VALUATION CHALLENGES AND INVESTOR INFLUENCE IN SUSTAINABLE HEALTH VENTURES

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Abstract

This study examines valuation challenges and investor influence in sustainable health startups, a sector characterised by regulatory complexity, high capital requirements, and increasing integration of environmental, social, and governance (ESG) factors. The research addresses the limitations of traditional valuation models in capturing early-stage success indicators and proposes a more nuanced approach. A mixed-methods design was employed, combining a systematic literature review with empirical cluster analysis using a dataset of 923 U.S.-based startups across 35 sectors. The analysis identified five distinct startup archetypes based on investor structure, funding levels, and exit outcomes. Startups with the most diverse investor base — engaging both angel and venture capital (VC) across multiple funding stages — exhibited the highest acquisition success rates (91.8 per cent). Sector-specific analysis revealed that health startups received above-average funding and achieved a 100 per cent acquisition rate, whereas medical startups displayed greater outcome variability. These findings highlight the need for multidimensional, sector-sensitive valuation frameworks that incorporate investor signalling, ESG orientation, and market timing. The findings of this study both support and build upon prior research on startup valuation and success factors. In line with Davila et al. (2003) and Lerner et al. (2018), the clustering analysis demonstrates that investor diversity — especially the combined involvement of angel and VC investors — substantially enhances the likelihood of acquisition. The results are also consistent with Somaya and You (2024) and Adner et al. (2016), underscoring scalability as a central determinant of valuation, particularly in technology-intensive sectors such as software, mobile, and biotechnology, which secured the highest levels of funding. The study offers new insights into the entrepreneurial finance literature and provides practical guidance for investors, founders, and policymakers aiming to scale sustainable innovation in the health sector.

Keywords: Cluster Analysis, ESG Integration, Investor Structure, Startup Valuation, Sustainable Health Ventures

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1. INTRODUCTION

The health sector occupies a distinctive position in the startup ecosystem, combining high growth potential with regulatory intensity, long development cycles, and substantial capital requirements that complicate early-stage valuation. Health startups — particularly in biotechnology and medical devices — often rely on venture capital (VC) and strategic partnerships, yet high funding levels do not consistently lead to successful exits due to scientific, operational, and compliance risks. Consequently, valuation approaches must account for regulatory progress, intellectual property, and clinical development pathways.

From a corporate finance perspective, traditional valuation methods such as discounted cash flow and market comparables are ill-suited to early-stage startups that lack financial histories. This challenge has intensified alongside rapid growth in global startup activity, with unicorns increasing from 81 to 150 and seed and angel investments rising from 2 billion to 10.3 billion USD between 2014 and 2024 ("Startups worldwide: Statistics report on startups globally", 2025). As a result, the need for robust alternative valuation frameworks has become increasingly urgent.

Existing research underscores the multidimensional nature of startup valuation, shaped not only by expected cash flows but also by behavioural factors and founder characteristics (Imbierowicz & Rauch, 2024; Colombo et al., 2022). Within this context, sustainable health ventures have gained prominence as environmental, social, and governance (ESG) considerations increasingly influence capital allocation and risk assessment in healthcare and financial markets (Paridhi & Kumar, 2024; Dsouza et al., 2025; Khalil et al., 2025), driven by regulatory pressures and growing demand for impact-oriented investment (Sinha, 2025; Yunus & Nanda, 2024; Bressan & Sabrina, 2025). Empirical evidence suggests that strong ESG performance is associated with higher investment volumes, enhanced valuations, and lower perceived risk (Paridhi & Kumar, 2024; Cappellari & Gucciardi, 2024; Kumar et al., 2025; Yang & Lindrianasari, 2025; Kim et al., 2024; Oanh et al., 2025).

However, valuation outcomes in sustainable health startups remain fragmented due to inconsistent ESG metrics, heterogeneous investor behaviour, and regional market differences (Mangla & Yadav, 2024; Xiao et al., 2024; Reis et al., 2025). While some studies link ESG engagement to improved investor sentiment and firm value, others highlight risks related to greenwashing and inconsistent disclosure (Que et al., 2023; Deng et al., 2024; Zhang, 2024; Matakanye et al., 2025; Grove et al., 2024). These challenges are compounded by cross-market differences in institutional and private investor influence (Voß et al., 2024; Tun et al., 2024) and by constraints in emerging economies, such as limited capital access and weaker regulatory frameworks (Agbloyor et al., 2023), underscoring the need for improved governance and harmonised ESG standards (Chang et al., 2022; Alduais, 2023).

Conceptually, sustainable health ventures embed ESG principles into their strategies, shaping valuation through risk mitigation, competitiveness, and investor perception (Li, 2024; Ma, 2024). ESG-adjusted valuation approaches reflect investor priorities and regional capital market dynamics (Bian et al., 2023; An & Jia, 2024), while stakeholder, agency, and signalling theories explain how ESG metrics translate into real and perceived firm value (Kim et al., 2024; Ma, 2024; Morina & Dinaj, 2024).

