

Pricing Model Configuration as a Driver of Retention: An Empirical Analysis of US-listed B2B SaaS Firms

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Abstract

This study investigates the relationship between the pricing structures of B2B Software-as-a-Service firms and their ability to retain and expand revenue from already existing customers. The analysis focuses on Net Revenue Retention, a key industry metric, and examines how pricing models relate to the transition from initial adoption to continuous customer expenditure. Crisp-set Qualitative Comparative Analysis is conducted on a sample of 27 US-listed B2B SaaS firms, evaluating three pricing model conditions: usage-based value metrics, self-serve expansion, and land-and-expand entry. The results show that the joint presence of all three conditions is associated with high Net Revenue Retention, rather than relying on any single element. On the other hand, low Net Revenue Retention is consistently associated with the absence of self-serve expansion across the sufficient configurations identified. This research contributes to the literature on SaaS pricing and model configuration by demonstrating that retention outcomes are associated with the combination of pricing elements. Consequently, pricing model design should be viewed not as the selection of individual features, but as a system that is associated with how existing customer relationships develop into sustained value capture.

Keywords

B2B SaaS, Pricing model, Net Revenue Retention, NRR, Software-as-a-Service

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1. Introduction

Software firms face a pricing problem that differs from many traditional industries. Once software has been developed, the marginal cost of serving an additional customer can be low, making pricing less a matter of cost recovery and more a matter of value capture (Shapiro & Varian, 1999). This issue is sharpened in Software-as-a-Service (SaaS), where customers access software continuously and firms generate revenue over time rather than through one-time license sales. Pricing model design therefore matters beyond the initial transaction. It is closely linked to how continued use, product expansion, and account growth are converted into recurring revenue.

This makes pricing model design directly relevant to Net Revenue Retention (NRR), a central metric in Business-to-Business (B2B) SaaS. NRR measures whether existing customers generate more or less revenue over time. In recurring revenue businesses, this is critical because firm value depends not only on acquisition, but also on the development of customer-level revenue streams over time (McCarthy, Fader, & Hardie, 2017).

Prior research has examined software pricing, subscription models, and customer retention. Yet the link between pricing model design and NRR remains underdeveloped, especially at the level of pricing model configurations. Much of the available work treats pricing features separately, for example by examining usage-based pricing, freemium entry, or self-service mechanisms in isolation. In practice, however, these elements would operate together. A SaaS firm may allow customers to enter through a free trial, charge them according to consumption, and let them expand through the product interface. Another firm may use only one of these elements, or none. The theoretical issue is therefore not whether one pricing feature is always superior, but whether particular combinations of pricing model elements are associated with different retention outcomes.

This thesis addresses that gap by examining pricing model configurations among B2B SaaS firms listed in the US. It focuses on three externally observable pricing model conditions: *value metric type*, *self-serve expansion*, and *land-and-expand entry*. These conditions capture three points in the customer revenue path. Value metric type concerns how product use is monetized. Self-serve expansion concerns how existing customers increase spending. Land-and-expand entry concerns how prospective customers first access and evaluate the product. Together, the three conditions describe how pricing model design connects payment, usage, and expansion.

1.1 Purpose and contribution

The purpose of this thesis is to examine which configurations of pricing model design are associated with high and low Net Revenue Retention levels among US-listed B2B SaaS firms. The study concentrates on the pricing model design since these basic choices are associated with how customer activity is translated into recurring revenue.

The contribution is not to establish a universal price formula for high retention. Instead, the thesis specifies pricing model design as a staged value-capture architecture. Value metric type captures the revenue basis, self-serve expansion captures the expansion path, and land and expand entry captures the entry path. Through examining these elements as configurations, the study provides a more precise account of how pricing model design may be associated with NRR.

1.2 Research question

The thesis aims to answer the following research question:

Which configurations of pricing model design are associated with high or low levels of firm NRR?

1.3 Research Outline

The thesis proceeds as follows. Section 2 reviews literature on NRR, SaaS pricing models, the three pricing model design conditions, and the configurational business model logic that guides the study. Section 3 presents the research design, sample, calibration rules, and QCA approach. Section 4 reports the necessity and sufficiency analyses for high and low NRR. Section 5 provides a qualitative complement using Snowflake as an illustrative case and Amplitude as the deviant case. Section 6 discusses the findings in relation to the theoretical framework. Section 7 presents limitations and future research. Section 8 concludes the thesis.

