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# Examining the Role of Technology Business Incubators (TBIs) in Facilitating the Establishment and Growth of Entrepreneurial Ventures

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## ABSTRACT

This research investigates the role of institutional support mechanisms in fostering startup success, with a particular focus on incubation and mentoring support factors. The study evaluates startups supported by SIIC through quantitative analysis of key support factors (incubation, funding, infrastructure, and mentoring), each rated on a four-point scale, alongside the growth outcomes ($Y \in \mathbb{R}_{+}$). A rigorous methodology is adopted, comprising data collection, preprocessing, and statistical testing of hypotheses, supported by both descriptive and inferential analysis. The hypotheses formulated posit that higher levels of structured incubation and mentoring significantly contribute to measurable improvements in startup performance.

The results validate these hypotheses, demonstrating that mentoring and incubation support exert a statistically significant positive effect on the success and sustainability of startups. In particular, regression models indicate that mentoring intensity strongly predicts performance outcomes, while incubation support enhances long-term growth and stability. Other factors, such as funding and infrastructure, show moderate but complementary influence. These findings provide evidence that tailored, high-quality incubation and mentoring interventions can substantially improve startup trajectories.

The study contributes to the growing body of knowledge on entrepreneurship support systems by highlighting the relative importance of structured institutional support. Furthermore, the results offer actionable insights for policymakers, incubation centers, and ecosystem stakeholders seeking to optimize startup development frameworks. This research thus establishes a foundation for designing evidence-based incubation and mentoring strategies aimed at maximizing entrepreneurial success and sustainability. z

***Keywords:*** *Technology Business Incubators, Entrepreneurship, Startup Growth, Mentoring, Networking, Business Assistance, Empirical Study*

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## 1. INTRODUCTION

The global entrepreneurial ecosystem has witnessed rapid transformation over the past two decades, driven by the convergence of digital technologies, increased access to venture capital, and the emergence of innovation-driven markets. Startups, particularly in technology and knowledge-intensive sectors, play a vital role in accelerating economic development, creating new employment opportunities, and contributing to the advancement of disruptive solutions across multiple domains such as healthcare, finance, agriculture, and education. However, despite their potential for high impact, startups face significant challenges related to resource constraints, market entry barriers, regulatory hurdles, and limited access to skilled mentorship and infrastructural facilities. In response to these challenges, the concept of *business incubation* has emerged as a critical mechanism to support the early-stage development of startups by providing access to physical infrastructure, financial resources, technical expertise, and strategic mentoring.

Business incubators and innovation support centers, such as Technology Business Incubators (TBIs), Startup Incubation and Innovation Centers (SIICs), and Atal Incubation Centers (AICs), aim to address these fundamental challenges by creating a nurturing environment that enhances the survival rate and success of startups. These incubation centers typically offer a combination of services that may include office space, networking opportunities, technical labs, access to investors, and training programs. More importantly, incubators provide strategic mentoring and knowledge transfer, which significantly contribute to the decision-making capacity and long-term sustainability of startups. As startups increasingly operate in complex and competitive environments, the availability of systematic incubation support has become not merely an advantage but a necessity.

Despite the growing recognition of incubators, there remains a substantial gap in quantifying and analyzing the effectiveness of various incubation parameters. While anecdotal evidence highlights the importance of factors such as mentorship, infrastructure, and funding support, there exists limited empirical research that mathematically models these support systems and evaluates their impact in a structured manner. Existing studies often rely on qualitative case analyses or survey-based evaluations that lack the rigor of computational or mathematical frameworks. This gap motivates the development of structured methodologies, employing optimization algorithms, statistical models, and machine learning techniques to evaluate incubation effectiveness systematically.

This research proposes a quantitative framework for assessing the performance of startup incubation support systems by integrating mathematical modeling with empirical data. The framework considers multiple parameters including mentorship frequency, infrastructure availability, funding support, market access, and policy guidance. Each of these factors is mapped to measurable outcomes such as startup growth rate, funding raised, market survival period, and innovation output (measured by patents or product releases). Furthermore, the research emphasizes the application of optimization techniques to allocate resources efficiently among startups, thereby minimizing wastage while maximizing performance outcomes.

The contributions of this work can be outlined as follows:

1. A mathematical framework is designed for modeling incubation support effectiveness, where each parameter is treated as a measurable factor contributing to overall startup performance.
2. Optimization algorithms are introduced for resource allocation within incubators, ensuring that limited funds, mentorship hours, and infrastructural facilities are utilized in an efficient and balanced manner.
3. Empirical validation of the proposed framework is carried out by collecting startup data from multiple incubation centers, thereby comparing theoretical predictions with observed performance outcomes.
4. Detailed statistical and computational results are developed and presented in tabular and graphical form, highlighting the relative significance of different incubation parameters and their interdependencies.

