Tech Startup Failure in India: Do Lifecycle Stages Matter?

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Abstract

Tech startups bring innovative products and services to the market, and entrepreneurs manage numerous challenges across startups' lifecycle stages. More than 90% of the startups experience failure despite the support from a startup ecosystem, and therefore, it throws open the following research questions. Why do tech startups fail? What are the causal attributes of startup failure across the lifecycle stages? What are the causal attributes that differentiate a failed tech startup from a successful one? Against this backdrop, this comprehensive study explored the causal attributes of startup failures in India, with the following two specific objectives: (i) Do causal factors vary within the lifecycle stage? and (ii) What are the attributes that differentiate a failed tech startup from a successful one?

We gathered primary data from 151 cofounders and analyzed using binomial logistic regression and identified causal attributes of startup failures. The startup's lifecycle stage plays a significant role and implies how entrepreneurs prioritize and allocate resources to maximize their returns. The other causal attributes that are statistically significant are revenue, product market fit, product roadmap, market promotion, conflict with investors, level of confidence at execution, extent of focus on current startups, and entrepreneur's experience level.

Keywords: Startup, Causal attributes, Failure, Entrepreneurship, Lifecycle

1 Introduction

Tech startups leverage innovation in product or service delivery and bestow creative utilization of entrepreneurs' potential. Consequently, entrepreneurs experience multiple challenges in their entrepreneurial journey (Roininen & Ylinenpaa, 2009). The challenges vary, right from idea generation, developing the proof of concept, identifying the initial customer, establishing product market fit, acquiring human resources, seeking potential investors, commercializing the product, realizing revenue, exploring a new market, and scaling up operations for regional and global growth. However, entrepreneurs try to address the challenges with resources available to them (internal factors) and also try to leverage the ecosystem's resources (external factors) (Amankwah-amoah, 2016; Pardo & Alfonso, 2017). If an entrepreneur fails to address the challenges, the startup experiences failure (Watson & Everett, 1996). About 90% of startups fail due to the lack of innovation, as observed in the US (Forbes, 2017). The phenomenon is the same in the Indian context. Moreover, 90% of startups fail in the first five years (Businessline, 2017). The situation may not be widely different in other economies (Startup Genome, 2019). Failure has lessons to offer to the entrepreneurs, the startups created by them, and the ecosystem in which the startups operate, apart from policy makers. This brings out the need and significance to examine the causal attributes of tech startup failures.

The startup failure phenomenon needs exploration with the following key research questions: Why do tech startups fail? What are the causal attributes of startup failure across the lifecycle stages? Do the causal attributes vary within the lifecycle stages? What are the causal attributes that differentiate failed tech startups from the successful ones? This research paper attempts to answer these questions based on primary data gathered from 151 cofounders. The startups are from India's six major startup hubs, and they are spread across the different lifecycle stages.

This paper has six sections. Section two deals with reviewing the literature relevant to startup failures to ascertain critical research gaps and propose a conceptual framework for the study. Section three describes the method of analysis and definitions of key variables. Section four talks about data collection, scope, and sampling. Section five presents the analyses and discussion using binomial logistic regression. Section six summarizes the findings of the study, followed by contributions, and its implications.

1.1 Objectives

This study on tech startup failures aimed to understand the following two specific objectives:

i. Do causal factors vary within the lifecycle stages?
ii. What are the attributes that differentiate a failed tech startup from a successful one?

These objectives will help us identify the causal attributes responsible for the critical incident leading to startup failures, against the successful ones, across its three different life cycle stages (Bala Subrahmanya, 2017).

2 Literature Review

Over the last decade, significant literature has sprouted around startup failure and the causal factors of startup failure, and we will explore the same.

2.1 Startup failure

In entrepreneurship research, the definition of startup failure has become an essential topic of discussion with various versions. Failure is the inability of an entrepreneur to achieve the desired results. The startup undergoes a steady decline in revenue and an increase in operational costs (Politis & Gabrielsson, 2007). Failure represents the termination or cessation of a startup operation (Cotterill, 2012a). Considering the planned exit strategy (R. Carter & Van Auken, 2006) and forced exits (Headd, 2003), these definitions of failure are insufficient. Failed startups take different exit routes (Jenkins & McKelvie, 2016), and therefore there is a need for a comprehensive definition of failure for this study. Failure is when the firm ceases operations and loses its identity because of its inability to adapt to market dynamics (Amankwah-amoah, 2016). After a careful review of startup failure characterizations, we have chosen the definition of Amankwah-Amoah (2016) as it comprises cessation of operation of the startup and the loss of its identity.

2.2 Startup lifecycle stages

Startup formation has a lifecycle, and it goes through a series of stages requiring a precise execution (N. M. Carter et al., 1996). We reviewed the following three options for stages:
Five stage model - Inception, Survival, Growth, Expansion, and Maturity (Scott & Bruce, 1987)
Four stage model - Conception, Gestation, Infancy, and Adolescence (Kessler et al., 2012)
Three stage model - Emergence, Survival, and Growth (Bala Subrahmanya, 2017)
After reviewing these models, we chose the three-stage model, mainly because it establishes distinct and mutually exclusive measurement criteria for each stage. To understand the critical activities involved in each of these three progressive stages, what each one focuses on has been summarized here.
Emergence: In this stage, the focus is on developing a proof of concept(POC), a prototype, and a minimum viable product (MVP). The key milestones are customer testing and market identification. The startup strives to establish the product market fit (PMF), and the startup is yet to earn revenue.
Stability: The focus gradually shifts to keeping the paying customer with consistent delivery in this stage. The key milestones are attracting repeat customers and market penetration with additional customers. The startup tries to establish an organizational framework for delivery. It continues to operate below break-even volume while earning revenue and incurring losses.
Growth: This stage establishes that the enterprise has gained ground and the focus shifts to increasing the market share. The key milestones are the scale of operations and market expansion. The market expansion effort results in crossing the break-even volume and earning a steady profit.

