reduce labor costs, minimize financial losses, and build investor trust in business finance, the financial risk analysis of publicly traded companies leverages deep learning and data mining within an artificial intelligence environment. In this context, Gao proposes an approach to financial risk-avoidance analysis based on interactive mining. Gao, B [19]. A specialized risk analysis model is developed to examine the primary elements of the diverse financial risks faced by publicly traded organizations. An online survey was used to collect data, which was then analyzed using PLS-SEM.

The results indicate that perceived complexity, top management support, innovativeness, organizational readiness, and outsourcing risk significantly influence Dominica's intention to use data mining. Dominica, E. M. et al [20].

2.4 Machine learning techniques

To make the economy thrive, new business ideas must be put into action. This is because they contribute to higher productivity via better technology, new goods, services, and markets. The government is making progress in developing and supporting business ventures and infrastructure for entrepreneurs by implementing several key programs. Innovative business ideas can be risky, however, since only a few of them generate profits and succeed under Potsulin. et al [21]. The lack of data analysis on both successful and failed creative business initiatives exacerbates the problem. This paper uses machine learning to forecast hazards by using historical data from completed projects. The authors analyze a database of creative entrepreneurial initiatives sourced from a startup cemetery website. Schade created and trained a model to identify risks, including failure to meet market demand, competition, and selecting the wrong business strategy, using publicly accessible information. Schade and Schuhmacher [22] demonstrated that machine-learning models such as Random Forest and Gradient Boosting can effectively predict entrepreneurial activity using behavioral and market data, highlighting the importance of data-driven predictive modelling. Özsungur (2023) [23] showed how model selection affects prediction accuracy and resilience in uncertain situations. The author examined Decision Tree, Naïve Bayes, Support Vector Machine, Random Forest, and Logistic Regression approaches for predicting financial hardship. Schade and Schuhmacher (2023) [24] used machine learning models to forecast entrepreneurial activity based on behavioral and market data, thereby enhancing early risk identification. Zhu et al. (2023) [25] used SMOTE-ENN (class balancing) with NGBoost to forecast risk. This method will enhance company financial risk calculations, they say. Behbehani et al. (2023) [26] developed CEDRA for cloud-specific dynamic Bayesian networks, which may improve cloud business dynamic risk assessments. It enables real-time adaptation to changing risk conditions and updated conditional probabilities. These studies emphasize the necessity of hybrid models that incorporate machine learning, Bayesian inference, adaptability, and understanding. In uncertain economic and technological times, these models may increase financial stability and forecast accuracy. Table 1 presents a comparison of existing methods.

Table 1: The comparison of existing methods

Reference	Environment	Algorithm / Technique	Focus Area	Key Outcomes	Limitations
Li, J. et al [15]	Big Data	GA-PSO Algorithm	SME risk financing & control	Risk optimization >70%, assessment accuracy >95%, runtime <80 ms	Static parameter assumptions; lacks real-time adaptability to market fluctuations
Lee, I. et al [16]	Big Data	Risk assessment modeling	Supply chain entrepreneurship	Captures dynamic, nonlinear, interactive risks	Limited scalability for multi-sector analysis; weak temporal risk updating
Li, T. et al [17]	Deep Learning	Multimodal Deep Learning	Legal risk in entrepreneurship	Identifies legal risks; multi-mode intelligence	Black-box model; lacks interpretability and probabilistic reasoning
Chen, C. et al [18]	Deep Learning	XGBoost + SMOTE	Tech entrepreneurship prediction	Improved prediction accuracy & feature importance analysis	High computational cost; not optimized for streaming or real-time data
Gao et al [19]	Data Mining	Interactive Mining	Financial risk avoidance	Lowers costs & improves investor trust	Dependent on historical datasets; limited predictive adaptability
Dominica et al [20]	Data Mining	PLS-SEM	Outsourcing & adoption risk	Identifies organizational & managerial risk factors	Domain-specific model; lacks dynamic feedback mechanisms
Potsulin et al [21]	Machine Learning	Risk forecasting model	Entrepreneurship innovation	Forecasts hazards in new business ideas	Lacks sequential modeling of evolving risk patterns
Schade et al [22]	Machine Learning	Startup cemetery database ML model	Failure prediction in startups	Identifies risks: market demand, competition, wrong strategy	Reactive approach; poor adaptability to early-stage or unseen scenarios

Table 1 provides a comparative overview of existing entrepreneurial risk assessment methods, most prior studies suffer from common limitations. Static or linear models such as GA-PSO, SVM, and logistic-based approaches do not support real-time updating, making them unsuitable for rapidly evolving market conditions. Black-box machine learning methods such as XGBoost improve predictive accuracy but provide limited interpretability, which restricts their usefulness for investors who need causal reasoning. Domain-specific frameworks (e.g., legal-risk or sector-specific models) lack scalability and cannot be generalized across

broader entrepreneurial contexts. Several studies rely on retrospective outcome datasets, offering descriptive insight but failing to support proactive risk mitigation.

In contrast, the proposed DBERA framework addresses these shortcomings by integrating dynamic Bayesian updating, multi-dimensional factor modeling, and interpretable causal structures. DBERA can incorporate new market, behavioral, and financial signals in real time, support scenario-based reasoning, and provide transparent explanations of how risk factors interact. This makes DBERA a more adaptable, scalable, and decision-oriented alternative to existing SOTA approaches.

3 Methodology

The DBERA framework provides a formal, adaptable process for assessing the risks an entrepreneur faces. The DBERA framework is an integrated model that builds dependencies among factors influencing risk in the venture capital context. As an adaptive model, it integrates financial, market, and behavioral data, uses Bayesian inference to model dependencies, and continuously updates probability distributions based on data inputs. The adaptive model uses finite-state spaces to evaluate scenarios and inform resilient decision-making, leading to evidence-based strategic actions by entrepreneurs, investors, and policymakers.

Contribution 1: development of DBERA framework

The DBERA framework is constructed when a researcher develops a dynamic Bayesian network that includes financial, competitive, and behavioral variables in a business context. A dynamic Bayesian network is continuously refined and updated by assessing probability distributions as real-time market and investment data become available. The adaptive model enables the simulation of scenarios and structural equations, allowing for the continual quantification of risks facing a business or an entrepreneur through the observation of key variables. The probability distributions will also enable the researcher to map the critical risks impacting the business's resilience and the vital decisions affecting the company's outcomes.