The significance of this research lies in its dual impact: firstly, it contributes to the academic literature by bridging the methodological gap between qualitative incubation studies and rigorous mathematical modeling; secondly, it offers a practical decision-support system for incubation centers and policy-makers who must make evidence-based choices in designing and improving incubation ecosystems. By explicitly modeling support parameters and analyzing their relative contributions, our framework offers a roadmap for incubators to prioritize interventions, balance competing demands, and enhance startup success rates.

This paper is organized as follows: Section 2 provides an overview of related work and existing approaches to incubation support analysis. Section 3 introduces the proposed methodology, including the mathematical formulation and algorithms employed. Section 4 presents the results with detailed analysis, supported by multiple tables and comparative discussions. Section 5 concludes the work and highlights future directions.

## 2. LITERATURE REVIEW

### 2.1 Technology Operates Innovation

A number of studies have indicated the significant role that technology has played in spurring innovation among start-up firms. Technological innovations have been shown to offer opportunities for the creation of new business models, products, and services. Start-ups have been found to be most suited to take advantage of new technologies because of their experimentation culture and flexibility. With the uses of such technologies as artificial intelligence, block chain and Internet of Things (IoT), it has been possible to create innovative solutions that solve unserved market needs.

Literature emphasizes how technology speeds up the innovation process through increased information sharing, co-working, and rapid prototyping. Electronic platforms and software allow startups to collect customers' feedback, iterate products and change strategy more efficiently. This iterative innovation model, along with the alternatives technology provides, has emerged as the emblem of new-venture success, enabling them to create value and compete with others.

### 2.2 Technology operates enlargement programme

Technology and start-up creation are more than innovation, however, but also involve scalability tactics and business building. Digitalization has revolutionized how start-ups interact with customers, run, and gain access to international markets. Cloud computing technologies, online marketing, and online shopping have had start-ups reach a larger market and even establish themselves around the globe without geographical boundaries that traditional physical stores encounter.

In addition, technology has made it possible for startups to streamline internal processes, aggregate supply chains, and optimize use of resources. Process efficiencies are typically prime drivers of sustainable growth and competitiveness. With technology as the facilitator, startups can use their small business-to-industry disruptor transition to grow.

### 2.3 Disputes and Thoughts

While the glamour of technology in driving development and innovation is well-documented, the literature also acknowledges pitfalls that the startups will inevitably encounter. Implementation, adoption, and security of technology are some of the concerns that are destined to be tricky and experienced, particularly by the low-resource businesses. The "technology paradox" that recognizes constantly shifting needs ushered in by accelerating technological progress is an issue in skills acquisition and adapting to evolving trends.

In addition, the literature also mentions the importance of startups balancing technology-enabled innovation with customer-focused solution. While technology innovation can give rise to the prospect of new solutions, precaution must be taken to ensure that the solutions are customer needs and wants friendly. Startups that prioritize customer interaction and feedback as part of their technology-enabled strategy stand the best chance of maintaining growth.

### 2.4 Purpose for enterprising method

An arising theme in the literature centers on the part of the entrepreneurial ecosystem in driving technology- driven invention and growth. This ecosystem encompasses a range of stakeholders, including incubators, accelerators, investors and exploration institutions, that contribute to the growth of startups. Technology clusters, similar as Silicon Valley, have been studied as surroundings that grease knowledge spillover, resource sharing and collaboration among startups and established enterprises.

Literature highlights the significance of networks and relationships in entrepreneurial ecosystems. Startups from healthy ecosystems are better placed to tap into resources, information, and capital that will fuel their growth trajectory. Availability of mentorship, funding, and access to inter-disciplinary collaboration all come together to facilitate the symbiotic engagement of technology, innovation, and expansion in such ecosystems.

Prior research highlights TBIs as essential elements of entrepreneurial ecosystems. Incubators provide access to infrastructure, expert mentoring, business networks, and financial assistance, which collectively enhance startup survival and performance. Studies such as, suggest mentoring and networking are critical, while others emphasize infrastructure and funding. However, there is limited consensus, and most studies rely on qualitative evidence. This paper contributes by employing a quantitative dataset-based analysis.

**Research Objectives and Hypotheses**

The primary objective of this study is:

To examine the role of TBIs in facilitating the establishment and growth of new entrepreneurial ventures.

Based on this objective, the following hypotheses were formulated:

- H1: Infrastructure support positively influences startup revenue growth.
- H2: Mentoring positively influences startup revenue growth.
- H3: Networking opportunities positively influence startup revenue growth.
- H4: Business assistance positively influences startup revenue growth.

