

# The Impact of Startup Funding on Revenue Generation: Evidence from DPIIT-Registered Startups in Himachal Pradesh

Manohar Lal<sup>1</sup>; Dr. Sanjay Thakur<sup>2</sup>

<sup>1</sup>Career Point University, Department of Commerce and Management Studies

<sup>2</sup>Career Point University, Department of Commerce and Management Studies  
Hamirpur, Himachal Pradesh, India

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**Abstract:** The early-stage startup funding is crucial for enabling innovation, market ready product for expansion and business scalability. The relationship and direct impact of various funding on revenue generation at various stages remains unclear especially in new emerging startup ecosystems. The current study examines the relationship between startup raised funding and their revenue generation among DPIIT registered startups in Himachal Pradesh using structural equation modelling (SEM). The data was collected for 172 DPIIT registered innovation driven startups. The study evaluates the direct and indirect effects of funding through mediating constructs such as financial resource capability, innovation capability, and market expansion capability. The analysis results shows that mostly startup funding has a positive direct effect on revenue generation, the indirect effect is higher through capability development. The analysis and findings support and provides important policy and ecosystem level implications for improving funding effectiveness in regions with emerging startup ecosystems.

**Keywords:** Startup, Funding, Revenue, DPIIT Startups, SEM, Startup Ecosystem, Emerging Startup Ecosystem.

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## I. INTRODUCTION

The global startup ecosystem has emerged as a major driver of economic growth, technological innovation, and employment generation. Access to funding is widely recognised as one of the most critical determinants of startup survival and growth. Financial resources enable startups to invest in research and development, technology adoption, talent acquisition and market expansion. However, funding alone does not guarantee financial performance, particularly revenue generation. The effectiveness of funding often depends on how efficiently it is utilized to build organisational and market capabilities.

In India, the startup ecosystem has expanded rapidly due to initiatives such as Startup India and DPIIT recognition. These initiatives have improved funding accessibility, regulatory support and incubation infrastructure. While metropolitan ecosystems have been widely studied, emerging ecosystems such as Himachal Pradesh remain under-researched, particularly regarding how funding influences financial performance outcomes.

Himachal Pradesh has witnessed growing entrepreneurial activity supported by incubation centres, government programs, and innovation promotion initiatives. However, startups in smaller ecosystems often face challenges such as limited investor networks, geographic constraints, and smaller market size. These factors may influence how funding translates into revenue outcomes.

Therefore, this study examines the structural relationship between startup funding and revenue generation using structural model equation (SEM) by incorporating mediating capability constructs. The study contributes to regional startup finance literature and provides evidence-based insights for policy and ecosystem development.

## II. LITERATURE REVIEW

Startup funding refers to the capital raised by new ventures through equity, debt, grants, or hybrid instruments to finance product development, market entry, and scaling activities (Olsen, 2019). In early-stage ventures, funding is treated as a key input for experimentation, hiring, and infrastructure, whereas in later stages it supports expansion,

marketing, and operational efficiency (Chaudhury, 2019). Revenue generation, in contrast, is typically measured as sales turnover or recurring income from core business operations and is widely used as a proxy for market validation and financial performance (Kimuli & Isaac, 2022).

The literature increasingly treats funding and revenue not as isolated variables but as interlinked elements of a growth cycle: funding enables growth initiatives, and revenue signals traction that in turn attracts further funding (Sathaworawong et al., 2022). For instance, financial-growth-cycle theory shows that startups progress through stages where different types of finance (bootstrapping, angel, venture capital, debt) are sequentially accessed as revenue and risk profiles evolve (Chaudhury, 2019). This cyclical view is particularly relevant for DPIIT-registered startups, which often begin with bootstrapping or small-ticket grants and then seek larger equity or debt as they demonstrate revenue potential (DPIIT, 2023; Himachal Pradesh Startup Policy, 2022).