Against this backdrop, this study synthesises the literature and empirically examines valuation challenges and investor influences in sustainable health startups. Using a mixed-methods design that combines a preferred reporting items for systematic reviews and meta-analyses (PRISMA) based systematic review (Mangla & Yadav, 2024; Yunus & Nanda, 2024; Tun et al., 2024) with unsupervised K-means clustering of 923 U.S.-based startups across 35 sectors, the study identifies five startup archetypes. The findings show that diversified investor structures — particularly those combining angel and VC — are most strongly associated with acquisition success, while sectoral analysis reveals pronounced heterogeneity within healthcare: health startups achieved a 100% acquisition rate, whereas medical startups exhibited lower success despite higher funding. Overall, the study advances valuation research by demonstrating the need for multidimensional, context-aware frameworks that integrate financial, structural, and qualitative factors, offering practical insights for investors, founders, and policymakers in sustainable health and technology-intensive sectors.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 presents the research methodology. Section 4 provides the research findings. Section 5 discusses the main results. Section 6 concludes the paper.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This study begins with a thematic analysis of key information areas that frame the research, including investor typologies, traditional startup valuation models, and alternative assessment approaches. It then reviews the most frequently cited literature to identify dominant themes in the field and trace the evolution of core research areas over time.

Startup valuation is shaped by the interaction of funding sources, valuation methodologies, and a growing set of qualitative and structural factors. Investor composition plays a central role, particularly in the early stages, when information asymmetry is high. Angel investors provide not only capital but also expertise and networks, acting as important quality signals; Lerner et al. (2018) show that angel-backed startups exhibit higher survival, growth, follow-on funding, and exit probabilities. VC firms further influence valuation through industry knowledge, governance, and staged financing (Hall & Hofer, 1993). Funding rounds themselves function as signals under uncertainty, increasing the informational value of VC participation (Davila et al., 2003). In addition to equity financing, startups may access crowdfunding, initial coin offerings (ICOs), or debt, which offer varying degrees of market validation and dilution (Reiff, 2025; Mansouri & Momtaz, 2022). Most ventures progress through sequential funding rounds — Seed to Series C and beyond — each involving valuation reassessment and trade-offs between capital access and founder control.

Despite the importance of funding structure, traditional valuation models face substantial limitations in early-stage contexts. Startups often lack revenues, long operating histories, and stable cash flows, rendering standard assumptions unreliable (Damodaran, 2009). Approaches such as discounted cash flow, market multiples, scorecard, and Berkus methods rely heavily on speculative projections or comparable firms that may not exist for innovative or niche ventures (McClure, 2025; Sarath, 2021b, 2021c). Similarly, the VC method, cost-to-duplicate, and risk factor summation approaches remain constrained by subjectivity, limited disclosure, and an inability to capture upside potential ("409a Valuation vs Venture Capital (VC) Valuation", 2025; Sarath, 2021a). As a result, these models often fail to reflect the full risk–return profile of early-stage ventures.

Recent research, therefore, emphasises additional valuation drivers beyond financial metrics. Sustainability and ESG orientation have become increasingly salient. Mansouri and Momtaz (2022) find that startups with strong ESG characteristics receive significantly higher initial valuations but tend to underperform post-funding, highlighting trade-offs between impact and short-term returns. Scalability is another key determinant: scalable ventures attract higher valuations and often delay initial public offerings to exploit growth opportunities when VC financing is available (Somaya & You, 2024; Adner et al., 2016). Such firms benefit from economies of scale and declining marginal costs (Giustiziero et al., 2023). Technological sophistication — particularly in cleantech, big data, mobile, and augmented reality — also contributes positively to valuation across sectors (Hidayat et al., 2022).

For technology-intensive startups, patents serve as strong quality signals. Patent activity is positively associated with VC financing (Baum & Silverman, 2004; Haeussler et al., 2014) and indicates technological maturity, given the cost and scrutiny of the application process (Tumasjan et al., 2021). Founder and chief executive officer (CEO) characteristics further shape valuation outcomes: while industry experience is generally beneficial, excessive reliance on parent-firm knowledge may reduce survival (Bahoo-Torodi & Torrisi, 2022), whereas founder CEO attractiveness can positively influence valuation under uncertainty (Colombo et al., 2022). Finally, the control dilemma highlights a trade-off between autonomy and value creation; relinquishing founder control is associated with significantly higher valuations (Wasserman, 2017).

Taken together, the literature suggests that startup valuation is inherently multidimensional. Investor structure, funding dynamics, scalability, ESG orientation, technological assets, and founder characteristics jointly influence valuation and exit outcomes, underscoring the need for integrative, context-aware valuation frameworks that extend beyond traditional financial models.

The most cited literature on startup valuation reflects the breadth of perspectives used to explain how funding structures, governance, sustainability, and behavioural signals shape venture outcomes. Early foundational work by Davila et al. (2003) examines the relationship between VC financing and startup growth using event studies and regression-based methods. Their findings show that pre-funding growth is not a strong predictor of future VC investment, highlighting the importance of qualitative and signalling factors in investment decisions.

Governance and control emerge as another central theme. Wasserman (2017) analyses the trade-off between founder control and startup valuation, demonstrating that founders who retain excessive control may constrain firm value. His empirical results suggest that strategically relinquishing control — such as stepping aside as CEO or board chair — can unlock higher valuations and attract greater external investment. Complementing this governance perspective, Pollman (2019) shows that startup governance differs fundamentally from traditional corporate models, as overlapping roles among founders, investors, and executives create persistent tensions, particularly as venture capitalists gain influence during scaling.

Sustainability and ESG considerations have gained increasing prominence in valuation research. Mansouri and Momtaz (2022) apply machine-learning techniques to quantify ESG orientation in startups and show that strong sustainability profiles lead to significantly higher initial valuations, albeit at the cost of weaker post-investment financial performance. Similarly, Moro-Visconti et al. (2020) demonstrate that sustainability-oriented, highly scalable FinTech business models command higher market valuations than traditional banks, underscoring the valuation premium associated with scalable and technology-driven models.