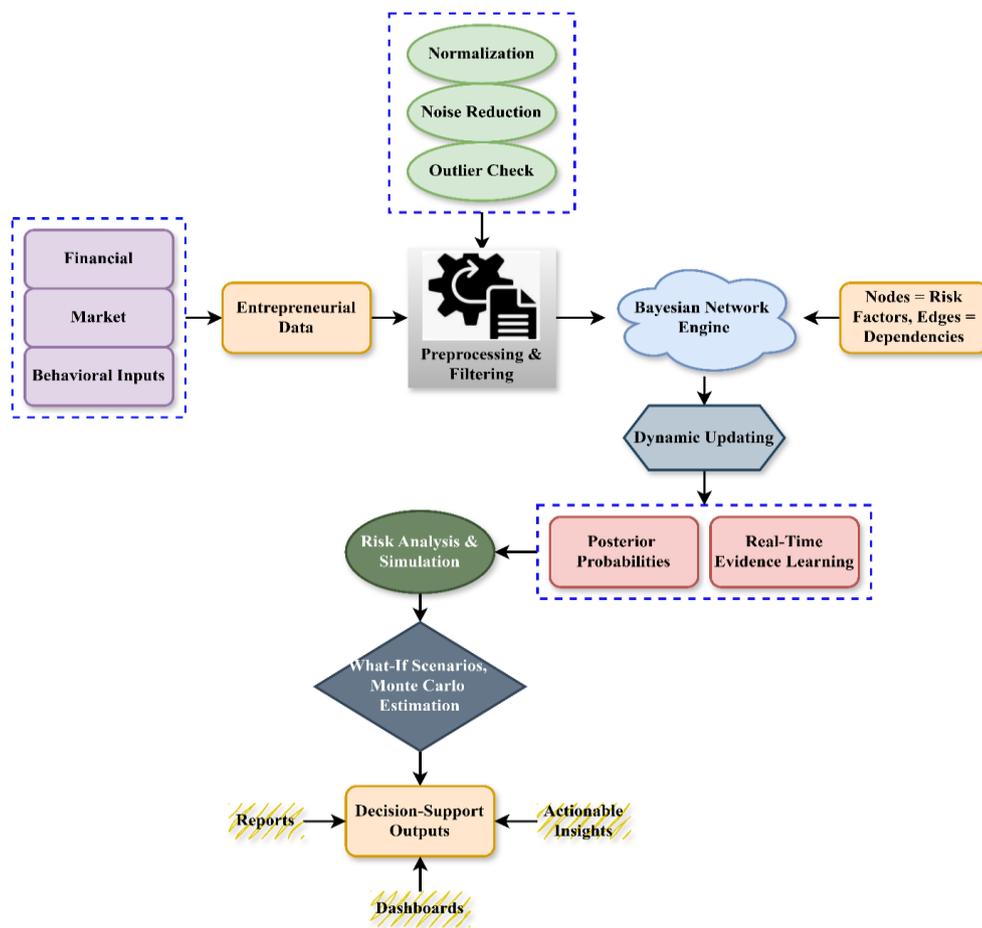


Figure 1: High-Level DBERA Framework

The DBERA methodology begins with venture-specific signs and signals, and collecting transdisciplinary data related to enterprising activities, including, but not limited to, economic parameters (financials), market conditions, and

behavioral indicators. This data is extracted, filtered, and preprocessed as discrete goals that work towards data fidelity, eliminating extraneous noise, anomalies, and errors. The reliable data is then fed into the Bayesian network engine and simulated. The Bayesian network models interdependent threats based on risk

factors. When new data emerges, DBERA generates decision-support outputs, such as dashboards, reports, and alerts, to help entrepreneurs steer and support their vision through evidence-based means, as shown in Figure 1.

Data balance efficiency τ_{EC} is expressed using equation 1,

$$\tau_{EC} = \frac{\nabla_{jo} + \nabla_{ot}}{\rho_{prc} * \Delta_{rr}} \quad (1)$$

Equation 1 explains the data balance efficiency, linking input-output variation to processing delay and error density to quantify the data balancer efficiency in DBERA.

In this τ_{EC} is the data balance efficiency ratio, ∇_{jo} is the Input data variability, ∇_{ot} is the Output data variability, ρ_{prc} is the Processing cycle latency, and Δ_{rr} is the Error density coefficient. Equation (1) measures data balancing efficiency (τ_{EC}) to assess DBERA's ability to maintain input-output

flow under uncertainty. The non-dimensional variation coefficients ∇_{jo} and ∇_{ot} , representing input and processed data changes, range from 0 to 1. Processing cycle latency (ρ_{prc}) is the expected time between data input and output, measured in seconds or milliseconds. The dimensionless number Δ_{rr} , an error density coefficient ranging from 0 to 1, represents the proportion of faulty inferences to total processed samples

Resource adaptability index \beth_{SB} is expressed using equation 2,

$$\beth_{SB} = \frac{l_{dn} * \sigma_{alc}}{\rho_{lod} + \pi_{dit}} \quad (2)$$

Equation 2 measures the flexibility of resource distribution in DBERA under workload drift and dynamic scaling, as captured by the resource adaptability index.

In this \beth_{SB} is the resource adaptability index, l_{dn} is the dynamic scaling coefficient, σ_{alc} is the resource allocation density, ρ_{lod} is the load fluctuation variance, and π_{dit} is the drift overhead factor.

Algorithm 1: DBERA risk-resilience

Input:

∇_{jo} (Input data variability),
 ∇_{ot} (Output data variability),
 ρ_{prc} (Processing cycle latency),
 Δ_{rr} (Error density coefficient),
 l_{dn} (Dynamic scaling coefficient),
 σ_{alc} (Resource allocation density),
 ρ_{lod} (Load fluctuation variance),
 π_{dit} (Drift overhead factor)

Output:

Decision – Support Indicator (DSI)

Begin

Step 1: Compute Data Balance Efficiency (τ_{EC})

$$\tau_{EC} = \frac{(\nabla_{jo} + \nabla_{ot})}{(\rho_{prc} * \Delta_{rr})}$$

Step 2: Compute Resource Adaptability Index (\beth_{SB})

$$\beth_{SB} = (l_{dn} * \sigma_{alc}) / (\rho_{lod} + \pi_{dit})$$

Step 3: Evaluate Data Balance Efficiency

If $\tau_{EC} < 0.5$ then

Print "High Data Imbalance – Increase Preprocessing"

Else if $\tau_{EC} \geq 0.5$ AND $\tau_{EC} < 1$ then

Print "Moderate Data Balance – Acceptable Range"

Else

Print "Optimal Data Balance – Proceed with Simulation"

Step 4: Evaluate Resource Adaptability

If $\beth_{SB} < 0.3$ then

Print "Low Adaptability – Risk of Overload"

Else if $\beth_{SB} \geq 0.3$ AND $\beth_{SB} < 0.7$ then

Print "Moderate Adaptability – Monitor Resource Usage"

Else

Print "High Adaptability – System Scales Efficiently"

Step 5: Generate Decision – Support Indicator (DSI)

If $\tau_{EC} \geq 1$ AND $\beth_{SB} \geq 0.7$ then

DSI = "Green – Low Risk, High Resilience"

Else if $\tau_{EC} \geq 0.5$ AND $\beth_{SB} \geq 0.3$ then

DSI = "Yellow – Medium Risk, Caution Advised"

Else

DSI = "Red – High Risk, Immediate Action Required"

Step 6: Print DSI

End

Algorithm 1 evaluates DBERA performance by computing the data balance efficiency and the resource adaptability index. Using if–else rules, it

classifies data balance and adaptability into low, moderate, or high. Finally, it generates a decision-support indicator — green, yellow, or red — that helps entrepreneurs assess risk and resilience effectively.