2.3 Startup formation and critical incident leading to a startup failure

The startup formation requires the triangulation of behavioral characteristics of an entrepreneur, firm-level internal factors, and external factors leveraged by an entrepreneur:
Firstly, entrepreneurs hone their professional skills and exhibit specific behavioral characteristics. We focus on three distinct attributes: Confidence from Hubris theory (Hayward et al., 2006), the risk-seeking ability from Prospect theory (Kahneman & Tversky, 1979; Shepherd & Kuratko, 2009), and decision-making ability from Real options theory (Mcgrath, 1999).
Second, entrepreneurs command firm-level internal factors (Amankwah-amoah, 2016) under their control, such as finance, product, marketing, organization, human resources, and environment (Pardo & Alfonso, 2017).
Third, entrepreneurs effectively leverage an ecosystem's components, such as mentorship, formal institutions, infrastructure amenities, and information technology (Audretsch & Belitski, 2017). Entrepreneurs do not have any control over such resources and are hence known as external factors. The startup creation happens when an entrepreneur fusions these three factors competently. But it poses several challenges, which requires an elaboration.

2.3.1 Behavioral characteristics

Professional entrepreneurs may be a novice with their maiden startup, whereas serial entrepreneurs, with a sequential startup, might go on a spree. They include portfolio entrepreneurs, who have a basket of startups, or hybrid entrepreneurs, who engage in entrepreneurship while maintaining wage work (Khelil, 2016). The initiation into entrepreneurial activity requires entrepreneurs to overcome the fear of failure; one should have the confidence (Hubris theory) to confront unknown territory. They would encounter the outcome that may involve risk (Prospect theory), and there would be a need to exhibit courage in their decision making (Real options theory). Entrepreneurs exhibit key behavioral characteristics in establishing and executing a startup, such as overconfidence, risk-seeking ability, and being decisive. While these characteristics are critical and responsible for launching a startup, we can find how the same entrepreneur's characteristics are detrimental during a startup's execution, especially when there is a downward spiral. We have understood that an entrepreneur's behavioral elements are essential for startup creation and have also seen that these characteristics' flipside leads to a startup failure. After the entrepreneur's behavioral characteristics, we will understand the internal factors.

2.3.2 Internal factors/attributes

An entrepreneur has limited resources, and they need to allocate the resources judiciously to maximize the returns to meet their business plan. The proportion of factor/attribute requirements varies based on the startup's lifecycle stage. The effective delivery of a product or service requires an entrepreneur to provide and control the internal factors at different lifecycle stages. They command resources such as finance, product, market, organizational, human resources, and environment, and they can vary the same to get the desired outcome (Bajwa et al., 2017; Khelil, 2016; Pardo & Alfonso, 2017). The internal factors are limited, and entrepreneurial execution requires applying the resources judiciously to a varying magnitude at different stages to maximize the returns. They have command over it and can vary it to achieve the desired result. While an entrepreneur uses internal factors, they will always be interested in leveraging the benefits they can gain from an ecosystem. Reaping the benefits from the startup ecosystem necessitates an understanding of the external factors.

2.3.3 External attributes

An entrepreneur tries to leverage an ecosystem's components such as mentorship, formal institutions, infrastructure amenities, and information technology (Audretsch & Belitski, 2017). These resources that are not controlled, but leveraged by entrepreneurs, are known as external factors (Khelil, 2016; Watson & Everett, 1996). The availability of infrastructure through tech incubators, accelerators, and coworking spaces enables entrepreneurs to initiate their startups with minimal establishment costs. The exposure and consumption of products/services in the market provide quick validation of the idea. Financial assistance through different government and private grants encourages entrepreneurs to exhibit a competitive edge. The educational institution helps in validating research as much as in the initiation and commercialization of ideas.

We have understood that the startup lifecycle requires the triangulation of entrepreneur behavioral characteristics, deploying internal factors efficiently, and availing ecosystem leverage by an entrepreneur. When the triangulation fails, and the challenges remain unaddressed, it may lead to a critical incident causing a startup failure. We will proceed to understand "Critical Incident," causing startup failures.

2.3.4 The critical incident leading to startup failure

As entrepreneurs have limited resources, they need to allocate the resources judiciously to maximize the returns. Uncertainty surrounding the decisions can lead to actions or inactions (Shepherd, 2003). There are two possible conditions: first, failing to act when action is required; and second, acting when inaction is needed. The above conditions can trigger the "Critical Incident," leading to a startup failure. The critical incident can be a single episode or a series of episodes whose complexity is influenced by multiple attributes. One episode triggering a few more series of episodes can lead to catastrophic situations, and the complexity escalates, cumulatively leading to a startup failure. As entrepreneurs are emotionally attached to the venture, the struggle for survival precedes the actual failure event (Cotterill, 2012b). The steep learning curve of an entrepreneur and the lasting memories help to describe what is known as a critical incident (Cope & Watts, 2000). The harsh and expensive lessons learned by an entrepreneur involve intense feelings, and they experience the emotional event of grief recovery (Cope, 2011).