2. Literature review

Research on pricing for software and information goods has long examined how firms structure access and define units of charge. Prior studies distinguish fixed-fee or subscription pricing from pay-per-use and usage-based pricing, showing that information goods, including software, can be monetized through access rights, consumption, or combinations of both (Fishburn & Odlyzko, 1999; Sundararajan, 2004). In SaaS markets, this pricing problem is further shaped by ongoing service delivery, owing to the fact that it differs from traditional software through its internet-based delivery and multitenancy (Li & Kumar, 2022).

The dependency on continued customer relationships rather than a single license transaction for SaaS revenues, makes pricing model design relevant to Net Revenue Retention. A SaaS pricing model extends beyond determining how the customer pays at the point of adoption, it also shapes how continued use, product expansion, and account growth are converted into revenue over time. The literature reviewed below, therefore, proceeds in four steps. First, it defines Net Revenue Retention as the outcome of interest. Second, it defines pricing models as the object of analysis. Third, it develops three pricing model design conditions that are expected to matter for revenue expansion in B2B SaaS firms: value metric type, self-serve expansion, and land-and-expand entry. Fourth, it integrates these conditions into a configurational view of pricing model design, where the main theoretical interest lies.

2.1 NRR as an outcome

Net Revenue Retention (NRR), also referred to as net retention rate, net dollar retention, and similar synonyms, measures annual revenue retained from an existing customer cohort after accounting for churn, contraction, and expansion, including revenue generated through upselling and increased usage (High Alpha, 2025). Mechanically, the metric is calculated as the ratio of recurring revenue generated by a fixed cohort of customers at the end of a period to the recurring revenue generated by the same cohort at the beginning of the period. The end-period revenue reflects the combined effects of expansion, contraction, and churn within that cohort. Revenue from newly acquired customers is excluded from the calculation.

NRR reflects the combined effects of multiple processes within the installed customer base. Revenue expansion through increased usage, cross-selling, or upgrades contributes positively to the metric, whereas downgrades and customer churn reduce it. The metric, therefore, captures both revenue growth and revenue loss within ongoing customer relationships.

These revenue dynamics are central to firm performance in SaaS settings. Under recurring revenue models, firm value depends on the evolution of customer relationships over time rather than on one-time transactions. Research on subscription-based businesses shows that firm value depends on customer lifetime value and the evolution of customer-level revenue streams over time (McCarthy, Fader, & Hardie, 2017). The profitability implications of retention are also emphasized in research on service businesses, where reductions in customer defections can materially increase firm profits (Reichheld & Sasser, 1990). NRR provides a direct empirical measure of these dynamics by linking customer behavior to realized revenue outcomes.

In summary, NRR is a particularly appropriate outcome variable for this study, as it captures whether firms are able to generate sustained revenue growth from their existing customer base and directly reflect the monetization of ongoing customer usage. This aligns closely with the mechanism through which pricing model design is expected to influence firm performance in B2B SaaS contexts.

2.2 Defining pricing models

In a B2B SaaS context, a pricing model refers to the set of design choices that governs how a firm charges customers for access to and use of its software. Rather than representing a single price point, prior research analyzes software pricing in terms of multiple interrelated elements, including payment flow, assessment base, price discrimination, bundling, and dynamic pricing strategies (Lehmann & Buxmann, 2009). Bontis and Chung (2000) similarly emphasize that software pricing cannot be reduced to a generic formula, since pricing must reflect how customers realize value from the software and how the vendor seeks to structure revenue.

Drawing on software pricing research, two components are particularly relevant for this study, payment structure and pricing metric. These correspond to what Lehmann and Buxmann (2009) describe as the structure of payment flow and the assessment base of software pricing. The first specifies how and when charges occur. In SaaS settings, this typically involves recurring payments linked to continued access, although alternative periodic billing arrangements may also apply. The second defines the unit on which charges are based. This metric sets the basis for calculating the customer's bill and governs how charges evolve as usage changes, for instance through variation in users, transactions, or resource consumption.

Taken together, these elements define how customer interaction with the software is converted into revenue. Because software is costly to produce but cheap to reproduce, pricing cannot be understood primarily as marginal-cost recovery and instead becomes closely tied to customer value (Shapiro & Varian, 1999).

In this study, pricing model design is understood as a firm-level monetization structure rather than as a set of transaction-specific price decisions. The focus is therefore on externally observable and relatively stable design features that characterize the firm's core B2B SaaS offering. Temporary discounts, promotional pricing, and individually negotiated contract terms are excluded because they reflect short-term or customer-specific price variation rather than the underlying pricing model.

