A valuation blueprint for Software-as-a-Service startups

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Acknowledgement

Dear reader,

You are about to read my bachelor's thesis, which completes my degree in Industrial Engineering and Management (IEM) at the University of Twente. The research presented in this report was conducted at Akela Hub. Before delving into the content of the thesis, I would like to express my gratitude to those who supported me throughout this journey.

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With that said, enjoy reading my thesis!

Kind regards,

Roy Mulder

Enschede, June 2025

Management Summary

Akela Hub is a Dutch Software-as-a-Service (SaaS) startup that spun out from the Unknown Group in early 2024. Operating with a SaaS revenue business model, Akela Hub faces a common challenge among early-stage startups: determining the value of the startup. Traditional valuation methods, such as Discounted Cash Flow (DCF) or market comparables, often fall short for startups like Akela Hub due to their limited financial history, intangible asset structure, and high growth uncertainty. This resulted in the following research question:

How can a valuation blueprint for Akela Hub be developed and applied to address the limitations of traditional valuation methods and support strategic decision-making for exit strategies?

To address this, we developed a lifecycle-based SaaS valuation blueprint through a combination of literature research, expert validation, and regression analyses. The blueprint utilises Annual Recurring Revenue (ARR) as a proxy to categorise startup stages and offers tailored metrics and valuation methods for each stage. Additionally, two Multiple Linear Regression (MLR) models, using exit data from acquisitions and Initial Public Offerings (IPO), further revealed valuation insights. For example, acquisitions in North America tend to yield a valuation approximately 21% higher than in Europe, and the valuation of an IPO exit increases over time due to company maturity, even when funding is held constant.

Applying the blueprint to Akela Hub, the company was classified in the seed stage. As a result, the VC method was used to estimate the valuation under different growth scenarios, resulting in a current valuation range of €2,900,000 to €20,100,000. Although this is a broad range, it reflects the expected uncertainty of early-stage forecasting.

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Abbreviations

ACV	Average Contract Value
AI	Artificial Intelligence
ARR	Annual Recurring Revenue
BP	Breusch-Pagan
CapEx	Capital Expenditures
CAC	Customer Acquisition Costs
CCA	Comparable Company Analysis
CCF	Capitalised Cash Flow
CLV	Customer Lifetime Value
COGS	Costs Of Goods Sold
CRM `	Customer Relationship Management
DCF	Discounted Cash Flow
DRSM	Design Science Research Methodology
EBIT	Earnings before interest and taxes
EBITDA	Earnings before interest, taxes, depreciation, and amortisation
EV	Enterprise Value
FCFF	Free Cash Flow of the Firm
FCVM	First Chicago Valuation Method
IAS	International Accounting Standards
IEM	Industrial Engineering & Management
IPO	Initial Public Offering
LM	Lagrange Multiplier
MAE	Mean Absolute Error
M&A	Mergers and Acquisitions
MLR	Multiple linear regression
MPSM	Managerial Problem-Solving Method
MRR	Monthly Recurring Revenue
NPV	Net Present Value

NRR	Net Revenue Retention
OLS	Ordinary Least Squares
PTA	Precedent Transaction Analysis
R&D	Research and Development
RESET	Regression Specification Error Test
RMSE	Root Mean Squared Error
ROV	Real Option Valuation
RQ	Research Question
SaaS	Software as a Service
SE	Standard Error
SG&A	Selling, General, and Administrative
T2D3	Triple, triple, double, double, double rule
TAM	Total Addressable Market
VC	Venture Capital
VIF	Variance Inflation Factor
WACC	Weighted Average Cost of Capital
WLS	Weighed Least Squares
YoY	Year-on-year

1. Introduction

1.1. Company description

Akela Hub, a Dutch spin-off company from the Unknown Group, began operations in 2024. Akela Hub enables organisations to discover and connect with innovative companies using its scouting platform and human expertise. Akela Hub gathers data and uses an Artificial Intelligence (AI) algorithm to organise the data. It includes a comprehensive database of over six million companies, offering features such as customer relationship management (CRM) integration for data enrichment and targeted scouting services. This helps users discover prospective partnerships and gain insights into the competitive landscape. Akela Hub operates with seven employees from The Hague, located in the Titaan, an impact hub.

1.2. Action problem

The number of Software as a Service (SaaS) startups is rising. These relatively new companies follow non-traditional business models, mostly subscription-based. Instead of selling complete products, they provide software access and licenses, making traditional valuation methods inaccurate (Cohen & Neubert, 2019).

With its distinct business model and financial structure, Akela Hub relies on monthly licenses and singular software sales, presenting valuation challenges. Selling startups in the early stages is common, but determining the right selling price and timing for Akela Hub is difficult. Inaccurate SaaS valuations risk sub-optimal selling prices that investors may exploit or prevent a successful exit.

Heerkens and Winden (2017) define an action problem as a discrepancy between the norm and reality the problem owner perceives. For Akela Hub, the norm is the ability to determine a selling price, which we need for making strategic decisions and maximising the company's valuation during a potential exit. In reality, existing valuation methods fail to meet SaaS startups' needs, leading to risks in a potential exit. Therefore, we define the action problem as:

SaaS startups face difficulties in determining a selling price, leading to risk in a potential exit.

1.3. Core problem

After defining the action problem, we identify the core problem by creating a problem cluster by mapping out different problems and their mutual relationship (Heerkens & Winden, 2017). The action problem relates to the risk of a potential exit of Akela Hub due to the difficulties in determining an exit price and other problems, such as negotiation challenges and reduced market confidence.

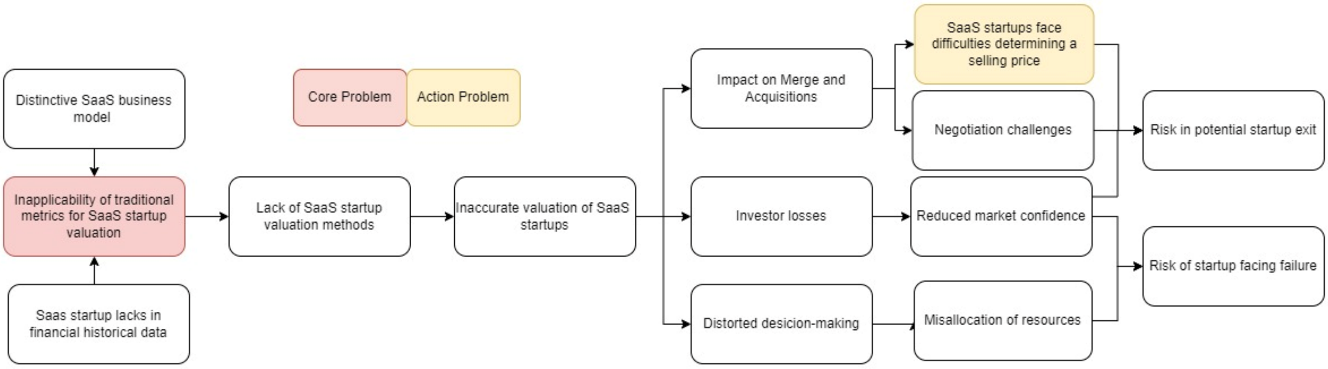
In Figure 1.1 we observe that inaccurate valuations have several consequences, including impacts on mergers and acquisitions, investor losses, and distorted decision-making. However, these inaccurate valuations are caused by unsuitable valuation methods for SaaS startups. Cohen and Neubert (2019) explain that the relatively new SaaS business model creates a misalignment between traditional valuation methods and the needs of SaaS startups. Traditional valuation methods are inapplicable to SaaS start-ups due to their business models and the lack of historical financial data, resulting in inaccurate valuations that fail to capture both the characteristics of SaaS business models and the expected above-average free cash flow growth rate (Cohen & Neubert, 2018).

According to Heerkens and Winden (2017), a core problem must occur early in the causal chain, trigger other problems, and be influenceable. While the distinctive SaaS business models and the lack of financial data are root causes, they cannot be directly addressed. SaaS business models are fundamental to the industry, and the lack of financial data is an unavoidable consequence of startups' relatively early stage. Therefore, these issues are not influenceable and cannot be considered core problems.

Instead, the focus must shift towards developing a solution to address the challenges caused by the inapplicability of the traditional valuation metrics. By creating a tailored valuation blueprint for SaaS startups, we can introduce alternative valuation methods or metrics to resolve the problem and its consequences. Therefore, we define the core problem as follows:

Traditional valuation metrics are inapplicable to SaaS startup valuation.

Figure 1.1 Problem cluster



1.4. Measurement of norm and reality

This research norm is to develop a tailored solution to address the inapplicability of traditional metrics for SaaS startup valuation, specifically focusing on Akela Hub. This involves developing a valuation blueprint for Akela Hub that integrates insights from a literature review, relevant data, and expert interviews. We adjust the blueprint to Akela Hub's business model and strategic priorities.

The gap between the norm and reality is evident since there is no tailored valuation blueprint for startups like Akela Hub. Our research bridges this gap by creating a customised solution that identifies valuation metrics for the SaaS industry and is tailored to Akela Hub. With this blueprint, Akela Hub better understands the important metrics driving its value.

1.5. Problem-solving approach

We adopt a clear methodology to address complex problems, such as the core problem. A well-suited methodology provides structure and breaks down the problem into manageable steps. The Design Science Research Methodology (DSRM) focuses on developing an artefact, such as models, methods, or frameworks (Peffers et al., 2007).

On the other hand, the Managerial Problem-Solving Method (MPSM) is a more general method applicable to problems across various areas of expertise and focuses on identifying, analysing, and resolving managerial problems (Heerkens & Winden, 2017). While MPSM effectively addresses managerial challenges, it does not inherently involve creating, testing, or validating new frameworks like a blueprint.

Since we aim to develop a valuation blueprint for SaaS startups, including its testing and validation, DRSM is a more appropriate methodology. Additionally, DSRM emphasises the importance of iterative processes, as shown in Figure A.1. These iterative steps are essential for evaluating and refining the blueprint to ensure it meets the research objectives.

The DSRM model consists of six activities: problem identification and motivation, defining the objectives for a solution, design and development, demonstration, evaluation, and communication (Peffers et al., 2007).

1. ***Problem identification and motivation***
   This activity identifies the research problem and justifies the value of a solution.
2. ***Define the objectives for a solution***
   This activity outlines the goals or criteria the solution must meet and considers what is feasible with current knowledge and technology.
3. ***Design and development***
   This activity determines the artefact's desired functionality and architecture and involves creating the actual artefact.
4. ***Demonstration***
   This activity demonstrates the usability of the artefact and the solvability of the problem. Case studies or real-world applications could be involved as well.
5. ***Evaluation***
   This activity observes and measures the artefact's performance and checks whether the defined objectives meet and perform well in practice.
6. ***Communication***
   This activity shares the problem, its importance, and the research findings with researchers and other relevant audiences.

1.6. Research question

We address the core problem identified in the problem cluster. We aim to develop a valuation blueprint for SaaS startups to address the limitations of traditional valuation metrics and support Akela Hub in its future exit strategy. Therefore, we define the Research Question (RQ) as follows:

RQ: *How can a valuation blueprint for SaaS startups be developed and applied to address the limitations of traditional valuation methods and support strategic decision-making for exit strategies?*

1.7. Sub-research questions

We have developed several sub-research questions to support the main RQ, categorised into exploratory, descriptive, explanatory, and evaluative questions, breaking down the RQ into smaller, more manageable parts and providing structure to our research.

First, exploratory analysis seeks to learn about current valuation methods. These sub-research questions provide a foundation for understanding existing techniques.

> **RQ1:** *Which traditional valuation methods exist, and which characteristics of SaaS startups challenge their applicability?*
>
> - Aim: To explore traditional valuation methods and the characteristics of SaaS startups that make them challenging to apply.
>
> **RQ2:** *How are SaaS startups currently valued, and which factors contribute to the limitations of these valuations?*
>
> - Aim: To understand the current valuation methods for SaaS startups, identify the factors contributing to their limitations, and identify areas for improvement.

After we establish the foundational knowledge about the valuations of traditional and SaaS businesses, descriptive analysis identifies the key metrics for SaaS start-up valuation from both investor and business perspectives.

> **RQ3:** *What are the most appropriate metrics for valuing SaaS startups, considering the limitations of traditional methods?*
>
> - Aim: To identify relevant metrics for SaaS valuation, addressing the limitations of traditional and current methods. These metrics form the foundation of the valuation blueprint.

Furthermore, we investigate correlations between key metrics and the SaaS startup's growth stage, quantitatively assessing the possible relationship between the funding record, exit record, and startup valuation.

> **RQ4:** *How does the growth stage of a SaaS startup correlate with the selection of appropriate metrics and the valuation?*

- Aim: To evaluate how the growth stage of a SaaS startup influences the selection of appropriate metrics and to determine whether different stages require distinct metrics and valuation methods.

RQ5: *How do a SaaS startup's funding and exit records (e.g., total funds, number of rounds, funding timing, exit strategy, and exit timing) correlate with its valuation?*

- Aim: To quantitatively analyse the relationship between the funding record, exit record, and startup valuation based on the available data.

Finally, we integrate the findings through the evaluative analysis to create the blueprint. This analysis includes a qualitative validation method. The following sub-research questions guide the final crucial steps in addressing the research question.

RQ6*: How can we integrate the metrics and insights we identified into the proposed SaaS valuation blueprint?*

- Aim: To develop a valuation blueprint by incorporating the findings related to appropriate metrics, growth stage consideration, and data analysis on the funding and exit history.

RQ7: *How can we validate the proposed SaaS valuation blueprint to ensure that it aligns with business requirements?*

- Aim: To validate and refine the metrics and blueprint using insights from investor expert interviews.

1.8 Scope

Our research has been conducted within the Akela Hub team, unrelated to their daily tasks. It focuses on creating a blueprint for valuing SaaS startups and aims to identify the key metrics necessary for accurately valuing a SaaS startup, such as Akela Hub.

Furthermore, Akela Hub identifies itself as a SaaS startup. Therefore, our research focuses on specific SaaS startups and, if necessary, on established firms. Since SaaS startups operate under distinct business models, we develop a blueprint tailored to their needs.

Moreover, we include both quantitative and qualitative methods. The qualitative approach includes interviews with investor experts and Akela Hub employees. The quantitative approach involves data analysis to examine the correlation between funding, exit records, and valuation prices.

1.9 Upfront limitations

Prior to our research, several limitations may arise that could influence its scope and outcomes. One of the most well-known limitations is the time constraint. Developing and validating a comprehensive blueprint requires significant time and resources, so we may need to make concessions.

Furthermore, a major upfront limitation is the limited availability of data due to the startup's focus. Early-stage startups often have minimal financial historical data, limiting the applicability of quantitative analysis methods. As previously mentioned, we cannot currently value Akela Hub exactly due to the lack of historical data from Akela Hub.

Funding records are a well-known type of data for startups and are well-represented in our database. Therefore, we mainly base our quantitative analysis on the funding records concerning the exit and valuation prices. However, there is limited exit data since most startups have not been acquired yet.

Due to the limited availability of financial data, validation methods are also limited. Therefore, expert investor interviews play a crucial role in validating the blueprint. Although this interview follows a clear structure, some subjectivity may still be present.

2. Theoretical framework

This chapter provides the theoretical foundation for the research by addressing the first four research sub questions through a comprehensive literature review. The first section examines traditional valuation methods and investigates their applicability to SaaS startups, identifying whether these approaches align with the characteristics of such businesses. Following this, we review current valuation practices for startups to identify possible challenges in achieving reliable assessments.

To put valuation practices in perspective, we analyse Akela Hub's business model, offering insights into its structure and financial framework. Finally, we explore SaaS key valuation metrics, evaluating their relevance and applicability in SaaS startup valuation. Through these sections, we ensure a robust framework based on literature to guide the blueprint's development.

2.1. Traditional valuation methods

Before we develop the blueprint, we need to understand the most common ways of traditional valuation approaches and why SaaS startups like Akela Hub face challenges when implementing them. According to Farahani (2024), business valuation methods are fundamental tools for determining the economic value of businesses, assets, or investments. These methods serve six primary purposes: Mergers and Acquisitions (M&A), investment analysis, equity financing, financial reporting, litigation and dispute resolution, and taxation (Farahani, 2024).

There are several approaches to business valuation based on unique assumptions and methodologies. As noted by Allee et al. (2020), the most common valuation approaches are categorised into:

- Income approach.
- Market approach.
- Asset approach.

Exploring these approaches helps us to evaluate their limitations and assess how well they align with the valuation needs of SaaS startups like Akela Hub.

2.1.1. Income approach

According to Allee et al. (2020), the income approach is the most frequently used valuation method, especially the discounted cash flow (DCF) method, standing out due to its focus on the ability to generate future cash flows. The DCF method determines the intrinsic value of a company's assets by analysing the cash flows generated over specified future periods (Su, 2024). These projected cash flows are adjusted to their present value using a discount rate, typically the Weighted Average Cost of Capital (WACC), which reflects the company's cost of finance through both debt and equity (Su, 2024).

The DCF method relies on four main components:

- Cash flows (projections) from existing assets.
- Expected growth from both new investments and improved efficiency on existing assets.
- Discount rates emerging from risk assessments in both the business and the equity.

- Assessments of when the firm reaches stable growth, allowing an estimate of the terminal value (Damodaran, 2009).

2.1.2. Market approach

According to Allee et al. (2020), the market approach is the second most commonly used valuation method. In this approach, we employ relative techniques, such as multiples and comparable market assessments (Damodaran, 2009). One of the most widely used market approaches is the Comparable Company Analysis (CCA) method, comparing the financial metrics of the firm to similar (listed) companies in the same industry (Farahani, 2024). Allee et al. (2020) highlight the popularity of CCA, particularly the use of multiples derived from the ratios of Enterprise Value (EV) to Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) or revenue.

We define multiples as a ratio calculated by dividing the market value of a firm (or asset) by a specific financial metric, such as earnings, revenue, or book value, and we use them to determine the value of a firm based on the value of a comparable firm in the same industry (Smith, 2024).

Allee et al. (2020) highlight the popularity of the following two multiples in CCA.

- $EV/EBITDA$
- $EV/Sales$

We calculate EV as follows:

$$EV = MC + D - CC \tag{2.1}$$

Where:

- $EBITDA$ = Net income + interest expense + taxes + depreciation + amortisation.
- MC: Market capitalisation, equal to the current stock price multiplied by the number of outstanding stock shares.
- D: Total debt, equal to the sum of short-term and long-term debt.
- CC: Cash and equivalents, a company's liquid assets, but may not include marketable securities.

Using the EV/EBITDA multiple, also known as the enterprise multiple, we evaluate the company's ability to generate operating cash flows by considering operating expenses in relation to its EBITDA (Hargrave, 2021). In contrast, the $EV/Sales$ multiple focuses on its revenue-generating ability with the $EV/Sales$, making it particularly useful for early-stage companies that have yet to achieve profitability (Hargrave, 2021). Furthermore, investors apply valuation multiples to assess whether a company is undervalued or overvalued. Generally, a lower multiple suggests undervaluation, implying the company may be trading below its intrinsic value. Conversely, higher multiples could indicate overvaluation, suggesting that the company's market price exceeds its intrinsic value (Hayes, 2024).

Another traditional valuation method within the market approach is the Precedent Transaction Analysis (PTA). Like CCA, we use multiples to estimate the potential sale price in M&A or restructuring scenarios (Rosenbaum & Pearl, 2009). In PTA, we select an appropriate set of comparable acquisitions, ideally involving fundamentally similar in terms of size, industry, and other characteristics, as potential buyers typically look closely at the multiples that have been paid for comparable acquisitions (Rosenbaum & Pearl, 2009). Additionally, we consider transactions from the most recent years to be the most relevant as they took place under similar market conditions, making the estimation more reliable (Rosenbaum & Pearl, 2009).

2.1.3. Asset approach

According to Allee et al. (2020), the asset approach is the third most commonly used valuation method. In this approach, we determine the equity value of a business based on the fair market value of its assets minus its liabilities, and it assumes that we determine a company's intrinsic worth by the net value of its tangible and intangible assets (Rosenbaum & Pearl, 2009).

A well-known asset approach is the book value method, which calculates the equity value of a business by subtracting liabilities from the historical cost of assets as reported on the balance sheet, making it straightforward and reliable for businesses with tangible assets (Farahani, 2024). However, internet companies, such as SaaS companies, offer high-value intangible products at marginal costs close to zero and have enormous potential customer bases compared to traditional companies, resulting in misleading book value valuation (Kossecki et al., 2023).

The adjusted net asset method improves upon the book value method by updating the values of assets and liabilities to reflect fair market values rather than historical costs. This method includes tangible, intangible, and off-balance sheet assets, as well as unrecorded liabilities such as leases, during the adjustment process (Kenton, 2021).

2.1.4. Challenges of traditional valuation methods

While traditional valuation methods offer structured frameworks for business valuation, their applicability may vary across industries due to the method-specific assumptions, each presenting unique advantages and challenges. We examine the income, market, and asset approach to assess their applicability for SaaS startup valuation.

2.1.4.1. Income approach

Damodaran (2009) explains that valuing existing assets in start-ups is challenging due to the limited financial history, making it difficult to determine whether revenues are sustainable or how they respond to changes, such as pricing strategy adjustments or new competition. Furthermore, start-ups often combine growth-related expenses with the expenses associated with current revenue generation, making it hard to distinguish between the two, so for example, Selling, General, and Administrative (SG&A) expenses can significantly exceed revenues because they include costs for acquiring future customers (Damodaran, 2009). Accurately valuing existing assets requires separating the growth expenses from operating costs, a process Damodaran (2009) identifies as particularly challenging for start-ups.

Valuing the growth assets presents significant challenges due to the absence or limited revenue history, causing the firms' value to depend on biased internal estimates and making it difficult to assess future profit margins (Damodaran, 2009). Additionally, the quality of growth depends on the company's ability to generate returns on capital that exceed the costs of capital (Damodaran, 2009). However, as noted by Damodaran (2009), the current return is generally negative for start-ups due to minimal investment history and the recency of existing investments, providing little meaningful data for valuation.