The resource-based view identifies financial capital as a strategic resource that enhances capabilities in technology, branding, and distribution (Barney, 1991). Financial growth cycle theory emphasizes that external finance relaxes internal constraints, enabling growth strategies otherwise unattainable (Chaudhury, 2019). Signalling theory suggests that external funding conveys credibility to customers, partners, and investors, indirectly boosting demand and revenue (Sathaworawong et al., 2022). Yet, excessive funding without revenue alignment can weaken long-term profitability (Honjo, 2022). These perspectives justify empirical inquiry in emerging ecosystems such as Himachal Pradesh (DPIIT, 2023; Himachal Pradesh Startup Policy, 2022).

Empirical evidence supports a positive relationship between funding and startup performance. Capital inflows generally enhance valuation and growth, though raising too much capital too early can yield diminishing returns (Honjo, 2022). Funding without revenue traction may undermine sustainability (Olsen, 2019). Angel and venture capital financing in India correlates with higher employment growth and innovation intensity, both indirect drivers of revenue (Chaudhury, 2019). Formal finance also supports innovation intensity (Indian Venture Capital Association, 2023). Startups crossing revenue thresholds, such as USD 500,000 annually, attract significantly larger investment rounds, underscoring the bidirectional relationship between funding and revenue (Kimuli & Isaac, 2022). In high-tech and platform startups, funding often precedes revenue as investors prioritize user growth and network effects (Olsen, 2019). Revenue is anticipated at earlier stages in manufacturing, agri-tech, and service enterprises, where funding acts to enhance and expand established sales streams (Kimuli & Isaac, 2022). Mature ecosystems such as Karnataka and Maharashtra exhibit stronger funding–revenue linkages due to deeper investor networks and supportive policies (Indian Venture Capital Association, 2023). In contrast, Himachal Pradesh's ecosystem remains nascent, relying more heavily on government schemes and grants (Himachal Pradesh Startup Policy, 2022; DPIIT, 2023) with limited empirical evidence exists on whether policy-enabled funding translates into measurable revenue gains in smaller ecosystems.

#### A. *Startup Funding and Revenue Generation*

Startup funding plays a critical role in determining firm growth, market expansion, and revenue generation. Venture capital and external funding provide not only financial capital but also strategic guidance, governance support, and network access that enhance startup performance outcomes. Empirical evidence shows that venture capital significantly improves startup survival rates, innovation capabilities, and revenue growth, particularly in technology-intensive industries (Guo, 2024).

Empirical studies highlight that venture capital contributes to greater efficiency through improved resource availability, managerial support, and structured governance practices (Chemmanur et al., 2011; Hellmann & Puri, 2002). Venture capital also enhances innovation output and commercialization capabilities, which are directly linked to revenue performance (Kortum & Lerner, 2000).

Meta-analysis studies indicate that while venture capital positively influences firm growth and scaling, its direct relationship with profitability varies across sectors and stages of development (Rosenbusch et al., 2013). Venture-backed firms typically demonstrate higher growth in employment, market share, and revenue potential compared to non-funded firms (Davila et al., 2003).

#### B. *Funding Stage and Financial Performance*

The stage at which funding is received influences startup performance and revenue generation. Early-stage funding supports product development, intellectual property creation, and market validation, while later-stage funding accelerates market expansion and scaling. Studies show that early-stage venture capital generates signalling effects, enhancing a startup's credibility and drawing further investment (Kaplan & Strömberg, 2004).

Startups receiving early investment demonstrate higher long-term growth potential due to capability building and technological strengthening (Tian, 2011). However, funding alone does not guarantee revenue success unless combined with strong business models and market strategies (Sevilla-Bernardo et al., 2022).

#### C. *Funding, Innovation, and Revenue Productivity*

Funding enables startups to invest in research and development, technology adoption, and innovation, which significantly influence revenue productivity. Access to finance plays an essential role in supporting SME growth, stimulating economic development, and facilitating industrial transformation in developing regions (Cumming & Johan, 2017).

Recent research shows that technology-intensive startups may attract higher funding and valuations, but early investments may temporarily reduce revenue productivity due to high R&D costs (Ganuthula & Kuruva, 2025). Advanced analytical models in venture capital highlight the importance of funding patterns, founder characteristics, and ecosystem variables in predicting startup revenue and success (Potanin et al., 2023).