Attribution is the process by which an entrepreneur explains the causes of the critical incident. In identifying the causes of failure, there is a need to understand the entrepreneurial execution and manage the attributes efficiently (Pardo & Alfonso, 2017). A cause indicates the reason, and attribution represents the perceived cause. An

entrepreneur's perception of why the startup had failed determines what attributes acted as the cause. Entrepreneurs elaborate at the attribute level (behavioral characteristics, firm-level internal factors/attributes, and ecosystem leverage availed) and identify the causes of a startup failure. With a detailed understanding of startup failure literature, it is imperative to identify the critical research gaps.

2.4 Gaps in the literature

The literature review provided a broad overview of startup failure and the need to study it comprehensively.
Firstly, to identify the attributes causing startup failures, causal attribution is required. The systematic literature review (Amankwah-amoah, 2016; Kraus et al., 2020) and the synthesis of a conceptual framework (Amankwah-amoah, 2016; Klimas et al., 2020; Pardo & Alfonso, 2017) provide this landscape for the causal analysis. The empirical investigation of this conceptual framework with additional components will help identify startup failure's causal attributes.
Secondly, the startup failure analyses (R. Carter & Van Auken, 2006; Pardo & Alfonso, 2017) consider startups a single entity (Headd, 2003; Watson & Everett, 1996). It is pertinent to break the startup evolution as challenges vary in magnitude across startup lifecycle stages (Bala Subrahmanya, 2017). There is limited empirical research delving into the causal factors and attributes of tech startup failures at different lifecycle stages. The causal attributes' understanding by startup lifecycle stages can help the stakeholders to plan their actions proactively.
To sum up, the research gap focusing on startup failures' causal attributes is addressed by trifurcating a startup evolution by its lifecycle stages. Keeping this in view, we have formulated a conceptual framework linking the key attributes leading to a critical incident/s, thereby causing startup failures.

2.5 Conceptual framework

In the light of the research gaps identified, we have proposed the following conceptual framework.

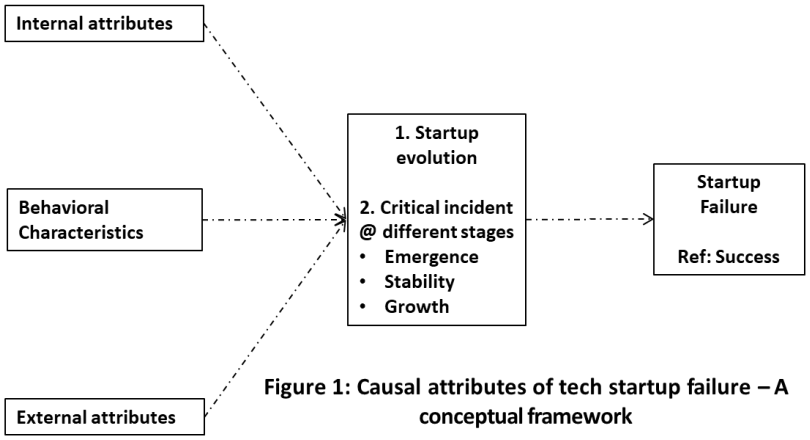


Figure 1: Causal attributes of tech startup failure – A conceptual framework

Firstly, the integrative process framework (Amankwah-amoah, 2016) covers both internal factors and external factors. The attributions based structure model (Pardo & Alfonso, 2017) provides a landscape detailing internal factors at an attribute level and behavioral characteristics. The triangulation of behavioral characteristics, firm-level internal attributes, and ecosystem external attributes leveraged by an entrepreneur is comprehensively addressed in the conceptual framework (Figure 1). We will examine the role of an entrepreneur's behavioral characteristics, such as confidence, risk seeking ability, and decision making ability at initiation and execution. The role of internal attributes controlled by an entrepreneur, such as finance, product, marketing, organizational, human resources, and internal environment, may lead to startup failures and must be investigated at an attribute level. We will also explore the impact of external attributes leading to startup failures.

Secondly, the startup lifecycle stages are introduced in the startup evolution and managing the execution (Bala Subrahmanya, 2017). The challenges vary across the lifecycle stages, which triggers the critical incident leading to startup failures when not addressed. The lifecycle stages are defined as follows: Emergence is the first stage where the startup does not earn any revenue, while stability is one in which it makes revenue but is not yet profitable. On the other hand, growth is a stage where the startup has established a revenue stream and operates with profits. Thus, this study proposes to explore the two research questions within this conceptual framework, with clearly demarcated stages of startup evolution. The methodology for the study is explained in the following section.