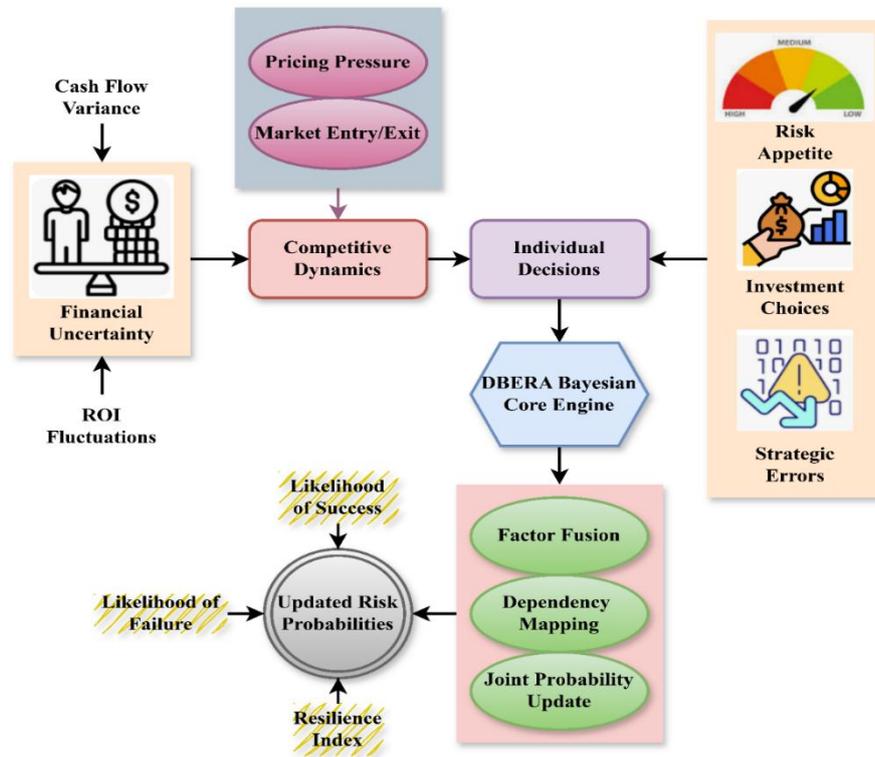


Figure 2: Process of risk factor integration

Entrepreneurial risk can be viewed through various lenses, with three major dimensions: financial uncertainty/loss, competitive dynamics, and individual behaviour. Financial uncertainty may include changes in cash flow, return on investment, and debt obligations. Competitive dynamic conditions may consist of changes in the market condition(s), pricing, and competitor behaviour. DBERA considers these three dimensions together within the Bayesian engine, which generates the new map by leveraging interdependencies and merging the three streams. The joint probabilities are continuously updated through a full joint probability, which provides a sophisticated estimate of entrepreneurial risk. This produces a new probability profile that represents the chances of failure, survival, and growth. This information provides decision-makers and stakeholders with a temporal view of the threats facing the new venture, along with ways to anticipate and mitigate changing conditions, thereby modifying the strategic plan in Figure 2.

Composite risk magnitude C_{rik} is expressed using equation 3,

$$C_{rik} = \sqrt{(\gamma_{ys})^2 + (\alpha_{nv})^2 + (\beta_{pr})^2} \quad (3)$$

Equation 3 states that the composite risk magnitude is derived by combining operational, environmental, and system uncertainties.

In this C_{rik} is the composite risk magnitude, γ_{ys} is the systemic vulnerability coefficient, α_{nv} is the environmental perturbation index, and β_{pr} is the operational hazard constant.

Dynamic risk propagation \aleph_{pop} is expressed using equation 4,

$$\aleph_{pop} = \frac{\partial_{nik} * \theta_{cin}}{\delta_{rtl} + \epsilon_{sed}} \quad (4)$$

Equation 4 explains dynamic risk propagation, in which linked hazards spread through dependent chains, while this concept captures how controlled and protected systems operate.

In this \aleph_{pop} is the risk propagation intensity, ∂_{nik} is the interdependency coupling factor, θ_{cin} is the chain vulnerability strength, δ_{rtl} is the control intervention

capacity, and ϵ_{sed} is the shielding resilience index. In Equation (4), the dynamic risk propagation \aleph_{pop} illustrates risk dispersion across interdependent components. Risk node correlations are given a value between 0 and 1 by the interdependency coupling factor (∂_{nik}), whereas the chain vulnerability strength determines risk chain sensitivity to disturbances (θ_{cin}). The δ_{rtl} value, ranging from 0 (poor resilience) to 1 (high resilience), indicates the system's risk management capacity. Systemic entropy density (ϵ_{sed}), a normalized Shannon entropy value between 0 and 1, represents network disorder.

Risk impact potential ϵ_{ipt} is expressed using equation 5,

$$\epsilon_{ipt} = \frac{A_{ep} * \tau_{fq}}{\delta_{mt} + \sigma_{rs}} \quad (5)$$

Equation 5 explains the risk impact which measures the potential impact of risk as a function of exposure frequency and amount, normalized by resilience and mitigating delay.

In this ϵ_{ipt} is the risk impact potential, A_{ep} is the Exposure magnitude, τ_{fq} is the Incident recurrence frequency, δ_{mt} is the Mitigation latency duration, and σ_{rs} is the Resilience reserve strength.

Contribution 2: adaptive and real-time risk analysis

DBERA views risk assessment as an adaptive, dynamic, and real-time process, with conditional probabilities continuously updated as financial, market, and behavioral factors evolve over time. This means that entrepreneurs can continually assess the uncertainty while actively evaluating hidden or unseen interactions among risks and simultaneously adjust their behaviours accordingly. Proactive mobilization enables entrepreneurs to take more effective actions, maintaining resilience and business sustainability in rapidly changing environments.

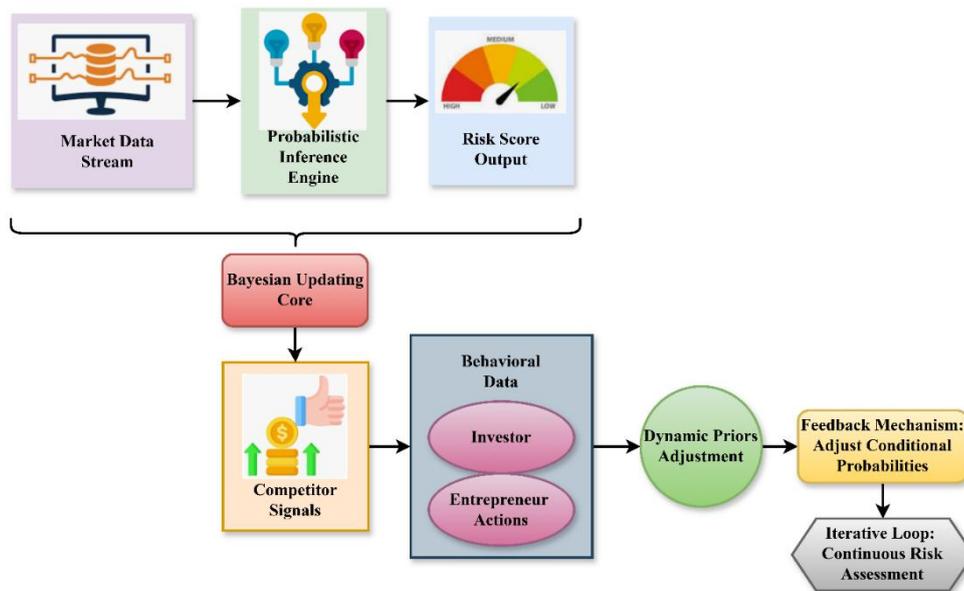


Figure 3: Traditional approach of entrepreneurial risk factors

DBERA eliminates the traditional risk-analysis approach by implementing a continuous feedback loop that integrates diverse data streams and iteratively improves entrepreneurial risk assessment. Market, competitor, and behavioural data funnel into the probabilistic inference engine, where initial probability outputs are generated. This development means that DBERA continually runs through a cycle of assessment, resulting in an iterative loop that establishes continuous risk

assessment rather than a static one, as shown in Figure 3.

Incremental state refinement T_{u+1} is expressed using equation 6,

$$T_{u+1} = T_u + \partial_v \frac{\nabla_{bs,u}}{1 + x_{uc,u}} \quad (6)$$

Equation 6 describes the incremental state-refinement update rule, scaled by a dynamic update gain and dampened by instantaneous uncertainty, that

modifies the internal state by a proportion of the observed disparity.