Investor type and composition also play a decisive role in startup success. Lerner et al. (2018) employ a regression discontinuity design to assess the global impact of angel investments, finding that angel-backed startups experience higher survival rates, faster growth, and improved access to follow-on financing. At the literature level, Cumming et al. (2023) provide a comprehensive bibliometric review of VC and private equity research, identifying core themes such as financing processes, governance mechanisms, and buyout strategies that shape valuation outcomes across contexts.

Recent studies further highlight the importance of informational signals and founder attributes under uncertainty. Tumasjan et al. (2021) show that venture capitalists incorporate both weak signals, such as Twitter sentiment, and strong signals, such as patent filings, into valuation decisions, although only patents reliably predict long-term success. Extending behavioural insights, Colombo et al. (2022) find that founder CEO physical attractiveness positively influences valuation and post-funding performance in ICOs, suggesting that investors rely on personal cues when objective information is limited.

Finally, strategic resource allocation decisions are shown to affect valuation trajectories. Joglekar and Lévesque (2009) use mathematical optimisation models to demonstrate that optimal startup valuation depends on balancing research and development (R&D) and marketing investments across financing stages, with these decisions shaped by productivity, market growth, and financial constraints. Together, these highly cited studies illustrate that startup valuation is influenced by a complex interplay of financial, strategic, governance, behavioural, and sustainability-related factors rather than by financial metrics alone.

The literature indicates that health-related startups often require larger capital investments due to regulatory complexity and R&D intensity (Haeussler et al., 2014; Hidayat et al., 2022), but their outcomes vary widely depending on technological maturity and commercialisation risk. Recent studies have examined success drivers in digital and health-related startups using sector-specific perspectives. Burton et al. (2024) analyse investor interest in digital health startups and show that patents, online presence, financial performance, and firm valuation significantly influence funding decisions, underscoring the importance of technological signals and market visibility. Complementing this work, Chakraborty et al. (2023) identify 18 critical success factors for e-health startups across five dimensions — actor knowledge and communication, service value and effectiveness, technological robustness, revenue generation capability, and regulatory management — using qualitative interviews and the Service–Technology–Organization–Finance (STOF) framework. While these studies provide valuable insights into health-tech success factors, they rely primarily on qualitative methods or investor-attention perspectives. The present study extends this literature by empirically identifying startup archetypes through unsupervised clustering and by examining how investor structure, ESG orientation, and sectoral context jointly shape valuation and exit outcomes.

H1: Startups in the health and medical sectors receive higher average funding per venture but exhibit more heterogeneous exit outcomes compared to startups in other high-growth sectors, such as software or mobile.

H2: Health sector startups with diverse investor backing — comprising both angel investors and VC — are more likely to achieve acquisition compared to those backed by a single investor type or alternative funding sources.

Prior research (Davila et al., 2003; Lerner et al., 2018) highlights that mixed investor structures not only provide funding but also validate market potential, a critical success factor in capital-intensive and high-risk sectors such as health and biotech.

H3: Startups in the health sector with strong sustainability orientation (e.g., ESG-aligned objectives) achieve higher initial valuations but are less likely to reach a rapid exit compared to health startups focused solely on financial or technological performance.

According to Mansouri and Momtaz (2022), sustainability-oriented ventures tend to attract greater early-stage valuations; however, their long-term financial outcomes may lag behind due to trade-offs between impact goals and growth velocity — especially relevant in health, where ESG goals intersect with public value creation.

This study is conceptually grounded in signalling theory, agency theory, and stakeholder theory, which together inform the analytical structure of the research. Signalling theory explains how observable characteristics — such as investor diversity, funding rounds, patent activity, and ESG orientation — function as quality signals under conditions of information asymmetry. Agency theory frames the trade-offs between founder control and external investor involvement across successive funding stages and their implications for valuation outcomes. Stakeholder theory underpins the role of ESG orientation in health startups, where legitimacy, social value creation, and regulatory alignment influence investor perception and long-term value. These theoretical perspectives jointly guide the selection of variables and the interpretation of patterns identified through the empirical clustering analysis.

3. RESEARCH METHODOLOGY

This paper adopts a mixed-methods approach that integrates qualitative insights from the background literature with empirical analysis of real-world data on startup valuations and outcomes, including acquisitions and closures. This design enables a holistic assessment of the features influencing future startup success.

The empirical analysis is based on the publicly available Startup Success Prediction dataset (Manish KC, 2025), which contains historical information on 923 startups founded in the United States (U.S.) between 1984 and 2013. The dataset was selected due to its comprehensive coverage of startup characteristics relevant to valuation and exit outcomes, including funding history, investor composition, sector classification, and exit status.

Startups were included in the sample if they contained complete information on 1) total funding amount, 2) number of funding rounds, 3) presence of angel and VC investors, 4) number of investor relationships, and 5) exit outcome (acquisition or closure). Observations with missing values in these core variables were excluded to ensure consistency and replicability of the clustering analysis. The focus on U.S.-based startups was motivated by data completeness and institutional comparability, though this choice limits the geographic generalizability of the findings.

The first part of the empirical analysis is a descriptive data overview and descriptive statistics. This creates a table with minimum value, 1st quartile, median, mean, 3rd quartile, and maximum value for numeric variables. The following formulas are used:

1st quartile:

$$Q_1 = 1 + (n-1) \times 0{,}25 \tag{1}$$

2nd quartile (median):

$$Q_2 = 1 + (n-1) \times 0{,}5 \tag{2}$$

3rd quartile:

$$Q_3 = 1 + (n-1) \times 0{,}75 \tag{3}$$

Mean:

$$\mu = \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

Here, in Eqs. (1), (2), (3), and (4), μ or $\bar{x}$ means the mean (average of the value) of the variable, x_i — the *i*-th data point, n — number of data points, Σ — the summation symbol.