3 Method of Analysis

The binomial logistic regression models estimate the probability of an event, predict variables' effect and classify observations into specific categories. This technique provides the odds of seeing an event, given a vector of regression predictor variables, either categorical or numerical. This regression equation expresses the predictor variables in logarithmic terms and thereby overcomes linearity violations. Outcome variable Y is dichotomous and ranges from 0 to 1, and Predictor variables X's can be categorical/numerical and ranges from -∞ to +∞

$$\ln(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_{2+} \ldots\ldots + \beta_n X_n \quad (1)$$

$$\ln(p / (1 - p)) = \beta_0 + \beta_1 X_1 + \beta_2 X_{2+} \ldots\ldots + \beta_n X_n \quad (2)$$

We will review the model fit measures and predictive measures for binomial logistic regression which are given in Table 1, in our analysis.

Table 1: Model fit measures and predictive measures

Model	Model Summary				Overall Model Test			HL Test	Predictive Measures	
	Deviance	R^2McF	R^2CS	R^2N	χ^2	df	p	p	Accuracy	AUC
Model Threshold for measures							< 0.05	> 0.05	> 0.8	> 0.85

Model fit measures

Deviance: -2 Log Likelihood

R^2_{McF}: McFadden R^2, **R^2_{CS}**: Cox & Snell R^2, **R^2_N**: Nagelkerke R^2: the pseudo R^2 indicates the percentage of variance accounted by the model.

χ^2, df, p: Overall model test and the low p-value indicate the model's statistical significance. We considered a threshold for accuracy below 0.05 for the p-value.

Hosmer and Lemeshow (HL) Test: The goodness of fit test indicates, how well the data fits the model. A low p-value will reveal the model is a poor fit. We considered a threshold for accuracy above 0.05 for the p-value.

Predictive measures

Accuracy indicates how far the model can predict the outcome, and we considered a threshold value of 0.8. Area Under the Curve (AUC) represent how far the model works well across the sample, and we considered a threshold value of 0.85. We will infer statistically significant attributes odds ratio provided by Exp(β) and confirm the directionality of the relation at 95% confidence interval. The value exp(β) < 1 would indicate that the outcome and predictor variables are negatively correlated, and exp(β) > 1 would indicate that the outcome and predictor variables are positively correlated. For this study, we used binomial logistic regression to explore the two objectives and ascertain the attributes that determine startup failures. It is pertinent to describe the variables required for the analysis.

3.1 Variables

The outcome variables, predictor variables, and control variables are defined as follows.

3.1.1 Outcome variables

Status: We have 101 failed startups with an exit event and 50 successful startups continuing their operations

3.1.2 Predictor variables

Startup lifecycle stages: Emergence, Stability, and Growth.

Internal attributes: The factors controlled by the entrepreneur are under six groups (with 33 attributes): Finance (7), Product (5), Marketing (5), organization (6), HR (4), and environment (6). The numbers in brackets show the number of causal attributes on a Likert scale of 1 to 5.

Entrepreneur behavioral characteristics: An entrepreneur exhibits specific behavioral characteristics in initiating and executing a startup, such as overconfidence, risk seeking ability, and being decisive.

External attributes: The factors leveraged by the entrepreneur are beyond his control, such as mentorship, seed grants, government policy benefits, and infrastructure availed.

3.1.3 Control variables

Startup Profile: We identified nine different startup profile attributes from the literature.

Entrepreneur Profile: We identified nine different entrepreneurial profile attributes from the literature.

3.2 Analysis approach

Since the number of predictor variables and control variables are on the higher side, the non-parametric Kruskal Wallis (KW) test will be used to identify the significant attributes. The statistically significant attributes of respective models will get into the binomial logistic regression model as predictor variables. We followed the stepwise backward conditional elimination method of binomial logistic regression. Only for model D4, the stage has been entered as an additional factor. For the statistically significant attributes with a low p-value, the odds ratio was inferred and interpreted with qualitative comments.

4 Data collection

4.1 Scope

India is the third biggest startup hub globally, as per the National Association of Software and Service Companies (NASSCOM, 2019). India is home to 31 unicorns (*Unicorn Startups in India | Venture Intelligence*, 2020), it has an exceptional talent pool, investors at different levels, and incubators with rapidly growing startup ecosystems. The presence of startups across deep tech and emerging tech, across significant business verticals, is a salient feature of the Indian startup ecosystem. Over the last five years, India has six established startup hubs with 51% CAGR, four emerging startup hubs with 55% CAGR, and four nascent startup hubs with 45% CAGR (NASSCOM, 2019). This report classifies the six Tier-one cities as established startup hubs: Bangalore, Delhi NCR, Mumbai, Pune, Chennai, and Hyderabad, and this study covers all of them. Incidentally, these six cities are also part of the Startup Genome report 2020, and it vindicates the sample selection.

4.2 Sampling

The sampling unit was a startup represented by one cofounder (CxO). We chose the sample startups from NASSCOM, LinkedIn, and the Department of Industrial Policy & Promotion (DIPP) databases. The data collection was carried out with a cofounder, a key informant, and had complete knowledge of their startup's evolution resulting in their success/failure. The cofounders share their entrepreneurial journey and provided quantitative data supported by qualitative narrations.