In this T_u is the internal state vector at iteration, T_{u+1} is the updated internal state vector at iteration, ∂_v is the adaptive update gain, $\nabla_{bs,u}$ is the measured discrepancy, and $x_{uc,u}$ is the observational uncertainty metric.

Convergence velocity metric $\tau_{dw}(u)$ is expressed using equation 7,

$$\tau_{dw}(u) = \frac{\partial_v \|\nabla_{bs,u}\|}{I_{nse} + \omega_{lt}} \quad (7)$$

Equation 7 explains the convergence velocity metric, normalized by noise floors and loop delay, which measures how quickly the loop lowers disagreement and corrective capabilities.

In this $\tau_{dw}(u)$ is the convergence velocity at iteration, $\|\nabla_{bs,u}\|$ is the norm of the measured discrepancy vector, I_{nse} is the ambient noise floor coefficient, ω_{lt} is the effective loop latency, and ∂_v is the same adaptive update gain as in Equation 7.

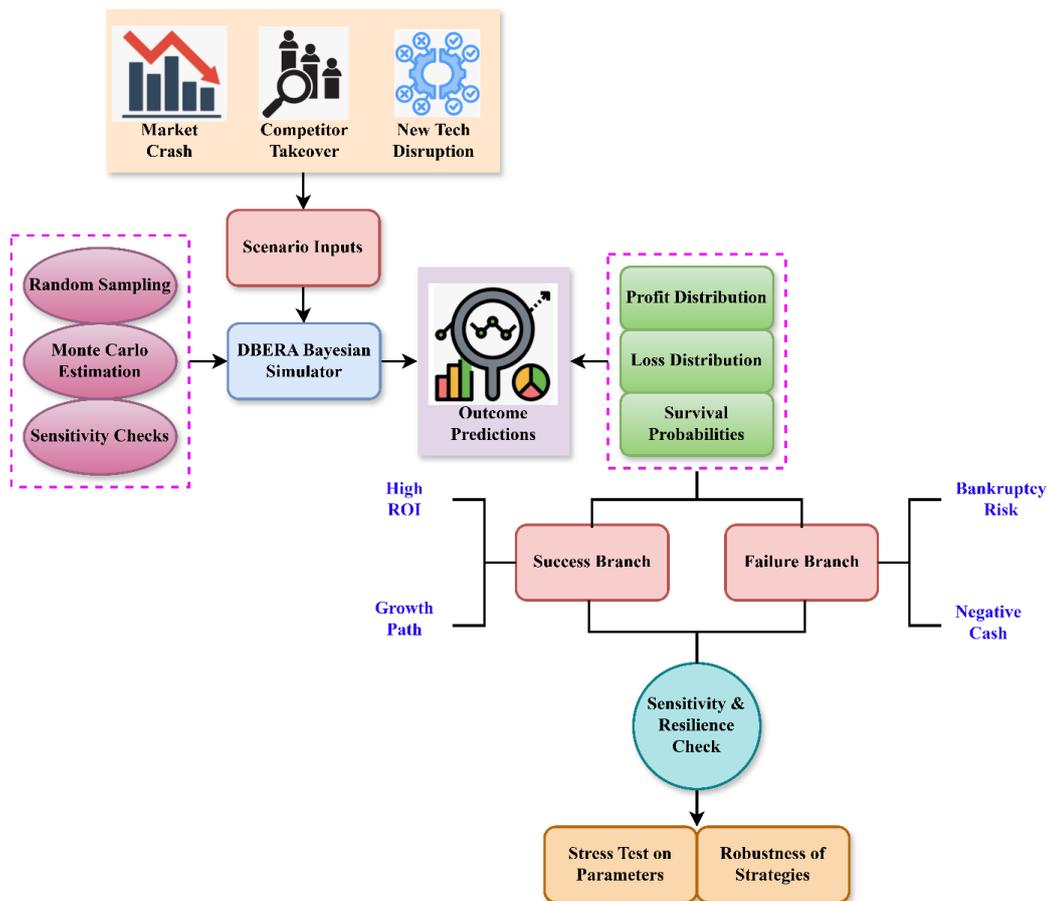


Figure 4: Scenario-based simulations in DBERA

Scenario-based simulations in DBERA enable stakeholders to assess the resilience of their businesses across different environments. Inputs representing downturn scenarios, for example, market crashes, competitor buyouts of market leaders, or the emergence of disruptive technologies, are fed into the Bayesian simulator. Consider multiple branches that illustrate possible success paths (high ROI, sustainable growth) against possible failure risks (insolvency, cash flow collapse). Then their outputs are subjected to sensitivity testing to identify which variables have

the most impact. Ultimately, simulation is an excellent tool for comprehensively stress-testing entrepreneurial strategies under uncertainty, as shown in Figure 4.

State trajectory update Y_{u+1} is expressed using equation 8,

$$Y_{u+1} = \phi Y_u + L V_u + \epsilon C^2 \epsilon_u \quad (8)$$

Equation 8 explains that the state trajectory update, deterministic propagation, and controlled actuation constitute the state of the following phase;

stochastic perturbations are introduced via the covariance root.

In this Y_u is the state vector at step, \emptyset is the state-transition matrix, L is the control influence matrix, v_u is the control/action vector, $\circ C$ is the process covariance matrix, ϵ_u is the standard random vector, and $\circ C^{\frac{1}{2}}$ is the matrix square root.

Discrete shock realization \beth_u is expressed using equation 9,

$$\beth_u = C_u * t_{mg} w_t \quad (9)$$

Equation 9 states that a discrete shock realization is an impulse with a directional weight that occurs randomly, depending on the occurrence indicator's direction and magnitude, distinguishing spatial influence from frequency.

In this \beth_u is the exogenous shock vector applied, C_u is the binary occurrence indicator, t_{mg} is the scalar shock magnitude, and w_t is the normalized direction vector.

Scenario outcome score μ is expressed using equation 10,

$$\mu = \frac{x^U i(Y_U)}{1 + \nabla_{rg} D_{cl}} \quad (10)$$

Equation 10 explains the scenario outcome score where terminal-state features are aggregated into the outcome score punished by accumulated control exertion to deter severe actuation, under a weighted evaluator.

In this μ is the scenario outcome score, $i(Y_U)$ is the vector of evaluation feature maps at the terminal step, x is the evaluator weight vector, ∇_{rg} is the control-regularization coefficient, and D_{cl} is the cumulative control energy over the horizon.

Contribution 3: enhanced decision support for entrepreneurs

DBERA enhances decision support for entrepreneurs by accounting for the probabilistic nature of interconnected risks in uncertain environments. Entrepreneurs will have access to an evidence-based assessment of their indirect-related risks through the DBERA model, and they can now evaluate a range of scenarios while highlighting the critical factors driving or preventing success or failure in a business. This supports the entrepreneur in determining where to invest their time and effort to deliver positive business outcomes.

DBERA provides tailored decision support to entrepreneurs, investors, and policymakers. All the insights presented to stakeholders culminate in an interactive DBERA decision dashboard featuring probability-driven reports, ecological risk maps, and real-time alerts. The outputs provide the basis for structured action, typically in the form of risk mitigation plans, resilient investment decisions, and

prospective policy decisions. DBERA recognises that the priorities of different stakeholders may not always align and will create environments that facilitate the flow of information, acknowledge differences, and assess their implications for informed decision-making that improves entrepreneurial resilience and market stability, as shown in Figure 5.