The next step involves selecting an empirical analysis method. To identify feature combinations associated with startup success, this study employs cluster analysis, which detects naturally occurring groupings within the data. As an unsupervised learning technique, clustering does not rely on predefined classes but derives structure directly from the data. The method aims to produce clusters with high intra-cluster similarity and low inter-cluster similarity. In this context, clustering enables the comparison of venture groups to identify feature sets most strongly associated with funding levels and exit outcomes, specifically acquisition or closure.

The first step in data preparation is cleaning it from outliers and standardising. The following formulas are used for this:

1st quantile:

$$Q_1 = 1 + (n - 1) \times 0{,}01 \tag{5}$$

99th quantile (median):

$$Q_2 = 1 + (n - 1) \times 0{,}99 \tag{6}$$

Scaling:

$$x' = \frac{x-\mu}{\delta} \tag{7}$$

Here, in Eq. (7), x means original value, μ — mean of the variable, δ — standard deviation of the variable, x' — scaled (standardized) value.

To identify naturally occurring startup archetypes, this study employs K-means clustering, an unsupervised learning technique that groups observations based on similarity across selected variables. Prior to clustering, all continuous variables were standardised to ensure equal weighting, and extreme outliers were removed using the 1st and 99th percentile thresholds to prevent distortion of cluster centroids.

The clustering was conducted using five variables capturing core valuation-related dimensions: total funding amount (USD), number of funding rounds, number of investor relationships, presence of VC investors (binary), and presence of angel investors (binary). These variables operationalise funding intensity, investor structure, and relational depth, which are central to valuation signalling in early-stage ventures.

The optimal number of clusters was determined using the elbow method based on within-cluster sum of squares, and cluster quality was evaluated using the Silhouette score. Startups were assigned to clusters based on minimum Euclidean distance to cluster centroids, resulting in five distinct and interpretable startup archetypes.

ESG orientation is not directly quantified at the firm level in the clustering analysis due to data limitations. Instead, ESG considerations inform the conceptual framework and the interpretation of sectoral results — particularly in health-related sectors where sustainability objectives, regulatory compliance, and social impact are integral to valuation dynamics.

In order to create clusters, the first step is defining the number of meaningful clusters that can be created with the used dataset, a typical technique for that is the elbow method. The elbow method is a visual evaluation technique, based on the calculations of the Within-Cluster Sum of Squares (WSS).

For any given number of clusters k:

$$WSS(k) = \sum_{j=1}^{k} \sum_{x_i \in C_j} \left\| x_i - \mu_j \right\|^2 \tag{8}$$

Here, in Eq. (8), x_i means a data point, μ_j — the centroid of cluster C_j, $\left\| x_i - \mu_j \right\|^2$ is squared Euclidean distance between the point and its cluster centre, C_j — set of all points in cluster j, k — number of clusters. The elbow method means calculating the WSS for each potential number of clusters, plotting that, and visually looking for a point where the rate of decrease slows sharply; this is the number of clusters that should be used.

The K-means clustering method will be chosen for the analysis. The approach of this method is to group data points into clusters in a way that the total within-cluster variance is minimised. It is defined by the following formula:

$$\min_{C} \sum_{j=1}^{k} \sum_{x_i \in C_j} \left\| x_i - \mu_j \right\|^2 \tag{9}$$

Here, in Eq. (9), x_i means a data point, μ_j — the centroid of cluster C_j, $\left\| x_i - \mu_j \right\|^2$ is squared Euclidean distance between the point and its cluster centre, C_j — set of all points in cluster j, k — number of clusters.

Once the clusters are created, their quality needs to be assessed. The main criterion to assess is the Silhouette score. Silhouette score measures how well a data point fits within its cluster compared to the next-closest cluster.

For each point i, the formula is:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{10}$$

Here, in Eq. (10), $a(i)$ means the average distance from point i to all other points in the same cluster (intra-cluster distance), $b(i)$ means the lowest average distance from point i to all points in the nearest cluster (nearest-cluster distance). The average (8) silhouette score to assess the quality of the entire clustering:

$$S = \frac{1}{n} \sum_{i=1}^{n} s(i) \tag{11}$$

For a clustering analysis to be successful, in addition to a reasonable silhouette score (above 0.4–0.5), clusters have to be visually separated (with minimal or no overlap) and have to be logically interpretable. To meet these conditions, only key variables should be used, and these variables have to be scaled and cleaned for outliers.

Coming across a dataset containing up-to-date and meaningful, and sometimes quite sensitive information about startups can be really challenging. The dataset used for this work comes from the open-source dataset platform Kaggle (Manish KC, 2025), which contains information about 923 startups from 35 categories within the U.S. The timeframe is between 1984 and 2013. About each of the ventures dataset provides — U.S. state where startup was created, city, time of creation, time of closure (if the venture was closed during the timeframe), date of first and last fundings, date of first and last milestone, number of milestones, number of investors, number of funding rounds, funding amount in USD, sector, VC presence among investors, angel investor presence, participation in different investment rounds, belonging in the list of top 500 startups and exit status.