4.3 Data sources

India's brand identity that was once perceived as the world's back office has now transformed. The emergence and rapid expansion of the startup ecosystem in the last decade has forged a new identity, a knowledge-intensive delivery hub of both products and services. The Indian startup ecosystem is evolving at a rapid pace over the last decade. Although this growth is a positive sign, the dearth of authentic data and reliable sources are issues we have to contend with. The critical incident and startup exit analysis is an unexplored territory, as official or private data sources are non-existent. We chose the primary data collection method to gather data through semi-structured questionnaires and in-depth interviews with cofounders against this backdrop. The semi-structured questionnaire included the following sections: Startup profile, entrepreneur profile, entrepreneurs' behavioral characteristics, ecosystem leverage availed by the startup, firm-level internal factors followed by details of startup and entrepreneur exit information

The cofounders were reached out through various available channels for establishing the connection such as emails, Incubator, LinkedIn messaging, professional network, and NASSCOM. We did the follow-up mechanisms through WhatsApp and SMS messaging. We calendared the interview appointment, and through personal/telephonic interviews, we gathered qualitative and quantitative data. We experienced more challenges in data collection, and we professionally handled the experience of multiple rejections, rescheduling, and cancellation of interviews. Failure tolerance varies across geography, and it seems to be a cultural phenomenon, being high in the US and low in the UK (Cope et al., 2004; Cotterill, 2012b; Shepherd & Haynie, 2011). Whereas in India, there is a stigma attached to it which posed severe challenges for primary data collection, which we overcame with hard efforts and perseverance.
We collected primary data from 151 cofounders. We applied Slovin's formula and identified the confidence level at 92% with 151 data points. The study period corresponds to startups incorporated between January 2010 to June 2020, while the data collection period ranged from January 2019 to June 2020.

We checked the instrument's reliability on the 33 internal attributes, and the coefficient of reliability is at 0.737, indicated by Cronbach's alpha. As the value is significant (more than 0.7), it confirms the responses' unidimensionality and acceptability for further analysis. We have checked on the absence of common method bias using Harman's single factor test. The result was 9.71%, which is well below the 50% acceptable limit. With these two validations we proceeded further for a detailed statistical analysis.

5 Analysis results and discussion

We performed the preliminary analysis, explored the landscape of outcome variables, and analyzed predictor variables using the variable of importance analysis before we embark on the sophisticated binomial logistic regression.

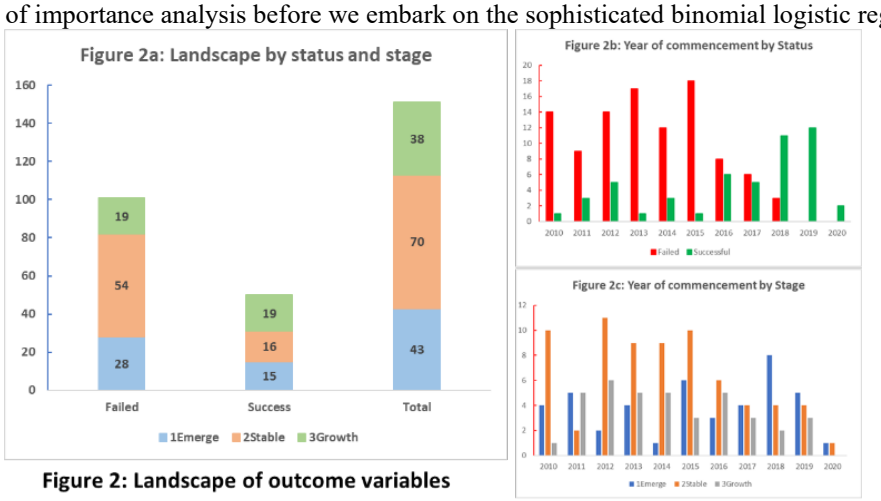


Figure 2: Landscape of outcome variables

5.1 Preliminary analysis

5.1.1 The landscape of outcome variables

We explored the landscape of outcome variables, namely, status and stages. Figures 2a, 2b, and 2c present the different dimensions of the startup's landscape. Figure 2a represents the failed and successful startups, which are segmented by the startup's lifecycle stage.

Ho: There is no association between the status and stage of the startup

Ha: There is an association between the status and stage of the startup

Our results indicate that there is a significant association between stage and status. They are not independent, and stage has a moderate effect (0.234) on status and it is evident from X^2 (2, N = 151) = 8.278, p = .016.

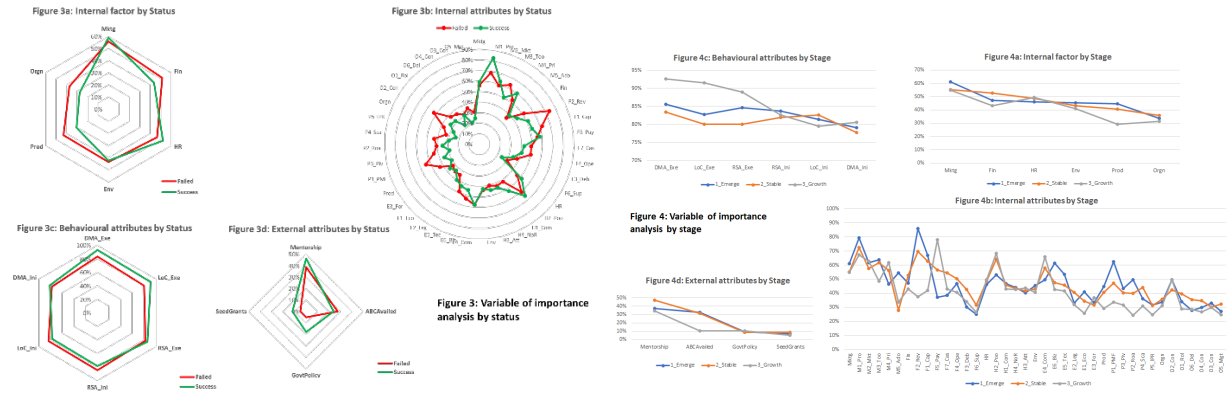
5.1.2 Visual inspection of predictor variables

We performed the variable of importance analysis of the predictor variable, dissecting it by status and stages. The predictor variables factor and attribute scores were arrived and plotted in graphs.