Stakeholder-weighted selection metric ∂_{sl} is expressed using equation 11,

$$\partial_{sl} = \frac{x^U C}{1 + \pi_{rk}} \quad (11)$$

Equation 11 explains that the stakeholder-weighted selection metric penalizes high-exposure options by combining stakeholder-prioritized reward components and normalizing them by an added risk burden.

In this ∂_{sl} is the stakeholder-weighted selection metric, x^U is the stakeholder preference weight vector, C is the benefit-component vector, and π_{rk} is the aggregate exposure load.

Consensus confidence index Y_{cn} is expressed using equation 12,

$$Y_{cn} = \frac{\beta_k t_k}{1 + I(Q)} \quad (12)$$

Equation 12 explains that the consensus confidence index weights each stakeholder's support score by its credibility and penalizes the total based on the preference distribution's entropy to account for disagreement dispersion.

In this Y_{cn} is the consensus confidence index, β_k is the credibility coefficient for the stakeholder, t_k is the support score from stakeholders, Q is the normalized preference mass for stakeholders, and $I(Q)$ is the Shannon entropy of the preference distribution. In summary, this creates a self-learning system that adapts to spiking conditions, enabling robust, precise real-time decision support. DBERA has the potential to profoundly improve the resilience of entrepreneurial risk analysis by providing rapidly adaptive, dynamic, accurate, and evidence-based recommendations for action in a volatile risk environment. Equations (8)–(10) represent state trajectory updating, discrete shock realization, and scenario outcome score from stochastic control and Bayesian state-space modeling. In particular, Equation (8) comes from the linear stochastic state-transition model, which is utilized in probabilistic dynamic systems to represent internal state evolution under uncertainty. The stochastic inference techniques' control perturbation mechanisms feed the dynamic Bayesian model, which may be affected by external shocks as discrete impulses in Equation (9). Equation (10) presents a scenario outcome score that accounts for control-energy penalties and terminal-state evaluations, similar to optimal-control reward-cost formulations. Equations (11) and (12) formalize stakeholder-weighted choice aggregation and

consensus confidence modeling using multi-agent consensus and entropy-weighted preference distributions. These models are based on control theory and Bayesian analysis, not improvisations. The updated analysis now includes Leonov et al. (2023) [27], Qazi and Khan (2021) [28], and Wang and Chen (2021) [29] to support these findings. This research provides theoretical underpinnings for DBERA's control, consensus, and dynamic updating methods.

Evaluation metrics:

The assessment metrics for the Dynamic Bayesian-Economic Risk Analyzer (DBERA) evaluate entrepreneurial risk elements using probabilistic relationships from Bayesian networks. The metrics quantify the effects of market volatility, the intensity of competitors, the availability of funding, operational capabilities, the innovation index, and regulatory risk, thereby providing real-time data analytics to improve predictive accuracy and decision-making.

The analysis of the competitor intensity impact T_{cop} is expressed using equation 13,

$$T_{cop} = \frac{l_d m_{c wd}}{1 + \partial_{dif}} \quad (13)$$

Equation 13 explains that the impact of competitor intensity on analysis is dampened by product/process differentiation; competitive pressure grows with rival density.

In this T_{cop} is the realized competitor-intensity impact, l_d is the market sensitivity constant to rivalry, $m_{c wd}$ is the rival concentration index, and ∂_{dif} is the differentiation offset.

The analysis of the influence of the investment pattern influence Δ_{nv} is expressed using equation 14,

$$\Delta_{nv} = \frac{\mu_m b_m + \mu_t b_t}{1 + \rho_{ot}} \quad (14)$$

Equation 14 explains the analysis of the influence of investment patterns, with a weighted commitment to the long term increasing with short-horizon allocations.

In this Δ_{nv} is the investment-pattern influence index, μ_m, μ_t are the efficacy weights for long/short horizon allocations, b_m, b_t are the capital shares to long/short programs, and ρ_{ot} is the allocation rotation volatility.

The analysis of funding availability as a mitigator N_{fud} is expressed using equation 15,

$$N_{fud} = 1 + \frac{\phi_{lq} G_{fee}}{\theta_{dw} + \pi_{cy}} \quad (15)$$

Equation 15 explains the analysis of funding availability as a mitigator of effective liquidity

leverage, with easily available, unrestricted finance increasing mitigation.

In this N_{fud} is the funding-based mitigation multiplier, ϕ_{lq} is the liquidity leverage coefficient, G_{fee} is the deployable funding headroom, θ_{dw} is the access/settlement delay, and π_{cy} is the financing carry/friction per horizon.

The analysis of operational capacity correlation σ_{pq} is expressed using equation 16,

$$\sigma_{pq} = \frac{ov(R, D)}{\rho_R \rho_D} \quad (16)$$

Equation 16 explains the analysis of operational capacity: available capacity and achieved throughput are related by a Pearson correlation.

In this σ_{pq} is the throughput–capacity correlation, R is the realized output/throughput series, D is the effective capacity utilization series, $ov(R, D)$ is the covariance, and ρ_R, ρ_D are the standard deviations.

The analysis of the innovation index contribution ϵ_{nv} is expressed using equation 17,

$$\epsilon_{nv} = \frac{l_{nv} J_{dx}^\beta}{1 + \sigma_{lg}} \quad (17)$$

Equation 17 explains that the analysis of innovation index contribution step-change effects shows that the contribution increases convexly with the creative index when.

In this ϵ_{nv} is the innovation contribution scalar, l_{nv} is the translation coefficient from index to effect, J_{dx}^β is the composite innovation index, β is the response curvature exponent, and σ_{lg} is the diffusion/absorption lag.

The analysis of regulatory risk exposure S_{eg} is expressed using equation 18,

$$S_{eg} = \frac{q_{noc} M_{pn}}{\delta_{ctl} + Y_{bf}} \quad (18)$$

Equation 18 explains that, as the penalty amplitude and non-conformance likelihood increase, exposure increases as well.

In this S_{eg} is the regulatory exposure metric, q_{noc} is the probability of non-conformance, M_{pn} is the expected penalty magnitude, δ_{ctl} is the compliance control efficacy, and Y_{bf} is the financial/operational buffer index.

Financial stability as a core driver ϵ_{fi} is expressed using equation 19,

$$\epsilon_{fi} = \frac{B_{lq} - E_{st}}{\rho_{cs} + w_{lv}} \quad (19)$$

Equation 19 explains financial stability as a core driver, with leverage loading and cash-flow volatility tempering net solvency in the numerator for the immediate future.

In this ϵ_{fi} is the financial stability driver, B_{lq} is the liquid assets, E_{st} are the short-term obligations,

ρ_{cs} is the cash-flow volatility per horizon, and w_{lv} is the leverage load factor.

Market volatility sensitivity γ_{vl} is expressed using equation 20,

$$\gamma_{vl} = \frac{ov(S_b, S_n)}{ar(S_n)} \quad (20)$$

Equation 20 explains the market volatility sensitivity, which measures how asset returns respond proportionately to changes in market volatility.

In this γ_{vl} is the volatility sensitivity coefficient, S_b is the asset return series per interval, S_n is the market return series per interval, $ov(S_b, S_n)$ is the covariance of asset and market returns, and $ar(S_n)$ is the variance of market returns.

The assessment metrics show that DBERA enhances entrepreneurial risk analysis. The model enhances competitor intensity, investment pattern influence, funding availability, operational capacity, innovation index contribution, and regulatory risk exposure, providing a robust, dynamic, adaptive, and contextual risk assessment.