2.3 Pricing model design conditions

2.3.1 Condition 1, C1

The first pricing model condition is *Value metric type*, the unit through which customer use is translated into revenue. In this study, the condition distinguishes between pricing models where expansion revenue is primarily *usage-based* and pricing models where expansion revenue is primarily *non-usage-based*. A firm employs a usage-based approach when the customer's bill scales directly with actual consumption of the software provider's services, such as transactions, data volume, compute usage, messages, or other measurable units of activity. By contrast, non-usage-based models include seat-based and *flat-rate pricing*. These models differ from one another, since *seat-based pricing* scales with the number of users while flat-rate pricing charges a fixed amount regardless of users or usage. However, for the purpose of this condition, they are grouped together because neither primarily scales with realized product usage. Lehmann and Buxmann (2009) identify the basis on which prices are determined, as a core parameter of software pricing models, a distinction this study applies through the concept of value metric type. This matters because C1 captures the basis on which product use is monetized, rather than the process through which customers expand spending, which is captured separately by C2.

The theoretical foundation for why the pricing metric matters can be found in software pricing research on assessment bases and in the economics of metered pricing. Oi (1971) established the two-part tariff model, showing how firms can separate the price charged for access from the marginal price charged for each unit of consumption. Sundararajan (2004) extends this economic logic to information goods by analyzing optimal pricing under incomplete information when both fixed-fee and usage-based contracts are feasible. The analysis by Sundararajan (2004) shows that the choice between charging per unit of consumption and charging a fixed fee changes how customer activity is linked to revenue. Although neither study directly looks at B2B SaaS, together they provide an economic foundation for understanding why pricing structures that meter consumption may link customer use more closely to continuous revenue capture. Lambrecht and Skiera (2006) complicate this economic logic and add a behavioral perspective by showing that customers do not necessarily prefer consumption-based pricing. In their empirical study of Internet access tariffs, many customers displayed a

flat-rate bias, choosing flat-rate contracts even when pay-per-use tariffs would have minimized their billing cost. This evidence is not specific to B2B SaaS, but it suggests that pricing metrics affect not only revenue mechanics but also customer perceptions of risk, predictability, and convenience.

Li and Kumar (2022) distinguish SaaS from traditional software through internet delivery and multitenancy, and note that SaaS differs from off-the-shelf software in its revenue structure, moving from one-time revenue toward revenue generated on a recurring billing-period basis. Within this recurring revenue structure, the pricing metric shapes how revenue evolves as customers continue using the product. Under usage-based pricing, customer growth in software consumption can translate more directly into revenue growth. Under seat-based pricing, by contrast, greater consumption intensity does not necessarily produce additional revenue unless it is accompanied by more users, additional modules, or plan upgrades. Expansion therefore depends more on a discrete commercial event than on consumption itself.

Saltan and Smolander (2021), in a systematic multivocal review of SaaS pricing sources, document that academic research on SaaS pricing has remained fragmented and weakly integrated with practitioner knowledge. This helps explain the limited direct academic evidence linking pricing metric type specifically to Net Revenue Retention. Several practitioner sources are nevertheless consistent with the logic that usage-based pricing may support higher expansion revenue and retention. Industry reports have argued that SaaS firms using usage-based or consumption-based pricing often display higher revenue expansion and stronger retention than firms relying primarily on non-consumption-based models (Heap & Brar, 2022; OXX, 2022).

2.3.2 Condition 2, C2

The second pricing model condition is *Self-serve expansion*, defined as whether existing customers can increase usage, upgrade their plan, or purchase additional product modules without requiring contact with a sales representative. This condition is distinct from whether a firm employs a sales team at all. Some firms operate both self-serve and sales-assisted channels simultaneously. What is relevant for this condition is whether customers can complete an

expansion journey through the product interface or customer account environment without sales involvement being required.

The theoretical basis for why this design choice affects NRR draws on transaction cost economics. Coase (1937) established that economic exchange involves costs beyond the price of the good itself, including the costs of search, negotiation, and contract execution. Williamson (1975, 1985) developed this insight into a broader framework, arguing that the structure of economic organization reflects efforts to minimize these transaction costs. Applied to the SaaS expansion context, a sales-led expansion motion introduces a transaction cost event at every point where a customer seeks to grow their usage. The customer must identify the appropriate sales contact, schedule a conversation, receive and evaluate a commercial proposal, and wait for contract execution before the expansion is realized. Each step represents a cost in time and effort that creates friction between the moment a customer perceives expansion value and the moment that value is converted into revenue for the firm. Susarla, Barua, and Whinston (2009) provide related evidence of these dynamics in an ASP context, a precursor model to SaaS, finding that contractual incompleteness generates renegotiation and monitoring costs that worsen performance when unaddressed. Applied here, each sales-mediated expansion event reintroduces these costs, whereas *self-serve expansion* can reduce this friction by allowing expansion events to occur without commercial intervention.