Su (2024) mentioned that the WACC typically represents the discount rate. We can calculate the WACC by determining the proportions of debt and equity financing a company uses to determine the total cost of capital in the following equation:

$$\text{WACC} = \left(\frac{E}{V} \times R_e\right) + \left(\frac{D}{V} \times \mathrm{R}_d \times (1 - \mathrm{T}_c)\right) \tag{2.2}$$

Where:

- E: Market value for the firm's equity.
- D: Market value of firm's debt.
- V: $E + D$.
- R_e: Cost of equity.
- R_d: Cost of debt.
- T_c: Corporate tax rate.

However, Damodaran (2009) notes that estimating the WACC for startups becomes less reliable due to the lack of market prices for securities to estimate R_e and R_d because most startups are privately held and do not have publicly traded stocks or bonds. Additionally, startup founders or venture capitalists typically hold equity, do not fully diversify and therefore demand compensation for at least some of the firm-specific risk that traditional models do not address (Damodaran, 2009). The complexity of WACC estimation further increases due to variations in equity terms across funding rounds, as startups often receive investments from multiple investors over time, each carrying different rights and claims (Damodaran, 2009).

According to Damodaran (2009), terminal value often accounts for a large proportion of a company's overall valuation in the DCF model. It represents a larger share for startups, often exceeding 90% of the total valuation. Estimating terminal value for startups requires assumptions about when the startup achieves stable growth and its characteristics during this phase, both impacting the valuation (Damodaran, 2009). These assumptions are particularly complex due to the uncertainty of when and whether a startup reaches stable growth, as we face a high failure rate of startups, estimating survival probability in the early stage is unreliable (Damodaran, 2009). Furthermore, determining the terminal value involves concurrent risk and excess returns assumptions during the stable phases (Damodaran, 2009). While these judgements are necessary for any firm, the absence of historical data on excess returns for startups complicates the estimation process.

2.1.4.2. Market approach

It seems like we can use these market approaches more easily than the income approaches for SaaS startup valuation; however, these approaches also have challenges. For the relative valuation of publicly traded companies, comparable firms are usually publicly traded counterparts in the same sector (Damodaran, 2009). So, when we value a SaaS startup using the market approach, we need a SaaS startup to make the comparison. However, these companies usually are not publicly traded and have no market prices. According to Damodaran (2009), we could use publicly traded firms within the same sector that are comparable, but these firms probably have different risk, cash flow and growth characteristics than the startup, leading to challenges for valuation.

Furthermore, Kossecki et al. (2023) highlight the challenges in applying the PTA to the relatively new SaaS industry, where limited relevant M&A transactions are available for reliable benchmarking. Rosenbaum and Pearl (2009) further emphasise these difficulties, noting that unique deal structures, such as performance-based earnouts, complicate multiples' reliability. Additionally, Damodaran (2009) argues that as the likelihood of startup survival increases, its relative valuation should also rise, given the high failure rate of startups. However, we face challenges when applying this principle in practice.

According to Damodaran (2009), another challenge in using multiples for startups is that we must scale the valuation multiples to measures like earnings, book value, or revenues. However, all these measures can pose problems since most startups report losses or small revenues early in the life cycle, so multiples such as EBITDA cannot be computed, and the book value is most likely a very small number that does not reflect the actual capital invested in the company (Damodaran, 2009). Cohen & Neubert (2018) highlight that relative valuation approaches do not consider SaaS startups' relatively high free cash flow growth rate and lower profitability in the early stage, leading to a potential underestimation in valuation. Therefore, selecting appropriate valuation methods for SaaS firms depends on the life cycle stage (Trinchkova & Kanaryan, 2015).

2.1.4.3. Asset approach

Although the net asset method includes intangible assets, we still need to value them, causing challenges due to unreliable benchmarks and the subjective nature of value estimation (Li, 2025). Examples of intangibles for SaaS startups include the stability of earning power, owner-specific business relationships, level of competition within the business niche, and type of customers targeted by the company (Cohen & Neubert, 2018). Furthermore, this approach fails to capture the strategic flexibility and growth potential of SaaS startups because it relies on static values rather than dynamic values, leading to an undervaluation (Milanesi, 2013).

Additionally, according to International Accounting Standards (IAS) 38, we record many Research and Development (R&D) costs as expenses during the research phase rather than being capitalised as intangible assets (Li, 2025). This accounting practice leads to an underrepresentation of the actual value of intangible assets on the balance sheet. It creates a disparity between the book value and the company's market value (Li, 2025). In the early stages, SaaS startups rely heavily on R&D to develop software and other valuable assets, further limiting the accuracy of the adjusted net asset method (Li, 2025). Consequently, the lifecycle stage of the company is a significant factor, as early-stage startups often have minimal tangible assets, and intangible assets are complex to value, causing challenges for the asset approach (Trinchkova & Kanaryan, 2015).

2.1.5. Summary

We can categorise traditional valuation methods into three primary approaches:

- Income approach (e.g. DCF).
- Market approach (e.g. CCA and PTA).
- Asset approach (e.g. book value method and adjusted net asset method).

While these methods provide valuable insights, their application to SaaS startups is often challenging due to the following characteristics:

Income approach

- Limited financial history for cash flow projections.
- Negative return of capital in early stages.
- Unreliable discount rates for privately held startups.
- Uncertainty in forecasting growth and terminal value.

Market approach

- Lack of comparable publicly traded SaaS firms.
- Low revenues or losses leading to unreliable multiples.
- Limited relevant M&A transactions for benchmarking.
- Variability in growth stages among startups.

Asset approach

- Reliance on intangible assets, which are complex to value.
- Complexity in valuing strategic flexibility and growth potential.
- High R&D costs are often expensed rather than capitalised.

Due to these challenges in the traditional valuation methods, we often undervalue SaaS startups, disadvantaging founders in negotiations. Allee et al. (2020) emphasise that valuation models must reflect the business's industry and track record. Farahani (2024) recommends combining traditional valuation methods into a hybrid valuation method that better reflects the characteristics of SaaS startups.

2.2. Startup valuation methods

Startups typically experience high uncertainty, intangible asset reliance, lack of historical data, rapid growth potential, and volatile market conditions (Damodaran, 2009). Therefore, we require tailored valuation methods to account for these characteristics. In this section, we delve into the specific valuation methods for startups, addressing these challenges.

According to Damodaran (2009), the most common approach to startup valuation is the Venture Capital (VC) method. Furthermore, Real Option Valuation (ROV), as discussed by Tellez & Rafiuddin (2023) and the first Chicago method (Trinchkova & Kanaryan, 2015) emerge as relevant approaches. These methods provide frameworks that better address the risks and uncertainties inherent in startup valuations.

2.2.1. Venture Capital Method

We often criticise the traditional DCF method for its limited applicability due to its reliance on the assumption of steady growth (Damodaran, 2009). Li (2024) highlights this limitation, noting that empirical tests show that only a small percentage of firms achieve stable growth over a period of three to five years. Consequently, as stated in Section 2.1.1, the usability of the traditional DCF model for startup valuation is limited. Damodaran (2009) emphasises the need to adjust the DCF method, leading to the development of the VC method. This method evaluates the valuation of a company from the investor's perspective, determining whether the valuation justifies the potential exit strategy and the likelihood of achieving it (Mol & Mensink, 2022).

The VC method builds upon the DCF method but offers a more pragmatic approach in early-stage valuations (Damodaran, 2009). Unlike the traditional DCF method, relying on detailed cash flow projections and the assumption of steady long-term growth, the VC method focuses more on a future exit value (e.g. Initial Public Offering (IPO) or acquisition) and reflects the high investment risk by applying higher discount rates (Damodaran, 2009). Therefore, this method is particularly relevant for early-stage startups relying heavily on future potential rather than present financial performance. According to Damodaran (2009), the VC method consists of four steps:

Step 1: Estimating the expected earnings in the near future

We begin with forecasting the expected earnings or revenues of the startups two to five years in the future, aligning with the expected exit of the startup (Damodaran, 2009).

Step 2: Estimating the expected terminal value

Here, we determine the expected exit value for the startup by using industry-specific valuation multiples that reflect publicly traded comparable companies. We determine the equity value at exit, also known as terminal value, by the following formula:

$$Terminal\ value = Expected\ earnings_{year\ n} \times P/E\ ratio \tag{2.3}$$

Where:

- $n :\ the\ end\ of\ the\ forecast\ horizon,$
- $P/E\ ratio\ = \frac{Market\ value\ per\ share}{Earnings\ per\ share}$

Alternatively, we can multiply the revenues at the end of the forecast period by the revenue multiple publicly traded firms trade at to estimate the value of the entire business instead of just equity (Damodaran, 2009). We use this approach for companies that may not be profitable until later in the life cycle by determining the expected enterprise value by the following formula:

$$Enterprise\ value\ at\ exit_{year\ n} = Expected\ revenue_{year\ n} \times\ EV/Sales\ ratio \tag{2.4}$$

Where:

- $EV/Sales\ ratio\ = \frac{Market\ capitalization + debt - cash\ and\ cash\ equivalents}{Annual\ sales}$

Step 3: Determining today's equity value

We discount the exit value to the present value using significantly higher target rates of return than the discount rate we used with publicly traded companies, reflecting the risk associated with startup investments (Damodaran, 2009). We determine today's equity value by using the following formula:

$$Equity\ value\ today = \frac{Equity\ value\ at\ exit_{year\ n}}{(1 + target\ rate\ of\ return)^n} \quad (2.5)$$

According to Damodaran (2009), the target rates of return for VC investments range from 25% to 70%, depending on the startup stage and risk level. Younger startups generally carry higher risk, resulting in higher required return rates.

2.2.2. First Chicago Valuation Method

The First Chicago Valuation Method (FCVM) is a multi-scenario framework that integrates the DCF method with probability-weighted outcomes to value startups with high uncertainties and volatile growth trajectories (Mashhadi, 2023). Unlike the VC method, valuing startups based on a single projected exit scenario (e.g. IPO or acquisition) and applying a high discount rate to account for risk (Damodaran, 2009), the FCVM considers multiple potential outcomes (best-case, base-case and worst-case) and assigns a weighted probability to each scenario (Mashhadi, 2023).

By incorporating both upside potential and downside risk, FCVM provides a more comprehensive and flexible valuation framework than the VC method, and therefore, we can use the FCVM for any type of business, but it best suits privately held companies with stable cash flow and an expected growth trajectory (Mashhadi, 2023). Its flexibility and focus on future cash flows allow us to make adjustments based on startup characteristics, such as life cycle stage, funding rounds, and the degree of risk, making it a more applicable valuation method for early-stage startups (Mashhadi, 2023).

The FCVM proceeds through a series of structured steps, which we outline below (Mashhadi, 2023):

Step 1: Defining the scenarios

The first step involves defining the three possible outcomes to gain a better understanding of how our investments are likely to perform in the future: a best-case scenario where we exceed expectations, leading to a high valuation; a base-case scenario where we perform as expected, in line with the business plan; and a worst-case scenario where we underperform, leading to slow growth, project delays and increased expenses (Mashhadi, 2023).

Step 2: Estimating future cash flows

In this step, we analyse historical financial data to make assumptions about future growth and profitability. We project the startup's financial performance over a typical five-year forecast period within the FCVM method. However, this leads to challenges in early-stage startups due to a lack of historical data and rapidly changing business models, especially in industries with high uncertainties and growth potentials, such as technology startups (Mashhadi, 2023).

We also include making assumptions based on historical performance and its potential, conserving sales and operating expense assumptions across the three scenarios, and targeting sales and employees at the end of the forecast period. Furthermore, we include capital expenditures (CapEx), depreciation, and working capital forecasts to forecast the free cash flows to the firm (FCFF) for all three scenarios (Mashhadi, 2023). We calculate the FCFF as follows:

$$FCFF = EBIT - Income\ Tax + Depreciation - CapEx - \Delta WC \tag{2.6}$$

Where:

- EBIT: Earnings Before Interest and Taxes.
- WC: Working Capital

Step 3: Determining the discount rate

According to Mashhadi (2023), the discount rate impacts a firm's valuation using the FCVM to determine the present value of future cash flows. The discount rate should align with the startup's life cycle stage and inherent risk profile (Mashhadi, 2023). Broadly, the discount rates vary as follows:

1. **Seed stage** – discount rate between 50% and 100%: Startups typically have a high degree of risk and uncertainty, as well as a lack of an established track record or well-developed business plan.
2. **Early stage** – discount rate between 40% and 70%: Startups making progress in development but may not have revenue or profit.
3. **Growth stage** – discount rate between 30% and 50%: Startups may demonstrate traction and generate substantial revenue, but there is still a degree of uncertainty regarding their future growth prospects.
4. **Later stage** – discount rate between 20% and 40%: Startups establish a track record of revenues and profit.

For seed and early-stage startups, we often employ the build-un method to determine the discount rate:

$$Discount\ rate = Risk\ free\ rate + startup\ specific\ risk\ premiums \tag{2.7}$$

In contrast, for growth and later-stage startups, we use the WACC (Equation 2.1) to determine the discount rate. The choice within each range should reflect factors such as country context, market conditions, competitive landscape, management quality, and industry trends (Mashhadi, 2023).

Step 4: Calculating terminal value

The next step involves estimating the terminal value, representing the company's value at some point in the future beyond the forecast period Damodaran (2009). The choice of a terminal valuation method depends on the startup's maturity and growth prospects (Mashhadi, 2023).

For growth-stage startups, a market multiple approach may be applicable, while for later-stage startups, we often employ the perpetual growth model (Mashhadi, 2023). The perpetual method refers to the expected long-term growth rate for the startup's cash flows beyond the projection period by utilising the Gordon Growth method, which assumes that the startup's cash flows grow at a constant rate in perpetuity (Mashhadi, 2023). Therefore, we use the following equation:

$$Terminal\ Value_i = \frac{CF_N \times (1 + g_i)}{(r - g_i)} \tag{2.8}$$

Where:

- i: Scenarios (worst-, base-, best-case).
- N: Forecast period.
- CF: Cash Flow
- g_i: Scenario-specific perpetual growth rate ($g_i < r$)
- r: Discount rate

Step 5: Present value of future cash flows

As we have estimated both future cash flows (years 1 to 5) and the terminal value, this step involves calculating the present value of each scenario (Mashhadi, 2023). We determine the valuation under each scenario as follows:

$$EV_i = \sum_{k=0}^{N} \frac{CF_k}{(1 + r)^k} + \frac{Terminal\ Value_i}{(1 + r)^N} \tag{2.9}$$

Where:

- CF_k: $Cash\ flow$ in year k.

Step 6: Assigning probabilities and calculating the weighted Enterprise Value (EV)

Finally, we assign the probabilities for each scenario to compute the expected enterprise value. Nylen & Pettersen (2017) provide a set of predetermined probability distributions based on the startup phase, as illustrated in Table 2.1:

Table 2.1: Predetermined probability scenario distribution

Scenario	Startups (%)	High-Growth (%)	Mature (%)
Worst-case	30	15	5
Base case	50	70	85
Best-case	20	15	10

Given these probabilities and the scenario-specific valuation results of Step 5, we determine the final weighted enterprise valuation by using the following equation:

$$\text{Valuation} = \sum_{i=1}^{n} p_i \times EV_i \tag{2.10}$$

Where:

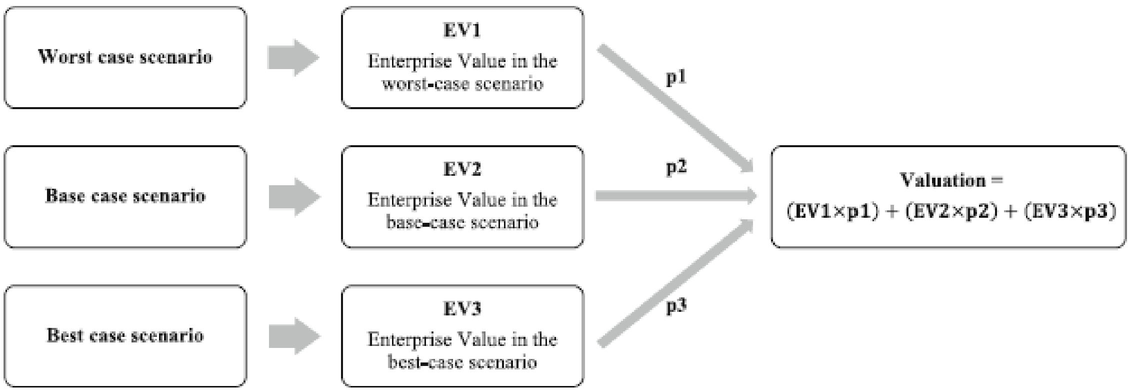
- p_i: Assigned probability under scenario i

For instance, in the case of an early-stage startup, we compute the valuation as follows:

$$Valuation = 0.3 * EV_{worst} + 0.5 * EV_{base} + 0.2 * EV_{best}$$

Figure 2.1 visually represents this process, including the flow from scenario-specific valuation to the final weighted outcome.

Figure 2.1 First Chicago Valuation Method diagram



2.2.3. Real option valuation

Real Option Valuation (ROV) is a startup valuation method addressing the shortcomings of static valuation methods, particularly under high uncertainty and rapid growth conditions (Damodaran, 2009). Unlike the VC method and FCVM, both relying on estimates of future scenarios, ROV assigns a measurable value to strategic flexibility, enabling managers or investors to adjust their decisions based on the changing market conditions (Milanesi et al., 2013). These changing market conditions may include new technological changes and the emergence of new competitors or market opportunities popping up (Damodaran, 2009).

Tellez and Rafiuddin (2023) highlight the utility of ROV for early-stage startups, emphasising that it provides a more accurate reflection of intangible growth options than traditional cash-flow-based methods. By incorporating elements of financial options pricing, such as the Black-Scholes model, ROV treats investment opportunities as real options, granting investors the right, not the obligation, to buy or sell something in the future (Tellez & Rafiuddin, 2023). By assigning a financial value to these potential actions, ROV helps estimate the valuation, capturing startup-specific uncertainties like technology changes and new competition (Moro-Visconti, 2021).

According to Tellez and Raffiuddin (2023), the ROV method consists of the following steps:

Step 1: Identifying the available real options.

First, we identify the types of real options available to an investor or manager. There are various types of options, but the following represent managerial flexibility and distinguish ROV from static valuation approaches like DCF (Tellez & Rafiuddin, 2023):

- **Defer option:** Investors can postpone investment decisions until market conditions improve, reducing uncertainty and maximising potential returns.

- **Time-to-build option:** Long-term projects require full completion before generating returns and often face delays due to external factors, such as technical challenges.
- **Scale of operations option:** Investors can expand operations when marketing conditions are important or scale down to minimise losses in weak market conditions.
- **Abandon option:** A company can terminate an unprofitable project to limit financial losses and reallocate resources.
- **Switch option:** This option enables firms to adapt production processes by modifying raw materials or adopting new technology, enhancing operational flexibility.
- **Growth option:** In industries like R&D and high-tech, companies can expand through strategic acquisitions to gain a competitive advantage (Tellez & Rafiuddin, 2023).

Step 2: Defining the Underlying Asset and Risk Factors

After identifying the available real options, Tellez and Rafiuddin (2023) emphasise that we must clearly define the underlying asset, often equal to the startup's expected future cash flows, and identify the risks affecting it. Brealey et al. (2020) define these risks as market volatility, technical risks due to rapid innovation, particularly in high-tech sectors, and competitive landscape due to new market competition or evolving competitor strategies.

Step 3: Selecting an option pricing model

Here, we choose the appropriate model for the startup situation, where many pick the Black-Scholes model, especially when the future cash flows are uncertain but can be treated as continuous (Tellez & Rafiuddin, 2023). Financial managers use the Black-Scholes model to estimate the value of various options (Brealey et al., 2020). However, binomial tree models may be preferable if the discount points are discrete or if the underlying assumptions of Black-Scholes do not hold (Brealey et al., 2020).

Step 4: Calculating the option value

After we selected the option price model, we can calculate the value of each identified option. If we choose the Black-Scholes model, we apply the following formula to determine the call option (Tellez & Rafiuddin, 2023):

$$C_{BS}(S_t, t) = S_t N(d_1) - X e^{-R(\tau)} N(d_2) \tag{2.11}$$

Furthermore, for the put option, we apply the following formula:

$$P_{BS}(S_t, t) = X e^{-R(\tau)} N(-d_2) - S_t N(-d_1) \tag{2.12}$$

Where we define the standardised random variables d_1 and d_2:

$$d_1 = \frac{\ln(\frac{S_t}{X}) + (R + \frac{1}{2}\sigma^2)\tau}{\sigma\sqrt{\tau}} \tag{2.13}$$

$$d_2 = d_1 - \sigma\sqrt{\tau} \tag{2.14}$$

Where (Tellez & Rafiuddin, 2023):

- $C_{BS}(S_t, t)$: European call option value as a function of the current underlying asset price S_t at time t.
- $P_{BS}(S_t, t)$: European put option value as a function of the current underlying asset price S_t at time t.
- N(d): Normal standard distribution as a function of d.
- X: Strike price, required investment cost
- R: Annual risk-free interest rate.
- τ: option maturity proportional to a yearly basis.
- σ^2: Annualised variance of the underlying asset returns.
- σ: Volatility, the standard deviation of asset returns.

To demonstrate the practical application of ROV, we consider a SaaS startup evaluating the strategic decision to expand into a new market using a defer option. This expansion presents an underlying asset value (S_t) of \$1,000,000. However, we require an upfront investment of X= \$900,000 when executing the expansion immediately. Furthermore, we assume a risk-free rate of 5% and a high volatility of 50%, and the firm has nine months (i.e. $\tau = 0.75$) to decide whether to proceed.