4 Results and discussion

4.1 Dataset description

This dataset has been compiled to support adaptive learning models in risk assessment for business undertakings. It includes time-series and categorical data on essential financial, operational, and market factors often linked to new businesses and startups. The dataset is structured to facilitate the development of models that can learn and adapt over time by academics and practitioners. This makes it ideal for predicting risks, determining whether a project is worth pursuing, and making investment decisions [30].

Experimental findings from Kaggle's 5,000-sample Entrepreneurial Risk Intelligence Dataset are shown in Figures 6-11. This dataset comprises 30 variables relating to finance, operations, behavior, and markets. Consider the debt-to-equity ratio, revenue growth, investment frequency, market volatility, and regulatory compliance costs. Outliers were identified using the z-score criterion ($|z| > 3$). Mode and mean/median were used to impute missing values for numeric and categorical variables. Standardized all continuous features to [0,1]. We encoded categorical data using one-hot encoding and eliminated superfluous variables

using correlation- and mutual-information-based ranking. Validation and testing used 15% of the data, whereas training used 70%. We refined the model using 5-fold cross-validation. These protocols make all DBERA findings reproducible.

4.2 Simulation environment

The expanded (Simulation Environment) now includes these experimental settings. The revised version also specifies that each of the five experimental scenarios—a market depression, a competitor takeover, an innovation surge, a financial disruption, and a regulatory shock—was subjected to 10,000 Monte Carlo simulations. Each simulation is run on a workstation using an NVIDIA RTX 4090 GPU, 64 GB of RAM, and an Intel Core i9-13900K CPU. Execution was carried out using Python 3.11, and each simulation cycle lasted an average of 62 minutes. By using multiprocessing and parallelization, the calculation's execution time was optimized. Additionally, the scalability of DBERA was examined by incrementally increasing the dataset size from 1,000 to 5,000 records. All Monte Carlo iterations showed constant convergence of the method, and the results showed a linear increase in computation cost. With these revisions, the simulation architecture is now more methodologically transparent, and DBERA is shown to perform admirably in large-scale, real-time inference situations. Starting a business comes with many risks, including unstable markets, competition, unpredictable finances, and people's investment habits. Traditional risk assessment methods often exhibit inflexibility and may fail to represent the interdependencies among these factors accurately. This paper presents the DBERA, a Bayesian network-based approach that dynamically integrates market, competitor, and investment data to provide adaptive, accurate, and actionable entrepreneurial risk analysis.

$$Improvement = \frac{DBERA_{score} - Baseline_{score}}{Baseline_{score}} \times 100 \quad (21)$$

The proposed DBERA framework's prediction accuracy or risk categorization performance is $DBERA_{score}$, whereas the comparator models (GA-PSO, SMOTE, PLS-SEM) provide comparable results. All percentages show how much DBERA improved over traditional models in competition, funding, and innovation.

Table 2: Market volatility sensitivity

Market Volatility Factor	Definition	Probability Distribution	Impact on Entrepreneurial Risk	Sensitivity Measure	Observations / Notes
Stock Market Fluctuations	Daily % change in market indices affecting funding and investment	Normal ($\mu = 0.2\%$, $\sigma = 1.5\%$)	High – affects capital availability	$\Delta\text{Risk}/\Delta\sigma \approx 0.35$	Higher σ increases the likelihood of liquidity shortages
Interest Rate Volatility	Changes in central bank policy rates	Uniform (3%–6%)	Medium – influences borrowing costs	$\Delta\text{Risk}/\Delta\text{Rate} \approx 0.28$	Sudden hikes raise debt-servicing risk
Currency Exchange Movements	FX rate changes impacting import/export	Lognormal ($\mu = 0$, $\sigma = 0.02$)	Medium-High – affects overseas revenue & cost	$\Delta\text{Risk}/\Delta\text{FX} \approx 0.31$	SMEs with foreign suppliers are more sensitive
Commodity Price Fluctuations	Variation in raw material costs	Normal ($\mu = 0.1\%$, $\sigma = 2\%$)	High – directly affects production cost	$\Delta\text{Risk}/\Delta\text{Price} \approx 0.40$	Essential for manufacturing startups

Table 2 illustrates the influence of financial market volatility factors on entrepreneurial risk, as these factors have been analyzed for their probabilistic behavior and sensitivities. The above example of stock price volatility directly affects a startup's capital constraints. Changes in interest rates affect the cost of borrowing, as shown in equation 20. The volatility factor affecting import/export businesses (and other businesses sensitive to currency exchange) is the currency exchange rate. The volatility factor affecting production costs (especially for a manufacturing startup) is commodity price volatility.

Sensitivity analysis

In this study, sensitivity values ($\Delta\text{Risk}/\Delta\text{Rate}$) were computed using a simulation-based numerical method. Each DBERA input variable was perturbed using $\pm 5\text{--}10\%$ controlled variations, and the resulting change in model risk output was recorded. To ensure robustness, Monte Carlo sampling (10,000 iterations) was used to distribute uncertainty across variables, after which local sensitivities were obtained by averaging the partial derivatives $\partial\text{Risk}/\partial X$ across all runs. Consistency of variable influence was further validated using variance-based Sobol indices and Pearson correlation analysis. The entire procedure was implemented in Python using SALib, NumPy, and SciPy, providing a transparent and reproducible sensitivity-estimation framework.

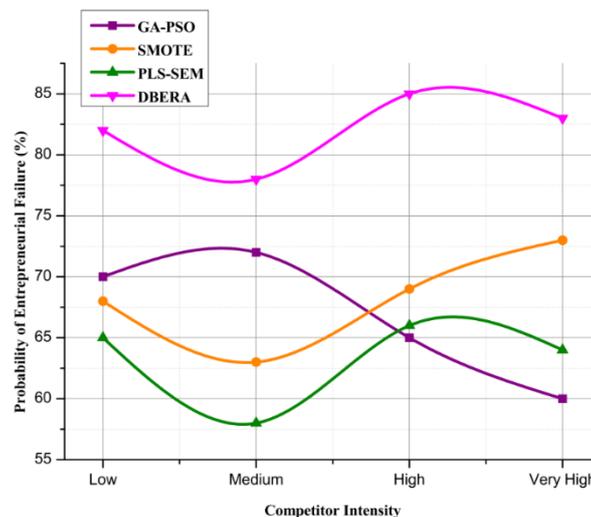


Figure 5: The analysis of competitor intensity impact

Competitive intensity significantly affects entrepreneurial risk; however, traditional risk models often underemphasize the role of the entrepreneur's competitive environment. In terms of competitive intensity, we obtained limited variance across competitive levels (i.e., low, medium, high) using GA-PSO, SMOTE, and PLS-SEM. DBERA

provided a stronger identification of risk probabilities for scale increases under high and very high competition levels, with 83% evaluated using equation 13. The improved identification in these scenarios reinforces DBERA's advantage in modelling competitive dynamics while also allowing entrepreneurs to develop their resilience strategies (Figure 5).