- Factor average = Factor Average converted to a percentage
- Attribute average = Attribute average converted to a percentage

5.1.3 Variable of importance by status

The radar charts by status are depicted in figures 3a, 3b, 3c, and 3d, along with the following inferences.



Internal factors in figure 3a and attributes in 3b: We observed a significant difference for failed vs. successful startups on finance, product, and organization. The attributes corresponding to the same factors show a variance.

Behavioral attributes in figure 3c: We observed the risk seeking ability and level of confidence at initiation are higher for the cofounders who have experienced tech startup failure. The decision-making and level of confidence at execution are lower for entrepreneurs who have experienced failure.

External attributes in figure 3d: The failed startups do not leverage the seed grants and government policy benefits. as much as the successful ones.

5.1.4 Variable of importance by stages

The radar charts by stages are presented in figures 4a, 4b, 4c, and 4d, along with the following inferences.
Internal factors in figure 4a and attributes in 4b: We observed a significant difference over the lifecycle stages on finance and product. The attributes corresponding to the same factors are showing a variance.
Behavioral attributes in figure 4c: All the three at execution vary significantly by startup lifecycle stage.
External attributes in figure 4d: The mentorship and ABC (Accelerator, Business incubator, and Coworking) availed by entrepreneurs vary significantly by stage.
The visual inspection through the variable of importance analysis indicates that the causal attributes vary between successful and failed startups by status and stage. The above observations set the platform for studying the startup failure phenomenon more intensely.

5.2 Causal attributes of startup failure

The startup failure phenomenon has considerable complexity. We propose the following hypotheses to explore the causal attributes of startup failure:

Ho: The causal attributes do not vary within the lifecycle stages of failed startups relative to successful startups.
Ha1: The causal attributes vary within the lifecycle stages.
Ha2: The causal attributes vary for failed startups relative to the successful ones.
Startup failure phenomenon is complex, and we need to segment the analysis into logical constituents (Figure 5): The attributes that differentiate failed startups from the successful ones within each of the three stages, namely: D1: Emergence, D2: Stability, and D3: Growth; followed by the attributes that differentiate overall, i.e., D4: Failed Vs Success

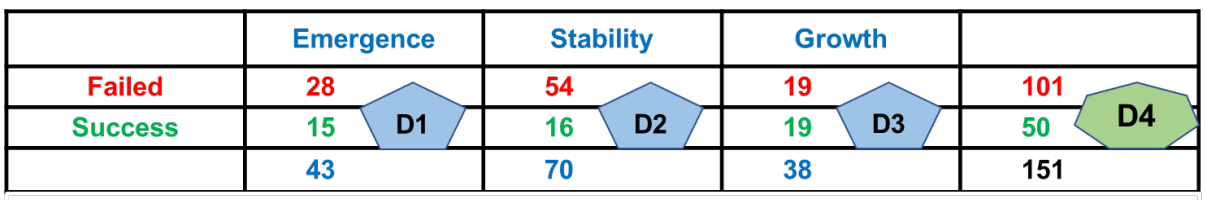


Figure 5: Analysis approach

5.2.1 What attributes differentiate failed Vs successful startups within stage and overall?

A summary of model fit measures and predictive measures of all the four models are presented in Table 2. The deviance and pseudo R^2 indicate that the percentage of variance accounted by the models are significant. The overall model test with a low p-value below 0.05 across all the models and HL test p-value above 0.05 confirm the model's statistical significance. The predictive measure threshold of accuracy above 0.8 and AUC above 0.85 vindicate the model's statistical significance. The detailed discussion on each of these models are in order:

Table 2: Summary of model fit measures and predictive measures across startup lifecycle stages

	Model	Model Summary				Overall Model Test			HL Test	Predictive Measures	
		Deviance	R^2McF	R^2CS	R^2N	χ^2	df	p	p	Accuracy	AUC
Within Stage	D1	25.8	0.54	0.50	0.69	29.8	4	< .001	0.780	0.91	0.93
	D2	44.5	0.41	0.36	0.54	30.8	5	< .001	0.224	0.90	0.88
	D3	16.3	0.69	0.62	0.82	36.3	4	< .001	0.748	0.90	0.97
Failed Vs Success	D4	115.0	0.40	0.40	0.56	77.1	10	< .001	0.337	0.83	0.89

5.2.2 D1: Emergence stage

The emergence stage startups have not earned revenue. We analyze 43 such startups (28 failed and 15 successful). The model coefficients are presented in Table 3 and are followed by a discussion on statistically significant attributes.