We apply the Black-Scholes model, so our first step is to determine the variables d_1 and d_2.

$$d_1 = \frac{\ln(\frac{1.000.000}{900.000}) + \left(0.05 + \frac{1}{2}(0.5)^2\right)0.75}{0.5\sqrt{0.75}} \approx 0.5464 \text{ and } d_2 = 0.5464 - 0.5\sqrt{0.75} \approx 0.1134$$

Using the standard normal distribution function, we obtain:

$$N(d_1) \approx 0.7071 \text{ and } N(d_2) \approx 0.5451$$

Substituting this into the Black-Scholes formula for a European call option yields:

$$C_{BS} = 1.000.000 \cdot 0.7071 - 900.000 \cdot e^{-0.05(0.75)} \cdot 0.5451 \approx \$234,420$$

This implies that the option to defer the investment is worth approximately \$234,420, which is higher than the earlier Net Present Value (NPV) $(S_t - X) = \$100,000$. This means that, under conditions of uncertainty and volatility, the strategic flexibility to defer investments creates an additional value of approximately \$ 134,420. Consequently, it is economically rational to delay the investment decision and preserve the right to expand rather than the obligation. By doing so, the firm optimises decision timing and minimises the downside risk.

On the other hand, when applying binomial tree models, we compute up and down factors for each period to derive multiple possible outcomes and compute the expected valuation under different scenarios (Brealey et al., 2020). Regardless of the approach, both approaches require discounting future payoffs at a risk-adjusted rate to reflect the uncertainties (Brealey et al., 2020).

Step 5: Making strategic investment decisions

Finally, Tellez and Rafiuddin (2023) highlight that managers and investors should carefully interpret the option values we calculated. Because the ROV model quantifies strategic flexibility and enhances decision-making by incorporating different startup growth stages and market uncertainties. Therefore, managers and investors decide whether to proceed, postpone or abandon the investment, allowing them to adjust based on the market dynamics and uncertainties (Tellez & Rafiuddin, 2023). Generally, we make strategic investment decisions based on the option value.

First of all, with a high option value, we should proceed with the investment and execute it immediately, as delaying could result in lost opportunities. This is particularly evident in the growth and majority stages, where the startup demonstrates financial stability and market potential, potentially leading to an IPO (Brealey et al., 2020).

Second, with an uncertain or slightly positive option value, postponing the investment may be preferable. We see this often in the early stage, where high uncertainty causes investment delay until the startup meets specific revenue targets or risk factors decrease (Tellez & Rafiuddin, 2023).

Lastly, with a negative or close to zero option value, the investor should reconsider or abandon the project. If a startup fails to meet expected targets, the ROV method can help the investors identify when to withdraw capital or shift resources rather than continuing in an unprofitable venture (Tellez & Rafiuddin, 2023).

2.2.4. Challenges

While startup valuation methods offer structured frameworks for startup valuation, their applicability may vary across industries due to the method-specific assumptions, each presenting unique advantages and challenges. We examine the VC, FCVM, and ROV methods to assess their startup valuation limitations.

2.2.4.1. VC method

While the VC method provides a structured approach to startup valuation, it presents several challenges. According to Goldenberg and Goldenberg (2009), valuation negotiations between founders and a VC often involve conflicting perspectives due to entrepreneurs inflating growth projections to get higher valuations. The VC may discount these estimates to secure a larger ownership share. Damodaran (2009) emphasises this and calls the projected values a bargaining point between the two sides rather than the subject of serious estimation.

While the VC method focuses on exit multiples, it assumes that long-term cash flows and market conditions at the exit date align with the current forecasts (Damodaran, 2009). Thus, it cuts off long-term cash flow estimates and assumes that the future valuations mirror the market condition at the time of exit. However, Damodaran (2009) argues that exit multiples three years from now are influenced by cash flows beyond that period, ignored by the VC model, resulting in uncertain estimated exit multiples and failing to accurately reflect the startup's actual value.

Although the VC method focuses on the exit value, it does not account for cash flow fluctuations, reinvestments needed, or capital expenses that may arise between the initial investment and the possible exit (Moro-Visconti, 2021). This can lead to working capital and liquidity challenges, as startups frequently experience fluctuating working capital needs driven by high Customer Acquisition Costs (CAC), delayed revenue recognition, or increased operational expenses (Moro-Visconti, 2021). Additionally, the VC method assumes a definitive exit, yet many startups never reach this stage.

Lastly, Damodaran (2009) clarifies that post-money valuation calculations only work if the new capital remains within the firm to fund future investments. If we use part of the new capital to cash out existing investors, we should not include that portion when determining the post-money valuation (Damodaran, 2009).

2.2.4.2. First Chicago Valuation Method

Although the FCVM offers a multi-scenario framework for startup valuation, it is unsuitable for all startups. Since it is primarily driven by cash flow forecast, it does not consider intangible assets, such as brand recognition and customer loyalty, potentially leading to undervaluation (Mashhadi, 2023). Moreover, the FCVM typically does not directly consider external factors such as competitors' relative valuation and market conditions.

Another challenge is the high sensitivity of assumptions, such as the weighted probabilities. This is especially relevant in high-uncertainty environments, where minor changes in assumptions can lead to substantial variation in valuation outcomes. (Mashhadi, 2023). Additionally, determining an appropriate discount rate could also cause challenges for early-stage startups due to the absence of reliable benchmarks and the potentially volatile nature of startups (Mashhadi, 2023).

Finally, while the FCVM is adaptable across various industries, it may not be suitable for startups with non-standard business models, such as SaaS startups (Mashhadi, 2023). However, given the model's flexibility in accounting for startup-specific risks and uncertainties, it remains a valuable tool for startup valuation when used alongside complementary analysis and informed managerial judgments to arrive at a reasonable estimate of the startups' value (Mashhadi, 2023).

2.2.4.3. Real Option Valuation

The ROV method is a well-suited approach for startups, especially due to its flexibility. However, including uncertainties by using options brings complexity to it. Advanced methods such as the Black-Scholes and binomial trees can be mathematically complex, making ROV more demanding than a more straightforward DCF method (Brealey et al., 2020). Furthermore, we again see the lack of long-term historical data on early-stage startups, leading to challenges in estimating the volatility of the underlying assets, causing potential over- or underestimation of the option values, reducing the reliability of ROV-based valuation (Milanesi et al., 2013).

Managers define and categorise the options, such as the ability to expand, delay or abandon a project, making it sensitive to bias and subjectivity, affecting valuation outcomes and strategic decision-making (Brealey et al., 2020). Additionally, they depend on external factors such as economic fluctuations and competitor action (Brealey et al., 2020). However, when a competitor also holds real options, their strategic decisions impact valuation, causing difficulties in assessing the true worth (Brealey et al., 2020).

Finally, the ROV is highly dependent on other valuation methods since we just use it as a complementary tool rather than a standalone method (Tellez & Rafiuddin, 2023). Because it typically relies on DCF calculations as an input, challenges regarding the DCF method may also affect the final ROV estimate.

2.2.5 Summary

We discussed the following three startup valuation approaches:

- Venture Capital (VC) method.
- First Chicago Valuation Method (FCVM).
- Real Option Valuation (ROV).

While these methods aim to address the characteristics of startup valuation, each comes with limitations due to the uncertainties of the startup:

Venture Capital (VC) Method

- Assuming a definitive exit, which may never occur.
- Relies on negotiated assumptions between founders and the VC.
- Overlooks cash flow fluctuations, such as reinvestments and capital needs.

First Chicago Valuation Method (FCVM)

- Highly sensitive to assumptions; small changes in probabilities or discount rates impact valuation results.
- Lacks include external factors.
- Unsuitable for non-traditional business models, such as SaaS startups with intangible growth drivers.

Real Option Valuation (ROV)

- Mathematical complexity incorporating Black-Scholes or binomial tree methods.
- Complexity in estimating volatility due to limited historical data.
- Dependent on subjective assumptions, as managers define the options.
- Primarily a supplementary tool relying on DCF-based calculations.

Due to these challenges in current startup valuation methods, we underscore the need for a tailored solution for Akela Hub's business model. Masshadi (2023) emphasises that when selecting the proper valuation approach, we should focus on future forecasts rather than historic data, use probability to evaluate different scenarios and pay attention to a startup's business model rather than historical data on comparable companies.

2.3. SaaS valuation metrics

The emergence of companies employing the relatively new SaaS business model has created a gap between the traditional valuation methods we use within this sub-industry (Cohen & Neubert, 2018). Since we cannot use the same criteria for all businesses, there is a need for a continuously evolving development of a multitude of valuation metrics for the new business industries and business models (Cohen & Neubert, 2018). In this section, we delve into the valuation metrics for the SaaS business model.

Slingerland (2024) identifies SaaS metrics as quantitative indicators that help analyse a business's health and performance over time to value the business and help it make data-based decisions. There are numerous SaaS valuation metrics, each with its own advantages. While we can apply many of these metrics to various business models, they particularly suit the SaaS firms well due to the recurring revenue structure and the customer retention focus, but are highly recommended for use in SaaS business models. Our research delves into the following categories: Financial metrics, growth metrics, customer metrics, and investor heuristics (Slingerland, 2024).

2.3.1. Financial metrics

First, we delve into the financial metrics, which provide insights into the stability and profitability of SaaS revenue. Furthermore, due to the subscription-based nature of SaaS business, the recurring revenue is interesting and can help us evaluate the total financial health of the business.

Monthly Recurring Revenue (MRR) And Annual Recurring Revenue (ARR)

MRR and ARR represent the recurring revenue generated from active subscriptions or contracts, calculated on a monthly or yearly basis (Kossecki et al., 2023). High MRR and ARR values indicate stable cash flows and financial health. Moreover, these metrics can serve as forecasting metrics, enabling companies to project future revenues and make strategic investment decisions (CFI, n.d.). We define the MRR as follows:

$$MRR = Number\ of\ subscriptions\ under\ a\ monthly\ plan \times ARPU \tag{2.15}$$

Where:

- ARPU: Average revenue per user.

To determine ARR, we must consider the billing structure. If the company only offers monthly subscriptions, we can calculate the ARR using a simple multiplication of MRR by 12. However, if the company also uses other billing types, such as annual or quarterly contracts, we define the ARR formula as follows:

$$ARR = \ Number\ of\ non\ monthly\ contracts \times \ ACV) \ + (MRR \times 12) \tag{2.16}$$

Where:

- ACV: Average Contract Value (annualised)

Gross margin

This metric measures the percentage of total revenue exceeding the costs of goods sold (COGS), excluding other expenses such as sales and administrative costs (Faisal, 2024). Higher gross margins indicate a strong core operation and business valuation, demonstrating pricing power and operational efficiency. In SaaS, we define the COGS as follows:

$$\begin{aligned} COGS \ = \ & Hosting\ and\ infrastructure\ costs\ +\ direct\ labour\ costs \\ & +\ Third\ party\ software\ and\ services\ costs \\ & +\ Other\ direct\ costs \end{aligned} \tag{2.17}$$

Other direct costs include payment processing fees for customer transactions, data storage for customer data, and security measures directly related to the service (Godick, 2024).

Furthermore, we calculate the gross margin as follows:

$$Gross\ Margin\ = \frac{Revenue - COGS}{Revenue} \times 100\%. \tag{2.18}$$

Net monthly burn rate

The burn rate refers to the rate at which a company consumes its cash reserves, indicating the negative cash flow rate over a specific time (McClure, 2024). It provides a measure of how quickly a startup utilises its available funding, especially an issue for early-stage startups operating within high-growth, low-profitability environments (Damodaran, 2009). Investors monitor this metric as it signals how long a company's current cash reserves last before additional funding becomes necessary (McClure, 2024). We calculate the monthly burn rate as follows:

$$Net\ monthly\ burn\ rate = Cash\ at\ beginning\ of\ month\ x - Cash\ at\ end\ of\ month\ x \tag{2.19}$$

2.3.2. Customer metrics

Second, we delve into the customer metrics, which provide insights into acquisition costs, retention, and the customer lifetime.

Customer churn

According to Kossecki et al. (2023), investors often use the customer churn rate, which shows the percentage of customers who cancel their subscriptions within a given period. As a negative customer satisfaction indicator, a high churn rate suggests that a relatively high number of customers are leaving, which may indicate issues such as a broken critical function or increased competition (Slingerland, 2024). Conversely, a low churn rate indicates customer loyalty and strong product market-fit. However, it could also indicate that we offer lower pricing to retain customers rather than delivering value. (Slingerland, 2024). The formula for the churn rate is as follows:

$$Churn\ rate\ = \frac{number\ of\ leaving\ customers\ in\ period\ x}{Total\ active\ customers\ at\ the\ start\ of\ period\ x} \times 100\% \tag{2.20}$$

Customer Acquisition Cost (CAC)

The CAC is the total amount we spend on marketing, advertising, sales and other expenses to acquire one new customer within a specific period (Kossecki et al., 2023). Ideally, we want to minimise the CAC as low as possible to improve profitability. However, in SaaS companies, upfront acquisition costs can be high due to initial investments in marketing and infrastructure, which repay over time as recurring revenue in the form of subscriptions or memberships (Slingerland, 2024). Meanwhile, we can use this metric to evaluate the pricing strategy and the SaaS business. With an unknown CAC, we lack clear visibility of our costs per customer, leading to challenges in creating healthy margins from each client or segment (Slingerland, 2024). Calculating the CAC may face difficulties due to the different time periods, therefore in our research we use a generalised formula to calculate the average CAC over a period x:

$$CAC = \frac{Total\ market\ expenses\ in\ period\ x}{Number\ of\ new\ customer\ in\ period\ x} \tag{2.21}$$

Customer Lifetime Value (CLV)

CLV quantifies the total profit a company can generate from a customer during the lifespan of the customer interaction (Kossecki et al., 2023). This metric incorporates factors such as customer retention, recurring revenue, and associated costs. Due to the advancements in data collection and processing, particularly in the SaaS industry, CLV has become a tool for managerial decision-making (Kossecki et al., 2023). Moreover, establishing long-term, profitable customer relationships is a fundamental aspect of most business models and is often regarded as a company's most valuable intangible asset.

The most accurate way to calculate the CLV involves estimating the contribution margins per customer after marketing expenses on an annual basis (Kossecki et al., 2023). In the early stages of customer engagement, costs typically exceed revenues, necessitating the following formula to determine the CLV:

$$CLV = \sum_{t=0}^{CL} \frac{ARPU_t - ACPU_t - SRC_t}{(1+r)^t} - CAC \tag{2.22}$$

Where:

- $ACPU_t$: Average cost per user in period t.
- SRC_t : Customer retention cost in period t.
- CL: Customer Lifetime.
- r: Discount rate (WACC or build-on method).

CLV/CAC ratio

Slingerland (2024) argues that a well-known way to measure the success of a business model is by using the CLV/CAC ratio. This ratio shows the return on investment per dollar spent on customer acquisition (Kossecki et al., 2023). According to Slingerland (2024), a ratio between three and five generally indicates an ideal situation. Lower ratios may indicate a lack of market fit, while higher ratios indicate a need to invest more in sales and marketing.

It is important to note that the interpretation of these customer metrics depends on the annualised Average Contract Value (ACV). When dealing with very high ACV (e.g., $20,000), lower CLV/CAC and higher CAC are generally acceptable. In contrast, low-ACV SaaS companies should aim for minimal CAC, low churn rates, and a relatively high CLV/CAC ratio. In our research, we use average values when accounting for ACV.

2.3.3. Growth metrics

Third, we delve into the growth metrics, which provide insights into how the SaaS companies are scaling their revenue and customer base. Investors can use these metrics to determine the potential for future expansion.

Net Revenue Retention Rate (NRR)

To have an indication of whether the business is growing or not, we use the NRR, which is the percentage of revenue retained from existing customers over a specific period (Faisal, 2024). We base this metric on the MRR or ARR since the NRR tells us the difference between the revenue retention relative to an earlier period (Faisal, 2024). An NRR lower than 100% indicates the business is declining, negatively impacting the valuation. While an NRR of over 100% indicates that the business is growing and positively impacting the valuation. The formula is as follows:

$$NRR = \frac{Starting\ MRR - Plan\ downgrade\ MRR - Churn\ MRR + Plan\ expansion\ MRR}{Starting\ MRR} \times 100\% \quad (2.23)$$

Year-on-year (YoY) ARR growth rate

Another way to define growth is by using a percentage of revenue growth relative to the previous year (Faisal, 2024). This metric reflects the company's ability to expand its operations and revenue. Again, a high rate has a positive impact on the valuation (Faisal, 2024). We determine the YoY ARR growth rate as follows:

$$YoY\ ARR\ growth\ rate = \left(\frac{Current\ year\ ARR - Previous\ year\ ARR}{Previous\ year\ ARR}\right) \times 100\% \quad (2.24)$$

Total Addressable Market (TAM)

This metric is broader, as it focuses on the size of the (potential) market to explore the growth potential of the business . We express TAM as the overall revenue that a company can generate with 100% market share. In contrast, a larger TAM leads to more attractiveness to investors unless it has already achieved 100% market share, since there is no potential to grow anymore (Faisal, 2024). Therefore, based on market research, we need to estimate the total number of potential customers to determine the TAM. The formula is as follows:

$$TAM = Number\ of\ potential\ customers \times Average\ revenue\ per\ customer \quad (2.25)$$

2.3.4. Investor heuristics

Investors in the SaaS sector can rely on a set of established rules, which we commonly refer to as rules of thumb, to assess a company's financial health and growth potential quickly (Mol & Mensink, 2022). These serve as a simple benchmark to determine investment attractiveness, particularly in high-growth environments like the SaaS sector. According to Mol & Mensink (2022), the two most commonly used principles by investors include the rule of 40 and the T2D3 rule. While the rule of 40 focuses on balancing growth and profitability (Slingerland, 2024), the T2D3 rule stabilises a structured pathway for rapid scaling (Mol & Mensink, 2022).

Rule of 40

This principle states that a SaaS company's combined revenue growth rate and profit margin should equal or exceed 40% (Slingerland, 2024). This concept, popularised by venture capitalist Brad Feld in 2015, is known as the rule of 40 because the 40% threshold serves as a benchmark for balancing growth and profitability. According to Feld, after extensive benchmarking, investors have adopted the 40% threshold as a practical guideline, balancing the trade-off between aggressive growth and operational profitability (Slingerland, 2024). The fundamental reasoning behind this principle is that we consider SaaS firms that meet or exceed this threshold financially sustainable, whereas those below 40% may face cash flow or liquidity issues. Therefore, they may require corrective financial strategies, such as cost optimisation or revised growth plans, to enhance their long-term viability (Slingerland, 2024).

This metric is particularly relevant for later-stage SaaS firms with over €50 million ARR, indicating whether they balance profitability with continued growth (Slingerland, 2024). Therefore, when raising VC funding or preparing for an IPO, we can apply the rule of 40 to evaluate our attractiveness to investors. The formula of the rule of 40 is as follows:

$$YoY\ ARR\ growth\ rate\ +\ EBITDA\ margin \geq 40\% \tag{2.26}$$

Where:

- $EBITDA\ margin\ = \frac{EBITDA}{Revenue} \times 100\%$

T2D3 rule

Neeraj Agrawal (2015) introduced the T2D3 (triple, triple, double, double, double) rule as a strategic framework for evaluating the scaling trajectory of SaaS startups. He developed this principle based on an empirical analysis of high-growth SaaS companies that successfully transitioned to public markets. According to Neeraj Agrawal (2015), the T2D3 framework is particularly effective for companies that have reached product-market fit and achieved an ARR of €2 million. The core of the T2D3 rule outlines that the startup should follow this structured growth pattern (Mol & Mensink, 2022):

- Triple its ARR in each of the first two years (T2), and
- Double its ARR in the subsequent three years (D3).

Following this pattern, a SaaS company expects to scale from an ARR of €2 million to €144 within five years. The rationale behind this aggressive scaling method is that investors, particularly VCs, prioritise companies capable of exceeding the €100 million ARR threshold, which is a widely recognised benchmark for high-value exit and IPO readiness among investors (Mol & Mensink, 2022). This framework serves as a guiding principle for growth-stage SaaS startups aiming to maximise their valuation potential through revenue growth.

2.3.5. Discussion

Investor heuristics tend to be more relevant in later stages, particularly as a startup approaches an exit. The applicability of the rule of 40 remains questionable, with different perspectives on when it becomes relevant. Slingerland (2024) argues that the rule of 40 is typically relevant for later-stage SaaS startups exceeding €50 million in ARR. In contrast, Brad Feld suggests we can use the heuristic once the company reaches approximately €1 million in MRR, equivalent to €12 million in ARR.

During my research, I engaged with leading VCs at several international tech startup events, such as Slush Helsinki and Web Summit Qatar. Insights from these interactions indicate that the rule of 40 is generally not applied to startups with less than €25 million in ARR.

2.4. Startup stages

While various metrics are valuable for SaaS startup valuation, their applicability varies depending on the lifecycle stage (Trinchkova & Kanaryan, 2015). For example, in the early stages, valuation focuses on growth potential and customer acquisitions, whereas in later stages, cash flows and profitability become more important (Neubert & Van Der Krogt, 2017). Therefore, this section delves into the different startup stages and their implication for SaaS valuation metrics.

2.4.1. Understanding the startup stages

Startup stages refer to distinct phases as a company evolves from an idea to a saleable business and, potentially, to an exit. Each stage has specific milestones, challenges, and funding requirements (Mol & Mensink, 2022). However, the transition between these stages is not always fully defined. Some startups may bypass certain stages or experience overlaps, while others may reach an exit without progressing through all phases (Mol & Mensink, 2022). This highlights the need for a valuation framework tailored to the specific trajectory of a startup.

The startup lifecycle typically consists of six distinct stages: pre-seed stage, seed stage, early stage, growth stage, expansion stage, and exit stage (Basel Area Business & Innovation, n.d.), as illustrated in Figure A.2.

2.4.2. Pre-seed stage

The pre-seed stage focuses on formulating the initial business concept, opportunity analysis, and initial validation of the startup concept. We aim to assess whether our proposed service addresses a real market problem (Basel Area Business & Innovation, n.d.). We bring in key stakeholders like a CTO and CFO during this phase.

Funding is typically very limited and comes from friends, family, and fools, individuals willing to invest in the idea at high risk (Mol & Mensink, 2022). Since we mainly focus on establishing a foundation for the company, we do not generate revenue. Therefore, the most relevant metrics are TAM and the net monthly burn rate. Where TAM help us estimate the potential market size, the burn rate indicates when we run out of money. Additionally, the quality of the founding team and key stakeholders is a relevant intangible factor in the pre-seed valuation.