Meuter, Ostrom, Roundtree, and Bitner (2000) provide a related but indirect basis through their study of technology-based self-service encounters across multiple service contexts. They define self-service technologies as technological interfaces that allow customers to produce a service without direct employee involvement. Meuter et al. 's (2000) findings suggest that successful self-service encounters can create satisfaction through convenience, time savings, access, and control. In a SaaS context, this logic applies to an expansion context when the service interface enables existing customers to add users, increase usage, upgrade plans, or purchase modules without direct sales involvement.

As Saltan and Smolander (2021) documented that SaaS pricing knowledge is split between academic research and practitioner expertise, this could support the notion to complement academic literature by evaluating additional source material from the industry. The practitioner literature describes this condition of self-service as a key component of product-led growth, which is defined as a growth model in which the product itself drives customer acquisition, expansion, and retention without requiring sales intermediation (Bartlett, 2019). Alaghband et al., (2023), analyzing publicly listed B2B SaaS firms, found that product-led companies on average outperform sales-led peers on revenue growth metrics, though their analysis also shows that performance gains are concentrated among a subset of high-performing product-led firms rather than distributed uniformly across all firms using this motion.

2.3.3 Condition 3, C3

The third pricing model condition is *Land-and-expand entry*, which captures whether a firm offers a permanent free tier or a substantive free trial that allows prospective customers to begin using the product without financial commitment or required sales contact. This condition reflects the entry path into the customer relationship. In contrast to C2, which concerns the process through which existing customers expand spending, C3 specifically concerns how prospective customers first experience and evaluate the product.

Cheng and Tang (2010) examine software free-trial strategies in the presence of network effects and demand cannibalization, showing that free trials may increase profitability by expanding the installed user base despite the risk of reducing paid demand. Cheng et al. (2015) extend this logic by emphasizing the role of free trials in reducing customer uncertainty about software quality and functionality. They argue that product experience allows potential customers to evaluate complex software offerings before purchase, an issue particularly relevant in B2B SaaS where products are often complex, context-dependent, and difficult to assess prior to adoption. Free trials may therefore not only increase acquisition volume, but also improve the quality of revenue by allowing prospective users to evaluate the product and ensure greater fit before committing financially.

Kumar (2014) examines the freemium model, under which users receive basic functionality for free while paying for access to more advanced features. The core argument is that freemium can reduce adoption friction and support customer acquisition by allowing users to experience the product before committing financially. However, Kumar (2014) also emphasizes that the model depends on balancing the value of the free tier against the incentives to upgrade. If the free offering is too limited, acquisition may suffer, while if it is too generous, too few users may convert to paid plans. Conversion from free to paid is therefore treated as an important indicator of whether the freemium model is functioning effectively. For NRR, the presence of a freemium tier may also suggest that customers who convert to paid plans have already demonstrated sustained product engagement and perceived sufficient value to upgrade.

The mechanism connecting C3, *Land-and-expand entry*, to NRR operates through the higher quality of paying customers it generates. That is, customers who experience the product before financial commitment can assess fit accurately, and those who convert already carry validated product engagement into the paid relationship. However, free access may also fail to support NRR if it attracts low-intent users, delays monetization, or does not lead to meaningful paid conversion. Thus, the merit of C3, *Land-and-expand entry*, relies on reducing friction at the evaluation and entry stage, helping customers discover product fit before purchase. Unlike C1 and C2, which reduce friction by removing sales intermediation from the usage and expansion stages. When combined with effective monetization and expansion mechanisms, *Land-and-expand entry* may therefore create a stronger foundation for later paid expansion and retention.

2.4 Pricing model configurations as business model design

The preceding sections identify three pricing model conditions that are theorized to matter for NRR in B2B SaaS firms. These conditions should not be read as isolated pricing features. They are better understood as related design choices within the firm's business model. Baden-Fuller and Haefliger (2013) define the business model as an integrated system through which firms engage customers and monetize value, emphasizing that its elements are interdependent rather than separable.

Baden-Fuller and Haefliger (2013) also argue that business models mediate the link between technology and firm performance, partly because firms must work out paths to monetization. This logic is consistent with Teece's (2010) view that a business model explains how a firm creates and delivers value to customers and how it captures part of that value through its revenue and profit architecture. For this study, the distinction between value creation and value capture is important. Michel (2014) makes the point that firms often focus heavily on creating customer value while underemphasizing the mechanisms through which value is captured. At the same time, value capture mechanisms cannot sustainably generate expansion revenue unless customers first derive value from the product. The mechanisms theorized here therefore assume a baseline level of validated customer value, defined by Zeithaml (1988) as customers' perceived utility based on what is received relative to what is given.