In addition to the mixed-methods approach adopted in this study, several alternative methodologies could be used to analyse startup valuation and success. Regression-based models, such as logistic or survival analysis, allow hypothesis testing and estimation of variable effects on exit outcomes but rely on strong assumptions and may struggle with heterogeneity in early-stage startup data. Supervised machine-learning methods (e.g., random forests or gradient boosting) are effective for prediction and capturing nonlinear relationships, yet require predefined outcome labels and often lack interpretability.

Qualitative case studies or qualitative comparative analysis (QCA) could provide deeper insight into regulatory, organisational, and sector-specific dynamics, particularly in healthcare, but are limited in scalability and generalisability. Network analysis may also be suitable for examining investor syndication and relational effects, though it depends on detailed network data that are often unavailable. Compared with these alternatives, the unsupervised clustering approach used in this study offers an effective balance between flexibility and interpretability, enabling the identification of natural startup archetypes without imposing prior assumptions about success.

The variables used in the clustering analysis were selected to reflect theoretically grounded valuation signals derived from signalling, agency, and stakeholder perspectives, including investor composition, funding dynamics, and sustainability orientation.

All data preprocessing steps, variable definitions, and clustering criteria are reported to ensure transparency and enable replication using the same open-access dataset.

4. RESEARCH RESULTS

Some variables were removed from the set, as they were less relevant for the objectives of the work or had missing values. Table A.1 in the Appendix provides descriptive statistics for the remaining variables in the dataset; the biggest variations of values are seen among the number of relationships (from 1 to 10) and in funding amount (from 11,000 to 5,700,000,000 USD).

Variables with a high proportion of zero values reflect the categorical and binary nature of startup characteristics rather than data sparsity. To enhance clarity, all variables are explicitly defined, and highly sparse indicators that are not central to the clustering procedure are excluded from the empirical analysis or reported in the supplementary material.

In addition to descriptive statistics, we take a look into few additional dimensions to get additional insights from the data. Table 1 shows, how startups in different sectors attract fundings, to understand whether some sectors are more interesting for investors than others — we see that the sector with highest investment levels are broadly technological — software is the main one with nearly 2,5 billion USD, however we see that it is also the most crowded sector in terms of startup amount and the average funding collected per startup is just nearly ~16 million USD. Following sectors — mobile, web, biotech, enterprise, semiconductor, having collected over 1 billion USD each, aside from the web category, the saturation is much lower, and in some sectors, like biotech and semiconductor, average funding per startup is higher, up to ~42 million USD.

Table 1. Startup funding distribution by industry

Industry	*Total funding (USD)*	*Average funding (USD)*	*Startups*
Software	2,419,388,866	15,917,032	152
Mobile	1,563,750,881	20,048,088	78
Web	1,429,509,436	10,138,365	141
Biotech	1,329,435,258	41,544,852	32
Enterprise	1,196,882,096	16,623,362	72
Semiconductor	1,105,156,970	31,575,913	35
Advertising	918,619,012	14,816,436	62
Games/Video	844,631,530	16,561,403	51
Network hosting	735,033,389	21,618,629	34
Hardware	625,938,873	24,074,572	26
Cleantech	578,881,730	27,565,797	21
Security	373,428,570	19,654,135	19
Ecommerce	329,047,922	14,306,431	23
Public relations	277,066,000	11,082,640	25
Analytics	276,415,182	14,548,167	19
Other	209,482,860	20,948,286	10
Finance	193,178,704	32,196,451	6
Medical	166,334,616	23,762,088	7
Search	156,300,000	13,025,000	12
Fashion	133,570,000	16,696,250	8
Transportation	127,704,370	63,852,185	2
Photo/Video	108,286,415	15,469,488	7
Music	99,725,019	16,620,836	6
News	95,380,000	11,922,500	8
Health	66,330,000	22,110,000	3
Messaging	59,053,000	5,368,455	11
Consulting	58,050,000	19,350,000	3
Automotive	52,000,000	26,000,000	2
Travel	48,575,000	6,071,875	8
Social	44,973,498	3,212,393	14
Education	43,263,835	10,815,959	4
Real estate	7,347,782	2,449,261	3
Manufacturing	4,662,000	2,331,000	2
Hospitality	3,750,000	3,750,000	1
Sports	2,000,000	2,000,000	1

In Table 2, we examine a portion of startups acquired by the sector to gain additional initial insights. First come the startups with 100% acquisition; however, we also see that the sample sizes here are very small. We also see that previously noted — Software, Web, and Biotech sectors have only ~66% acquisition rate. While some sectors have acquisition rates even below 50%, notable exceptions include e-commerce, cleantech, hardware, and public relations. This, in conjunction with findings from Table 2, suggests that strong funding does not necessarily translate into success, and that the more attractive the sector, the more competitors are trying to break through. Upon examining the sectors with fewer acquisitions, it becomes apparent that some are more challenging and costly to scale. In the following section, we will look at the data more closely.