2.4.3. Seed stage

The business model is validated further in the seed stage through market testing, and we create a prototype (Basel Area Business & Innovation, n.d.). We aim to refine the product-market fit and generate initial traction. Seed funding, coming from angel investors, small funds, and regional development companies, supports product development and early market entry (Mol & Mensink, 2022). In the Netherlands, seed funding rounds typically range between €500,000-€900,000 (Mol & Mensink, 2022).

Revenue generation remains limited, often due to early customer payments or pilot contracts. Therefore, MRR becomes relevant for signalling the first revenue. Furthermore, CAC reflects the efficiency of acquiring new customers. At the same time, the churn rate measures the initial level of customer retention, and burn rate in this stage indicates the company's financial sustainability and the need for (additional) fundraising.

Given the high uncertainty and limited financial history at this stage, we commonly apply the VC method to estimate the potential exit valuation while accounting for our early traction and the high risk levels (Damadoran, 2009).

2.4.4. Early stage

The early stage is characterised by achieving a strong product-market fit, a growing customer base, and a steady MRR. Only 7.5% of seed startups progress from the seed to the early stage, highlighting its competitive nature (Basel Area Business & Innovation, n.d.).

After the pre-seed and seed stages, startups usually seek institutional investments, such as venture capital funds. Serie A is the first significant round, focusing on scaling the startup. Followed by Serie B, typically aiming to accelerate growth. Serie C and beyond aim to increase the attractiveness of the startups' exit (Mol & Mensink, 2022). In the Netherlands, Series A funding rounds typically range between €2 million and €5 million (Mol & Mensink, 2022). From a revenue perspective, SaaS startups typically enter the market with between $1 million and $5 million in ARR (Preuss, 2024).

Strategically, the focus shifts towards growth through scalable customer acquisition, retention strategies, and achieving product-market fit. Therefore, CLV/CAC measures the return on customer investment, and the churn rate measures customer retention. A low churn rate indicates successful product-market fit and customer satisfaction. Additionally, ARR and NRR serve as indicators of new sales and revenue expansion.

Given the presence of some stable recurring revenue, we can apply ARR-based revenue multiples. According to Bailyn (2025), private SaaS companies at the early stage are typically valued 4.5 to 6.6 times their ARR. However, due to the ongoing uncertainty and risk, the VC method remains a relevant valuation approach, particularly for estimating exit-based scenarios.

2.4.5. Growth stage

At the growth stage, our primary focus shifts to scaling operations, expanding into new markets, and accelerating customer acquisition (Venturz, n.d.). Series B or C funding rounds often support this, enabling further growth. In the Netherlands, Series B funding rounds typically range between €9 million and €20 million, and Series C funding rounds range between €15 million and €30 million (Mol & Mensink, 2022).

The startup diversifies revenue streams to sustain rapid growth and seeks strategic partnerships with established brands or enterprises. Customer retention remains important, while customer growth becomes even more critical (Venturz, n.d.). Consequently, YoY ARR becomes relevant, serving as a primary indicator of revenue acceleration. Furthermore, the CLV/CAC, churn rate, and the NRR remain relevant.

According to Preuss (2024), startups in the growth stage typically generate between $5 million and $20 million in ARR. With more reliable financial data available, the valuation methods become more robust. A commonly used approach is the application of YoY ARR-based valuation multiples. According to Sullivan (2025), we can categorise the growth rates as follows:

- Low growth (<20% YoY ARR): ARR multiples between 3 and 5.
- Moderate growth (20% - 40% YoY ARR): ARR multiples between 5 and 7.
- High growth (>40% YoY ARR): ARR multiples between 7 and 9.

These multipliers reflect the scaling potential, revenue quality, and the risk level associated with each category.

As financial records become more consistent, cash flow projections begin to improve in reliability, particularly for startups with a positive return on capital (Damodaran, 2009). However, many startups remain unprofitable in this phase as they continue to prioritise growth investments. Consequently, uncertainties remain, especially in projecting long-term growth trajectories or estimating terminal value.

We can use the ROV method to address such strategic uncertainties as a supplementary tool to capture managerial flexibility (Tellez & Raffiuddin, 2023). However, applying DCF and ROV methods may still be unsuitable for certain high-growth startups or startups with a negative return on capital.

2.4.6. Expansion stage

The expansion stage represents a transition from a high-growth startup to a scalable, self-sustaining business (Venturz, n.d.). We already consider many companies in this phase as scaleups, as expansion often involves international market entry, product diversification, or vertical integration (Basel Area Business & Innovation, n.d.). According to Preuss (2024), startups typically generate between $20 million and $50 million in ARR.

Funding, if needed, usually comes from private equity firms or late-stage VCs (Venturz, n.d.). A standard indicator of whether we reached this stage is achieving at least 20% annual growth for three consecutive years, measured in revenue or employee count (Basel Area Business & Innovation, n.d.).

At this stage, startups emphasise transforming from a high-growth startup to a scalable, self-sustaining business, and investors begin to apply their valuation heuristics. Therefore, the Rule of 40 to balance revenue growth and profitability becomes increasingly relevant. Furthermore, we use gross margin to evaluate operational efficiency and financial health, while the NRR remains a relevant indicator of customer satisfaction and revenue stability.

The YoY ARR multiples remain applicable from the valuation perspective, especially for high-growth firms. However, the increasing maturity of the financials, the emergence of operational profitability, and decreasing uncertainty in discount rate estimates make the DCF method more appropriate than in earlier stages. The ROV method may still serve as a supplementary tool for capturing strategic flexibility under uncertainty. However, it is more commonly used in earlier stages (Tellez and Raffiuddin, 2023).

Moreover, as the startup's business model slowly stabilises, some startups begin to approach the scale and financial structure of publicly traded SaaS companies. A market-based valuation using publicly listed comparables becomes applicable for these firms, offering a more transparent and standardised alternative to the private ARR-based multiples used in earlier stages. However, applying such comparables depends on the availability of a sufficient number of relevant public companies, a possible limitation highlighted by Damadoran (2009).

2.4.7. Exit stage

The exit stage is not a requirement for every startup, as some may continue to operate independently for extended periods. If a startup does not reach an exit, this stage can be omitted. However, if the startup does proceed to an exit, we focus on the following different exit paths (Basel Area Business & Innovation, n.d.):

- Founder share sale: Selling ownership stakes to external investors or acquiring firms.
- Acquisition: Selling the entire company to another business for strategic integration.
- IPO: Transitioning into a publicly traded company.

Exit strategies should align with the startup's long-term vision and values. The founder must proactively build industry relationships, maintain financial transparency, and ensure operational efficiency to maximise the valuation at the exit (Venturz, n.d.). Therefore, in preparation for exit, we should monitor a comprehensive set of metrics. However, we should focus on the NRR, gross margin, investor heuristics, the rule of 40, and the T2D3, measuring the rapid growth in YoY ARR.

The valuation methods in the exit stage become more robust and align with the market. Therefore, market-based valuation using publicly traded comparables becomes a central approach, especially for IPOs and acquisitions. As Allee et al. (2020) note, EV/EBITDA and EV/revenue multipliers, adjusted for the sector benchmark and firm-specific factors, offer greater transparency and credibility than the private ARR-based multiples.

However, as Damadoran (2009) notes, we must critically evaluate the quality and relevance of the available public comparables, particularly for the business model of SaaS firms. Therefore, DCF analysis with possibly ROV as a supplementary method may still be valuable in estimating the expected future performance. Although the startup itself may not realise these future returns post-exit, these models remain highly relevant in negotiations and positioning as they provide a structural basis for assessing the long-term growth prospect that an acquirer or the public market is willing to pay (Damadoran, 2009).

2.4.8. Benchmarking metrics per stage

According to Rosenbaum & Pearl (2009), benchmarking involves analysing financial metrics and trading multiples of comparable companies to determine an appropriate valuation range and future estimations. By leveraging industry-specific SaaS benchmark reports, we can better position Akela Hub within its relevant valuation context. In this section, we focus on the 2024 SaaS benchmarks provided by High Alpha (Press, 2024) and Benchmark It (Rike, 2024).

We assume the SaaS startup stages are based on ARR to make simple comparisons. We exclude the pre-seed stage, since revenue typically does not exist in this stage.

We categorise them into (Preuss, 2024):

- Seed stage: Less than$ €1 million ARR.
- Early stage: Between €1 million and €5 million ARR.
- Growth stage: Between €5 million and €20 million ARR.
- Expansion stage: Between €20 million and €50 million ARR.
- Exit stage: Greater than €50 million ARR.

Notably, these benchmarks differ slightly in timing. High Alpha's data reflects Q2 2024, whereas Benchmark IT provides metrics from the entire calendar year 2023. Despite this difference, they collectively offer insights into SaaS companies' expected metric performance.

Table 2.2: SaaS metrics benchmark per lifecycle stage

Metric	<€1M ARR	€1-5M ARR	€5-20M ARR	€20-50M ARR	>€50M ARR
Gross margin subscriptions	65%, [50%-81%]	80%, [65%-85%]	80%, [75%-84%]	79%, [71%-85%]	75%, [70%-88%]
Gross margin services	41%, [5%-50%]	45%, [10%-65%]	50%, [28%-55%]	15%, [0%-29%]	10%, [10%-29%]
Net monthly burn rate	€50K, [€50-175k]	€175K, [€50-375k]	€375K, [€0-375k]	€625K, [€13K-1.25M]	€0K, [€0K-2.5M]
CAC (Payback months)	5,[2-11]	8, [5-16]	14, [8-22]	20, [13-22]	20, [11-27]
CLV/CAC ratio	3.2, [2.1-6.0]	3.7, [2.4-7.0]	3.6, [2.4-5.3]	3.0, [2.1-5.5]	3.5, [2.4-7.4]
NRR	100%, [93%-110%]	100%, [96%-110%]	105%, [95%-120%]	103%, [94%-112%]	102%, [93%-107%]
YoY ARR Growth rate	100%, [48%-250%]	50%, [20%-115%]	30%, [17%-59%]	30%, [20%-50%]	15%, [12%-25%]
Rule of 40	N/A	30%, [-2%-60%]	22%, [1%-40%]	22%, [2%-33%]	25%, [4%-33%]

Table 2.2 summarises the key SaaS benchmarks per defined stage. It shows the median values, with the lower and upper quartiles in brackets to illustrate the healthy range. In addition, customer churn rates require separate analysis due to their short-term sensitivity. Jain (2023) suggests measuring churn monthly for meaningful insights, particularly valuable in the early stages. The median monthly churn rate for SaaS startups generally falls between 3% and 4%, with higher variability in companies below $300,000 ARR, as illustrated in Figure A.4

These benchmarking insights clarify SaaS startups' typical financial and operational targets at various stages. Recognising these benchmarks helps Akela Hub align its growth trajectory towards strategically established industry standards.

2.4.9. Summary

SaaS valuation metrics vary in applicability depending on the startup's lifecycle stage. Consequently, industry-specific benchmarks help position a company by providing quantitative reference points for each phase. However, the transition between lifecycle stages is not strictly linear; some startups may skip or overlap certain stages, while others reach an exit without progressing through all defined phases (Mol & Mensink, 2022). Nevertheless, using ARR as a proxy effectively categorises and benchmarks the startups quantitatively by lifecycle stage.

Table 2.3 provides an overview of the key metrics and valuation methods for each stage, categorised by ARR threshold as a proxy, as mentioned in Section 2.4.8.

Table 2.3: Key SaaS metrics and valuation techniques per lifecycle stage

ARR range	Stage	Key metrics per stage	Key valuation methods
No substantial	Pre-seed	TAM, burn rate	Market potential, team quality
<$1M	Seed	TAM, burn rate, MRR, CAC, churn rate	VC method, Market potential, team quality
$1M-$5M	Early	ARR, NRR, CLV/CAC, churn rate	ARR multiples, VC method
$5M-$20M	Growth	NRR, churn rate, CLV/CAC, YoY ARR	YoY multiples, DCF + ROV
$20M-$50M	Expansion	Rule of 40, gross margin, NRR, YoY ARR	YoY multiples, DCF + ROV, or public multiples
>$50M	Exit	Rule of 40, T2D3, Gross margin, NRR	DCF + ROV, public multiples

3. Regression analysis framework

Regression is a classical statistical technique used to model and analyse the relationship between one or more independent variables and one dependent variable (Weisberg, 2014). Due to its simplicity and explanatory power, regression analysis is widely used by researchers and practitioners to understand the relationship between variables, make predictions, and generate data-driven insights (Hall & Horowitz, 2007). By applying regression analysis, we develop a mathematical model representing how the independent variables correlate with the dependent variable (Weisberg, 2014).

3.1. Regression models

There are multiple forms of regression analysis, with multiple linear regression being the most common. Additionally, more complex regression models such as polynomial, binomial, and Poisson regression are available (Weisberg, 2014). However, given the scope of the research, we focus on multiple and polynomial linear regression models.

3.1.1. Multiple Linear Regression (MLR)

Multiple linear regression extends simple linear regression by simultaneously evaluating the relationship between one dependent variable (Y) and two or more independent variables ($X_1, X_2, \dots, X_k$) This method is particularly useful in complex environments where interrelated variables influence outcomes (Weisberg, 2014). We model this as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \epsilon \tag{3.1}$$

Where:

- β_0: The intercept, indicating the expected value of Y when X=0.
- β_1,$\beta_2, \dots, \beta_k$: Regression coefficients representing each independent variable's impact on Y.
- ϵ: Random error term, representing the difference between actual and predicted values.
- k: Number of predictors

In this model, we assume that the relationship between the dependent and each independent variable is linear and that the error terms follow a normal distribution and are independent (Weisberg, 2014).

3.1.2. Polynomial linear regression

We employ linear polynomial regression when the relationship between the dependent and independent variables exhibits non-linear patterns. Unlike simple and multiple linear regression, polynomial regression incorporates higher-order terms to model complex, curvilinear patterns effectively (Weisberg, 2014). This approach is particularly useful in time series analysis, growth modeling, and engineering studies, where linear models may not adequately capture data trends (Weisberg, 2024). We model the polynomial regression model with a single independent variable (X) and a dependent variable (Y) as follows:

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \cdots + \beta_d X^d + \epsilon \tag{3.2}$$

Where:

- d: Degree of the polynomial (e.g. d=2 is quadratic, d=3 is cubic, etc.).

Higher polynomial degrees increase model flexibility but heighten the risk of overfitting, meaning the model might capture random noise rather than actual underlying patterns. Consequently, selecting an appropriate polynomial degree is crucial to balancing the trade-off between model complexity and prediction accuracy (Weisberg, 2024).

Furthermore, we can selectively include polynomial terms in an MLR model, allowing us to capture non-linear effects only when appropriate while keeping the overall model structure primarily linear.

3.2. Goodness-of-fit metrics

Evaluating the accuracy and reliability of the regression models involves using goodness-of-fit metrics and performance metrics to quantify how well the model fits the data. According to Weisberg (2014), the primary measure of model accuracy includes the coefficient of determination (R^2) and the Adjusted R^2. In addition, Hodson (2022) highlights the importance of the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) in assessing model quality and the extent to which the regression model accurately predicts condition outcomes.

3.2.1. R²

The coefficient of determination, commonly known as R-squared (R^2), measures the proportion of total variability in the dependent variable explained by the regression model. We calculate R^2 as follows:

$$R^2 = 1 - \frac{RSS}{SYY} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3.3}$$

Where:

- RSS: Residual sum of squares, measuring the unexplained variability by the regression model.
- SYY: Total sum of squares, quantifying the variability of observed values around their mean.

R-squared ranges from 0 to 1, with higher values typically indicating a better fit, meaning the model explains a more significant proportion of the variance in data (Weisberg, 2014).

3.2.2. Adjusted R²

While R^2 effectively assesses goodness-of-fit, it increases or remains constant with adding independent variables, even if these variables have minimal or no relationship with the dependent variable (Weisberg, 2024). The adjusted R^2 corrects this issue by penalising the inclusion of independent variables. We calculate it as follows (Ouko, 2024):

$$\text{Adjusted } R^2 = 1 - \left(\frac{(1 - R^2)(n - 1)}{n - k - 1}\right) \tag{3.4}$$

Where:

- n: number of observations.

The adjusted R-squared only increases when adding an independent variable significantly improves the model's explanatory power. Therefore, it provides a more reliable measure of model performance while avoiding unnecessary complexity (Weisberg, 2014).

3.2.3. Mean Absolute Error (MAE)

The MAE measures the average deviation of prediction errors by calculating the mean of the absolute differences between the actual and predicted values. We compute it as follows:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{3.5}$$

Furthermore, MAE is a scale-consistent metric that provides a precise, interpretable measure of the average deviation between predicted and observed values. In other words, it indicates, on average, how far predictions are from the true outcomes. According to Hodson (2022), MAE is particularly suitable for models where we do not overly penalise large deviations and residuals are not normally distributed.

3.2.4. Root Mean Squared Error (RMSE)

In contrast to MAE, the RMSE squares each prediction error before averaging and then takes the square root of this result.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3.6}$$

By squaring the errors, the RMSE gives more weight to larger deviations, making it more sensitive to outliers than the MAE. This can be either an advantage or a disadvantage, depending on the nature of the data. Hodson (2022) notes that RMSE is preferred when large errors are particularly undesirable, and it complements MAE by providing insights into the variance of the residuals

3.3. Significance testing

The R-squared metric verifies whether the model fits the data. However, it does not indicate whether the independent variables significantly contribute to explaining the dependent variable. Therefore, we incorporate significance tests, such as the t-test and the F-test, to assess whether the independent variables included in the regression model significantly affect the dependent variable (Weisberg, 2014).

3.3.1. The t-test

We assess the significance of individual regression coefficients by applying the t-test, which evaluates whether an estimated regression coefficient $\hat{\beta}_j$ differs from zero, thus determining whether the associated predictor X_j contributes meaningfully to explaining the dependent variable (Weisberg, 2014). To test this, we define a null hypothesis as follows:

$$H_0: \beta_j = 0 \tag{3.7}$$

To test the null hypothesis, we calculate the t-statistic as follows:

$$t = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \tag{3.8}$$

Where:

- $\hat{\beta}_j$ is the estimated regression coefficient for the independent variable X_j.
- $SE(\hat{\beta}_j)$ is the standard error for the coefficient estimate.

The Standard Error (SE) of a coefficient quantifies the level of uncertainty associated with the estimated regression coefficient for a particular predictor. A small SE suggests a reliable estimation, whereas a larger SE indicates uncertainty around that estimation. We derive the SE from the diagonal element of the variance-covariance matrix.

$$Var(\hat{\beta}) = \sigma^2 (X'X)^{-1} \tag{3.9}$$

Taking the square root of the diagonal element of predictor j, we obtain:

$$SE(\hat{\beta}_j) = \sqrt{\sigma^2 \cdot (X'X)^{-1}_{jj}} \tag{3.10}$$

Where the residual variance $(\hat{\sigma}^2)$ quantifies the unexpected variance in the model, which we compute as follows:

$$\hat{\sigma}^2 = \frac{RSS}{n-k-1} = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n-k-1} \tag{3.11}$$

Once we have calculated the t-statistic, we can determine its p-value based on the t-statistic using the t-distribution with $n-k-1$ degrees of freedom for linear regression. The decision rule for the t-test is as follows:

- $p < 0.05$: Reject H_0 i.e., the predictor is statistically significant.
- $p \geq 0.05$: Do not reject H_0, no significant effect.

3.3.2. F-test

While we use the t-test to assess the significance of individual coefficients, we apply the F-test to evaluate the joint significance of multiple predictors in a regression model. The overall F-test examines whether at least one of the independent variables contributes meaningfully to explaining the variation in the dependent variable by comparing the fitted regression model against a model without independent variables (Weisberg, 2014). We define the null hypothesis for the overall F-test as follows:

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_k = 0 \tag{3.12}$$

With:

- $p < 0.05$: Reject H_0 i.e., the model has explanatory power.
- $p \geq 0.05$: Do not reject H_0, the model is not statistically significant.

In addition to the overall F-test, we apply the partial F-test to evaluate the joint contribution of a subset of independent variables. This is particularly relevant when several predictors are not individually significant according to their t-test but may contribute collectively to the model. The partial F-test compares a full model with a reduced model (excluding a specific set of predictors). We define the null hypothesis for the partial F-test as follows:

$$H_0: \beta_{r+1} = \beta_{r+2} = \cdots = \beta_k = 0 \tag{3.13}$$

Where:

- r: is the number of included predictors in the reduced model.

With:

- $p < 0.05$: Reject H_0 i.e., the excluded predictors jointly improve the model fit.
- $p \geq 0.05$: Do not reject H_0 i.e., the excluded variables do not significantly improve the model fit.

We compute the F-statistic as follows:

$$\mathrm{F} = \frac{(\mathrm{RSS_F} - \mathrm{RSS_R})/(df_F - df_R)}{\mathrm{RSS_F}/df_F} = \frac{\mathrm{SS_{reg}}/\mathrm{df_{reg}}}{\hat{\sigma}^2} \tag{3.14}$$

Where:

- $\mathrm{RSS_F}$: Residual sum of squares of the full model
- RSS_R: Residual sum of squares of the reduced model
- $SS_{reg} = \mathrm{RSS_F} - \mathrm{RSS_R}$: Regression sum of squares
- $\mathrm{df_{reg}} = df_F - df_R$: Regression degree of freedom

A significant F-test (p-value < 0.05) supports the inclusion of the tested predictors in the model, even when their individual p-values are not statistically significant (Weisberg, 2014).

3.4. Multicollinearity analysis

Multicollinearity arises when two or more independent variables in our regression model exhibit high correlation, causing difficulties in accurately estimating the impact of each independent variable (Mahmood, 2024). High multicollinearity negatively affects the accuracy, stability, and interpretability of regression results by inflating the variance of coefficient estimates, thereby complicating the assessment of the true relationships between variables (Mahmood, 2024).

3.4.1. Variance Inflation Factor (VIF)

To diagnose multicollinearity, we employ VIF, a statistical measure quantifying the extent to which variance in regression coefficients inflates due to linear relationships among independent variables (Mahmood, 2024). We calculate the VIF per independent variable as follows:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{3.15}$$

Where:

- R_j^2 is the coefficient of determination of the independent variable X_j.
- $j = 1,2,3, \ldots, k$.