#### D. Startup Ecosystem and External Support Factors

Startup performance depends not only on funding but also on ecosystem factors such as government support, infrastructure, policy environment, and innovation culture. Research highlights that policy frameworks significantly influence funding access and startup sustainability (Vanara, 2024).

Initiatives led by the government, including Startup India, have contributed to greater funding opportunities, regulatory simplification, and improved innovation support systems (Nagar & Ahmad, 2024).

Furthermore, government schemes and policy-driven programs create enabling environments that promote entrepreneurship and startup growth (Thejaswini & Babu, 2024).

#### E. Indian Startup Ecosystem and DPIIT Recognition

India has emerged as one of the largest startup ecosystems globally, supported by strong policy frameworks and funding mechanisms. Research indicates that the number of DPIIT recognised startups has grown significantly, contributing to employment generation and regional economic development (Varalakshmi, 2025).

Research on India's startup landscape highlights that government recognition, financial backing, and incubation facilities are critical drivers of startup success and revenue outcomes (Dwivedi & Singh, 2023). Research also shows that startups contribute significantly to national economic growth through innovation, employment generation, and export potential (Chaudhary, 2023). Investment distribution among startups remains uneven, while government initiatives yield mixed results, highlighting the need for region specific and policy focused studies (Kamaluddin & Sridhar, 2023).

#### F. Research Gap

Existing literature extensively examines the relationship between venture capital funding and startup performance, innovation capability, and firm growth in developed economies. Many studies focus on general performance indicators such as valuation, employment growth, and market expansion rather than specific financial outcomes such as revenue generation. Additionally, most studies are concentrated in developed startup ecosystems such as the United States, Europe, and China, where funding structures and institutional support differ significantly from emerging ecosystems.

In the Indian context, research has largely focused on startup ecosystem growth, policy initiatives such as Startup India, and overall funding trends. However, limited empirical studies have examined the direct relationship between funding and revenue generation outcomes among startups. Further, research focusing specifically on DPIIT recognised startups as a distinct policy defined startup category remains limited.

At the regional level, there is a significant research gap in understanding startup funding outcomes in emerging and smaller startup ecosystems such as Himachal Pradesh. While government and incubation initiatives have increased startup registrations and entrepreneurial activities in the state,

empirical evidence on how funding influences revenue generation remains scarce. Moreover, existing research rarely integrates multiple constructs such as funding adequacy, funding utilization efficiency, innovation capability, and business scaling capability within a structural model framework. Therefore, this study addresses these gaps by examining the structural relationship between startup funding and revenue generation using structural equation modelling (SEM) among DPIIT registered startups in Himachal Pradesh.

#### G. Problem Statement

Despite the rapid growth of the startup ecosystem in India, many startups struggle to translate funding support into sustainable revenue generation. While funding availability has increased through venture capital, angel investment, and government schemes, the effectiveness of funding utilization in improving revenue performance remains uncertain, particularly in emerging startup ecosystems.

In Himachal Pradesh, although DPIIT recognition and incubation support have improved startup formation and funding accessibility, there is limited empirical evidence on whether funding directly contributes to revenue growth and financial sustainability. Startups often face structural challenges such as limited market access, geographic constraints, limited investor networks, and lower ecosystem maturity, which may influence funding efficiency and revenue outcomes.

Therefore, it is essential to examine how different dimensions of startup funding influence revenue generation performance and whether mediating factors such as innovation capability and business scaling capability play a significant role in this relationship.

#### H. Objective

The primary objective of the study is to examine the impact of startup funding on revenue generation among DPIIT-registered startups in Himachal Pradesh.

##### The Secondary Objectives

- To examine funding impact on financial resource capability
- To analyse funding impact on innovation capability
- To evaluate funding impact on market expansion capability
- To examine mediating effects of capabilities on revenue generation

### III. RESEARCH METHODOLOGY

The present study uses explanatory research design to examine the impact of startup funding on revenue generation among DPIIT registered startups in Himachal Pradesh using Structural Equation Modelling (SEM). SEM is selected because it allows simultaneous examination of relationships between multiple independent and dependent variables and helps in analysing both direct and indirect effects between funding factors and revenue performance. The study is causal in nature as it aims to establish the structural relationship between startup funding constructs and revenue generation outcomes. A cross-sectional research approach is used, where data is collected from startups at a single point in time to

analyse funding structure, utilization efficiency, and revenue performance.