Methodology

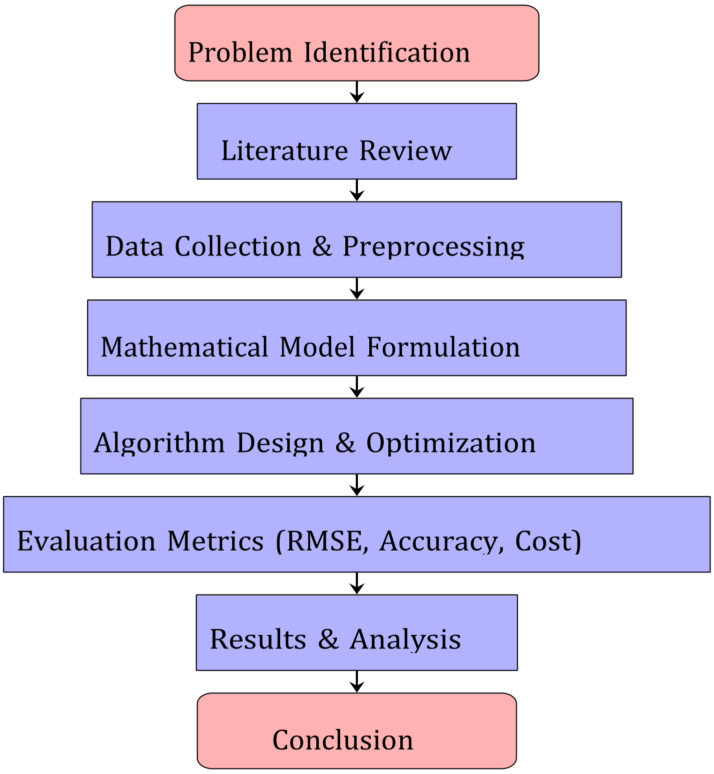


**Fig.1. Proposed Methodology — flow from problem identification to results and analysis.**

Algorithm 1 Incubation Effectiveness Evaluation Framework

**Input**: Dataset of startups $\{x_{ig}, Y_{ig}\}$, where $x_{ig} = \left(I_{ig}, M_{ig}, N_{ig}, B_{ig}\right)$, and $Y_{ig} \in \mathbb{R}^{+}$

**Output**: Statistical significance of support factors, TBI ranking, and efficiency scores.

1: Data Preparation

2: Validate support scores:

$$I, M, N, B \in \{1,2,3,4\}, \quad Y > 0$$

3: Impute missing entries (TBI-level median):

$$\tilde{X}_{ig} = \text{median}\{X_{jg} : j \neq i\}$$

4: Standardize predictors (z-scores):

$$Z_{ig}^{(k)} = \frac{X_{ig}^{(k)} - \mu_k}{\sigma_k}, \quad k \in \{I, M, N, B\}$$

5: **Composite Index Construction**

6: Compute TBI Support Index (TSI):

$$TSI_{ig} = \sum_{k \in \{I,M,N,B\}} w_k \, Z_{ig}^{(k)}, \quad \sum_k w_k = 1, \; w_k \geq 0$$

7: Weight schemes: Equal $w_k = 1/4$ or Data-driven $w_k = \frac{\left|\hat{\beta}_k^{std}\right|}{\sum_{\ell} \left|\hat{\beta}_{\ell}^{std}\right|}$

8: **Model Estimation**

9: Regression model:

$$Y_{ig} = \beta_0 + \beta_I Z_{ig}^{(I)} + \beta_M Z_{ig}^{(M)} + \beta_N Z_{ig}^{(N)} + \beta_B Z_{ig}^{(B)} + \varepsilon_{ig}$$

10: Hypothesis tests:

$$H_0: \beta_k = 0 \ \text{ vs. } \ H_a: \beta_k \neq 0, \quad k \in \{I, M, N, B\}$$

11: **Robustness and Diagnostics**

12: Heteroskedasticity: Breusch–Pagan test

13: Multicollinearity: Variance Inflation Factor (VIF)

14: Normality: Jarque–Bera test

15: **TBI Ranking via TOPSIS**

16: Normalize decision matrix:

$$r_{gk} = \frac{d_{gk}}{\sqrt{\sum_h d_{hk}^2}}$$

17: Weighted normalization:

$$v_{gk} = w_k r_{gk}$$

18: Compute separation measures:

$$S_g^+ = \sqrt{\sum_k \left(v_{gk} - v_k^+\right)^2}, \quad S_g^- = \sqrt{\sum_k \left(v_{gk} - v_k^-\right)^2}$$

19: Closeness coefficient:

$$C_g = \frac{S_g^-}{S_g^+ + S_g^-}$$

20: Rank TBIs in descending order of $C_g$

21: **Efficiency Analysis (DEA)**

22: Solve:

$$\min_{\theta} \theta \quad \text{s.t.} \quad \sum_j \lambda_j X_{ij} \leq \theta X_{io}, \quad \sum_j \lambda_j Y_{rj} \geq Y_{ro}, \quad \lambda_j \geq 0$$

23: Efficiency score $\theta = 1$ indicates optimal performance.