According to Mahmood (2024), we interpret the VIF values as follows:

- $VIF = 1$: No correlation among independent variables.
- $1 < VIF < 5$: Moderation correlation, typically acceptable.
- $5 \leq VIF < 10$: High correlation, potentially problematic.
- $VIF \geq 10$: Severe multicollinearity, causing unstable and unreliable coefficient estimates.

However, the VIF primarily evaluates pairwise relationships and might not detect multicollinearity resulting from interactions involving multiple variables simultaneously.

3.4.2. Eigenvalues and condition index

Mahmood (2024) suggests additional indicators, such as creating a correlation matrix and calculating its corresponding condition index, to achieve a comprehensive multicollinearity diagnosis. Including a correlation matrix makes us dive into the multicollinearity of individual variables by displaying the pairwise correlation coefficient r. High coefficients (r > 0.7) are likely to be multicollinear. We compute the correlation coefficient as follows (Weisberg, 2014):

$$r = \frac{Cov(x,y)}{\sqrt{Var(x) \cdot Var(y)}} = \frac{\sum_{i=0}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=0}^{n}(x_i - \bar{x})^2 \sum_{i=0}^{n}(y_i - \bar{y})^2}} \tag{3.16}$$

Additionally to formally assess the severity of multicollinearity, we compute the Eigenvalues (λ) of the correlation matrix R by solving the characteristic Equation (3.17):

$$|R - \lambda I| = 0 \tag{3.17}$$

Where:

- R is the correlation matrix with correlation coefficients (r).
- I is the identity matrix
- λ are the eigenvalues of the matrix R

Eigenvalues approaching zero indicate strong linear dependencies, signaling problematic multicollinearity (Mahmood, 2024). After identifying the eigenvalues, we can compute the condition index using the largest ($\lambda_{\max}$) and each ($\lambda_1, \lambda_2, \ldots, \lambda_k$) Eigenvalues are as follows (Kim, 2019):

$$K_s = \sqrt{\frac{\lambda_{\max}}{\lambda_s}} \, (s = 1,2, \dots, k) \tag{3.18}$$

A condition index exceeding 30 indicates severe multicollinearity, implying that the regression estimates become unstable (Kim, 2019).

3.5. Model validation

We use model validation to ensure that our regression models accurately generalise beyond the training data (Weisberg, 2014). Proper validation confirms the predictive performance and guards against overfitting (Mahmood, 2024). We evaluate the robustness and generalisability through two widely recognised methods: the train-test split and k-fold cross-validation.

3.5.1.Train-test split

The train-test split method divides a dataset into two disjoint subsets: training and testing sets. By separating these subsets, we ensure that we train the model based on one part of the data and evaluate it on a different part, helping us estimate the model's generalisation performance (Joseph, 2022).

Joseph (2022) discusses the commonly practiced splitting of 80:20 and 70:30 but highlights that the optimal splitting ratio can vary depending on the number of parameters in the model.

Therefore, we can calculate the optimal ratio as follows:

$$\gamma^* = \frac{1}{\sqrt{(k+1)} + 1} \tag{3.19}$$

Where:

- γ^* is the optimal ratio of the testing set size to the entire dataset.

The formula implies that as the number of parameters increases, we should allocate a larger proportion to the training set, as we need more data to estimate the coefficients accurately.

3.5.2. The k-fold cross-validation

A more comprehensive validation technique is the k-fold cross-validation, involving dividing the data into k equally sized subsets or folds. The model is iteratively trained on $k-1$ folds and validates it on the remaining fold. We repeat this process k times, with each fold serving as the validation set exactly once (Xu & Goodacre, 2018). Compared to the simpler train-test split method, k-fold cross-validation has the advantage of systematically utilising all available data for training and validation, resulting in robust performance estimates with reduced variability.

These model validation techniques ensure that our regression model maintains stability and performs accurately, including validating their reliability and applicability in practical scenarios (Xu & Goodacre, 2018).

3.6. Summary

Regression analysis models the relationship between independent and dependent variables using methods like simple, multiple, and polynomial linear regression (Weisberg, 2014). These methods assess the significance of variables through statistical tests, with the t-test evaluating individual coefficients and the F-test determining the overall model significance (Weisberg, 2014). We use the train-test split method to validate the model's predictive performance by dividing the dataset into a training and testing set (Joseph, 2022). Alternatively, the k-fold cross-validation method systematically utilises all data for training and validation by iterating across multiple subsets (Xu & Goodacre, 2018). Furthermore, we evaluate model accuracy using the goodness-of-fit metrics R-squared and adjusted R-squared (Weisberg, 2014) and the performance metrics MAE and RMSE. Additionally, we diagnose multicollinearity using VIF and the condition index to detect linear dependencies among the independent variables (Mahmood, 2024).

4. Regression analysis

In this chapter, we conduct regression analysis to identify and quantify the relationships between our selected independent variables and their impact on the dependent variables. We proceed with the analysis through several structured stages: initial data collection and cleaning, selection of the regression model, and execution of the regression model. We conduct all statistical analyses using Python. This approach allows us to quantitatively analyse the relationship between the SaaS startup exit prices and independent factors such as the funding history and company lifetime.

4.1. Data collection and cleaning

The regression analysis requires data collection and cleaning to ensure the accuracy and reliability of the analysis. Initially, the company provided the data consisting of 1442 observations related to SaaS companies with two distinct types: business acquisition (930 observations) and IPO (512 observations). Each observation includes information on the foundation year, exit date, type of exit, total funding received, date of last funding, location (continent), and either the acquisition price or IPO market capitalisation.

However, not all observations are complete. Among the 930 acquisition exits, only 496 include the disclosed acquisition price. Similarly, only 279 of the 512 IPO exits contain information about the market capitalisation at the IPO date. Our dependent variable is the exit price (acquisition price or market capitalisation). Therefore, we exclude all observations without the acquisition price or market capitalisation.

To analyse the data, we define four independent variables: total funding received, age at exit, months between last funding and exit, and geographical location. We derive the company's age in months at the exit by calculating the difference between the exit date and the assumed foundation date, July 1st of the known foundation year. We assume July 1st is the year's midpoint due to the unavailability of the precise foundation date. In a few cases, this calculation resulted in a negative age, which we treat as unreliable, and we exclude them from the analysis. We apply the same logic to calculate the interval between the last funding and exit dates.

Furthermore, we standardise the total funding, acquisition price, and IPO market capitalisation value in US dollars for consistency. Finally, we categorise the geographical location by continent rather than specific countries or cities to identify broader regional trends or variations

After these data collection and preparation processes, including removing incomplete and unreliable observations, the final dataset available for regression analysis includes 461 observations for business acquisitions and 254 observations for IPO exits.

4.2. Model selection and preparation

Before conducting the regression analysis, we must define the appropriate method. Given the presence of multiple explanatory variables, the simple regression model is unsuitable. Instead, we evaluate the four key assumptions Hair et al. (2010) outlined for multivariate data analysis. These assumptions include normality, homoscedasticity, linearity, and the absence of autocorrelation. Based on these outcomes, we determine whether MLR or an alternative regression approach is the most appropriate. Additionally, these results ensure that the selected model is both statistically valid and robust for interpretation

As our dataset includes two distinct exit types, business acquisition and IPO, we develop separate regression models for each group to ensure internal validity and accurate interpretation. Thus, we evaluate all the assumptions independently for both datasets.

4.2.1. Acquisitions dataset

The acquisition dataset consists of 461 complete observations, each containing the dependent variable (acquisition price) and the four independent variables:

- Y: Acquisition price ($)
- X_1: Total funding ($)
- X_2: Age at exit (m)
- X_3: Months between last funding and exit (m)
- Geographical location (categorical)

4.2.1.1. Normality

Normality, the most fundamental assumption in multivariate analysis, refers to the shape of the data distribution, ideally following a normal distribution. Hair et al. (2010) note that violations of this assumption can invalidate statistical inference. Weisberg (2014) adds that in linear regression analysis, the normality assumptions apply specifically to the residuals.

Therefore, we check the shape of the distribution with two measures: skewness and kurtosis. Skewness describes the balance of the distribution, where a negative skew denotes a distribution shift to the left, and a positive skewness reflects a shift to the right (Hair et al., 2010). Furthermore, the kurtosis refers to a distribution's "peakedness" and "flatness," so we compare the height of the distribution to the normal distribution. We statistically test normality by calculating the z-value for skewness and kurtosis:

$$z_{skewness} = \frac{skewness}{\sqrt{\frac{6}{n}}} \tag{4.1}$$

$$z_{kurtosis} = \frac{kurtosis}{\sqrt{\frac{24}{n}}} \tag{4.2}$$

Where n=461, the number of observations. Hair et al. (2010) suggest using critical z-values exceeding ± 1.96 (at a 95% confidence level) to indicate significant non-normality. Therefore, we define the following null hypothesis:

$$H_o: Skewness = Kurtosis = 0 \tag{4.3}$$

With:

- $|z| \geq 1.96$: Reject H_0 (non-normality).
- $|z| < 1.96$: Do not reject H_0 (normality).

Table 4.1: Normality test results

	Skewness	$z_{skewness}$	kurtosis	$z_{kurtosis}$
X_1:Total funding	2.7880	24.4385	8.7747	38.4573
X_2:Age at exit	0.5330	4.6721	-0.1737	-0.7613
X_3: Months between last funding and exit	1.3430	11.7722	2.0140	8.8269
Residuals	4.0918	35.8669	33.7104	147.7436

We reject H_o as all z-values exceed ± 1.96, indicating a strong right skewness and significant non-normality in all variables, especially in the residuals.

According to Hair et al. (2010), the remedy for non-normality is the transformation of the independent variables. To transform the severely right-skewed X_1 and X_3 we apply the Box-Cox transformation (Box & Cox, 1964), suitable for strictly positive and continuous data. We mathematically define as follows:

$$X_i^{(\lambda)} = \begin{cases} \frac{{X_i}^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ \ln(X_i), & \lambda = 0 \end{cases} \tag{4.4}$$

This transformation adjusts the skewness and kurtosis, and it may approximate a logarithmic, square-root, or linear transformation, depending on the optimal λ (Box & Cox, 1964). This flexibility makes the method particularly effective for correcting right-skewed positive data, like X_1 and X_3.

Hair et al. (2010) recommend log ($X' = log(X)$) or square root ($X' = \sqrt{X}$) transformation for mild skewness, like X_2. The logarithmic transformation overcorrects, and the square root transformation results in acceptable z-values. However, the Box-Cox transformation provides slightly better z-values. Consequently, we also transform X_2 using Box-Cox.

Table 4.2: Normality test results after Box-Cox independent variables transformation.

	Skewness	$z_{skewness}$	kurtosis	$z_{kurtosis}$	**Optimal λ**
X_1:Total funding	-0.0257	-0.2250	-0.4285	-1.8782	0.1096
X_2:Age at exit	-0.0295	-0.2588	-0.3557	-1.5590	0.4962
X_3: Months between last funding and exit	-0.0342	-0.2999	-0.2944	-1.2902	0.3158
Residuals	5.1403	45.0572	37.6310	164.9265	N/A

The predictors now meet the normality assumption. However, we have an even higher residual non-normality. Thus, we still reject H_o, indicating possible heteroscedasticity and the need for a transformation in the Y variable.

4.2.1.2. Homoscedasticity

To statistically test our second assumption, homoscedasticity, referring to the constancy of residual variance, we apply the Breusch-Pagan (BP) test (Breusch & Pagan, 1979). This method regresses the squared residuals from the original model onto the predictor variables. We evaluate whether the residual variance of our regression model depends on the predictor values by incorporating an auxiliary regression model, which we denote as follows:

$$\hat{\varepsilon}_i^2 = \gamma_0 + \gamma_1 X_{1i} + \gamma_2 X_2 + \gamma_{3i} X_{3i} + v_i \quad (4.5)$$

Where:

- $\hat{\varepsilon}_i^2$: Squared residual for the original regression model.
- v_i: Error term in the auxiliary regression model.
- i: The index of the observation. $(1,2, \ldots, n)$

Breusch & Pagan (1979) developed a Lagrange Multiplier (LM) statistic, which we define as follows.

$$LM = n \cdot R^2_{\hat{\varepsilon}_i^2} \quad (4.6)$$

This LM statistic follows a chi-squared distribution (χ_k^2) with k degrees of freedom. We can test the H_0 as follows:

$$H_0: Var(\varepsilon_i) = \sigma^2 \quad (4.7)$$

With:

- $p < 0.05$: Reject H_0 (heteroscedasticity).
- $p \geq 0.05$: Do not reject H_0 (homoscedasticity).

Our initial BP test results include an $LM \sim \chi_3^2$ statistic of 30.7221, yielding p<0.001, and thus we reject H_0 meaning there is heteroscedasticity present. Following Hair et al. (2010), we attempt to resolve this by transforming the dependent variable (Y) using log, square root, and Box-Cox transformations. The square root worsens the results; both log and Box-Cox provide normal distributions in residuals with approximately equal results. However, as the log transformation enables more practically meaningful and interpretable coefficient estimates, especially in percentage terms relevant for managerial decision-making, we proceed with the log-transformed model.

The transformation results in a new $LM \sim \chi_3^2$ statistic of 17.0310 , yielding p<0.001. This means we still suffer from heteroscedasticity. However, as Table 4.3 shows, we now ensure normality in the residuals

Table 4.3: Normality test Y after log transformation.

	Skewness	$z_{skewness}$	kurtosis	$z_{kurtosis}$
Y: Acquisition price	0.0071	0.0621	-0.2204	-0.9659
Residuals	-0.1707	-1.4961	0.0829	0.3634

4.2.1.3. Linearity

We statistically test linearity by applying the Regression Specification Error Test (RESET) developed by Ramsey (1969). This test adds squared and cubic terms to the model's predicted values to detect omitted non-linear relationships by incorporating an auxiliary regression model, which we specify as follows:

$$\log(Y_i) = \beta_o + \beta_1 X_{1i}{}^{(\lambda_1)} + \beta_2 X_{2i}{}^{(\lambda_2)} + \beta_{3i} X_{3i}{}^{(\lambda_3)} + \gamma_1 \hat{Y}_i{}^2 + \gamma_2 \hat{Y}_i{}^3 + v_i \quad (4.8)$$

Where:

- $\log(Y_i)$ is the log-transformed dependent variable Y
- $X_{1i}^{(\lambda_1)}$, $X_{2i}^{(\lambda_2)}$, $X_{3i}^{(\lambda_3)}$ are the Box-Cox transformed predictors X_1,X_2, X_3 with their corresponding optimal $\lambda_1, \lambda_2, \lambda_3$.
- $\hat{Y}_i^{\,2}$ and $\hat{Y}_i^{\,3}$ are the fitted values from the regression model.
- γ_1 and γ_2 are the coefficients for the squared and cubed fitted values.

The RESET test uses the F-test and its corresponding p-values, as mentioned in Section 3.3.2. To examine the significance, we mathematically define the null hypothesis as follows:

$$H_0 : \gamma_1 = \gamma_2 = 0 \tag{4.9}$$

With:

- $p < 0.05$: Reject H_0 (non-linearity).
- $p \geq 0.05$: Do not reject H_0 (linearity).

Our initial RESET test results include a p-value of 0.0085. Therefore we reject H_0, meaning there is non-linearity present. Consequently, we explore polynomial transformation or alternative model structures to adequately capture the underlying relationships. However, first, we need to detect which variable shows non-linearity. According to Hair et al. (2010), the most common way to detect the linearity of a variable is by examining scatterplots of the residuals and variables. Figure A5 shows us a u-shape of the residuals for X_1. Following Hair et al. (2010), we introduce a second-degree polynomial term (X_1^2) to account for the curvature. Therefore, we define our new auxiliary regression model as follows:

$$\log(Y_i) = \beta_o + \beta_1 X_{1i}^{(\lambda_1)} + \beta_2 X_{2i}^{(\lambda_2)} \beta_{3i} X_{3i}^{(\lambda_3)} + \beta_4 (X_{1i}^{(\lambda_1)})^2 + \gamma_1 \hat{Y}_i^{\,2} + \gamma_2 \hat{Y}_i^{\,3} + v_i \tag{4.10}$$

The inclusion of the new variable X_1^2 lead to a p-value of 0.8892. Therefore, we do not reject the H_0, meaning the model meets the linearity assumption.

4.2.1.4. Autocorrelation

Lastly, we assess the absence of autocorrelation and independent residuals using the Durbin-Watson test (Durbin & Watson, 1950), which detects first-order serial correlation in the residuals. We mathematically express the test as follows:

$$d = \frac{\sum_{i=2}^{n} (\hat{\varepsilon}_i - \hat{\varepsilon}_{i-1})^2}{\sum_{i=1}^{n} \hat{\varepsilon}_i^2} \tag{4.11}$$

The acceptable range for d includes: $1.5 < d < 2.5$ and $d \approx 2$ is the ideal situation, meaning no autocorrelation. Our test results in a d-value of 1.9501, which is within the acceptable range, meaning there is an absence of autocorrelation.

4.2.1.5. Addressing heteroscedasticity

Before proceeding to the final model estimation, one remaining concern is the presence of heteroscedasticity, even after transforming all variables. Wooldridge (2010) outlines two widely accepted approaches to address heteroscedasticity while maintaining consistency and a valid interface: using heteroscedasticity-robust standard error (White, 1980) or implementing the Weighted Least Square (WLS) method.

Using the heteroscedasticity-robust standard errors, we retain our ordinary least squares (OLS) coefficient estimates while modifying the associated variance-covariance matrix to correct for heteroscedasticity. As the assumption of constant error variance no longer holds when heteroscedasticity is present, each observation contributes to its own estimated variance, approximated by the squared residual ($\hat{\varepsilon}_i^2$). These residuals are then placed on the diagonal of the matrix $\widehat{\Omega}$, which we use to construct the heteroscedasticity-consistent variance estimator (White, 1980):

$$Var(\hat{\beta}) = (X'X)^{-1}(X'\widehat{\Omega}X)(X'X)^{-1} \tag{4.12}$$

Where:

- $\widehat{\Omega}$ is a diagonal matrix with $\hat{\varepsilon}_i^2$ on the diagonal.
- $(X'X)^{-1}$ is the standard OLS variance component.

This method, commonly called HC0, does not require prior knowledge of the heteroscedasticity pattern and is valid under any form. However, Long & Ervin (2000) recommend using the HC3 estimator, particularly in samples of moderate size with potentially influential observations, as it offers better control over Type I error (false positives). Consequently, we use the HC3 estimator, described as follows:

$$\hat{\varepsilon}_{i,HC3}^2 = \left(\frac{\hat{\varepsilon}_i}{1 - h_{ii}}\right)^2 \tag{4.13}$$

Where:

- h_{ii} is the leverage of observation i.

Alternatively, WLS attempts to address heteroscedasticity by reducing the influence of observations with higher variance. We achieve this by weighting each observation based on the inverse of its estimated residual variance (Wooldridge, 2010). We define the weights as follows:

$$w_i = \frac{1}{\hat{u}_i^2 + \epsilon} \tag{4.14}$$

Where ϵ is a small constant to avoid division by zero. In theory, WSL can lead to more efficient estimators than OLS with robust standard errors. However, Wooldridge (2010) warns that if the conditional variance model is incorrectly specified, WSL estimators may be inconsistent.

To assess this risk, we apply HC3 and WSL to our transformed model to check the goodness-of-fit metrics mentioned in Section 3.2. The WSL model yields a nearly perfect R^2 and adjusted R^2 of both 0.9966. We use the 10-fold cross-validation mentioned in Section 3.5.2 to validate this result. This results in a dramatic drop of fit to a mean R^2 of 0.5991 and a mean adjusted R^2 of 0.5600. This drop signals overfitting and undermines the reliability of the WSL model, as it affects.

In contrast, the HC3 model retains its original coefficients and model fit, as robust standard errors do not change the predictor or R^2 values. Given its ability to correct heteroscedasticity without affecting the model structure and its cross-validation performance, we adopt the OLS model with HC3 robust standard errors.

4.2.1.6. Categorical variable implementation

We use dummy coding to incorporate geographical location into the regression model, following the recommendations of Hair et al. (2010). This approach enables the model to account for systematic differences in acquisition valuations across regions. According to Hair et al. (2010) a categorical variable with k categories require the inclusion of $k-1$ dummy variables to avoid multicollinearity.

In our data, the location includes four groups: North America (Canada and the United States), Asia, Europe, and Oceania. However, Asia includes only five observations and Oceania only one, violating the statistical requirement for reliable estimations. Hair et al. (2010) suggest a minimum of 10-15 observations per predictor to ensure coefficient stability and avoid inflated standard errors. Consequently, we exclude Asia and Oceania from dummy encoding, although we retain the observations in the dataset.

The remaining valid groups with sufficient sample sizes are Europe (n=81) and North America (n=374). Due to its dominant sample size, we select North America as a reference group and construct a single dummy variable for Europe. To maintain statistical robustness, we group the six observations in Asia and Oceania within the North America category, whose large sample size ensures that these additional data points have minimal influence on coefficient estimations. As such, we denote our dummy variable $D_{Europe,i}$ as follows:

$$D_{Europe,i} = \begin{cases} 1, & if\ located\ in\ Europe \\ 0, & otherwise \end{cases} \tag{4.15}$$

This allows for a clean and interpretable comparison between European-based companies and those in North America without undermining the validity of the regression model. The dummy variable is binary and not continuous, so it is not subject to assumption testing (Hair et al., 2010).

4.2.2. IPO dataset

The IPO dataset contains 254 complete observations. Compared to the acquisition model, we exclude the variable representing the time between funding and the exit, as many companies receive funding after IPO, making this variable unreliable. Therefore, we include the following variables for our IPO model:

- Y_{IPO}: Market cap at IPO ($)
- $X_{1,IPO}$: Total funding ($)
- $X_{2,IPO}$: Age at exit (m)
- Geographical location (categorical)

4.2.2.1. Normality

To test for normality, we again apply the z-test for skewness and kurtosis using Equations 4.1 and 4.2. Table 4.4 shows us these results:

Table 4.4: Normality test results for IPO dataset.