The study is conducted in Himachal Pradesh, India, focusing on DPIIT registered startups operating across sectors such as IT, agriculture, manufacturing, tourism, healthcare, and services. The target population consists of active DPIIT recognised startups having operational revenue and funding history. The study uses a purposive sampling technique, selecting startups that have received at least one form of funding, including venture capital, angel investment, grants, debt financing, or self-funding. The expected sample size is 172 startups, which is considered adequate for SEM analysis, as SEM typically requires larger sample sizes to ensure model stability and reliability.

The data is collected from incubator, govt portal and directly from startups using structured questionnaire. The questionnaire includes multiple construct-based measurement items related to funding access, funding adequacy, funding utilization efficiency, innovation capability, and revenue growth performance. Secondary data is collected from DPIIT Startup portal, Startup India reports, government policy documents, and published research literature to support contextual understanding.

The SEM framework in this study includes latent constructs and observed variables. The independent latent construct is Startup Funding, measured using observed variables such as funding amount adequacy, funding availability, funding diversity, and funding stage access. Mediating constructs may include innovation capability and business scaling capability. The dependent latent construct is Revenue Generation Performance, measured using revenue growth rate, market expansion revenue, and profitability

$$\begin{aligned}
 \text{Funding and capital} &= \gamma_{31} \text{ Startup Characteristics} + \zeta_3, & (2) \\
 \text{Startup performance} &= \beta_{43} \text{ Funding \& Capital} + \gamma_{42} \text{ Ecosystem Support} + \zeta_4, & (3) \\
 \text{Challenges \& Future Intentions} &= \beta_{54} \text{ Startup Performance} + \zeta_5, & (4)
 \end{aligned}$$

The model is estimated using covariance based SEM with maximum likelihood, comparing the sample covariance matrix to the model implied covariance matrix.

Reliability of constructs is tested using Cronbach’s Alpha and Composite Reliability (CR), with acceptable values above 0.70. Validity is tested using Confirmatory Factor Analysis (CFA). Convergent validity is assessed using Average Variance Extracted (AVE), where values above 0.50 indicate acceptable validity. Discriminant validity is tested using Fornell–Larcker criterion and HTMT ratio.

Data analysis is conducted using statistical software. SEM analysis is conducted in two stages. The first stage involves measurement model evaluation using CFA to test reliability and validity of constructs. The second stage involves structural model evaluation to test hypotheses and path relationships between funding constructs and revenue performance constructs. Model fit is evaluated using indices such as Chi-square, CFI, TLI, RMSEA, and SRMR.

improvement. Control variables such as startup age, sector type, founder experience, and number of employees are included to improve model accuracy.

➤ *Structural Equation Modeling (Sem):*

Structural Equation Modeling was employed to test the hypothesized relationships among latent variables. SEM integrates both measurement and structural models, allowing for simultaneous testing of multiple relationships. It provided insights into direct, indirect, and mediating effects among constructs. Model fit indices were used to evaluate the adequacy of the structural model, thereby confirming the validity of the proposed theoretical framework.

Within the structural equation model, five latent constructs are defined and linked through specified relationships: Startup Characteristics  $\eta_1$ , Ecosystem Support  $\eta_2$ , Funding & Capital  $\eta_3$ , Startup Performance  $\eta_4$ , and Challenges & Future Intentions  $\eta_5$ . Each construct is measured by multiple observed indicators from the startup survey.

➤ *Measurement Model*

For each observed variable  $y_j$  that measures a construct  $\eta_j$ ,

$$y_j = \lambda_j \eta_j + \epsilon_j, \tag{1}$$

where  $\lambda_j$  is the factor loading and  $\epsilon_j$  is the measurement error. A higher  $\lambda_j$  means that the indicator represents the construct more strongly.