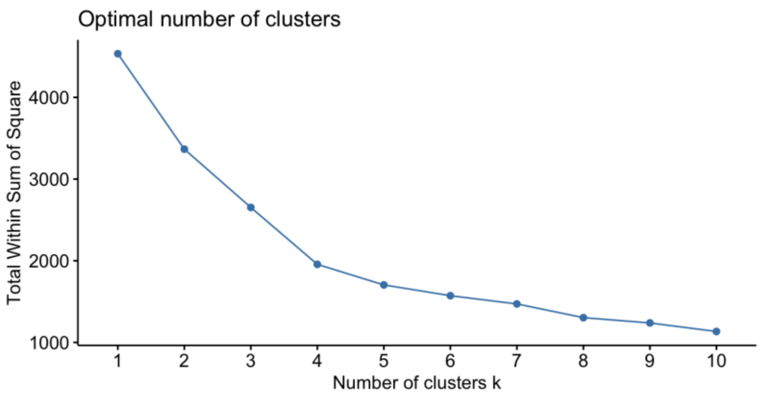
Table 2. Startup acquisition distribution by industry

Industry	*Startups*	*Acquired*	*Closed*	*Acquisition (%)*
Music	6	6	0	100%
Health	3	3	0	100%
Hospitality	1	1	0	100%
Transportation	2	2	0	100%
Sports	1	1	0	100%
News	8	7	1	88%
Travel	8	7	1	88%
Analytics	19	16	3	84%
Security	19	15	4	79%
Enterprise	72	55	17	76%
Education	4	3	1	75%
Advertising	62	45	17	73%
Photo/Video	7	5	2	71%
Network hosting	34	24	10	71%
Semiconductor	35	24	11	69%
Consulting	3	2	1	67%
Finance	6	4	2	67%
Software	152	100	52	66%
Biotech	32	21	11	66%
Mobile	78	51	27	65%
Web	141	92	49	65%
Messaging	11	7	4	64%
Fashion	8	5	3	63%
Games/Video	51	31	20	61%
Search	12	7	5	58%
Social	14	8	6	57%
Medical	7	4	3	57%
Automotive	2	1	1	50%
Ecommerce	23	11	12	48%
Cleantech	21	10	11	48%
Hardware	26	11	15	42%
Public relations	25	10	15	40%
Real estate	3	1	2	33%
Other	10	1	9	10%
Manufacturing	2	0	2	0%

When conducting cluster analysis, we look to meet quality criteria; therefore, we minimise the number of variables used, scale the data, and remove outliers (1st and 99th quantiles). While the values are scaled, it is still beneficial to remove the outliers to get better clusters, as extreme values could distort the cluster centroid and provide misleading groupings. The variables used for the clustering are the following: *funding_total_usd*, *funding_rounds*, *relationships*, *has_VC*, and *has_angel*.

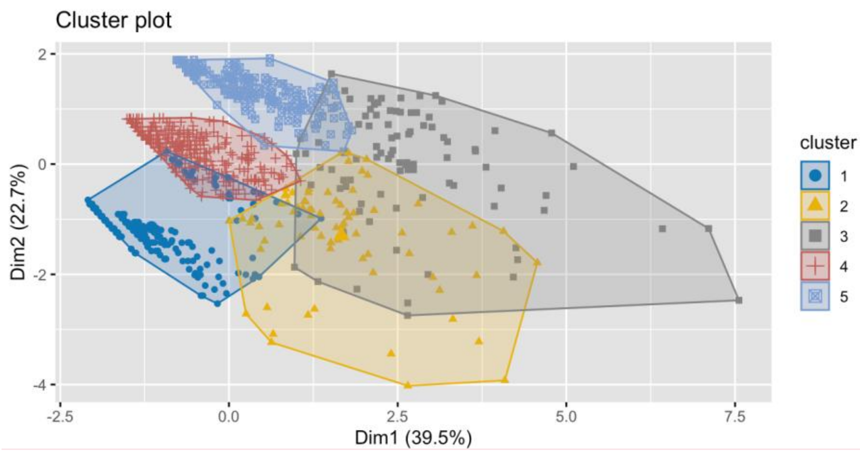
The first step of the analysis is to determine the number of clusters using the elbow method. Figure 1 shows that in this case, it should be 4 or 5 clusters, as the sharpness of the decline slows down at 4–5 clusters.

Figure 1. Elbow chart



The next step is to create and visualise the clusters. Figure 2 represents dimensionally reduced clustering results — five segments, positioned across two primary components that together explain nearly ~62% of the variance in the dataset. Silhouette score for the clustering is 0.4158764 (acceptable).

Figure 2. Startup clusters



Cluster 1 (blue dots) is a tight group of young startups similar in small funding amounts (on average ~2,8 million USD), all the startups in Cluster 1 are angel-backed and have a relatively small portion of VC investment, predominantly having participated only in Series A funding round, dominant industry — web.

Cluster 2 (yellow triangles) is the smallest cluster with only 73 startups — the differentiator for this segment is the highest amount of different investor participation in Series A, B, C, and D investment rounds — balanced involvement of angel investors and VC. This cluster also has the second-highest funding on average (~30.6 million USD). Dominant industries — web and advertising.

Cluster 3 (grey squares) is also relatively small and contains startups of the highest funding (on average, ~62.4 million USD). Similar to Cluster 2, this cluster also participates in multiple investment rounds (Series A, B, C, and D), but it is more heavily backed by VC investors and has more substantial involvement in late-stage funding (Series C and D). Dominant industry — mobile.

Cluster 4 (red pluses) is the largest in the set, containing over a third of the startups. It primarily contains startups from the web and software industries. The differentiating aspect here is that none of the startups in the cluster have angel or VC backing. Participation in investment rounds is moderate (higher than that of Cluster 1, however, much lower than that of Clusters 2 and 3); therefore, key sources of investment are likely bootstrapping or other options (like loans).

Cluster 5 (light blue crosses) is the second largest cluster with 190 startups, achieving mid-level funding (on average, 14.7 million USD). The difference of this cluster is that it is 100% backed by VC investments and has zero angel investors. Dominant industry — software.

Table 3 provides more context about the clusters, and Table 4 provides a summarised view.