	Skewness	$z_{skewness}$	kurtosis	$z_{kurtosis}$
$X_{1,IPO}$:Total funding	5.1631	33.5934	38.6943	125.8805
$X_{2,IPO}$:Age at exit	0.5629	3.6623	0.3960	1.2884
Residuals	4.3777	28.4833	36.3646	118.3016

As for z-values exceeding ± 1.96, we again apply transformations in the independent variables. Due to the severe right-skewed nature of $X_{1,IPO}$, we apply the Box-Cox transformation using Equation 4.4 (Box & Cox, 1964). Furthermore, for $X_{2,IPO}$. Besides the Box-Cox transformation, we test the log and square root transformations as Hair et al. (2010) recommend for mild skewness. However, only the Box-Cox transformation ensures the normality of $X_{2,IPO}$. Table 4.5 shows us the results of the z-tests using Box-Cox transformation for both predictors.

Table 4.5: Normality test results after Box-Cox independent variables transformation.

	Skewness	$z_{skewness}$	kurtosis	$z_{kurtosis}$	Optimal λ
$X_{1,IPO}$:Total funding	-0.0446	-0.2902	-0.5754	-1.8718	0.1019
$X_{2,IPO}$:Age at exit	-0.0367	-0.2389	-0.0344	-0.1119	0.6398
Residuals	4.5506	29.6079	29.3824	95.5868	N/A

The predictors now meet the normality assumptions. However, the residuals are still indicating non-normality, indicating possible heteroscedasticity.

4.2.2.2. Homoscedasticity

We apply the BP test (Breusch & Pagan, 1979) using Equation 4.6 to examine heteroscedasticity. The initial BP test results in an LM $\sim\chi^2_2$ statistic of 16.8900, yielding p<0.001. Therefore, we reject the null hypothesis (Equation 4.7), indicating heteroscedasticity.

To fix the heteroscedasticity, we try the log, square root, and Cox-Box transformations for the dependent variable. Only the Box-Cox transformation results in homoscedasticity, reducing the LM$\sim\chi^2_2$ statistic to 0.0072, yielding a p-value of 0.0994. Table 4.6 shows us that we also ensure normality in the residuals after the transformation, as we do not reject H_0 (Equation 4.3).

Table 4.6: Normality test Y after Box-Cox transformation.

	Skewness	$z_{skewness}$	kurtosis	$z_{kurtosis}$	Optimal λ
Y_{IPO}:Market cap at IPO	-0.0181	-0.1175	-0.2795	-0.9093	0.0799
Residuals	-0.1605	-1.0442	-0.0338	-0.1098	N/A

4.2.2.3. Linearity

To statistically test for linearity, we employ the RESET test (Ramsey, 1969) as defined in Equation 4.8. This results in an F-statistic of 2.287 with a p-value of 0.1037, meaning that we do not reject the H_0 (Equation 4.9) as our model satisfied the linearity assumption.

4.2.2.4. Autocorrelation

We test first-order autocorrelation using the Durbin-Watson test (Durbin & Watson, 1950), as expressed in Equation 4.11. This results in a d-value of 1.9043, which lies within the acceptable range of $1.5 < d < 2.5$, and therefore, we do not suffer from autocorrelation.

4.2.2.5. Categorial variable implementation

Like the acquisition regression model, we implement dummy coding to include the categorical variable, geographical location, in the IPO regression model. Hair et al. (2010) recommend a minimum of 10-15 observations per category to ensure coefficient stability. In this dataset, all four continents meet this requirement: North America (n=128), Asia (n=82), Europe (n=28) and Oceania (n=16). We use North America as the reference group due to its sample dominance. Therefore, we define the dummy variables as follows:

$$D_{Europe(IPO),i} = \begin{cases} 1, & if\ located\ in\ Europe \\ 0, & otherwise \end{cases} \tag{4.16}$$

$$D_{Asia(IPO),i} = \begin{cases} 1, & if\ located\ in\ Asia \\ 0, & otherwise \end{cases} \tag{4.17}$$

$$D_{Oceania(IPO),i} = \begin{cases} 1, & if\ located\ in\ Oceania \\ 0, & otherwise \end{cases} \tag{4.18}$$

Integrating these dummy variables enables a clear interpretation of differences in market capitalisation at IPO across different continents relative to North America.

4.3. Model implementation

After data preparation and assumption testing, we estimate our final regression models using MLR. We adapt each model to satisfy the statistical assumptions identified in Sections 4.2.1. and 4.2.2.

For the acquisition model, to ensure normality, we log-transform the dependent variable Y, and we transform the predictors X_1, X_2, and X_3 using the Box-Cox method. Following the findings of Section 4.2.1.3, we include a second-degree polynomial term for X_1 to capture the observed non-linearity. Furthermore, we add a dummy variable for the geographical location to evaluate the effect of operating in Europe, with all other regions serving as a reference group. We define our acquisition regression model as follows:

$$\log(Y_i) = \beta_o + \beta_1 X_{1i}{}^{(\lambda_1)} + \beta_2 X_{2i}{}^{(\lambda_2)} + \beta_{3i} X_{3i}{}^{(\lambda_3)} + \beta_4 (X_{1i}^{(\lambda_1)})^2 + \beta_5 D_{Europe,i} + \epsilon_i \tag{4.19}$$

To address heteroscedasticity, we apply HC3 heteroscedasticity-consistent standard errors as described in Section 4.2.1.5.

For the IPO regression model, we apply the Box-Cox transformation to both the dependent variable Y_{IPO} and the predictors $\mathrm{X}_{\mathrm{IPO},1}$and $\mathrm{X}_{\mathrm{IPO},2}$, as determined in Section 4.2.2.1. Additionally, we incorporate dummy variables representing the geographical locations, with North America as the reference group. We define our IPO regression model as follows:

$$\mathrm{Y}_{IPO,i}{}^{(\lambda_y)} = \beta_{IPO,o} + \beta_{IPO,1} X_{IPO,1i}{}^{(\lambda_{IPO,1})} + \beta_{IPO,2} X_{IPO,2i}{}^{(\lambda_{IPO,2})} + \beta_{IPO,3} D_{Europe(IPO),i} + \beta_{IPO,4} D_{Asia(IPO),i} + \beta_{IPO,5} D_{Oceania(IPO),i} + \epsilon_{IPO,i} \tag{4.20}$$

To ensure statistical sufficiency, we apply the rule of thumb proposed by Green (1991), for the minimum sample size in MLR:

$$N = 50 + 8g \tag{4.21}$$

Where N represents the minimum required sample size and g denotes the number of predictors. With five predictors, a minimum of 90 observations is required to achieve a statistical power of 0.8, meaning an 80% probability of correctly identifying significant relationships if they exist (Green, 1991). The acquisition datasets (n=461) and the IPO datasets (n=254) exceed this threshold, validating the model's empirical foundation.

4.4. Multicollinearity

As discussed in Section 3.4, multicollinearity arises when two or more independent variables in our regression model exhibit high correlation, causing difficulties in accurately estimating the impact of each independent variable (Mahmood, 2024). In the context of our research, multicollinearity may complicate the interpretation of each predictor's individual effect. Therefore, we diagnose the extent of multicollinearity among the predictors to validate the robustness of our model.

First, we constructed a correlation matrix to assess the pairwise linear relationships between all predictors. The resulting heatmaps, presented in Figures A.6 and A.7, display the correlation coefficients r (Weisberg, 2014). As expected, we observe a very high correlation between the total funding and its squared term ($r = 0.99$), which naturally results from including both a variable and its non-linear transformation in the same model. Therefore, we do not consider this to be problematic. All the other pairwise correlations fall well below the threshold of $r = 0.7$, indicating no signs of problematic multicollinearity among the remaining predictors within both models.

To deepen the multicollinearity diagnosis, we computed the VIF value for each predictor, as described in Section 3.4.1. The results are presented in Tables 4.4 and 4.5. A VIF value of 1 implies no correlation with other predictors, while values between 1 and 5 are regularly considered acceptable, and a VIF value above 10 indicates severe multicollinearity (Mahmood, 2024). All predictors fall within the acceptable VIF ranges, except for total funding (67.56) and their squared term (66.69), which we again do not consider as problematic due to its nature.

In addition to the correlation matrix, a condition index analysis was conducted to evaluate multicollinearity from a multivariate perspective. As mentioned in Section 3.4.2, we derive the condition index from the eigenvalues of the predictor correlation matrix. A condition index exceeding 30 suggests severe multicollinearity (Kim, 2019). Tables 4.7 and 4.8 display the computed eigenvalues and their condition indices. The highest condition index observed is 17.27, which is below the critical threshold, indicating that although the total funding and its squared form are highly correlated, the extent of multicollinearity does not threaten the stability of the acquisition model estimates.

Table 4.7: VIF values and Condition index acquisition model.

Predictor	VIF	Eigenvalue	Condition Index
Total funding	67.56	2.232778	1.0000
Total funding^2	66.69	0.007485	17.2712
Age at exit	1.55	0.410280	2.3328
Exit timing	1.42	0.899939	1.5751
Dummy (Europe)	1.07	1.449518	1.2411

Table 4.8: VIF values and Condition index IPO model.

Predictor	VIF	Eigenvalue	Condition Index
Total funding	1.10	0.546041	1.5606
Age at exit	1.06	0.795785	1.2927
Dummy (Europe)	1.14	1.329903	1.0000
Dummy (Asia)	1.16	1.126482	1.0865
Dummy (Oceania)	1.10	1.201789	1.0520

4.5. Cross-validation method

As introduced in Section 3.5.2, k-fold cross-validation is a comprehensive and systematic model validation technique. It divides the dataset into k equally sized folds, where the model is iteratively trained on $k - 1$ subsets and validated on the remaining fold. We repeat this process k times so that we use each observation exactly once for validation, resulting in robust and unbiased performance estimates (Xu & Goodacre, 2018). In our study, we adopt 10-fold cross-validation, a method widely recognised for evaluating general performance on medium-sized datasets (n= 100-1000) (Xu & Goodacre, 2018). Increasing the number of folds from 5 to 10 leads to more accurate and stable performance estimates, while further increases yield marginal improvements (Xu & Goodacre, 2018). Based on these findings, we select 10-fold cross-validation as the appropriate method for validating our acquisition and IPO model's performance.

4.6. Coefficient significance and interpretation

4.6.1. Acquisition regression model

In this section, we evaluate the outcome of our acquisition MLR model with a log-transformed dependent variable. Following the t-test described in Section 3.3.1, the coefficients, Standard errors (SE), t-values, and p-values are reported for each predictor. We consider a predictor to be statistically significant when its p-value is below the widely accepted threshold of 0.05 (Hair et al., 2010). Table 4.9 presents the results of the t-test:

Table 4.9: The t-test of the predictors (Log-transformed model).

Predictor	Coef	SE	t-value	p-value
Constant	15.5670	0.930	16.739	0.000
Total funding	0.0113	0.037	0.304	0.761
Total funding^2	0.0011	0.000	2.948	0.003
Age at exit	-0.0107	0.011	-0.996	0.319
Exit timing	0.0114	0.021	0.590	0.590
Dummy (Europe)	-0.2353	0.108	-2.188	0.029

Constant term

The constant coefficient 15.5670 is statistically significant ($p<0.05$) and relatively high. However, its interpretation is very limited. It reflects the expected log acquisition price when all predictors equal zero. In this scenario, a startup with no funding history and no age does not correspond to any realistic business situation and is, therefore, not practically interpretable. As Weisberg (2014) notes, intercepts in MLR models often serve more as mathematical references than interpretable values.

Total funding

The coefficient for total funding is 0.0113, suggesting that a one-unit increase in the Box-Cox transformed total funding is associated with an increase of 1.13% in the log-transformed acquisition price. However, the high p-value (0.761) indicates that this relationship is not statistically significant. In contrast, the squared term of total funding is statistically significant ($p=0.003$), confirming a non-linear relationship. This suggests that acquisition prices respond to funding in a non-linear relationship and highlights that including a second-degree polynomial is statistically supported.

Given that both the dependent variable and the main predictor are transformed, and our model includes both a linear and a squared term, careful interpretation is required. This is because coefficients estimated on the transformed scale are challenging to interpret. Therefore, we reformulate the model using the original funding variable. The Box-Cox transformation used for the total funding is defined as:

$$X = \frac{TF^{\lambda}-1}{\lambda}, \tag{4.22}$$

With:

- $\lambda = 0.1096$, the optimal λ at the initial transformation.
- TF: total funding in dollars.

Although the linear term for total funding is not statistically significant on its own, we retain it in the model to ensure the theoretical completeness of the polynomial specification. Hair et al. (2010) explain that higher-order polynomial terms, such as squared or cubic variables, should not be included without their respective lower-order terms. Excluding the linear terms would violate the model hierarchy and could distort interpretation and prediction accuracy. Therefore, to ensure consistency and to enable interpretation of the model as estimated, we substitute the coefficients into the polynomial expansion on the log scale:

$$\log(Y_i) = 15.5670 + 0.0113X + 0.0011X^2 \tag{4.23}$$

Applying the inverse of the log transformation (Equation 4.22) and substituting Equation 4.23 for X yields the predicted acquisition price in real-world terms:

$$Y_i = e^{15.5670+0.0113\cdot\frac{TF^{0.1096}-1}{0.1096}+0.0011\cdot\left(\frac{TF^{0.1096}-1}{0.1096}\right)^2} \tag{4.24}$$

This defines an exponential-quadratic function that captures the combined influence of the linear and non-linear effects of total funding. At lower funding levels, the linear term dominates and causes modest increases in the predicted exit price. However, as the funding increases, the squared term becomes more influential, leading to an accelerating growth pattern in the predicted exit prices.

To confirm this curvature visually, we created Figure A.8 using Python. The Box-Cox transformation further increases the valuation sensitivity at higher funding levels, meaning that larger funding rounds may boost the exit valuations for SaaS startups.

Age at exit and exit timing

Both age at exit and exit timing are not statistically significant (p=0.319 and p=0.590, respectively). This indicates that these predictors do not significantly explain the variation in acquisition prices. Although their coefficients suggest potential effects, such as the negative relationship between the age at the exit and acquisition price, the lack of statistical evidence implies that we should interpret these results carefully. Therefore, we cannot consider these effects to be reliable within this model.

Dummy (Europe)

The dummy (Europe) variable is statistically significant (p=0.029) with a negative coefficient (-0.2353). This suggests that we associate being a European Saas firm with a lower acquisition price than in North America. By transforming the log-acquisition back to the real-world scale, we derive $e^{-0.2353} \approx 0.790$, indicating a 21% reduction in acquisition price.

4.6.2. IPO regression model

In this section, we evaluate the outcome of our IPO MLR model with a Box-Cox transformed dependent variable. Following the t-test described in Section 3.3.1, the coefficients, Standard errors (SE), t-values, and p-values are reported for each predictor. We consider a predictor statistically significant when its p-value is below the widely accepted threshold of 0.05 (Hair et al., 2010). Table 4.10 presents the results of the t-test.

Table 4.10: The t-test of the predictors (Box-Cox transformed IPO model).

Predictor	Coef	SE	t-value	p-value
Constant	12.2950	2.101	5.852	0.000
Total funding	0.6357	0.033	18.982	0.000
Age at exit	0.0931	0.037	2.520	0.012
Dummy (Europe)	-2.1534	1.436	-1.500	0.135
Dummy (Asia)	-0.5804	0.969	-0.599	0.550
Dummy (Oceania)	-0.5662	1.819	-0.311	0.756

Total funding and age at exit

Both total funding and age at exit are statistically significant ($p<0.05$), with coefficients 0.6357 and 0.0931, respectively. These values indicate that a one-unit increase in the Box-Cox transformed total funding or age at exit leads to an increase of 63.57% and 9.31% in the Box-Cox transformed IPO market capitalisation. However, as we estimate the model on a transformed scale, we cannot interpret the model directly in real-world terms.

To derive meaningful insights, we need to retransform the results in real-world terms by inverting the Box-Cox transformation as follows:

$$Y = \begin{cases} (\lambda \cdot Y^{(\lambda)} + 1)^{1/\lambda}, & \lambda \neq 0 \\ e^{Y^{(\lambda)}}, & \lambda = 0 \end{cases} \tag{4.25}$$

By substituting the Box-Cox transformation (Equation 4.22) and the inverse transformation for Y (Equation 4.25) into the regression function, we derive the predicted market capitalisation at IPO as a function of the total funding (TF), while holding all other variables constant:

$$\mathrm{Y}_{IPO,i} = \left(0.0799\left(12.2950 + 0.6357 \cdot \left(\frac{TF^{0.1019} - 1}{0.1019}\right)\right) + 1\right)^{\frac{1}{0.0799}} \tag{4.26}$$

Similarly, we express the predicted market capitalisation at IPO as a function of the company age at exit (A) as follows:

$$\mathrm{Y}_{IPO,i} = \left(0.6398\left(12.2950 + 0.0931 \cdot \left(\frac{A^{0.6398} - 1}{0.6398}\right)\right) + 1\right)^{\frac{1}{0.0799}} \tag{4.27}$$

Figure A.9 illustrates that the relationship between the total funding and the IPO market capitalisation shows an approximately linear and modest growth pattern. This contrasts with the acquisition regression model, where including a quadratic term results in an exponential-quadratic growth pattern. This implies that, for an equal level of total funding, the expected acquisition exit price is higher than the corresponding IPO market capitalisation. Nonetheless, the total funding variable remains a key positive valuation driver for both exit types, confirming the relevance of funding in both exits.

Furthermore, Figure A.10 illustrates that the predicted market capitalisation at IPO increases with the company's age when total funding is held constant at its mean. This suggests that older companies tend to achieve higher IPO exits, highlighting the potential benefit of postponing the IPO to create more operational track record and maturity. This contrasts with the acquisition model, where the age at exit is not a statistically significant predictor of the acquisition price, implying that maturity plays a more influential role in the IPO exits than in acquisition exits.

Dummy variables

We cannot reject the H_0 for all dummy variables (p=0.135, p=0.550, and p=0.756), meaning that the location of the IPO exits does not significantly explain the variance in the market capitalisation at IPO . Although their coefficients all suggest potential negative effects relative to North America, the lack of statistical evidence implies we should interpret these results carefully. Therefore, we cannot consider the effects on the location to be reliable within our model.

4.6.3. Overall model significance

We perform an overall F-test as outlined in Section 3.3.2 to evaluate the joint explanatory power of all predictors. The F-statistics of 160.6 and 87.51 for the acquisition and IPO models, respectively, with their corresponding p-values of 4.60e-98 and 9.51e-53, confirm that we can reject the null hypothesis stating that none of the predictors has explanatory power. Thus, the full set of predictors collectively contributes significantly to explaining variation in the log-transformed acquisition prices and the Box-Cox transformed market capitalisations at the IPO (Hair et al., 2010).

To further evaluate the inclusion of individually insignificant variables in t-tests, we conduct partial F-tests. Table 4.6 shows that the total funding, age at exit and exit timing are insignificant for the acquisition model. However, we cannot exclude the total funding due to its mathematical relationship with the polynomial term total funding², which is significant. Therefore, we test whether the age at exit and exit timing contribute meaningfully to the model when considered jointly. This results in a F-statistic of 0.41, with a p-value of 0.6632. As this exceeds the threshold, we fail to reject H_0, indicating that these variables do not jointly enhance the model's explanatory power, and we can exclude them without a loss of fit.

Similarly, Table 4.7 shows that all geographic dummy variables (Europe, Asia, and Oceania) are individually insignificant in the IPO model. To determine their joint relevance, we perform a partial F-test by excluding these variables from the model. The resulting F-statistic is 0.76, with a p-value of 0.5179. Again, we fail to reject H_0, as p>0.05, indicating that including the dummy variables does not jointly improve the model's performance.

These results support the exclusion of the statistically insignificant predictors that do not contribute meaningfully when considered together. Removing such variables improves the clarity, efficiency, and statistical robustness of the final models. Therefore, we define our final acquisition model as follows:

$$\log(Y_i) = \beta_o + \beta_1 {X_{1i}}^{(\lambda_1)} + \beta_2 (X_{1i}^{(\lambda_1)})^2 + \beta_3 D_{Europe,i} + \epsilon_i \tag{4.28}$$

And our final IPO model as follows:

$$\mathrm{Y}_{IPO,i}{}^{(\lambda_y)} = \beta_{IPO,o} + \beta_{IPO,1} X_{IPO,1i}{}^{(\lambda_{IPO,1})} + \beta_{IPO,2} X_{IPO,2i}{}^{(\lambda_{IPO,2})} + \epsilon_{IPO,i} \tag{4.29}$$

4.7. Model performance and validation

To evaluate the quality and robustness of our regression models we asses both in-sample and out-of-sample performance, following the metrics as outlined in Sections 3.2 and 3.5.2. These include R^2, adjusted R^2, RMSE, and 10-fold cross-validation.

For the full acquisition and IPO models, the R^2 is 0.6288 and 0.6349, and the adjusted R^2 is 0.6227 and 0.6320, respectively. These values indicate that the predictors can approximately explain 63% of the variance in the log-transformed acquisition prices and the Box-Cox transformed market capitalisation at the IPO. The small differences between the R^2 and the adjusted R^2 suggest that our models do not overfit due to irrelevant predictors. Since the adjusted R^2 penalises the inclusion of the predictors, a large gap between these metrics would imply that some predictors do not contribute meaningfully to the explanatory power.

To evaluate the models' generalisability, we implement the 10-fold cross-validation for our models as discussed in Section 4.5. After implementation, the mean R^2 across all validation folds is 0.6095 for the acquisition model and 0.6104 for the IPO model. The mean adjusted R^2 values are 0.5608 and 0.5559, respectively. This results in modest decreases of 0.0193 and 0.0245 in R^2 and 0.0619 and 0.0761 in the adjusted R^2. These differences are well within acceptable bounds, indicating that the models retain generalisability and do not overfit against the training data.