Product Market Fit (P1_PMF): The odds ratio of 2.02 indicates a startup's vulnerability reporting product issues (64% failed Vs. 27% successful). As an entrepreneur quoted, "PMF was a major opportunity miss. The focus was on B2B while it should have been on B2C." Another one mentioned, "product was technically good but missed on user experience, and execution was bad, leading to failure." This emphasizes the need for a product solving the critical problems of customers who are willing to pay for the solution.
Market entry timing (M3_TooEL): The odds ratio of 1.75 shows a startup's sensitivity reporting market entry timing issues (72% failed Vs. 27% successful). As an entrepreneur quoted, "the product launch was three years ahead of time." Another one mentioned, "execution delays resulted in missing the product launch time, missed the early bird benefit." This reiterates the time of market entry and the need to execute the plan. Early entry may not be appreciated, whereas customers may not welcome late entry.
Conflict with cofounders (O2_ConFou): The odds ratio of 2.22 highlights a startup's susceptibility reporting cofounder issues (54% failed Vs. 7% successful). As an entrepreneur quoted, "we pulled the cart in different directions. Huge mismatch in expectation in each others' delivery." Another one mentioned, "absence of conflict resolution mechanism led to the storming phase." The alignment between cofounders is critical to the success of a startup in the emergence stage.
Cofounder experience (Cof_Exp): The odds ratio of 0.82 shows that cofounders with lesser experience are prone to failure. This highlights the need to have a complementary skillset amongst the cofounders.
The emergence stage results indicate that product market fit, market entry timing, and conflict with cofounder positively correlate, and cofounder experience negatively correlates to the failure outcome.

Table 3: Model coefficients of emergence stage startups (D1)

Predictor	Estimate	Odds ratio	p
Intercept	-2.46	0.09	0.045
P1_PMF	0.71	2.03	0.019
M3_TooEL	0.56	1.76	0.047
O2_ConFou	0.80	2.22	0.029
Cof_Exp	-0.19	0.82	0.011

Table 4: Model coefficients of stability stage startups (D2)

Predictor	Estimate	Odds ratio	p
Intercept	4.88	131.36	0.029
F2_Revenue	0.41	1.51	0.067
M1_Promo	-0.44	0.65	0.136
SeedGrants	-3.50	0.03	0.014
Age_Cof	-0.09	0.91	0.024
Inv_Fund	1.89	6.59	0.033

5.2.3 D2: Stability stage

In the stability stage, startups earn revenue but not profitable. We analyze 70 such startups (54 failed and 16 successful). The model coefficients are presented in Table 4 and are followed by a discussion on statistically significant attributes.
Revenue (F2_Revenue): The odds ratio of 1.51 indicates a startup's fragility in the form of revenue issues (65% failed Vs. 50% successful). Entrepreneurs highlight the challenges of getting the contract extension from significant customers, poor unit economics making the operation unsustainable, and difficulty in addressing the startup's working capital needs. As an entrepreneur said, "revenue sufficed and kept the lights on and survive. But it did not allow us to expand the scale, and funds were insufficient for growth. Expansion and scaling called for additional costs". Another entrepreneur said, "losses were mounting, and they cannot sustain the rate of cash burn." This emphasizes the importance of revenues for sustainable operations. Though the startups earned income, it was not good enough to pull on and survive.
Investor fund (Inv_Fund): The odds ratio of 6.58 opens up a counter-intuitive inference. We observe that 61% of the failed startups Vs only 19% of successful startups have obtained investor funds. In aligning with the investors, 28% of failed startups had conflicts with investors, while successful startups had zero disputes with investors. A successful entrepreneur said, "I am ready to grow slowly but surely. Having the investor on board is a pain, and I strongly recommend entrepreneurs to go with bootstrapping." Another successful entrepreneur mentioned, "let the focus be on the product and never run behind investors. If the product is good, you will get the investor queue up." While most of the failed startups are running behind investor funds, the successful startups focused on their own source of funds and remained to operate that way. This also implies that investors are ready to forgo startups if reasonable returns do not flow in.

Seed grants (SeedGrants): The odds ratio 0.03 highlights that failed startup founders could not access seed grants, and government policy benefits as much as the successful ones. This indirectly explains the useful role that seed grants and government policy support play in startup promotion and the need to make them widely accessible.
Age of cofounder (Age_Cof): The odds ratio of 0.91 shows that successful cofounders are older and proxy to have the relevant experience and take the startup to success.
At the stability stage, the attributes of finance sources such as revenue, investor fund, and availing seed grants from the ecosystem are statistically significant besides the cofounders' age.

5.2.4 D3: Growth stage

In the growth stage, startups have established a revenue stream and are operating with profits. We analyze 38 such startups (19 failed and 19 successful). The model coefficients are presented in Table 5 and are followed by a discussion on statistically significant attributes.
No. of current startups (Cur_Sup): The odds ratio of 37.7 highlights the absolute focus required in making a startup successful. About 79% of the successful entrepreneurs do not have any other startup, while only 11% of the failed startups are with their current startup without any other startup. If the entrepreneurs have more than one startup, it diverts their focus unduly to the detriment of startups in general and is reflected in startups' downfall under reference.
Level of confidence at execution (LoC_Exe): The odds ratio of 0.013 shows that successful entrepreneurs exhibit greater confidence. A confident one will confront and overcome challenges even in the most difficult times, in contrast to those who lack confidence and succumb under pressure.
At the growth stage, focussed execution with the current startup is required.