Table 3. Cluster summary

Metric	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 5*
No. of startups	209	73	89	347	190
Avg funding (USD)	2,860,659	30,646,151	62,414,173	12,979,978	14,679,960
Avg funding rounds	2.11	3.34	4.52	1.62	2.26
Avg relationships	5.94	23.52	10.75	6.20	4.69
Avg age first funding (years)	0.78	1.48	2.00	2.69	3.37
Avg age last funding (years)	1.86	4.81	6.37	3.57	5.26
% VC-backed	13.88%	20.55%	68.54%	0.00%	100.00%
% Angel-backed	100.00%	12.33%	13.48%	0.00%	0.00%
% Round A	34.45%	80.82%	64.04%	63.40%	30.00%
% Round B	9.09%	78.08%	75.28%	43.52%	33.16%
% Round C	0.48%	60.27%	71.91%	20.17%	16.32%
% Round D	0.00%	23.29%	39.33%	8.65%	3.16%
Dominating sectors	Web (29%)	Web and advertising (24% each)	Mobile (32%)	Software (20%), Web (15%)	Software (31%)

Table 4. Summarized cluster overview

Cluster	*Overview*
1	100% angel-backed, early-stage investments, low funding, fresh startups
2	Solid, mid-level funded startups, the biggest set of investors
3	Big, successful & highest funded startups, strongest in late-stage funding
4	Largest cluster, alternative funding (no angel investors and no VC investors)
5	100% VC-backed, zero angel investors

Cluster analysis provided five quite distinct startup clusters, each with a differentiating feature. The next step in the analysis involves comparing the clusters to determine the most successful one based on exit status. Table 5 shows us that the highest portion of acquisitions was reached in Cluster 2, followed by Cluster 3.

Table 5. Cluster acquisition

Cluster	*Total*	*Acquired*	*Closed*	*Acquisition (%)*
1	209	118	91	56.5%
2	73	67	6	91.8%
3	89	74	15	83.1%
4	347	228	119	65.7%
5	190	104	86	54.7%

From a sectoral perspective, health-related startups demonstrate distinctive investment and outcome characteristics compared to the broader startup ecosystem. The health sector, although comprising only three ventures in the sample, exhibited an exceptional acquisition rate of 100%, with an average funding level of 22.1 million USD per startup. Similarly, the medical sector, composed of seven ventures, showed a higher average funding of 23.8 million USD, though with a lower acquisition rate of 57.1% and a notable closure rate of 42.9%. These outcomes indicate that while health and medical startups generally receive above-average funding — in comparison to the overall sectoral mean of 17.7 million USD — they are subject to heterogeneous risk profiles. The health sector may benefit from the growing strategic demand for digital and preventive health solutions, often leading to earlier acquisitions, while the medical sector, despite attracting larger investments, faces more complex regulatory, technological, and clinical risks that increase failure probability.

When benchmarked against dominant sectors such as software, web, and mobile, a more nuanced picture emerges. The software sector, representing the largest group with 152 startups, attracted a total of 2.42 billion USD, yet its average per-startup funding was 15.9 million USD, significantly lower than in the health and medical sectors. Its acquisition rate was 66%, close to the dataset-wide average of 65.7%. Similarly, the web sector, with 141 startups, received 1.43 billion USD in total funding, averaging 10.1 million USD per venture and an acquisition rate of 65%. Interestingly, while sectors like biotech and semiconductors had fewer startups (32 and 35, respectively), their average funding levels exceeded 30 million USD, yet their acquisition rates remained around 66–69%, suggesting a moderate risk-return profile similar to medical startups.

Taken together, these findings underscore that health-related sectors tend to attract fewer but more heavily funded startups and, in the case of the health sector specifically, exhibit higher-than-average success in exit outcomes. This supports the argument that investor evaluations in the health and medical sectors are likely more selective and driven by high-impact potential, although this also entails greater variance in success probability, particularly in research-intensive subsectors. These observations highlight the need for sector-sensitive valuation frameworks that integrate not only funding levels and investor composition but also regulatory dynamics, time-to-market factors, and strategic acquisition drivers unique to healthcare innovation.

5. DISCUSSION OF THE RESULTS

The results of this study identify systematic associations between startup characteristics, investor structure, and exit outcomes. Given the exploratory and unsupervised nature of the clustering methodology, the findings should be interpreted as revealing patterns and regularities in the data rather than causal relationships. Accordingly, the discussion emphasises how specific combinations of funding intensity, investor diversity, and sectoral affiliation are associated with higher acquisition likelihood, rather than implying direct causal effects.

The results of this study both corroborate and extend existing research on startup valuation and success factors. Consistent with Davila et al. (2003) and Lerner et al. (2018), the clustering analysis confirms that investor diversity — particularly the joint presence of angel and VC investors — significantly increases acquisition probability. The cluster with the broadest investor base achieved a 91.8% acquisition rate, reinforcing the view that the funding structure serves as both capital provision and a quality signal under information asymmetry. The findings also align with Somaya and You (2024) and Adner et al. (2016), highlighting scalability as a key valuation driver, especially in technology-intensive sectors such as software, mobile, and biotech, which attracted the highest funding levels.

Health-related sectors exhibit more nuanced patterns. While health startups showed a 100% acquisition rate, medical startups achieved only 57.1%, despite receiving even higher average funding. This contrasts with generalized assumptions that higher funding uniformly leads to better outcomes (Hidayat et al., 2022) and underscores heterogeneity within healthcare subdomains. Moreover, the results support Mansouri and Momtaz (2022), indicating that strong ESG orientation boosts initial valuations but may hinder short-term performance — particularly relevant in health ventures, where impact objectives can delay monetization.