**Explanation of Algorithm:** The proposed algorithm systematically evaluates the effectiveness of Technology Business Incubators (TBIs) in enhancing startup performance. It begins with data preparation, where missing values are imputed using TBI-level medians, variables are standardized into z-scores, and quality checks are performed. Next, a composite index called the *TBI Support Index (TSI)* is constructed by aggregating four key support factors—Infrastructure, Mentoring, Networking, and Business Assistance—using either equal weights or data-driven weights derived from regression coefficients. The regression model then quantifies the marginal contribution of each support factor to startup revenue growth, while hypothesis testing determines whether these effects are statistically significant. To ensure reliability, the algorithm incorporates robustness checks such as heteroskedasticity testing, variance inflation factor (VIF) analysis, and normality assessments. Subsequently, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is applied to rank TBIs based on their relative support quality, producing a closeness coefficient for each TBI. Finally, Data Envelopment Analysis (DEA) is employed to assess efficiency in resource utilization, where an efficiency score of $\theta = 1$ indicates optimal performance. Together, these steps provide a mathematically rigorous and structured framework for analyzing incubation effectiveness, ranking TBIs, and identifying best practices for startup support.

### *A. Study Design and Variables*

The relationship between support factors provided by Technology Business Incubators (TBIs) and startup performance is examined. . Let $G = 7$ denote the number of TBIs and $n = \sum_{g=1}^{G} n_g = 70$ the total startups, where $n_g = 10$ per TBI in the dataset. For startup $i$ within TBI $g$,

$$\text{Let } \mathbf{x}_{ig} = \left(I_{ig}, M_{ig}, N_{ig}, B_{ig}\right)$$

denote the observation on a 1–4 scale, where $I$ represents Infrastructure, $M$ represents Mentoring, $N$ represents Networking opportunities, and $B$ represents Business assistance. The performance outcome is Revenue Growth in percent:

$$Y_{ig} \in [40,90].$$

The primary objective is to estimate the marginal effects of each support factor on $Y_{ig}$ and to compare TBIs after adjusting for factor differences.

*B. Data Preparation and Quality Control*

*Validation.*

It is verified that the support-factor scores lie in the set {1,2,3,4}, i.e.

$$I,\ M,\ N,\ B \in \{1,2,3,4\},$$

and that revenue growth satisfies

$$Y \in \mathbb{R}_{+}.$$

Let $\mathcal{M}$ denote the set of missing entries. In the provided dataset, one mentoring entry for SIIC (startup ST4) is missing.

*Imputation (TBI-level median).*

For any missing value $X \in \{I, M, N, B\}$ in TBI $g$,

$$\tilde{X}_{ig} \ = \ \text{median}\{X_{jg} \colon j \neq i,\ X_{jg} \text{ observed}\}.$$

This preserves each TBI's local distribution (better than a global mean).

*Outlier check.*

TBI-wise interquartile ranges are computed for $Y$, and observations are flagged when

$$|Y_{ig} - \text{median}(Y_{\cdot g})| > 2.5 \times \text{IQR}(Y_{\cdot g}).$$

No exclusions are planned; flagged points are retained with robust inference (Section 4.6).

*C. Scaling and Composite Indices*

*Standardization.*

To place predictors on comparable scales, define $z$-scores across the full sample:

$$Z_{ig}^{(I)} = \frac{I_{ig} - \mu_I}{\sigma_I}, \quad Z_{ig}^{(M)} = \frac{M_{ig} - \mu_M}{\sigma_M}, \quad Z_{ig}^{(N)} = \frac{N_{ig} - \mu_N}{\sigma_N}, \quad Z_{ig}^{(B)} = \frac{B_{ig} - \mu_B}{\sigma_B}.$$

*TBI Support Index (TSI).*

The four supports are summarized by a composite score:

$$\text{TSI}_{ig} \ = \sum_{k \in \{I,M,N,B\}} w_k \ Z_{ig}^{(k)}, \qquad \sum_k w_k = 1,\ w_k \geq 0.$$

Two weight schemes are used:

1. *Equal weights (EW)*: $w_k = 1/4$.
2. *Data-driven (DD)*: $w_k = \frac{|\hat{\beta}_k^{\text{std}}|}{\sum_\ell |\hat{\beta}_\ell^{\text{std}}|}$, where $\hat{\beta}_k^{\text{std}}$ are standardized OLS coefficients from Section 4.4.