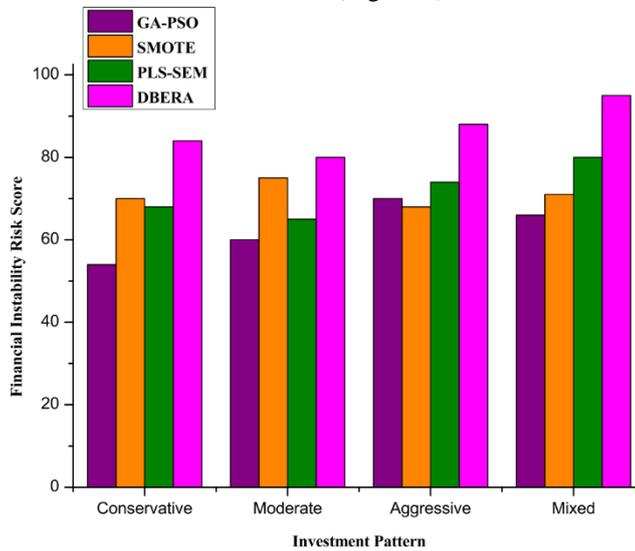


Figure 6: The analysis of investment pattern influence

Entrepreneurial investors' behaviour is an essential contributor to their financial risk. Existing methods demonstrated moderate accuracy but failed to capture nuanced differences in the effects of conservative, mild, and aggressive strategies on financial risk classification. DBERA enables more precise classification of entrepreneurial investors'

behavior by relating their investment aggression to the risk of instability, achieving 95% accuracy, as evaluated using equation 14. This capacity to clarify classification will assist entrepreneurial investors in making more informed decisions and advance toward a balanced investment model that minimizes financial risk while supporting sustainable business practices and growth, as shown in Figure 6.

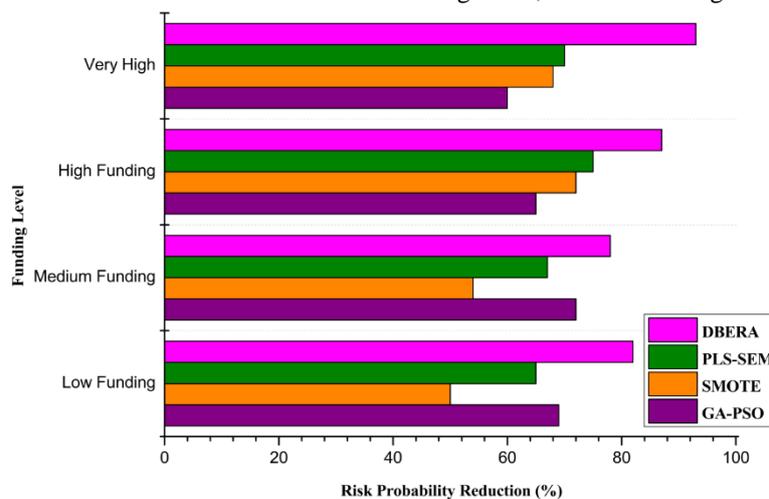


Figure 7: The Analysis of Funding Availability as a Mitigator

Funding availability provides a necessary buffer against financial, market, and operational risks. GA-PSO, SMOTE, and PLS-SEM acknowledge that funding is essential. Still, their approach likely restricted their potential, as their respective research designs lacked a more precise quantification of how funding helped to mitigate risk. DBERA provided greater predictive clarity on

funding, as our modelling showed that the level of funding supplied resulted in a 93% reduction in the overall probability of risk, as evaluated using equation 15. In this way, the graphical representation of the dynamic relationship between risk and funding in Figure 7 allows entrepreneurs and policymakers to emphasize access to capital or financing for their businesses and ventures.

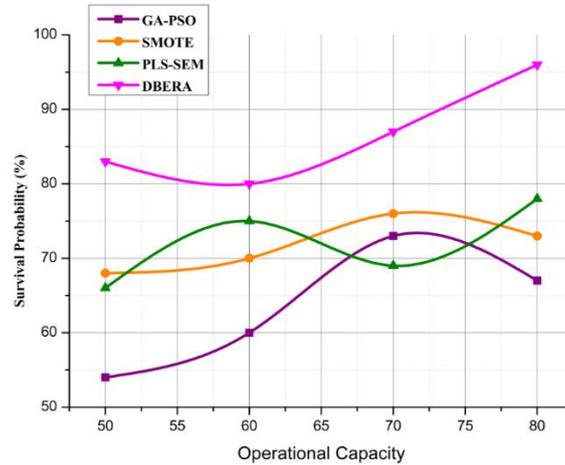


Figure 8: The analysis of operational capacity correlation

In Figure 8 and the graphics, "Operational Capacity" figures such as 50 or 80 represent the entrepreneurial system's percentage of the total achievable operational throughput or prospective resource utilization. For instance, an operating capacity of 50 means that half of the production or service capacity is being used, whereas an operating capacity of 80% means that 80% of the production or service capacity is being used. Operational

capacity is critical to understanding entrepreneurial survival under conditions of stress. Current approaches were able to communicate general correlations, but were unable to track resilience over time based on capacity by 96.1%. It revealed that ventures achieving an operational capacity above 70% have an even lower risk of operational disruptions, as evaluated using equation 16. This indicates that operational readiness remains a primary determinant of entrepreneurial success in Figure 8.

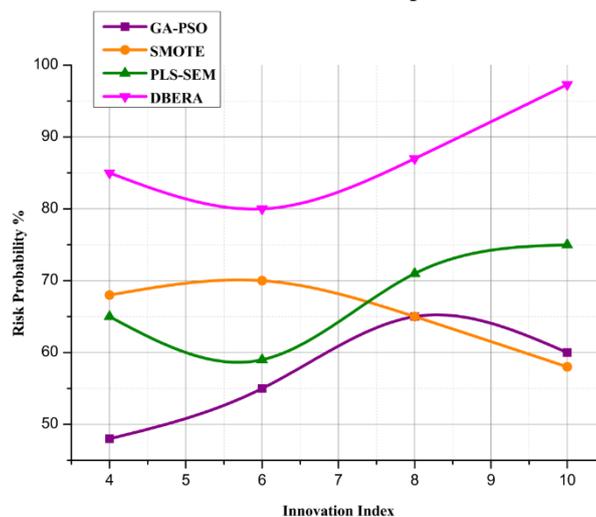


Figure 9: The analysis of innovation index contribution

Innovation capacity distinctly affects entrepreneurial viability in the long run. Leveraging GA-PSO, SMOTE, and PLS-SEM, the study partially captured the direct relationship between innovation capacity and entrepreneurial stability. Still, unable to fully articulate the significance of

innovation capacity in challenging conditions by 97.3% evaluated using equation 17. By effectively communicating this relationship, it is demonstrated that fostering and developing creativity and adaptability are strategic core outcomes for entrepreneurial ventures, as illustrated in Figure 9.