To further evaluate model performance, we calculate the RMSE and express it as a percentage of the observed range of the acquisition prices and market capitalisations. This yields a normalised RMSE (nRMSE) of 7.55% and 9.68% for the training sets and 7.11% and 8.32% for the respective cross-validation datasets. Normalising by range allows for a scale-independent evaluation of prediction error, particularly suitable given the Box-Cox and log-transformed dependent variables and the Box-Cox-transformed predictors. According to Moriasi et al. (2007), nRSME values below 10% typically indicate good model performance. As both training and cross-validation nRMSE values fall below this threshold, these results further support our models' reliability, robustness and predictive validity.

Furthermore, to validate the impact of the applied transformations, we benchmark the model performance against the raw (untransformed) versions of the acquisition and IPO datasets. For the acquisition model without transformations and the polynomial term, the R^2 is 0.5290 and the adjusted R^2 is 0.5249. After 10-fold cross-validation, the mean R^2 dropped to 0.4490 and the mean adjusted R^2 to 0.3954. For the IPO model without transformations, the R^2 is 0.4071 and the mean adjusted R^2 is 0.3951. After 10-fold cross-validation, the mean R^2 dropped to 0.1378, and the mean adjusted R^2 dropped to 0.0418.

Compared to the transformed models, these results indicate an improvement in mean adjusted R^2 after cross-validation of 0.1515 for our acquisition model and 0.5148 for our IPO model, demonstrating the significant performance gains achieved through the transformations and the inclusion of the polynomial term.

4.8. Summary

We developed and evaluated two separate MLR models using Python to explain SaaS startups' exits: acquisitions and IPOs. We constructed both models while ensuring the four key assumptions according to Hair et al. (2010): linearity, homoscedasticity, and absence of autocorrelation.

Our acquisition dataset initially violated non-normality, heteroscedasticity, and nonlinearity. We applied Box-Cox transformations to the numeric predictors and log-transformed the dependent variable to correct non-normality. A second-degree polynomial term for total funding was added to resolve the nonlinearity. This leads to an exponential-quadratic relationship where the linear component dominates at lower levels, and the squared term leads to high acceleration at higher funding levels. Despite all transformations, heteroscedasticity remained and is corrected using HC3 robust standard errors. The model shows no problematic multicollinearity, apart from the expected correlation between the total funding and its squared term. Furthermore, the geographical location is statistically significant, where we associate European startups with 21% lower acquisition prices than North America, holding all the other variables constant. Finally, neither the age at exit nor the exit timing is statistically significant in our acquisition regression model.

We followed a similar procedure for our IPO model. We Box-Cox transformed all numeric variables, including the dependent variable. By doing so, we satisfied all assumptions without needing a polynomial term. In this model, the total funding remains a strong and statistically significant predictor of the IPO exit, although its effect is more linear and milder than in the acquisition model. Furthermore, age at exit has a positive and statistically significant effect, highlighting the role of organisational maturity in IPO exits. Unlike the acquisition model, the geographical location has no statistically significant influence on IPO exits.

Both models demonstrate a significant explanatory power, with R^2 values of approximately 0.63. 10-fold cross-validation results in a minimal decrease in R^2 and adjusted R^2 for both models, supporting the models' generalisability. Moreover, the normalised by range RMSE values remain below the 10% threshold, indicating both models' strong predictive validity and robustness (Moriasi et al., 2007).

Overall, total funding is the most influential variable across both models. However, the nature of the effects varies, exponential-quadratic for acquisitions and approximately linear for IPOs. Additionally, the age at exit is more relevant for IPOs, while geographical location significantly affects the acquisition price based on our models. These findings highlight the need for exit-specific valuation approaches and underscore that strategic planning should be tailored to the chosen exit route.

5. The blueprint

5.1 introduction

In this chapter, we present the valuation blueprint, visualised as a decision tree in Figure 5.1 and outlined in Section 5.7, which serves as the core artifact of our study and marks the conclusion of the design and development phase of the Design Science Research Methodology (DSRM). This blueprint addresses the first part of our central research question: *"How can a valuation blueprint for SaaS startups be developed?"*

Building on the findings from Chapters 1 through 4, we integrate theoretical insights and empirical results into a comprehensive and actionable blueprint. Specifically:

Chapter 1 highlights the need for a tailored valuation solution for SaaS startups, given their characteristics, including recurring revenue streams, high scalability, and dependence on intangible assets.

Chapter 2 forms the theoretical framework, focusing on the challenges of traditional valuation methods for SaaS startups (RQ1), current valuation techniques for SaaS startups (RQ2), and analysing appropriate SaaS-specific valuation metrics (RQ3). It further examines the influence on valuation at different growth stages of a SaaS startup (RQ4).

Chapters 3 and 4 provide the empirical framework by analysing the correlation between SaaS funding and exit records, by applying Multiple Linear Regression (MLR) to support quantitative decision-making for exit strategies (RQ5).

5.2. Traditional valuation challenges for SaaS startups

After analysing some of the most common traditional valuation approaches, income, market, and asset-based approaches, we conclude that several structural and financial characteristics of SaaS explain the misfit of traditional methods for SaaS valuation:

- Limited financial historical data for early-stage comparables (Damodaran, 2009).
- Lifecycle stage variation of SaaS startups, each requiring specific metrics (Trinchkova & Kanaryan, 2015).
- Heavy reliance on intangible assets and high upfront R&D investments (Li, 2025).
- Exceptional growth potential of SaaS startups, which traditional methods cannot capture (Milanesi, 2013).

5.3. Startup valuation methods

Given these challenges, we reviewed three relevant startup-specific valuation methods:

- **VC method**: Projects future exit values based on expected growth, using high discount rates to reflect the high startup risks. This is particularly good for the very early stages.
- **First Chicago Valuation Methods (FCVM):** Uses probability-weighted scenarios for a more robust valuation. However, its reliance on tangible metrics makes this method less suitable for SaaS startups.

- **Real Option Valuation (ROV):** Captures strategic flexibility by valuing managerial decisions as options, making it useful for dynamically adjusting valuations in highly uncertain environments. However, this supplementary tool relies on the fundamentals of DCF-based calculations, limiting its applicability in the earliest stages.

5.4. SaaS valuation metrics

In addition to the startup valuation methods, SaaS-specific valuation metrics are crucial for capturing the key value drivers of the business model. We focus on a selection of SaaS-specific valuation metrics categorised into four dimensions:

Financial metrics: Annual Recurring Revenue (ARR), Monthly Recurring Revenue (MRR), Gross margin, Net monthly burn rate.

- **Customer metrics:** Customer Acquisition Cost (CAC), Customer Lifetime Value (CLV), Customer churn.
- **Growth metrics:** (Net Recurring Revenue (NRR), Year-over-Year (YoY) ARR growth rate, Total Addressable Market (TAM)
- **Investor heuristics:** Rule of 40, and Triple 2 Double 3 (T2D3) growth trajectory.

5.5. Startups lifecycle considerations

As proposed by Trinchkova & Kanaryan (2015), the selection of valuation methods or metrics corresponds to the stage of the startup's lifecycle. Since qualitative classification can be subjective, we use ARR as a proxy to quantify the lifecycle stages.

While not all startups follow a strictly linear progression, ARR provides a scalable and objective measure for defining six lifecycle stages:

- **Pre-Seed stage:** No substantial ARR
- **Seed stage:** < $1M ARR
- **Early stage:** $1M-$5M ARR
- **Growth stage:** $5M-$20M ARR
- **Expansion stage:** $20M-$50M ARR
- **Exit stage:** > $50M ARR

5.6 Long-term exit strategy

In the empirical part of our research, we distinguish between two primary exit strategies for ARR startups: acquisition and Initial Public Offering (IPO). We apply two multiple linear regression models to provide actionable recommendations depending on the exit strategy:

Acquisition exit insights

- Total funding has an exponential-quadratic effect on the acquisition valuation ($p<0.001$), suggesting that valuation increases disproportionately as funding rounds increase.
- The age of the startup is not statistically significant ($p=0.319$), indicating that rapid scaling and early product-market fit are advised over organisational maturity.

- The geographical location significantly impacts valuation (p=0.029), with European startups facing a 21% valuation discount compared to those in North America, underscoring the importance of regional adjustments when applying market-based valuation multiples.

IPO exit insights

- Total funding has a positive, approximately linear, and highly significant relationship with the IPO valuation (p<0.001).
- The age of the startup significantly improves the IPO valuation (p=0.012), suggesting that organisational maturity and stability are advised over rapid scaling.
- All geographical locations are not statistically significant (p>0.05), suggesting that global benchmark and valuation multiples may be applied more universally in IPO scenarios.

Strategic implications

- For **acquisition** exits, we advise SaaS startups to prioritise rapid growth, securing funding, and seeking early exit opportunities. Additionally, founders should consider the geographic location of the startup.
- For **IPO** exits, we advise SaaS startups to adopt a longer-term trajectory that emphasises operational maturity, financial discipline, and investor-attractive metrics such as the Rule of 40.

5.7. Integrated lifecycle blueprint

By integrating previous findings, we present an integrated lifecycle blueprint that connects valuation methods, SaaS-specific metrics, and the startup lifecycle stages. We structure the blueprint along three dimensions:

First, Figure 5.1 visualises the complete valuation pathway as a decision tree, guiding users from identifying the startup's lifecycle stage to selecting the most suitable valuation method and corresponding SaaS metric.

Second, Table 5.1 aligns the key valuation methods and SaaS metrics with each lifecycle stage, clarifying which metrics are relevant at each phase and which methods should be used to value the startups.

Finally, Table 5.2 presents the SaaS industry benchmark values per stage, based on the median scores and interquartile ranges. The benchmarks serve as reference points for interpreting the performance of SaaS metrics across the different lifecycle stages..

Figure 5.1: Visualisation of valuation methods and metrics, and lifecycle stages

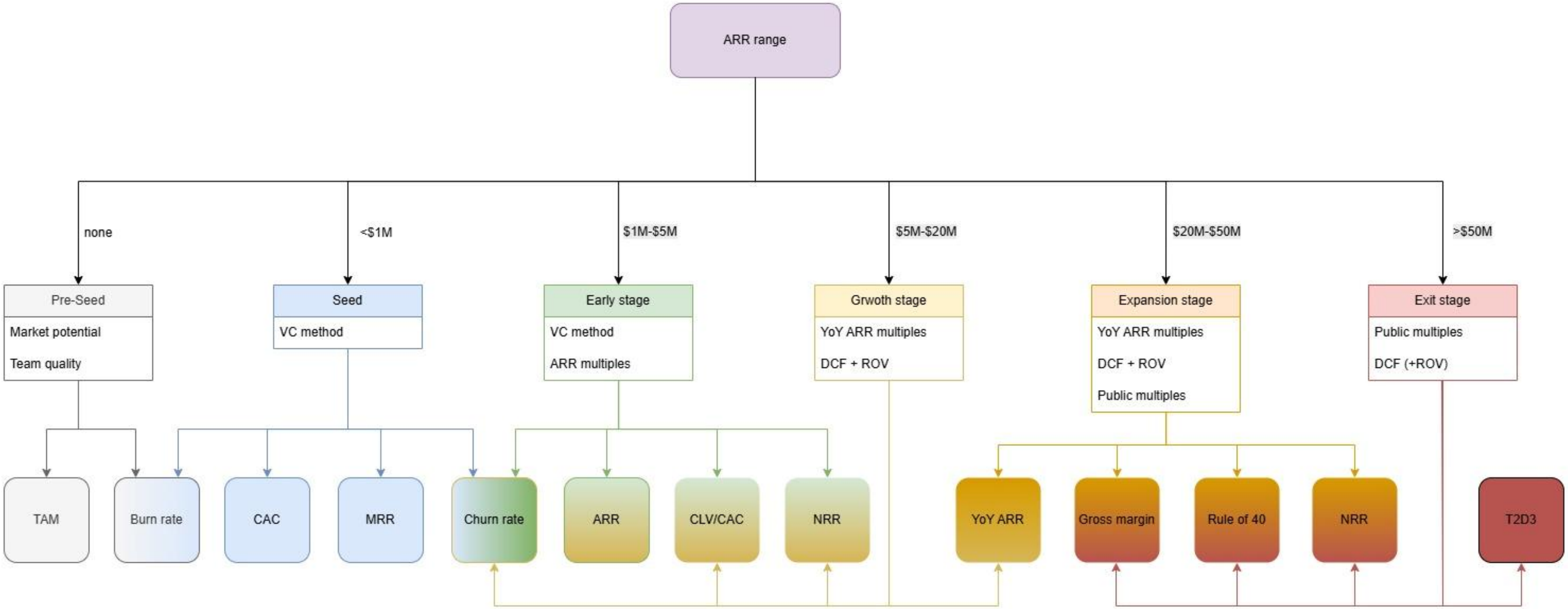


Table 5.1: Valuation methods and metrics per lifecycle stage.

ARR range	Stage	Key metrics per stage	Key valuation methods
No substantial	Pre-seed	TAM, burn rate	Market potential, team quality
<$1M	Seed	TAM, burn rate, MRR, CAC, churn rate	VC method, Market potential, team quality
$1M-$5M	Early	ARR, NRR, CLV/CAC, churn rate	ARR multiples, VC method
$5M-$20M	Growth	NRR, churn rate, CLV/CAC, YoY ARR	YoY multiples, DCF + ROV
$20M-$50M	Expansion	Rule of 40, gross margin, NRR, YoY ARR	YoY multiples, DCF + ROV, or public multiples
>$50M	Exit	Rule of 40, T2D3, Gross margin, NRR	DCF + ROV, public multiples

Table 5.2: SaaS metrics Benchmark per lifecycle stage.

Metric	<€1M ARR	€1-5M ARR	€5-20M ARR	€20-50M ARR	>€50M ARR
Gross margin subscriptions	65%, [50%-81%]	80%, [65%-85%]	80%, [75%-84%]	79%, [71%-85%]	75%, [70%-88%]
Gross margin services	41%, [5%-50%]	45%, [10%-65%]	50%, [28%-55%]	15%, [0%-29%]	10%, [10%-29%]
Net monthly burn rate	€50K, [€50-175k]	€175K, [€50-375k]	€375K, [€0-375k]	€625K, [€13K-1.25M]	€0K, [€0K-2.5M]
CAC (Payback months)	5,[2-11]	8, [5-16]	14, [8-22]	20, [13-22]	20, [11-27]
CLV/CAC ratio	3.2, [2.1-6.0]	3.7, [2.4-7.0]	3.6, [2.4-5.3]	3.0, [2.1-5.5]	3.5, [2.4-7.4]
NRR	100%, [93%-110%]	100%, [96%-110%]	105%, [95%-120%]	103%, [94%-112%]	102%, [93%-107%]
YoY ARR Growth rate	100%, [48%-250%]	50%, [20%-115%]	30%, [17%-59%]	30%, [20%-50%]	15%, [12%-25%]
Rule of 40	N/A	30%, [-2%-60%]	22%, [1%-40%]	22%, [2%-33%]	25%, [4%-33%]

6. Validation and application of the blueprint

In this chapter, we qualitatively validate the proposed valuation through an interview with Investor X. Additionally, we apply the blueprint to a real-world case study, Akela Hub, to estimate its valuation and derive strategic insights.

6.1. Validation with investor X

6.1.1. Blueprint validation

To qualitatively validate the proposed blueprint, we interviewed Investor X, a highly experienced investor with a strong track record in the startup and scaleup investments. He confirmed using ARR as a logical proxy for SaaS startup stage classification, noting that ARR is the most important metric in SaaS due to the need to scale revenue rapidly in an intense market. Unlike other industries like deep tech, where a single company may offer a unique solution, SaaS solutions are often (easily) replicable. Therefore, fast ARR is also a strong indicator of product-market fit.

When discussing valuation metrics per stage, Investor X agreed that the team's quality and market potential are typically the primary value drivers in the pre-seed stage. He added that in some cases, valuation is not based on any metric but on strategic potential and fit for integration into the company. Furthermore, he suggests adding the TAM and team quality to the Seed stage, as these factors remain relevant, particularly when startups lack sufficient financial data to apply the VC method. Based on this feedback, we refined the blueprint and added the TAM and team quality as criteria in the seed stage.

Investor X also validated our use of private ARR benchmarking and the VC method in the seed and early stages. Moreover, he strongly supports using YoY ARR growth as a valuation method during the growth stage and compares results with public benchmark multiples for later stages. However, he cautioned that many exits do not disclose the valuation prices, which we practically encountered during our regression data preparation. As such, the benchmark multiples may carry some bias or incomplete information, which should be considered when applying them in valuation methods.

6.1.2. Regression results validation

Regarding the regression analysis, Investor X agrees with our findings on the exit acquisition gap between European and North American startups. He confirmed that American-based startups often raise more capital and scale faster, making higher acquisition prices a logical outcome. This supports the use of region-specific benchmarks in future valuation models.

Furthermore, he also supported our finding that acquisition exits tend to result in higher valuations than IPOs, when all else is equal. According to him, IPOs are often a strategic decision made by the founders, whereas an acquisition may occur when a buyer offers a premium above the estimated IPO value. He refers to acquisition as "strategic exits", often executed through a dual-track process where both IPO and acquisition remain open options until late in the exit planning. He emphasised that the exit strategies should not be fixed in the early stages, as company circumstances and market opportunities evolve over time. While IPOs may offer a higher long-term valuation due to access to additional capital, many founders still prefer an acquisition depending on their goals.

Finally, Investor X confirmed the validity of our regression results, which show that maturity is a significant driver of IPO outcomes. This aligns with the reality that IPO valuations rely heavily on a company's track record, which strengthens over time.

6.2. Application of the blueprint

We applied the validated blueprint to the real-world case of Akela Hub. Based on the firm's characteristics, we classify Akela Hub as a Seed-stage SaaS startup, for which we use the VC method. Using scenario-based growth projections and benchmark ARR multiples, the estimated valuation range lies between €2,900,000 and €20,100,000, depending on the projected growth scenarios. We provide a detailed elaboration of the application in Appendix B.

7. Conclusions and recommendations

7.1. Conclusion

Our research demonstrates that traditional valuation methods are often inadequate for early-stage Software-as-a-Service (SaaS) startups, primarily due to the characteristics of these business models, including limited historical financial data, intangible assets, and rapid growth trajectories. Through a comprehensive literature review and expert insights, it becomes evident that traditional approaches, such as Discounted Cash Flow (DCF) and standard multiples, do not fully capture the value drivers for SaaS startups, particularly not in a generalised way.

To address this, we developed a lifecycle-based SaaS valuation blueprint that emphasises aligning valuation methods with the specific lifecycle stage, using Annual Recurring Revenue (ARR) as a proxy for categorization. Our findings suggest that the Venture Capital (VC) method is appropriate when limited but consistent financial data is available in the early stages. In contrast, Real Option Valuation (ROV) proves effective in later stages, when sufficient financial data is available, and can be used as a supplementary tool to DCF to capture strategic flexibility under uncertainty.

Additionally, the relevance of qualitative factors, such as team quality and founder track record, was reinforced by investor perspectives gathered through attending Web Summit Qatar and Slush Helsinki, where we spoke with several experienced SaaS investors. An expert validation interview with Investor X further supported this. In the earliest stages, Total Addressable Market (TAM) and burn rate emerged as critical quantitative metrics.

Empirical analyses revealed regional differences and valuation drivers. Acquisition exits were observed to be 21% higher in North America compared to Europe, whereas the company's location did not significantly influence Initial Public Offering (IPO) outcomes. Moreover, company maturity proved to be a stronger predictor of IPO exits, while total funding played a more influential role in acquisition exits.

To answer our research question: *"How can a valuation blueprint for* SaaS *startups be developed and applied to address the limitations of traditional valuation methods and support strategic decision-making for exit strategies?"* We refer to our developed valuation blueprint. It integrates quantitative and qualitative metrics within a lifecycle-based decision roadmap tailored to each stage of a SaaS startup. We applied this blueprint to a real-world case of Akela Hub, which we categorise as being in the Seed stage, leading to the selection of the VC method as the most suitable valuation approach. Using scenario-based growth trajectories informed by benchmark data, Akela Hub's estimated valuation ranges from €2,900,000 to €20,100,000, depending on the projected growth scenarios. Although this is a broad range, it reflects the expected uncertainty of early-stage forecasting.

7.2. Contribution to knowledge

Our research contributes to both academic knowledge and practical application. From a theoretical perspective, we introduce a generalised SaaS startup valuation blueprint. Furthermore, the blueprint introduces a decision roadmap that guides SaaS startups through relevant valuation methods and metrics depending on their lifecycle stage. As such, it may serve as a practical tool for SaaS company founders to understand how to value early-stage SaaS ventures in uncertain environments.

On the practical side, the research offers direct value to Akela Hub. By applying the blueprint to its current situation, the company gained an understanding of which metrics matter most at its current stage and how the valuation can develop under different growth scenarios. The valuation range and the regression analysis both support strategic decision-making, particularly in the context of exit planning. With this blueprint, Akela Hub is better positioned to align its internal strategies with investor expectations and drive long-term value creation.

7.3. Limitations

During the development of the valuation blueprint and the regression model, several limitations emerged that should be considered by Akela Hub and other SaaS startups when utilising the blueprint.

First, although the blueprint aims to provide a generalised valuation blueprint for SaaS startups, it assumes comparability across all SaaS business models. In practice, a difference exists, for example, in the average contract value, depending on whether a startup operates in a B2B or B2C environment. Since the blueprint uses ARR as a proxy for lifecycle classification, it may lack the flexibility to fully account for these distinctions. As a result, the choice of generalisation could limit the applicability to specific business types.

Second, working with early-stage startups presents the inherent limitation of lacking historical data. Due to this lack of long-term financial information, applying specific valuation models remains challenging, resulting in a wide range of valuations. This is particularly evident in Akela Hub's case, where we have future growth uncertainty in the seed stage.

Third, the exit dataset used for regression analysis introduces another limitation. Although the dataset includes a reasonable number of observations, many exit evaluations remain undisclosed. As Investor X also mentioned, this introduces a potential bias into both the regression model and the benchmarking multiples.

Finally, the regression model was limited in terms of the variables that could be included. Ideally, we would have incorporated key SaaS metrics, such as CAC, churn rate, and (YoY) ARR, to examine their influence on the valuation. However, due to limited data, we could only include the variables for location, total funding, age at exit, and exit timing. This results in a limitation in the depth of insights of the regression analysis, as it may overlook relevant factors.