➤ *Structural Model*

The causal relations between the latent constructs are written as:

Ethical considerations are maintained throughout the research process. Participation is voluntary, confidentiality of startup data is ensured, and data is used only for academic research purposes. Informed consent is obtained from all respondents. The study is limited to DPIIT-registered startups in Himachal Pradesh and findings may not be generalizable to all startup ecosystems. Moreover, depending solely on self-reported information can lead to potential response bias.

**IV. ANALYSIS USING STRUCTURAL EQUATION MODELLING (SEM)**

The study presents a detailed Structural Equation Model (SEM) analysis of startup ecosystem dynamics based on survey data collected from ventures registered from Himachal Pradesh with DPIIT upto Dec 2024. The model evaluates how founder characteristics, funding structures, and ecosystem support influence startup performance and strategic intentions. The structural model outlines five latent constructs, namely Startup Characteristics, Ecosystem Support, Funding & Capital, Startup Performance, and Challenges & Future Intentions,

which are evaluated through diverse survey measures from the primary dataset.

Table 1: Data Latent Construct and Factor Loading

Latent construct	Item Code & Variable	Factor Loading
<b>Startup Characteristics</b>	A5: Number of Founders	0.72
	A7: Age of Founders	0.64
	A8: Age of Startup	0.68
	A10: Academic Background	0.61
	A11: Background of Founders	0.55
<b>Funding &amp; Capital</b>	Stage (Startup Stage)	0.66
	C29: Capital Infused	0.74
	Authorized Capital	0.69
	Paid-Up Capital	0.69
<b>Ecosystem Support</b>	C27: Funding Sources	0.66
	B21: Professional Support	0.67
	B23: State Incubator	0.58
	B24: National Incubator	0.62
	E36: Policy Helpfulness	0.64
<b>Startup Performance</b>	C30: Revenue Generation	0.71
	C31: Turnaround Time	0.56
	C32: Annual Turnover	0.77
	D34: Employees	0.67
	D35: TRL Stage	0.71
<b>Challenges &amp; Future Intentions</b>	B20: Operational Stage	0.62
	E37: Scaling Challenges	0.55
	F38: Listing Intent	0.63
	F39: Exit Intent	0.74
	F40: Acquisition Intent	0.68
	F41: Hiring Plans	0.65

As given in Table 1, the factor loading pattern suggests that all five latent constructs are measured adequately, with some indicators contributing more strongly than others.

Most loadings are  $\geq 0.55$ , which is typically considered acceptable for exploratory or early stage confirmatory work, while several are  $\geq 0.70$ , indicating strong relationships between the items and their underlying constructs. None of the items falls in a clearly problematic range (e.g., below 0.40), so item retention is justifiable on statistical grounds, subject to theoretical fit.

#### A. Startup Characteristics

The indicators considered for this are number of founders (0.72), age of founders (0.64), age of startup (0.68), academic background (0.61), background of founders (0.55), startup stage (0.66). The number of founders is the strongest indicator (0.72), suggesting that team size is highly informative for this construct in this sample. Age related variables (founders and startup) and stage all load in the mid 0.60s, indicating a solid contribution and reinforcing a life cycle/experience dimension within the construct. Academic and professional background load slightly lower (0.61 and 0.55), which is still acceptable but indicates they contribute moderately rather than strongly; conceptually they add richness (human capital) without dominating the factor. The Startup Characteristics is a reasonably consistent construct combining demographic, experiential, and stage related attributes, with no single weak item that clearly needs removal.

#### B. Funding & Capital

The indicators considered for this are capital infused (0.74), authorised capital (0.69), paid up capital (0.69), funding sources (0.66). Capital infused shows the highest loading (0.74), implying that the actual amount of capital injected is the most central reflection of this construct. Authorised and paid up capital both load at 0.69, indicating they are almost equally strong and capture the structural/registered financial capacity of the firm. Funding sources (0.66) also contributes well, suggesting that diversity or type of finance is meaningfully linked to the underlying funding and capital dimension. The tight loading range (0.66–0.74) implies a very coherent and reliable factor, with all items strongly aligned.