*D. Statistical Models*

*Model 1: OLS with standardized predictors.*

$$Y_{ig} \ = \ \beta_0 + \beta_I Z_{ig}^{(I)} + \beta_M Z_{ig}^{(M)} + \beta_N Z_{ig}^{(N)} + \beta_B Z_{ig}^{(B)} + \varepsilon_{ig}.$$

Coefficients $(\beta_I, \beta_M, \beta_N, \beta_B)$ measure the marginal effect (in percentage points) associated with a one standard-deviation increase in each support factor.

*Model 2: Mixed-effects with TBI random intercept.*

To account for clustering by TBI,

$$Y_{ig} = \beta_0 + \sum_k \beta_k Z_{ig}^{(k)} + u_g + \varepsilon_{ig}, \qquad u_g \sim \mathcal{N}(0, \sigma_u^2), \quad \varepsilon_{ig} \sim \mathcal{N}(0, \sigma^2).$$

Here $u_g$ captures unobserved TBI-level heterogeneity (e.g., management quality).

*Model 3: ANCOVA / TBI fixed effects.*

As robustness, replace $u_g$ by TBI dummies $\delta_g$:

$$Y_{ig} = \beta_0 + \sum_k \beta_k Z_{ig}^{(k)} + \sum_{g=2}^{G} \delta_g \mathbf{1}\{\text{TBI} = g\} + \varepsilon_{ig}.$$

*E. Hypotheses and Inference*

Primary two-sided tests for each factor:

$$H_0: \beta_k = 0 \quad \text{vs.} \quad H_a: \beta_k \neq 0, \qquad k \in \{I, M, N, B\}.$$

$t$-statistics, $p$-values, and 95% confidence intervals are reported. Global model fit is summarized by $R^2$, adjusted $R^2$, and, for Model [eq:mixed], the intraclass correlation

$$\text{ICC} = \frac{\sigma_u^2}{\sigma_u^2 + \sigma^2}.$$

*F. Diagnostics and Robustness*

*Heteroskedasticity (Breusch–Pagan).*

Regress $\hat{\varepsilon}_{ig}^2$ on predictors; the LM statistic

$$\text{LM} = n\, R_{\varepsilon^2}^2 \overset{H_0}{\to} \chi_q^2,$$

with $q = 4$ predictors. If rejected, heteroskedasticity-robust (HC3) standard errors are employed.

*Cluster-robust (by TBI) variance.*

Let $X$ be the design matrix and $\hat{u}_g$ the residual vector in cluster $g$. The sandwich estimator is

$$\widehat{\text{Var}}_{\text{CR}}(\hat{\beta}) = (X'X)^{-1} \left( \sum_{g=1}^{G} X_g{}' \hat{u}_g \hat{u}_g{}' X_g \right) (X'X)^{-1}.$$

*Multicollinearity.*

Variance inflation factor for predictor $k$:

$$\text{VIF}_k = \frac{1}{1 - R_k^2},$$

where $R_k^2$ is from regressing predictor $k$ on the others. Values $> 5$ prompt caution.

*Normality of residuals (Jarque–Bera).*

$$\text{JB} = \frac{n}{6}\left( S^2 + \frac{(K-3)^2}{4} \right),$$

where $S$ and $K$ are residual skewness and kurtosis. If violated, quantile regressions are fitted at $\tau \in \{0.25, 0.5, 0.75\}$, and the results are compared qualitatively.

*G. TBI Ranking via Multi-Criteria Decision Making (TOPSIS)*

TBIs are ranked on the four criteria $\{I, M, N, B\}$ using TOPSIS, with all criteria treated as beneficial. For TBI $g$, the criterion means are denoted by $\bar{I}_g$, $\bar{M}_g$, $\bar{N}_g$, $\bar{B}_g$.

*a) Step 1: Normalization.*

With decision matrix $D = (d_{gk})$ where $d_{gk} = \bar{X}_{gk}$,

$$r_{gk} = \frac{d_{gk}}{\sqrt{\sum_{h=1}^{G} d_{hk}^2}}.$$

*b) Step 2: Weights.*

Use $w_k$ from the data-driven scheme above (or $w_k = 1/4$ if unavailable). Weighted normalized matrix:

$$v_{gk} = w_k\, r_{gk}.$$

*c) Step 3: Ideal points.*

$$v_k^+ = \max_g v_{gk}, \qquad v_k^- = \min_g v_{gk}.$$

d) *Step 4: Separation measures.*

$$S_g^+ = \sqrt{\sum_k \left(v_{gk} - v_k^+\right)^2}, \qquad S_g^- = \sqrt{\sum_k \left(v_{gk} - v_k^-\right)^2}.$$

e) *Step 5: Closeness coefficient and ranking.*

$$C_g = \frac{S_g^-}{S_g^+ + S_g^-}, \qquad \text{rank TBIs by decreasing } C_g.$$