7.4. Recommendations

Based on the application of the blueprint and supporting data analysis, we can provide several recommendations for Akela Hub. First, the churn rate is relatively high, as it exceeds industry benchmarks. This could mean Akela Hub has challenges defining its product-market fit or has insufficient customer engagement. Therefore, Akela Hub should investigate the causes of customer churn and attempt to reduce it, thereby improving retention and stability.

Second, Akela Hub should actively utilise the valuation blueprint to monitor the most relevant metrics at each lifecycle stage. Currently, beyond churn, Akela Hub should track its CAC and burn rate and compare them with industry benchmarks. Once the ARR exceeds the threshold of € 1,000,000, the focus shifts to the next stage metrics, as indicated in the blueprint.

Third, regarding the long-term desired exit objective of Akela Hub, it should remain aligned with the ARR targets established in this study. Akela Hub should also be aware of the valuation differences between European- and North American-based startups. As many exit benchmarks are based on North American data, ensuring the regional applicability of multiples is essential when planning a future acquisition exit.

Finally, although the current burn rate is sustainable, we recommend considering additional funding rounds in the near future. As Investor X pointed out, rapid growth is a critical success factor in SaaS markets where competitors can scale quickly. To avoid falling behind, we recommend strategic investment in team expansion, market and product development, provided that the firm has reached product-market fit.

7.5. Future research

Building on the outcomes and limitations of this study, future research could further refine and expand the blueprint. First, future research could focus on sector-specific adaptations of the blueprint by tailoring it to subcategories such as enterprise SaaS, fintech SaaS, or e-commerce SaaS. This would improve the blueprint's precision and practical relevance across different startups. Additionally, future work could expand on the observed valuation differences by region, incorporating location-specific benchmarks.

Second, future studies could attempt to integrate qualitative valuation approaches. Although this is challenging, developing a method to evaluate intangible assets, such as team quality, founder experience, and strategic potential, would enhance valuation in the pre-seed and seed stages, where financial metrics are less applicable.

Third, while ARR was used in this study as a proxy for lifecycle classification, a more flexible and multi-metric stage classification framework could improve the accuracy. This would involve incorporating multiple SaaS metrics into the framework. Although this would be complex, it could result in more precise boundaries between growth stages.

Finally, a more practical recommendation is to develop a user-friendly valuation tool based on the blueprint. Instead of manually following the whole framework, users could input their key metrics and immediately receive validation outputs based on the appropriate method and stages.

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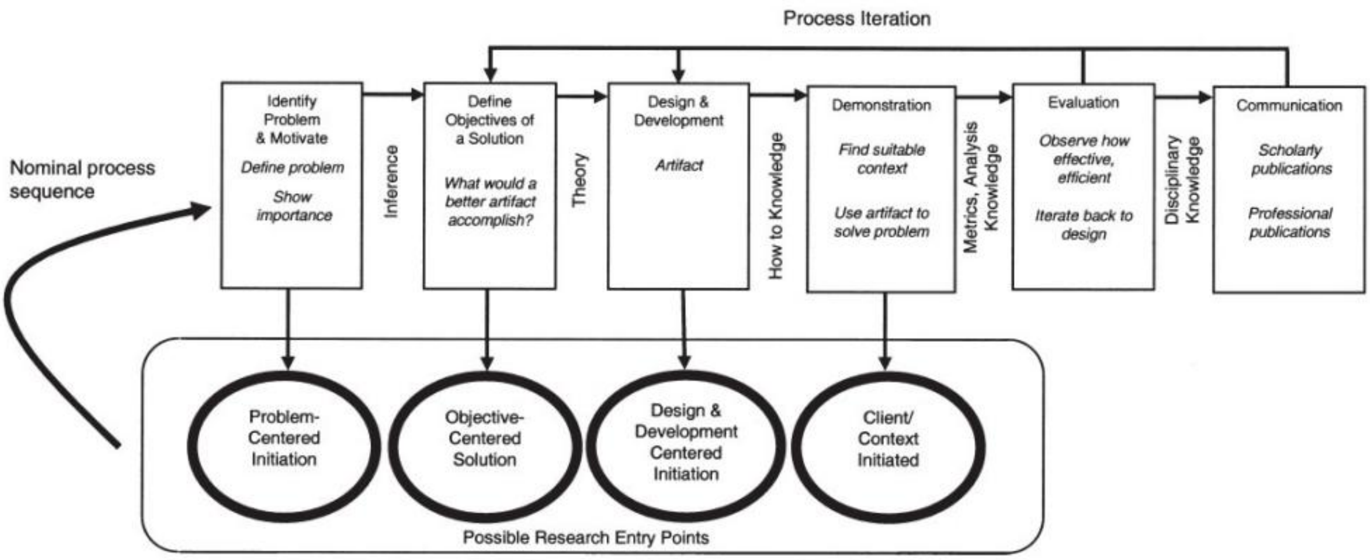
Appendix A

A.1: Introduction

Figure A.1: DSRM process model



A.2: The startup lifecycle and funding

Figure A.2: The startup lifecycle

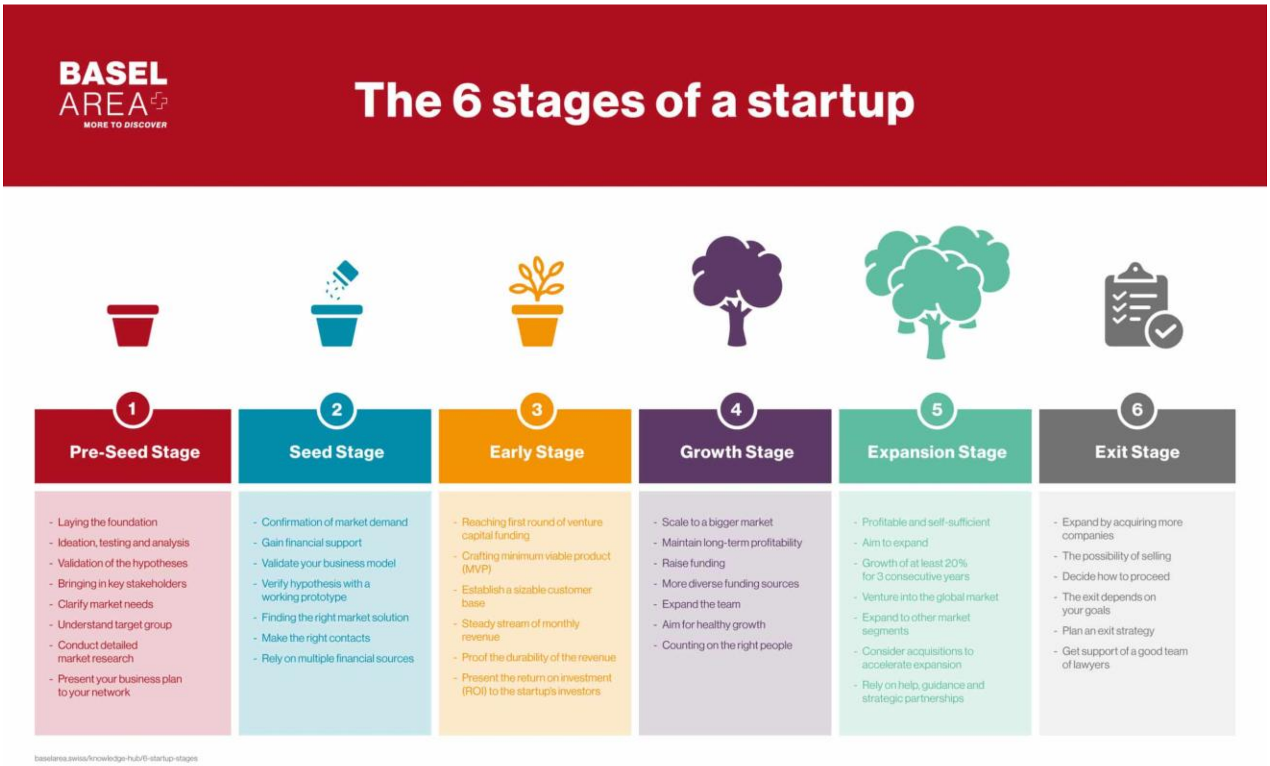
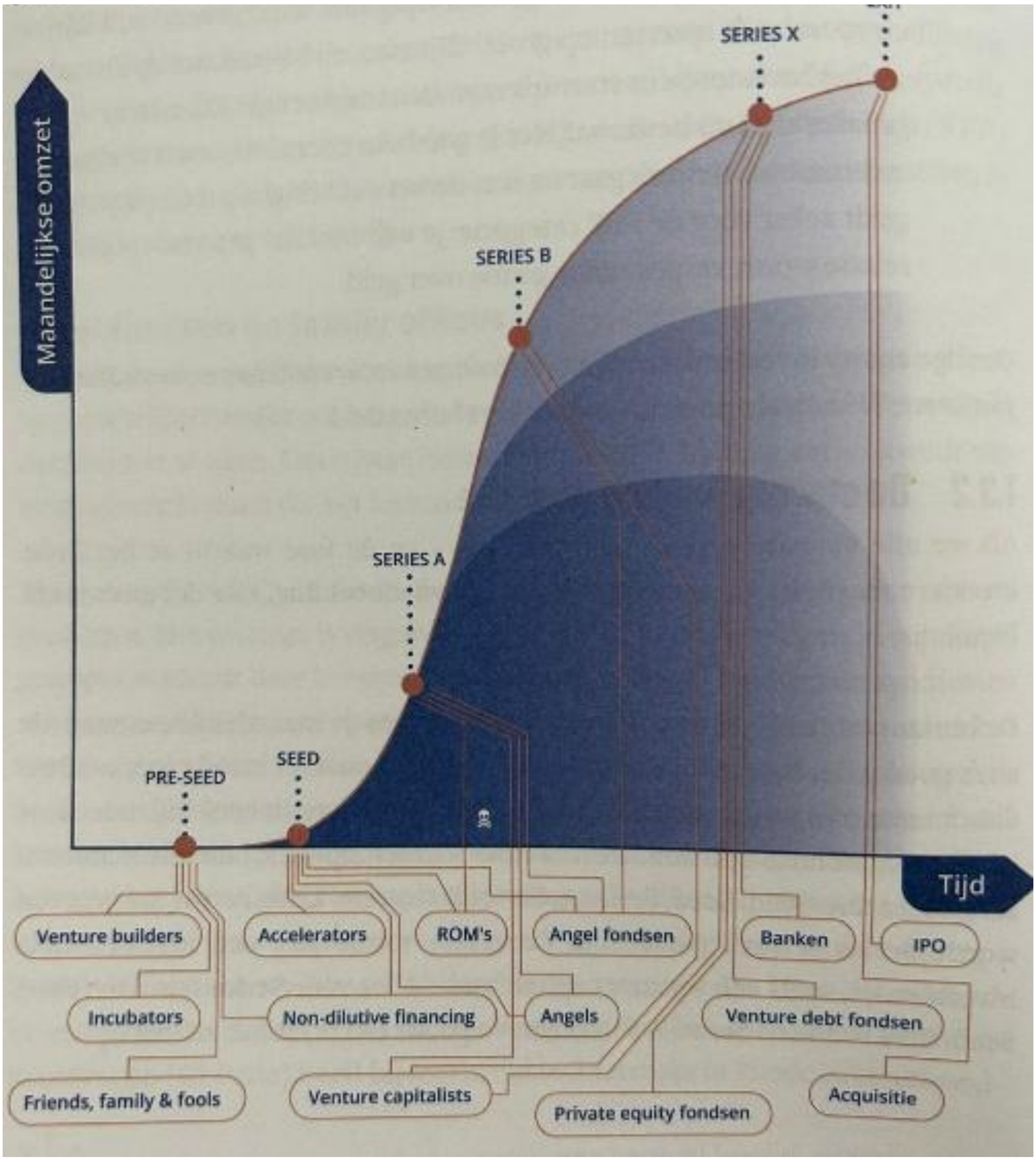
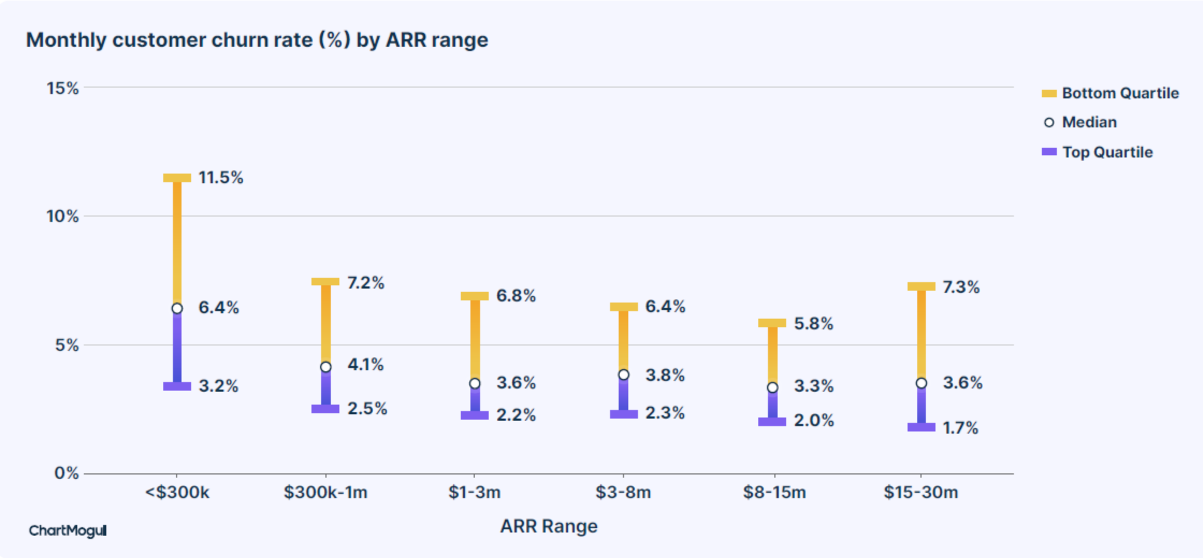


Figure A.3 The startup funding stages



A.3. Customer churn benchmark

Figure A.4: Monthly customer churn benchmark by ARR range



A.4 Multiple Linear Regression (MLR)

Figure A.5:Residuals of the total funding acquisition model

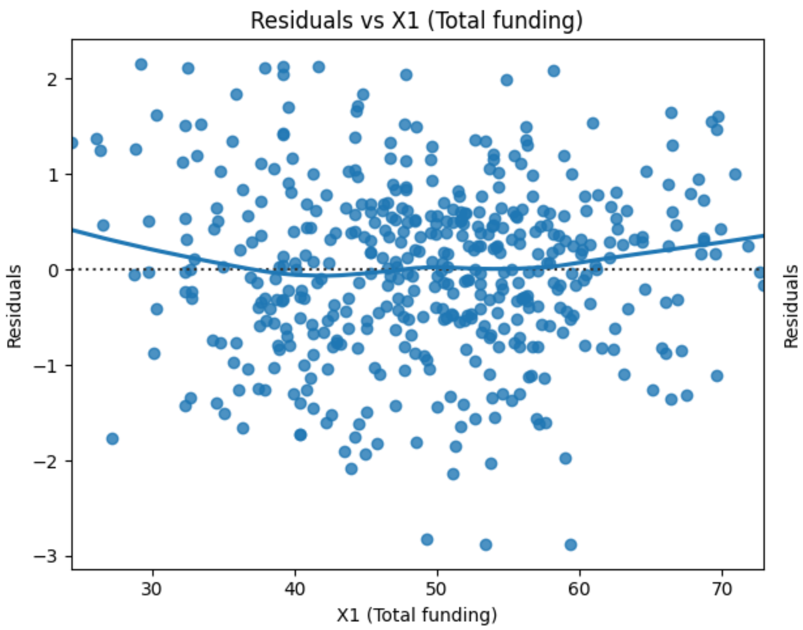


Figure A.6: Correlation matrix heatmap acquisition model

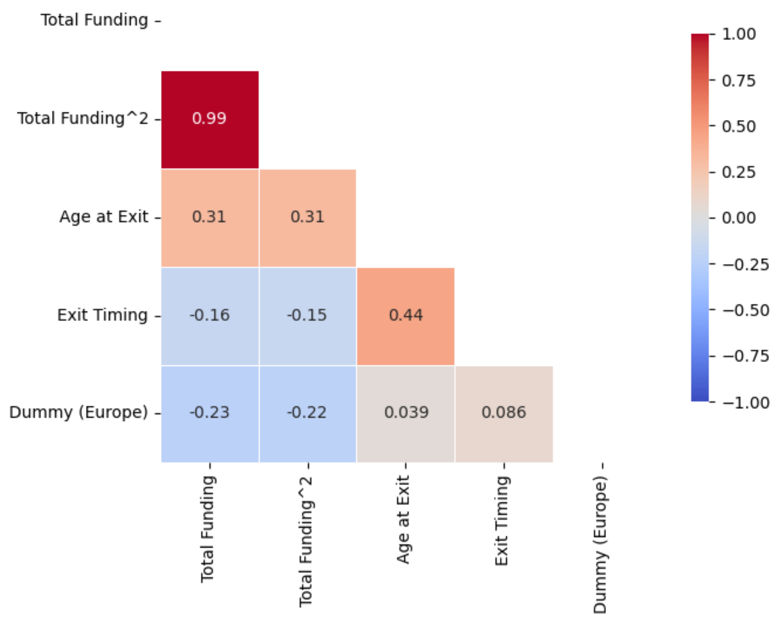


Figure A.7: Correlation matrix heatmap IPO model

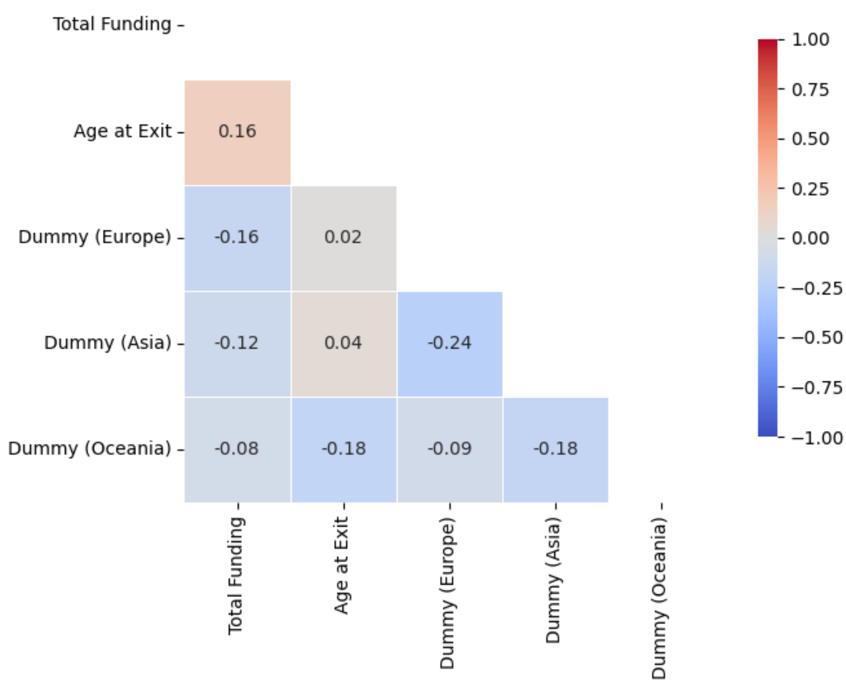


Figure A.8: Visualisation of the relation between IPO exit price and total funding

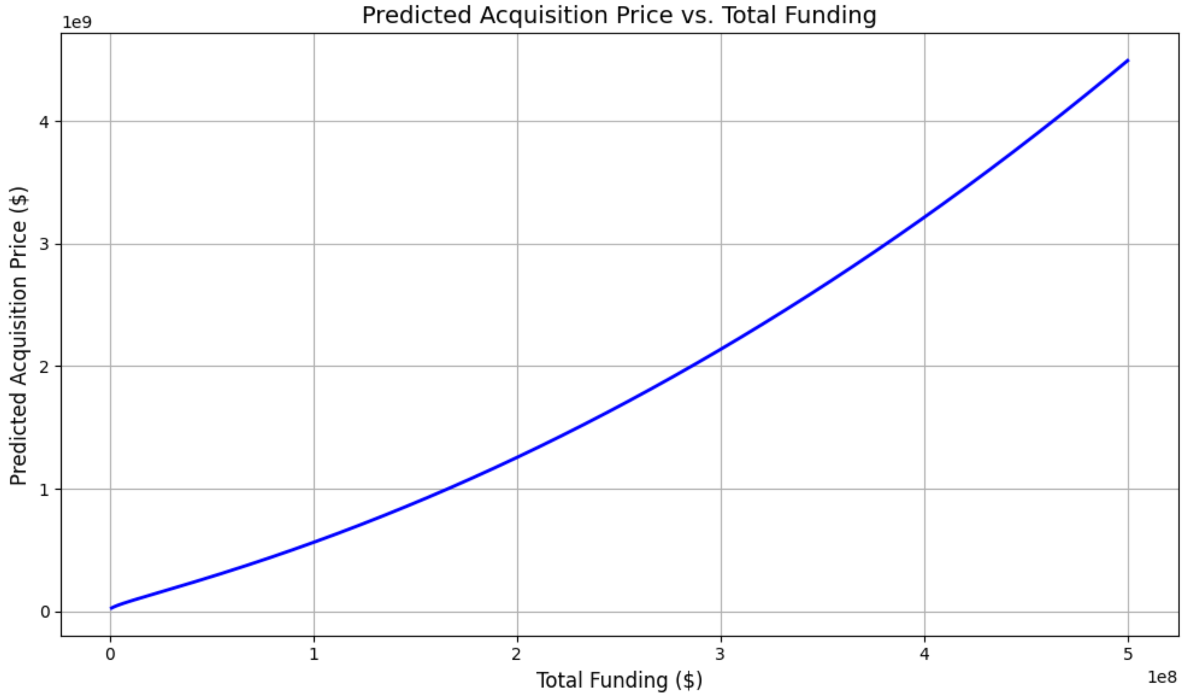


Figure A.9: Visualisation of the relation between IPO exit price and the age at exit.