A configurational view is appropriate because business model elements are unlikely to operate independently. Their performance relevance may depend on how they are combined with other business model elements (Aversa, Furnari, and Haefliger, 2015). In their study, Aversa et al. (2015) examine which business model configurations are associated with high and low performance and frame their analysis as exploratory, focusing on associations and underlying mechanisms rather than precise causal patterns. This same logic is useful for the present study because pricing model design in B2B SaaS also consists of interrelated choices.

Taken together, these conditions describe how a SaaS firm structures the path from initial adoption to recurring revenue expansion. C1 captures the revenue basis: whether revenue growth occurs automatically as customers consume more, or requires a discrete commercial trigger (Oi, 1971; Sundararajan, 2004). C2 captures the expansion path: whether existing customers can increase spending without sales intermediation, or whether expansion requires a sales event at every step (Meuter et al., 2000; Susarla et al., 2009). C3 captures the entry path: whether customers realize product value before or after financial commitment, shaping the quality of the paying accounts base (Cheng & Tang, 2010; Cheng, Li, and Liu, 2015; Kumar, 2014). Collectively, they form a restricted but theory-guided conceptualisation of pricing model configuration in B2B SaaS. That said, software pricing models can include several parameters beyond those examined here, including payment flow, price discrimination, and

dynamic pricing strategies (Lehmann & Buxmann, 2009). Although these elements may theoretically matter, they are less readily externally observable and less like-for-like comparable. By contrast, value metric type, self-serve expansion, and land-and-expand entry are treated here as transparent higher-level pricing model features.

Across these three conditions, a common theoretical logic emerges. Each condition marks a point at which commercial intervention either is or is not required for customer activity to become revenue. Pricing model configurations therefore vary in the degree to which they automate, and create a smoother path for converting customer-derived product value into revenue. Configurations that minimize commercial intervention at each stage of the customer journey, usage, expansion, and entry are expected to produce higher NRR because they may reduce the friction that otherwise decouples customer activity from revenue outcomes.

Figure 1. Pricing model configuration as a low-friction value-capture architecture

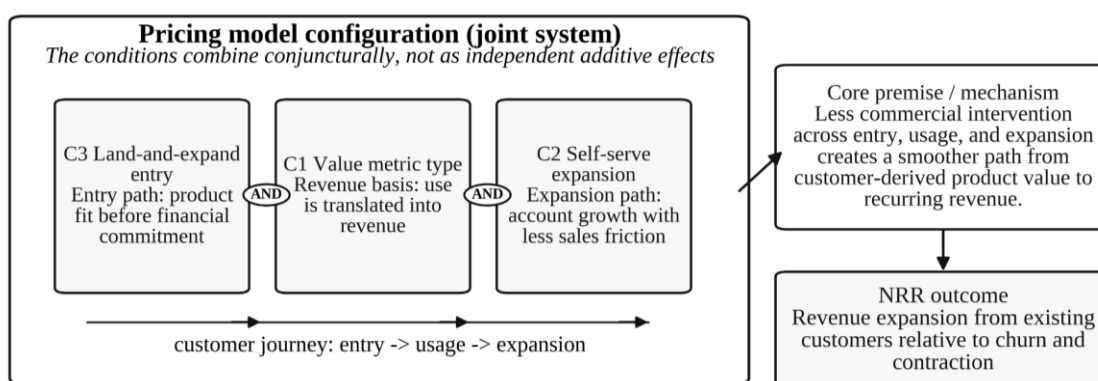


Table 1. Pricing model conditions and their role in customer expansion

Condition	Role in the configuration	Link to NRR
<i>Value metric type</i>	Reflects how revenue scales with customer use	Links customer use to revenue capture
<i>Self-serve expansion</i>	Reflects how easily existing customers can expand spending	Reduces friction in account expansion
<i>Land-and-expand entry</i>	Reflects how customers enter and test product fit	Better fit may support later paid expansion