Compared with traditional valuation approaches reliant on financial projections (Damodaran, 2009), the clustering-based methodology captures qualitative, structural, and sector-specific factors that are often unobservable in early-stage ventures. This supports critiques that conventional models underrepresent positive risks and long development cycles, especially in regulated or innovation-driven sectors.

The study contributes to the literature in several ways. First, it advances a holistic valuation framework by integrating thematic literature analysis with empirical clustering. Second, it identifies five distinct startup archetypes based on investor composition, funding intensity, and exit outcomes, demonstrating that diversified investor bases are strongly associated with acquisition success. Third, it provides sector-specific insights into health and medical startups, highlighting divergent risk-return profiles despite similar funding levels. Fourth, it critiques the limitations of traditional valuation models and advocates for adaptive, multi-factor approaches. Finally, it introduces a methodological contribution by applying unsupervised machine learning (K-means clustering) to real-world startup data, offering a flexible pattern-recognition tool with practical implications for investors, accelerators, and policymakers, particularly in strategically important sectors such as health and biotechnology.

6. CONCLUSION

This study contributes to the startup valuation literature by combining a thematic literature review with an empirical clustering analysis to identify characteristics associated with successful startup outcomes. The findings demonstrate that traditional valuation models, while suitable for mature firms, are insufficient for early-stage startups, where intangible assets, investor diversity, and scalability are central drivers of success. A more holistic assessment framework is therefore warranted, integrating quantitative indicators with qualitative factors such as founder characteristics, sustainability orientation, and investor composition.

The empirical analysis identifies five distinct startup archetypes and shows that ventures with broad investor diversity — particularly balanced participation of angel and VC across funding stages — exhibit the highest likelihood of acquisition. This supports theoretical perspectives that diversified investor bases provide not only capital but also strategic validation, expertise, and signalling benefits. In contrast, startups with limited or concentrated funding structures display lower success probabilities, even when achieving moderate funding levels.

Sector-specific analysis reveals meaningful differences across industries. Health-related ventures display distinctive dynamics: health startups achieved a 100% acquisition rate with above-average funding, while medical startups — despite higher investment levels — showed lower acquisition rates (57.1%) and higher closure risk. Compared to high-volume sectors such as software, web, and biotech, health-related ventures appear fewer in number but higher in strategic value, underscoring the importance of sector-sensitive valuation frameworks, particularly in regulated and R&D-intensive domains.

Several limitations apply. The dataset is restricted to U.S. startups founded between 1984 and 2013, limiting temporal and geographic generalizability, and some sectors have small sample sizes. Success is measured solely through acquisition versus closure, omitting alternative outcomes such as sustained private operation or licensing. Additionally, key qualitative factors discussed in the literature — such as ESG integration, patent quality, and founder psychology — could not be directly incorporated due to data constraints.

Future research should extend the analysis to more recent and internationally diverse datasets, incorporate longitudinal valuation data, and apply broader success metrics. Integrating structured financial information with unstructured data sources, such as pitch materials or founder narratives, could further enhance valuation models. Sector-focused studies — particularly in healthcare, climate technology, and artificial intelligence — are especially needed to develop tailored frameworks that better capture innovation intensity, regulatory complexity, and impact potential.

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APPENDIX

Table A.1. Descriptive statistics

	Name	*founded_at*	*closed_at*	*first_funding_at*	*last_funding_at*	*age_first_funding_year*	*age_last_funding_year*	*category*	*Avg_participants*	*status*
Length	923	923	923	923	923	923	923	923	923	923
Class	char	char	char	char	char	char	char	char	char	char
Mode	char	char	char	char	char	char	char	char	char	char
	Relationships	***funding_rounds***	***funding_total_usd***	***category_code***	***Is_software***	***Is_web***	***Is_mobile***	***Is_enterprise***	***Is_advertising***	***Is_gamesvideo***
Min	0.000	1.000	11000	1.000	0.0000	0.000	0.00000	0.00000	0.00000	0.00000
1st qu	3.000	1.000	2725000	2.000	0.0000	0.000	0.00000	0.00000	0.00000	0.00000
Median	5.000	2.000	10000000	7.000	0.0000	0.000	0.00000	0.00000	0.00000	0.00000
Mean	7.711	2.311	25419749	8.381	0.1658	0.156	0.08559	0.07909	0.06717	0.05634
3rd qu	10.000	3.000	24725000	11.000	0.0000	0.000	0.00000	0.00000	0.00000	0.00000
Max	63.000	10.000	5700000000	35.000	1.0000	1.000	1.00000	1.00000	1.00000	1.00000
	Is_ecommerce	***Is_biotech***	***Is_consulting***	***Is_othercategory***	***has_VC***	***has_angel***	***has_roundA***	***has_roundB***	***has_roundC***	***has_roundD***
Min	0.00000	0.00000	0.00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.00000
1st qu	0.00000	0.00000	0.00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.00000
Median	0.00000	0.00000	0.00000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.00000
Mean	0.02709	0.03684	0.00325	0.3229	0.3261	0.2546	0.5081	0.3922	0.2329	0.09967
3rd qu	0.00000	0.00000	0.00000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0000	0.00000
Max	1.00000	1.00000	1.00000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.00000

Note: Several variables in this table are binary indicators (e.g., sector classification and investor presence), which explains the high frequency of zero values. These variables capture whether a startup belongs to a specific category or has received a particular type of funding, rather than intensity measures.