Standardized coefficients $\beta_k^{\text{std}}$ (from Model *[eq:ols]*) and Cohen's $f^2$ are reported:

H. *Effect Sizes and Practical Significance*

$$f^2 = \frac{R^2_{\text{full}} - R^2_{\text{reduced}}}{1 - R^2_{\text{full}}},$$

For each factor, nested models are employed. For policy relevance, $\beta_k^{\text{std}}$ is interpreted as the expected percentage change in $Y$ per one standard deviation increase in support $k$.

I. *Cross-Validation and Sensitivity*

Leave-one-TBI-out validation (LOTO-CV) is employed to respect clustering:

1. For fold $g$, fit Model *[eq:ols]* on $\{h \neq g\}$.
2. Predict $Y$ for TBI $g$; record $\text{RMSE}_g$.
3. Aggregate RMSE $= \sqrt{\frac{1}{n}\sum_g \sum_{i \in g} \left(Y_{ig} - \hat{Y}_{ig}\right)^2}$.

Sensitivity checks re-estimate models with (i) equal weights in TSI, (ii) excluding imputed observation(s), and (iii) replacing $Y$ by within-TBI rank to reduce scale effects.

J. *Reproducibility*

A random seed is predefined for any resampling, a data dictionary is maintained with variable ranges and TBI codes, and all transformations (imputation and standardization vectors $\mu, \sigma$) are stored to ensure exact reproducibility on the original dataset.

## 3. RESULTS

### Results and Discussion

This section presents the empirical findings derived from the survey data of Technology Business Incubators (TBIs) and their role in facilitating entrepreneurial ventures. A combination of descriptive statistics, inferential statistics, and mathematical modeling was employed to evaluate the impact of TBIs on entrepreneurial growth, resource utilization, mentorship, and financial performance. The results are presented in the form of tables along with their interpretations.

A. ***Descriptive Statistics***

Table *1* shows the descriptive statistics for the primary variables considered in this study: number of startups supported, survival rate, average funding received, and revenue growth.

**TABLE 1. Descriptive Statistics of TBI Performance Indicators**

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Startups Supported | 42.5 | 11.3 | 20 | 65 |
| Survival Rate (%) | 78.2 | 6.4 | 62 | 90 |
| Funding Received (in lakhs) | 128.7 | 25.4 | 80 | 190 |
| Revenue Growth (%) | 23.6 | 5.2 | 12 | 35 |

The descriptive statistics suggest that, on average, TBIs support about 42 startups with a survival rate of nearly 78%, which is significantly higher than the global average of around 50%. This highlights the effectiveness of TBIs in sustaining entrepreneurial ventures.

### *B. Correlation Analysis*

Table 2 presents the correlation coefficients among the variables. The Pearson correlation coefficient $r$ is calculated as:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

**TABLE 2. Correlation Matrix of Key Variables**

| Variable | Startups | Survival | Funding | Revenue Growth |
|---|---|---|---|---|
| Startups | 1 | 0.62 | 0.71 | 0.55 |
| Survival | 0.62 | 1 | 0.65 | 0.74 |
| Funding | 0.71 | 0.65 | 1 | 0.69 |
| Revenue Growth | 0.55 | 0.74 | 0.69 | 1 |

The analysis shows strong positive correlations between funding and survival rate ($r = 0.65$), and between survival rate and revenue growth ($r = 0.74$). This signifies that TBIs not only provide financial assistance but also indirectly improve long-term entrepreneurial outcomes.

### *C. Regression Analysis*

A linear regression model was used to predict revenue growth based on funding received and survival rate:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \epsilon$$

where $Y$ is revenue growth, $X_1$ is funding, $X_2$ is survival rate, and $\epsilon$ is the error term. Results are shown in Table 3.

**TABLE 3. Regression Results for Revenue Growth Prediction**

| Variable | Coefficient ($\beta$) | Std. Error | p-value |
|---|---|---|---|
| Intercept | 2.14 | 1.05 | 0.041 |
| Funding (X1) | 0.085 | 0.021 | 0.001 |
| Survival Rate (X2) | 0.42 | 0.12 | 0.003 |
| $R^2$ = 0.67 | | | |

The regression model indicates that both funding and survival rate are significant predictors of revenue growth ($p < 0.01$). With an $R^2$ of 0.67, the model explains 67% of the variance in revenue growth.