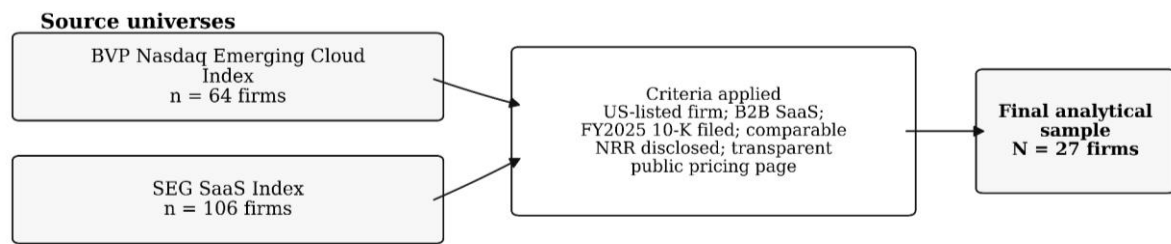
3. Method

This study utilizes a qualitative comparative analysis to examine how configurations of pricing model design elements are associated with net revenue retention across a sample of public US-listed B2B SaaS firms. Rather than estimating the average effect of individual pricing characteristics, the design treats firm-level outcomes as products of condition combinations, reflecting the theoretical premise that pricing model elements operate jointly rather than in isolation. Following learnings from Rihoux and Lobe (2009), the analysis is understood as an iterative process involving continuous engagement with the cases throughout data collection, calibration, and interpretation.

3.1 Data and sample

The sample consists of publicly traded US-listed B2B SaaS firms selected on three criteria: the firm's primary revenue model must be recurring income through software delivered as a service, sufficient public data must be available to code all three conditions, and the firm must disclose net revenue retention or a functionally equivalent metric in its investor communications. Firms where pricing structure could not be established from public sources and firms where NRR was not disclosed were excluded. The final sample comprises N=27 firms. Pricing model conditions were measured as of the year-end 2024 (the closest snapshot available to December 31, 2024), NRR was measured for Calendar Year 2025 (CY2025), using annualised figures (standardized to the closest available reporting date to December 31, 2025), with a maximum deviation of one quarter for those firms with split fiscal years. Given the twelve-month nature of the metric and the gradual pace at which NRR typically moves in established SaaS businesses, this is unlikely to affect crisp-set codings.

Figure 2. Flow chart of the sample selection¹



Of the firms in the two source universes that were excluded from the final sample, the primary reasons for exclusion were absence of a disclosed NRR metric, followed by an insufficient public pricing information to code all conditions. Excluded firms tended to be smaller by market capitalization and revenue, more recently listed, or operating in segments with less standardized reporting practices, such as vertical specific SaaS. This pattern is consistent with the selection bias discussed in our Limitations (section 7): NRR disclosure is more prevalent among firms that are larger, more mature, and more oriented toward recurring revenue transparency in investor communications. The final sample of 27 firms therefore represents a subset of publicly listed B2B SaaS firms with above-average disclosure maturity, which should be borne in mind when interpreting the generalizability of the findings.

¹ The BVP Nasdaq Emerging Cloud Index and SEG SaaS Index track publicly listed cloud and SaaS software companies. These two indices were used as starting points for identifying the sample of relevant companies.

Table 2. All firms in sample and their corresponding NRR and revenue for CY2025

Firm	NRR	Revenue	Product category	Fiscal year ended²
Crowdstrike	115%	\$4.81B	Security	January 31, 2026
Okta	106%	\$2.92B	Security	January 31, 2026
Box	104%	\$1.18B	Content/Collaboration	January 31, 2026
Gitlab	118%	\$955.2M	DevOps	January 31, 2026
Workiva	113%	\$885M	Finance/Compliance	December 31, 2025
Sprout social	100%	\$457.5M	Marketing	December 31, 2025
Datadog	120%	\$3.43B	Infrastructure	December 31, 2025
Fastly	110%	\$624.0M	Infrastructure	December 31, 2025
Amplitude	104%	\$343.2M	Analytics	December 31, 2025
CS Disco	98%	\$156.8M	Legal (vertical)	December 31, 2025
Braze	109%	\$738.2M	Marketing	January 31, 2026
Cloudflare	120%	\$2.17B	Infrastructure/Security	December 31, 2025
N-able	103%	\$511.4M	Security/IT	December 31, 2025
Asana	96%	\$790.8M	Collaboration	January 31, 2026
Yext	97%	\$446.6M	Marketing	January 31, 2026
Jfrog	119%	\$531.8M	DevOps	December 31, 2025
Bandwidth	99%	\$753.8M	Communications	December 31, 2025
Pagerduty	98%	\$492.5M	IT operations	January 31, 2026
Blackline	105%	\$700.4M	Finance/Compliance	December 31, 2025
Monday	110%	\$1.232B	Collaboration	December 31, 2025
Hubspot	104%	\$3.13B	Marketing/CRM	December 31, 2025
Figma	136%	\$1.056B	Collaboration/Design	December 31, 2025
Klaviyo	110%	\$1.234B	Marketing	December 31, 2025
Vertex	105%	\$748.4M	Finance/Compliance	December 31, 2025
Zscaler	115%	\$2.673B	Security	July 31, 2025
Intapp	113%	\$504.1M	Professional services	June 30, 2025
Snowflake	125%	\$4.684B	Data/Infrastructure	January 31, 2026

All source material was collected from publicly available archival sources.³ This approach is appropriate given that the conditions under study concern the externally visible pricing design choices a firm makes, which by definition are observable from public-facing materials such as

² When the fiscal year did not correspond to the calendar year, Form 10-Q filings were used. This regards the two firms Zscaler and Intapp. For all other firms, Form 10-K filings were used for review.