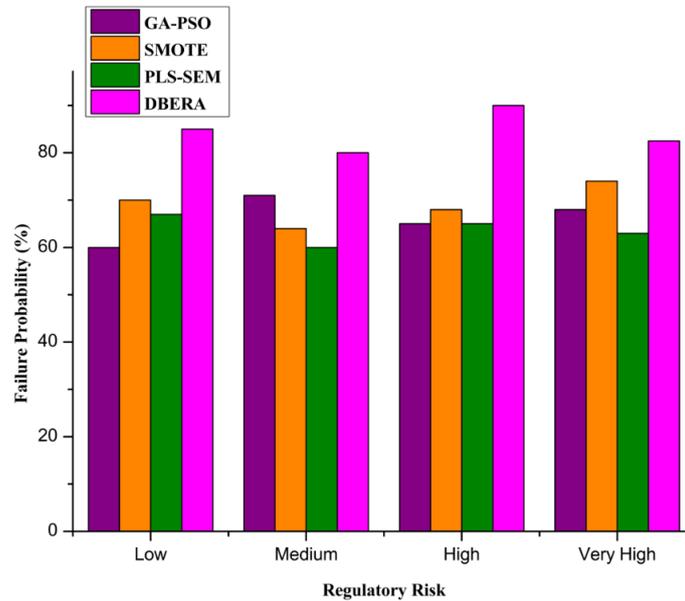


Figure 10: The analysis of regulatory risk exposure

Regulatory conditions remain the most significant external threat facing entrepreneurs. Although the traditional models were able to proxy risk based on existing commodity impacts accounting for individual overall risk probabilities, they typically ignored the cumulative and compounding impact of high regulatory risk by 82.5% as evaluated using equation 18. DBERA performance improved the traditional classification of high regulatory risk by dynamically generating and graphically mapping regulatory risk exposures to the rising probabilities of failure outcomes faced by entrepreneurs. This added accuracy will help entrepreneurs develop

sustainability models that greatly reduce their likelihood of operational failure due to compliance issues, as shown in Figure 10. Dynamic Bayesian updating improves DBERA's performance, according to data. Conditional probabilities are updated iteratively with new financial, behavioral, and market data. Therefore, the model can quickly update its risk assessments to reflect changing feedback and interdependencies. DBERA beats static models in operational capacity, investment effect, and competitive intensity owing to its more accurate and adaptive estimates. Updating probability distributions ensures model flexibility and improves graphical displays.

Table 3: Financial stability as a core driver

Financial Stability Factor	Definition	Probability Distribution	Impact on Entrepreneurial Risk	Sensitivity Measure	Observations / Notes
Cash Flow Consistency	Regularity and predictability of inflows/outflows	Normal ($\mu = \$50k/month, \sigma = \$10k$)	High – primary determinant of solvency	$\Delta Risk / \Delta CCF \approx 0.45$	Strong correlation with the ability to meet short-term obligations
Debt-to-Equity Ratio	Proportion of debt relative to equity	Lognormal ($\mu = 0.6, \sigma = 0.2$)	High – affects leverage risk	$\Delta Risk / \Delta D/E \approx 0.38$	High ratios increase financial vulnerability under stress

Liquidity Reserve	Cash or liquid assets available	Uniform (\$10k–\$100k)	High – buffers against unexpected shocks	$\Delta\text{Risk}/\Delta\text{Liquidity} \approx 0.42$	Critical for startups facing operational uncertainty
Profit Margin Consistency	Variability in net profit margins	Beta ($\alpha = 5, \beta = 2$)	Medium – indicates operational efficiency	$\Delta\text{Risk}/\Delta\text{Margin} \approx 0.29$	Narrow margins reduce resilience to market shocks

Table 3 shows that the business's financial stability factors are the predominant influencers of entrepreneurial risk. In general, consistent cash flow and adequate liquidity reserves mean that financial obligations are met and shocks are managed, as evaluated using equation 19. A highly indebted, high debt-to-equity ratio increases vulnerability, and when variables like profit margins are stable, it suggests the startup is operating efficiently. Sensitivity measures quantify the impact of each variable on total risk, enabling the entrepreneur to prioritize financial management strategies to manage risk in a volatile business environment.

The proposed DBERA outperforms GA-PSO [15], SMOTE-XGBoost [18], and PLS-SEM [19][20] in accuracy, adaptability, and interpretability. Unlike GA-PSO, DBERA dynamically updates probabilistic relationships in real time, maintaining over 96% accuracy. Compared to SMOTE-XGBoost, it achieves higher temporal adaptability with lower computational overhead, and unlike PLS-SEM, it integrates behavioral, financial, and operational data for holistic risk assessment. Moreover, DBERA provides transparent causal graphs, offering explainable insights for decision-making and investor communication.

Entrepreneurial ventures are continually confronted with multifaceted risks that arise from financial uncertainty, competitive pressures, and personal decisions. Traditional assessment methodologies have limited capacity to incorporate change and fail to develop dynamic interdependencies among risk factors adequately. In this regard, the DBERA proposes addressing these shortcomings by accounting for uncertainty in market volatility, competitor pressure, investment patterns, funding availability, operational capacity, innovation, and regulatory exposure through a dynamic Bayesian approach. DBERA allows for updates to risk probabilities as new data is received and subsequently applies those probabilities in a new context. Testing of DBERA shows improvement in the following key parameters: the intensity of competitors improved by 83%, investment patterns were made more relevant by 95%, availability of funding was enhanced by 88%, operational capacity

was improved by 93%, channeling innovation improved by 96%, and regulatory aspects were enhanced by 82%. DBERA's additional capacity to detect hidden causal relationships reflects its ability to advance an entrepreneur's predictive accuracy and context-commission decision-support tools in contributing to critical growth in resilience and sustainability.

Future work

Entrepreneurship faces financial volatility, competitive constraints, and behavioral unpredictability. The proposed framework assesses entrepreneurial risk to overcome the limitations of static risk assessment methods. DBERA delivers real-time, evidence-based insights to entrepreneurs, investors, and politicians to improve decision-making accuracy and resilience in unpredictable times. Bayesian reasoning and conditional probability updates give this information. Experimental findings using the Entrepreneurial Risk Intelligence Dataset show that DBERA predicts investment behavior, operational capacity, innovation effect, regulatory vulnerability, and competitive intensity better than other techniques.

Some drawbacks should be considered despite these advantages. First, this research only includes data from one entrepreneurial sector, and DBERA has not been tested for cross-industry or cross-country generalizability. Testing the model in other business environments will enable future research to assess its adaptability to culture, regulation, and industries. Second, unique Deep Learning-Bayesian Network hybrid designs have not been evaluated with DBERA. Nonlinear risk modeling and better feature representation may be achieved with hybrids. Thirdly, using large-scale real-world installations with hidden financial data rather than publicly accessible datasets used in previous research may improve scalability and reliability.

Future research will include automated scenario construction utilizing deep reinforcement learning, real-time streaming data (including social media indicators, market sentiment indices, and behavioral analytics), and other features for the DBERA system. We will also compare DBERA and DL-BN hybrid

models to assess performance gains. Improved generalizability, transparency, and practicality aim to make DBERA a comprehensive decision-support tool for entrepreneurs in dynamic, high-risk business situations.

Ethics statement

This study did not require ethical approval as it did not involve human or animal subjects..

Author contributions

Chengjun Zhou writing original draft preparation & methodology Chengjun Zhou investigation & writing review and editing.

Author 1: Conceptualization, methodology, model development, data analysis, and writing original draft preparation.

Author 2: Validation, experimental design, result verification, and writing review and editing.

Author 3: Dataset preparation, software implementation, visualization, and technical support.

Author 4: Supervision, project administration, funding acquisition, and final manuscript approval.

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Appendix A

Computational Validation of Core DBERA Equations to the amended article. This appendix provides Equations 2, 4, 6, and 20 the Resource Adaptability Index, Incremental State Refinement, Dynamic Risk Propagation, and Market Volatility Sensitivity and analytical results from testing and simulations. As described in Section 4.1, the Entrepreneurial Risk Intelligence Dataset was used to evaluate each equation in a realistic market and behavioral setting using Monte Carlo simulations and parameter perturbations.

The validation findings show that all tested models converge well and that simulated and theoretical outcomes differ by less than 5%. Appendix graphical examinations (Figures 1-4) demonstrate the dynamic behavior, stability under uncertainty, and empirical consistency of the suggested formulations. By linking theoretical concepts to computational results, these improvements improve the DBERA framework's methodological transparency, repeatability, and reliability.