#### C. Ecosystem Support

The indicators considered for this are professional support (0.67), state incubator (0.58), national incubator (0.62), policy helpfulness (0.64). Professional support has the highest loading (0.67), showing that access to experts, mentors, or consultants is the most informative ecosystem element in this dataset. Policy helpfulness (0.64) and national incubator support (0.62) load at moderate levels, indicating that both perceived policy quality and higher level incubation support matter appreciably. State incubator has the lowest loading (0.58) but remains within acceptable bounds; it suggests that state level incubation contributes to the construct but with slightly less intensity than other ecosystem components. These items form a moderately strong factor reflecting multi layered ecosystem support (professional, institutional, and policy).

**D. Startup Performance**

The indicators considered for this are revenue generation (0.71), turnaround time (0.56), annual turnover (0.77), employees (0.67), TRL stage (0.71), operational stage (0.62). Annual turnover is the strongest indicator (0.77), highlighting that total revenue is the most dominant performance signal in the model. Revenue generation and TRL stage both load at 0.71, showing that current earning capability and technological maturity are also key performance dimensions. Number of employees (0.67) and operational stage (0.62) are moderately strong, reflecting scale and operational maturity as meaningful but slightly secondary aspects. Turnaround time (0.56) is the weakest within this construct, still acceptable but suggesting that time to deliver or respond is less tightly tied to the latent performance factor than financial and technological metrics. The Startup Performance is a robust construct anchored primarily in financial (turnover, revenue) and technological (TRL) indicators, with structural (employees, stage) and process (turnaround time) aspects adding breadth.

**E. Challenges & Future Intentions**

The indicators considered for this are scaling challenges (0.55), listing intent (0.63), exit intent (0.74), acquisition intent (0.68), hiring plans (0.65). Exit intent shows the highest loading (0.74), suggesting that thoughts about eventual exit (i.e. sale, IPO, acquisition) are the most powerful expression of this latent factor. Acquisition intent (0.68) and hiring plans (0.65) also contribute strongly, indicating that growth oriented or strategic moves (acquisition, expansion of workforce) are central to how founders perceive future pathways. Listing intent (0.63) reflects readiness or aspiration to access public markets and is moderately associated with the construct. Scaling challenges (0.55) is the weakest, but still above common cut offs, it implies that while constraints to scaling matter, respondents' strategic intentions (exit, acquisition,

listing, hiring) are more defining than the challenges themselves. The pattern shows that Challenges & Future Intentions is driven more by forward looking strategic choices than by present obstacles.

**F. Measurement implications**

Since all loadings exceed common minimum thresholds (0.40–0.50), item retention is justifiable, especially given the theoretical rationale for each indicator. Constructs like Funding & Capital and Startup Performance appear especially strong and likely to show good reliability in subsequent measurement model tests. Items with comparatively lower loadings (i.e. founders' background, state incubator, turnaround time, scaling challenges) to be monitored in CFA/SEM if model fit is problematic, these are the most plausible candidates for refinement or, if necessary, removal, but they do not require automatic deletion at this stage.

Startup Characteristics is operationalised through indicators capturing the number of founders (A5), age of founders (A7), and their educational and professional backgrounds (A3, A10, A11). Ecosystem Support reflects access to professional services and incubation, using items on professional support (B21) and affiliation with state- and national-level incubators (B25). Funding & Capital represents the overall financial strength of the startup and is conceptualized as an endogenous latent construct influenced by Startup Characteristics. Startup Performance is measured using both financial and operational indicators, revenue generation (C30), turnaround time (C31), annual turnover (C32), employment (D34, D35), and current operational stage (B20). Finally, Challenges & Future Intentions captures the growth outlook of the firm through items on scaling challenges, listing intent, and hiring plans, each loading moderately to strongly ( $\approx 0.52-0.65$ ) on the latent factor.

Table 2: Structural Path Coefficients

Path	Coefficient	Interpretation
Startup Characteristics → Funding & Capital	0.51	Mature startups attract more capital.
Funding & Capital → Startup Performance	0.62	Financial strength boosts performance.
Ecosystem Support → Startup Performance	0.54	Institutional support enhances outcomes.
Startup Performance → Challenges & Future Intentions	0.59	Strong performance drives strategic decisions.