³ Further details on data sources and source categories are provided in the Appendix (Table 12).

pricing pages on websites and investor disclosures. Information collection followed a source hierarchy applied consistently across all firms and conditions. Company websites and pricing pages served as the primary source, accessed directly through the Wayback Machine for the relevant pricing state present at the year-end of 2024. Financial filings, such as the Form 10-K and Form 10-Q, to the United States Securities and Exchange Commission (SEC) and company disclosures, including SEC EDGAR filings and earnings call transcripts, served as the secondary source, particularly for the identification of product category and input of NRR, revenue figures and for firms whose pricing structure required corroboration beyond what the pricing page alone established. Each coding decision, the process of transforming qualitative observations into data, was documented with the specific source.

To assess the comparability of NRR figures across the sample, each firm’s disclosed metric definition was reviewed against its source filings. Material definitional differences identified include the treatment of overage charges, currency effects, revenue categories, and customer cohorts. A more detailed discussion is provided in our Limitations (section 7). However, no firm was found to use a definition so divergent as to render its figure non-informative as a retention measure.

In addition, input from discussions with experts was used to validate calibration thresholds and decision rules, but not to directly inform individual coding decisions. Two industry experts with extensive experience in SaaS pricing were consulted: a partner at a management consulting firm specializing in SaaS pricing, and an operations director at a private equity firm with substantial SaaS investments. Their input was used to assess the appropriateness of key calibration choices, including threshold selection and decision-rules for calibration.

Table 3. Experts’ professional profiles

Role	Profile
Partner	Strategy, pricing, and growth expert at a management consultancy firm.
Operations Director	Commercial excellence expert at a leading Nordic private equity firm.

3.2 Analytical approach

Qualitative comparative analysis (QCA) is a case-oriented method that examines how combinations of conditions produce a given outcome (Ragin, 2014; Rihoux & Lobe, 2009). Rather than estimating the average effect of individual variables, QCA treats each case as a member of sets and examines whether particular configurations of conditions are consistently associated with an outcome across cases (Arora-Jonsson et al., 2024). The method draws on Boolean algebra and set-theoretic logic to compare cases systematically and reduce the observed configurations to their analytically essential elements.

Several concepts are central to QCA as a method. Conditions are factors that prior research has identified as plausibly causally related to the outcome. A configuration is a specific combination of conditions, and each case in the analysis is understood as one such combination rather than as a row of independent variable values. The truth table lists every logically possible combination of conditions and records, for each combination, whether the associated cases display the outcome or not (Arora-Jonsson et al., 2024). A necessary condition is one that appears in every instance of the outcome, though its presence does not on its own produce the outcome. A sufficient condition is one whose presence is consistently followed by the outcome, though the outcome may also occur through other configurations (Arora-Jonsson et al., 2024). These two types of conditions are assessed against different consistency thresholds, as elaborated in the evaluation of solutions below.

A minimization algorithm is then used to reduce the truth table to simplified configurations that are associated with the outcome (Arora-Jonsson et al., 2024). Specifically, the minimization process produces three solution types: a conservative solution that uses only empirically observed configurations, a parsimonious solution that freely incorporates unobserved configurations as logical remainders, and an intermediate solution that uses only theoretically grounded remainders. For the high NRR analysis, all three conditions are assigned a positive directional expectation, reflecting the theoretical premise that their combined presence creates a path from customer adoption to revenue expansion with minimal commercial intervention at each stage. For the low NRR analysis, directional expectations are inverted, with all three conditions assigned an absence expectation, reflecting the premise that

their absence is associated with low NRR. Following Ragin's (2008) recommendation that intermediate solutions are generally preferable, this is reported as primary in this study. Conservative and parsimonious solutions are reported alongside for transparency.