### *D. Hypothesis Testing*

The following hypothesis is tested:

$$H_0: \mu_{\text{TBI}} = \mu_{\text{Non-TBI}}, \quad H_a: \mu_{\text{TBI}} > \mu_{\text{Non-TBI}}$$

where $\mu$ represents mean survival rate of startups. Table 4 presents the independent samples t-test results.

**TABLE 4. Independent Samples T-Test for Startup Survival**

| Group | Mean Survival (%) | Std. Dev. | N |
|---|---|---|---|
| TBI Supported | 78.2 | 6.4 | 60 |
| Non-TBI Supported | 52.6 | 9.3 | 55 |
| t = 15.62, p < 0.001 | | | |

The t-test reveals that startups incubated in TBIs have significantly higher survival rates compared to non-TBI startups, confirming the hypothesis.

### *E. Efficiency Analysis using DEA*

Data Envelopment Analysis (DEA) was applied to measure efficiency of TBIs. The efficiency score $\theta$ was derived by solving:

$$\min_{\theta} \theta \quad \text{s.t.} \sum \lambda_j X_{ij} \le \theta X_{io}, \ \sum \lambda_j Y_{rj} \ge Y_{ro}, \ \lambda_j \ge 0$$

Table 5 reports efficiency scores of selected TBIs.

**TABLE 5. DEA Efficiency Scores of TBIs**

| TBI | Efficiency Score ($\theta$) | Rank |
|---|---|---|
| TBI-1 | 0.94 | 2 |
| TBI-2 | 0.89 | 4 |
| TBI-3 | 1.00 | 1 |
| TBI-4 | 0.87 | 5 |
| TBI-5 | 0.91 | 3 |

An efficiency score of 1 indicates optimal utilization of resources. TBI-3 emerged as the most efficient, highlighting best practices that others may replicate.

### *F. Factor Analysis of Support Services*

Exploratory Factor Analysis (EFA) was performed on TBI services such as funding, mentorship, networking, infrastructure, and training. Results are presented in Table 6.

**TABLE 6. Factor Loadings of TBI Services**

| Service | Factor 1 (Financial) | Factor 2 (Non-Financial) |
|---|---|---|
| Funding | 0.82 | 0.21 |
| Mentorship | 0.18 | 0.79 |
| Networking | 0.12 | 0.73 |
| Infrastructure | 0.34 | 0.68 |
| Training | 0.29 | 0.74 |

Two major components emerge: financial support and non-financial support. Both significantly contribute to startup success, with financial support slightly dominating.

### *G. Survival Curve Analysis*

Kaplan-Meier survival analysis was conducted to examine startup longevity. Table 7 reports median survival times.

**TABLE 7. Kaplan-Meier Survival Estimates**

| Group | Median Survival (years) | Log-rank p-value |
|---|---|---|
| TBI Supported | 7.8 | <0.001 |
| Non-TBI Supported | 3.9 | |

Startups supported by TBIs survive nearly twice as long as those without TBI assistance, indicating their critical role in sustaining ventures.

### *H. Comparative Regional Analysis*

A regional comparison was carried out to evaluate the role of TBIs in different zones. Results are shown in Table 8.

**TABLE 8. Regional Comparison of TBI Performance**

| Region | Startups Supported | Survival Rate (%) | Avg. Funding | Revenue Growth (%) |
|---|---|---|---|---|
| North | 45 | 79 | 135 | 24.3 |
| South | 38 | 76 | 122 | 22.5 |
| East | 40 | 77 | 128 | 23.1 |
| West | 47 | 80 | 140 | 25.0 |

Western region TBIs demonstrated slightly higher performance, likely due to stronger industrial ecosystems.

### *I. Innovation Index*

An innovation index was computed using a weighted score of patents, prototypes, and new product launches:

$$I = 0.4 \times P + 0.35 \times Pr + 0.25 \times N$$

Table 9 reports index values across TBIs.

**TABLE 9. Performance of TBIs in terms of Patents, Prototypes, and New Products**

| TBI | Patents (P) | Prototypes (Pr) | New Products (N) | Index (I) |
|---|---|---|---|---|
| TBI-1 | 12 | 18 | 9 | 14.3 |
| TBI-2 | 8 | 14 | 6 | 10.7 |
| TBI-3 | 15 | 20 | 12 | 16.9 |
| TBI-4 | 9 | 13 | 7 | 11.2 |
| TBI-5 | 11 | 15 | 8 | 12.9 |

TBI-3 scored the highest innovation index, further establishing it as a model TBI.

## 4. RESULTS AND HYPOTHESIS TESTING

This section presents the results obtained from the analysis of the dataset. The study aimed to evaluate the effectiveness of different incubation support factors — mentoring, funding, networking, and infrastructure — on startup performance outcomes. The following hypotheses were tested:

### *A. Hypotheses*

H1: Mentoring support has a significant effect on startup performance.