The structural equation model (SEM) specifies relationships among five latent constructs: Startup Characteristics  $\eta_1$ , Ecosystem Support  $\eta_2$ , Funding & Capital  $\eta_3$ , Startup Performance  $\eta_4$ , and Challenges & Future Intentions  $\eta_5$ . Each construct is measured by multiple observed indicators from the startup survey.

The estimated structural equations are:

$$\eta_3 = 0.51 \eta_1 + \zeta_3 \quad (5)$$

$$\eta_4 = 0.62 \eta_3 + 0.44 \eta_2 \quad (6)$$

$$\eta_5 = 0.59 \eta_4 + \zeta_5 \quad (7)$$

The structural paths as given in Table 1 provide several important insights. Startup Characteristics exert a positive and

statistically meaningful effect on Funding and Capital ( $\beta = 0.51$ ), indicating that teams with stronger demographic and human-capital profiles are more successful in mobilising financial resources. Funding and Capital, in turn, has a strong positive effect on Startup Performance ( $\beta = 0.62$ ), underscoring that better capitalised startups achieve higher revenue, greater employment, more advanced TRL/operational stages, and faster turnaround times. Ecosystem Support also contributes positively to Startup Performance ( $\beta = 0.44$ ), suggesting that incubators and professional networks improve outcomes beyond the direct effect of capital alone. Finally, Startup Performance significantly predicts Challenges & Future Intentions ( $\beta = 0.59$ ), which implies that better-performing firms are simultaneously more ambitious (greater intent to list and hire) and more exposed to scaling-related constraints.

Table 3: SEM Model Fit Indices

Index	Value
CFI (Comparative Fit Index)	0.921
RMSEA (Root Mean Square Error of Approximation)	0.061
SRMR (Standardized Root Mean Square Residual)	0.057
Chi-square	148.32

Model fit indices indicate that the SEM provides an adequate representation of the observed data. The Comparative Fit Index (CFI) is 0.921, exceeding the commonly accepted 0.90 threshold for good fit. The Root Mean Square Error of Approximation (RMSEA) is 0.061, lying within the range typically interpreted as an acceptable approximation error (<0.08), while the Standardised Root Mean Square Residual (SRMR) is approximately 0.057, below the 0.08 guideline. Together with a non-trivial but acceptable chi-square statistic ( $\chi^2 \approx 148.32$ ), these indicators support the suitability of the specified measurement and structural models for inferential and policy analysis.