Table 5: Model Coefficients of growth stage startups (D3)

Predictor	Estimate	Odds ratio	p
Intercept	19.26	2.31E+08	0.014
F2_Revenue	0.59	1.81	0.292
M1_Promo	-0.69	0.50	0.098
Cur_Sup	3.63	37.72	0.011
LoC_Exe	-4.48	0.01	0.012

Table 6: Model Coefficients of failed Vs success startups (D4)

Predictor	Estimate	Odds ratio	p
Intercept	7.35	1558.74	< .001
F2_Revenue	0.39	1.47	0.019
P1_PMF	0.38	1.46	0.028
P2_Roadmap	-0.42	0.65	0.032
M1_Promo	-0.26	0.77	0.079
O3_ConInv	0.94	2.55	0.018
LoC_Exe	-1.03	0.36	0.004
Cur_Sup	0.99	2.70	0.004
Age_Cof	-0.10	0.91	0.001
Emergence – Stability	-1.08	0.34	0.077
Growth – Stability	-1.03	0.36	0.112

5.2.5 D4: What attributes differentiate failed Vs. successful startups?

We analyzed the overall model with the stage as a predictor variable with 151 startups (101 failed and 50 successful). The model coefficients are presented in Table 6 and are followed by a discussion on statistically significant attributes.
Stage: We observe that stage is a significant attribute in the entrepreneurial journey. Our explorations through models D1 and D3 point out the importance of stage, which is a significant milestone. We have identified the attributes which differentiate startups at each stage, failed Vs successful, and this logical approach provided a clear overview of the entrepreneurial journey.
Internal attributes: Product evolution requires accommodating the ever-changing customer requirement. This calls for a strategic product roadmap addressing the long-term product requirement while delivering the tactical product pivots addressing the short-term customer requirements. The focus on product issues (P1_PMF: 41% Failed Vs. 20% Success) with a strategic product roadmap (P2_Roadmap: 22% Failed Vs. 20% Success) and drive market promotion (M1_Promo: 63% Failed Vs. 80% Success). The market promotion activities fetch and establish the revenue stream (F2_Revenue: 65% Failed Vs. 40% Success). The sources of finance for growth should leap beyond operational

revenue and attract external funds. In attracting the external funds, avoiding conflict with investors (O3_ConInv: 18% Failed Vs. 2% Success) differentiates a startup to be successful.

Entrepreneur profile: We note age as a proxy to professional experience, and successful entrepreneurs get into the entrepreneurial journey with the required professional experience. The level of confidence at execution should be brimming (LoC_Exe: 25% Failed Vs. 68% Successful) and undivided focus on the current startup (Cur_Sup: 41% Failed Vs. 70% Successful) differentiates a startup to be successful.

6 Conclusions, contributions, and implications

6.1 Conclusions

This research study started with the following two objectives.

i. Do causal factors vary within the lifecycle stages?
ii. What are the attributes that differentiate a failed tech startup from a successful one?

To start with, we addressed the first objective. We have identified the causal attributes of emergence, stability, and growth stages to determine a successful startup compared to a failed one. The statistical significance of the models D1, D2, and D3 and the identification of statistically significant attributes paves the way for rejecting the null hypothesis. The emergence stage startups have minimal resources, and the need to remain focused on the milestones will help the startup to sail further. The cofounders with the required experience, should drive the startup unidirectionally and strive to deliver the product that meets market requirements at the right time. In the stability stage, startups scramble for the available resources to retain existing customers while attracting new customers for volume growth. One critical resource is financing and generating their funds through operational revenue, while exploring to obtain investor funds or seed grants from the ecosystem to spur growth. The entrepreneur's experience comes in handy in generating funds, avoiding conflicts with investors to navigate the startup to success. The growth stage startup entrepreneurs focus on the current startup, and a healthy level of confidence at the execution time is essential.

Subsequently, we addressed the second objective. The statistical significance of model D4 and the identification of statistically significant attributes paves the way for rejecting the null hypothesis. The causal attributes' identification within the lifecycle stages provides a clear picture of managing the entrepreneurial journey. The startup's lifecycle stage plays a significant role (Bala Subrahmanya, 2017), and it implies how entrepreneurs prioritize and allocate their resources in maximizing the returns. The stage information helps in prioritizing internal firm-level resource allocation. The other causal attributes that are statistically significant are revenue, product market fit, product roadmap, market promotion, conflict with investors, level of confidence at execution, focus on current startup, and entrepreneur experience level.

6.2 Contributions

This empirical study on tech startup failure has the following two key contributions. First, this study by lifecycle stage provides detailed insights on startup failures. The conceptual framework is replicable, scalable, and distinctly measurable for studying the startup failure phenomenon by lifecycle stages. Second, the identification of attributes impacting lifecycle stages will benefit the stakeholders, namely entrepreneurs, investors, and ecosystem policymakers.

6.3 Implications

This empirical study on the tech startup life expectancy has the following implications. Entrepreneurs' awareness of startup failure's causal attributes by life cycle stages will help them explore their ideas rationally and reduce the socio-economic cost of startup failures. The policymakers of the Indian startup ecosystem are currently focussed on enabling the emergence of more startups. The stability and growth stage startups need more attention. Preventing the exit of grown-up startups is more critical, and policies should be tailored to support the lifecycle stages.

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