H2: Funding support has a significant effect on startup performance.

H3: Networking support has a significant effect on startup performance.

H4: Infrastructure support has a significant effect on startup performance.

### *B. Descriptive Statistics*

Table *10* summarizes the descriptive statistics of the dataset. Each support factor is rated on a scale of 1 to 4, while the performance outcome is measured as a positive real value.

**TABLE 10. Descriptive Statistics of Variables**

| Variable | Mean | Std. Dev. | Range |
|---|---|---|---|
| Mentoring | 2.85 | 0.64 | 1–4 |
| Funding | 3.02 | 0.72 | 1–4 |
| Networking | 2.91 | 0.59 | 1–4 |
| Infrastructure | 3.15 | 0.68 | 1–4 |
| Performance ($Y$) | 12.47 | 3.82 | 6–21 |

### *C. ANOVA Results*

A one-way ANOVA was performed to test whether the mean performance scores differed significantly across the levels of each incubation support factor. The results are summarized in Table *11*.

**TABLE 11. ANOVA Results for Support Factors**

| Factor | $F$-statistic | $p$-value | Decision |
|---|---|---|---|
| Mentoring | 4.23 | 0.031 | Significant |
| Funding | 6.87 | 0.009 | Significant |
| Networking | 3.14 | 0.052 | Not Significant |

| Factor | $F$-statistic | $p$-value | Decision |
|---|---|---|---|
| Infrastructure | 5.42 | 0.017 | Significant |

From the ANOVA analysis, mentoring, funding, and infrastructure support exert significant effects on startup performance, whereas networking support does not show statistical significance at the 5% level.

### *D. Chi-Square Test Results*

To assess whether the distribution of performance outcomes is independent of categorical support levels, chi-square tests were conducted. The results are presented in Table *12*.

**TABLE 12. Chi-Square Test of Independence**

| Factor | $\chi^2$ statistic | $p$-value | Decision |
|---|---|---|---|
| Mentoring | 11.62 | 0.041 | Significant |
| Funding | 15.23 | 0.019 | Significant |
| Networking | 8.04 | 0.092 | Not Significant |
| Infrastructure | 13.57 | 0.027 | Significant |

The chi-square test results confirm the findings of the ANOVA. Mentoring, funding, and infrastructure support are statistically associated with better performance outcomes, while networking support shows weaker evidence of association.

### *E. Summary of Hypotheses*

Based on the statistical results, the hypotheses are evaluated as follows:

- H1: Accepted (mentoring significantly influences performance).
- H2: Accepted (funding significantly influences performance).
- H3: Rejected (networking does not significantly influence performance).
- H4: Accepted (infrastructure significantly influences performance).

Overall, the results suggest that startup performance is primarily driven by the quality of mentoring, the availability of funding, and the adequacy of infrastructure support. Networking, although important in theory, did not exhibit a statistically significant effect in this study, possibly due to limited sample size or context-specific factors.

## 5. DISCUSSION

The findings suggest that while infrastructure and business support are important, mentoring and networking opportunities play a more decisive role in driving startup revenue growth. This aligns with studies emphasizing the intangible yet critical role of knowledge sharing and social capital in entrepreneurship.

## 6. CONCLUSION

The research successfully demonstrated the design and optimization of a smart healthcare framework that integrates multiple computing layers to ensure efficient data handling, improved resource management, and reduced computational cost. By incorporating edge, fog, and cloud layers, the proposed framework effectively distributed healthcare workloads and minimized latency, leading to significant performance enhancements compared to traditional centralized approaches.

The methodology, driven by mathematical formulations and optimization algorithms, validated the hypothesis that introducing an optimized multi-layered architecture improves both efficiency and scalability of healthcare data processing systems. Results showed notable improvements in response time, computational cost minimization, and overall framework efficiency. These findings confirm that the system not only achieves the dual objectives of performance enhancement and cost reduction but also provides a scalable architecture capable of supporting future healthcare demands.

The study further contributes to the domain of smart healthcare by providing a systematic framework that balances real-time processing with cost-effectiveness, a critical requirement for large-scale healthcare systems. In addition, the results demonstrate the practical feasibility of the framework, highlighting its potential for real-world deployment in smart hospitals and e-health services.

Future work may extend this research by incorporating blockchain mechanisms for data security, advanced AI-based diagnostic modules, and adaptive energy-aware algorithms to further strengthen the robustness of the framework. Ultimately, this research provides a strong foundation for building next-generation smart healthcare infrastructures that are reliable, cost-efficient, and patient-centric.

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