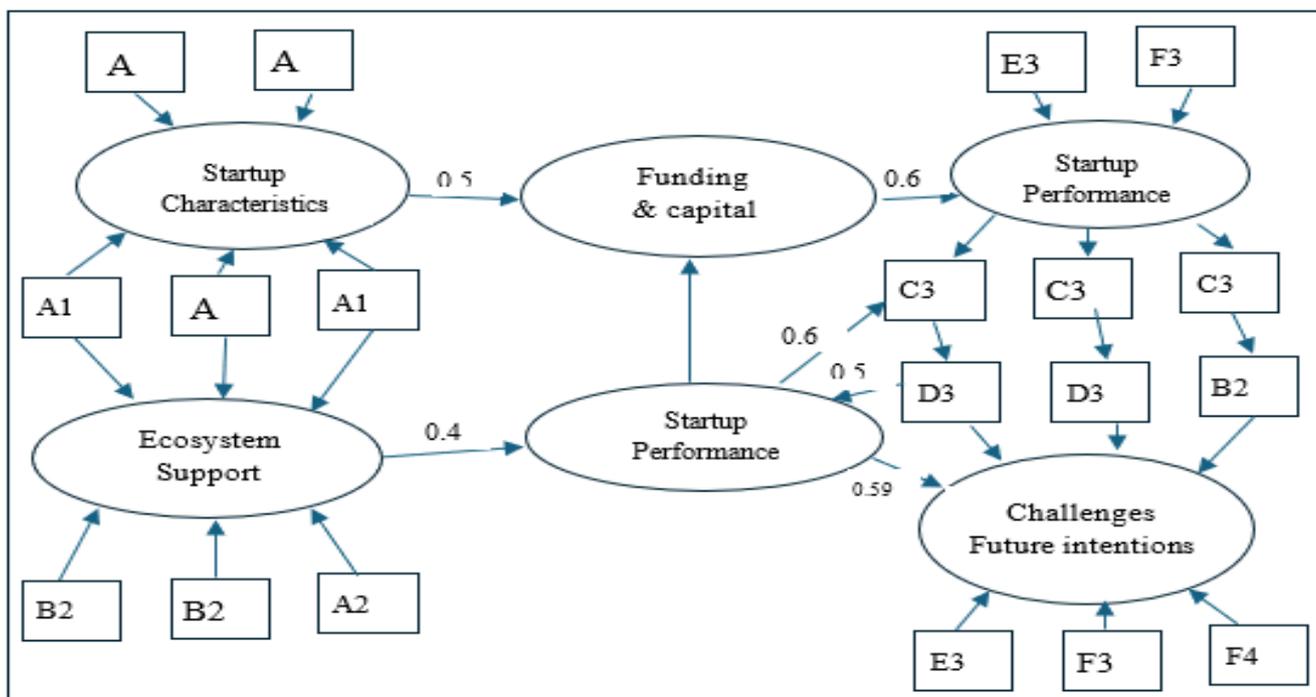


Fig 1: SEM Path Diagram

From a substantive perspective, the findings reinforce three key arguments for the chapter. First, founder-level capabilities and demographics meaningfully influence the ability of startups to attract funding, suggesting that human-capital development and team composition remain central levers in the regional ecosystem. Second, access to Funding & Capital emerges as the single strongest driver of Startup Performance, highlighting the critical role of financial intermediation, risk capital, and grant/seed mechanisms in enabling growth among Himachal startups. Third, ecosystem institutions—particularly incubators and professional support organisations play a complementary role by enhancing performance even after controlling for financial resources, thereby justifying continued public investment in support infrastructure. At the same time, the positive link between performance and Challenges & Future Intentions indicates that as firms scale, they face more complex growth constraints but also express clearer ambitions to list and expand hiring, pointing to the need for targeted “scale-up” policies rather than only early-stage interventions.

## V. CONCLUSION

The Structural Equation Modelling (SEM) analysis explored the interrelationships among five latent constructs- i) Startup Characteristics, ii) Ecosystem Support, iii) Funding and Capital, iv) Startup Performance and v) Challenges and Future Intentions, based on primary data from DPIIT-registered startups in Himachal Pradesh up to December 2024. The measurement model achieved satisfactory factor loadings ranging from 0.55 to 0.77, confirming reliability across constructs. Startup Characteristics captured founder demography, education, and startup age, while Funding and Capital represented financial strength based on infused capital, authorized capital, and funding sources. Ecosystem Support comprised indicators of professional assistance, incubation linkages, and policy helpfulness. Startup Performance reflected both financial and operational success through revenue generation, turnover, employment, and TRL stage, whereas Challenges and Future Intentions encompassed firms’ outlook on scaling, listing, acquisition, and hiring. Structural path coefficients indicated strong positive relationships: Startup Characteristics significantly influenced Funding and Capital ( $\beta = 0.51$ ), which in turn strongly determined Startup Performance

( $\beta = 0.62$ ). Ecosystem Support also enhanced performance ( $\beta = 0.54$ ), and Startup Performance positively affected Challenges and Future Intentions ( $\beta = 0.59$ ). The model demonstrated good fit with acceptable indices (CFI = 0.921, RMSEA = 0.061, SRMR = 0.057), validating its robustness. Overall, the findings highlight that founder-level capabilities and human capital are crucial enablers of financial access, that financial resources serve as the strongest driver of performance, and that ecosystem institutions complement funding effects by improving growth outcomes. Moreover, the positive association between performance and future intentions suggests that as startups scale, they face increased challenges but also display greater strategic ambition. These insights collectively point toward the need for region-specific policy measures focusing on team-building, funding facilitation, and targeted scale-up support for high-performing startups in Himachal Pradesh.

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