Solutions are evaluated on consistency and coverage. Consistency captures the degree to which cases sharing a configuration also share the outcome (Aversa et al., 2015). We follow the commonly applied minimum threshold of 0.80 for sufficient conditions (Aversa et al., 2015; Ragin, 2008). Coverage captures how much of the outcome a given configuration accounts for (Arora-Jonsson et al., 2024), indicating how empirically relevant the findings are. Raw coverage reflects the share of outcome cases that a configuration explains, without accounting for overlap with other configurations in the solution, while Unique coverage reflects only those outcome cases that a specific configuration explains and no other configuration does (Arora-Jonsson et al., 2024). However, it should be noted that in a small sample, consistency and coverage values should be interpreted cautiously, as there are simply fewer observations available for the pattern to be contradicted (Aversa et al., 2015).

Three properties of the causal processes under study make QCA an especially suitable analytical approach for this study. The first is equifinality, meaning that distinct configurations may each independently lead to the same outcome (Arora-Jonsson et al., 2024). Given that the conditions under study can plausibly interact in more than one way to produce expansion revenue, as established in the literature review, it is possible that more than one pricing model configuration is associated with the presence of the NRR outcome. The second is causal asymmetry, meaning that the configurations associated with high NRR may differ fundamentally from those associated with low NRR, rather than being their mirror image (Arora-Jonsson et al., 2024). Regression-based approaches typically estimate net effects and are less well suited to capturing equifinal and configurational causal relationships, while interaction terms can partially address this, the results often become difficult to interpret, particularly in small samples (Arora-Jonsson et al., 2024). The third is conjunctural causation, meaning that a condition, typically, contributes to the outcome when present alongside specific other conditions, such that outcomes are produced by configurations rather than individual factors (Arora-Jonsson et al., 2024; Rihoux & Lobe, 2009). This is consistent with the

theoretical premise of this study that pricing model elements operate jointly rather than independently. The sample size also points toward QCA. With $N=27$ firms, the sample is still large enough that systematic cross-case comparison by hand would be difficult (Ragin, 2014; as cited in Arora-Jonsson et al., 2024), while too small to support the number of parameters that a regression with interaction terms would require.

The conditions in this study are classified based on whether firms adopted specific characteristics of pricing model components, or not. The outcome variable, NRR, is coded with each firm placed either in or out of the high-NRR set, based on the calibration described below in section 3.3. In line with Arora-Jonsson et al. (2024), we opted for a crisp-set approach as it allows for clearer calibration and more straightforward interpretation. Consistent with their reasoning, this approach is appropriate given that both the outcome and the conditions in our study can be meaningfully represented in binary terms. The frequency threshold of the analysis is set at 1, due to the small- N nature of our sample, mirroring the approach of Aversa et al. (2015). That is, we kept all observed configurations, even those represented by just one firm, instead of filtering out rare ones.

As defined in Section 3.1, pricing model conditions were measured for 2024 while NRR was measured for CY2025. This ordering places the pricing configuration prior to the NRR outcome, reducing the risk that observed associations simply reflect contemporaneous decisions rather than the effect of a pricing model that was already in place. The reasoning is inspired by the temporal lag applied by Aversa et al. (2015), who observed business model configurations at one point in time and performance outcomes at a later point, on the grounds that strategic configurations may require time before their effects are realized. We apply the same logic to pricing model configurations.

Additionally, we analyze both the presence and the negation of the outcome, meaning the configurations associated with low NRR are examined separately from those associated with high NRR (Arora-Jonsson et al., 2024). Because causal asymmetry means the absence of conditions leading to high NRR does not necessarily produce low NRR, the two analyses cannot be assumed to be symmetric and are treated as distinct (Arora-Jonsson et al., 2024).

3.3 Calibration

The outcome in this study is high Net Revenue Retention (NRR), as defined in Section 2.1. The analysis applies a crisp-set calibration, in which firms are classified as either members or non-members of the high-NRR set. In line with QCA methodology, calibration requires an explicit threshold that separates cases displaying the outcome from those that do not (Ragin, 2008; Aversa et al., 2015; Arora-Jonsson et al., 2024).

The primary threshold is set at 110%. Firms with NRR at or above 110% are coded as 1 (high NRR), and those below 110% are coded as 0. This threshold is justified using both benchmark evidence and the empirical distribution of the sample.

Benchmarking is based primarily on the 2025 SaaS Benchmarks Report (High Alpha), which provides recent evidence on NRR across SaaS firms. Median NRR ranges between approximately 101% and 104%, while upper-quartile performance reaches approximately 108-116% depending on company size. These values indicate that NRR levels at or above 110% are associated with stronger-than-average retention performance. This interpretation is consistent with public market evidence reported in the 2024 SaaS Benchmarks Report material, also from High Alpha (2024), where net dollar retention for publicly listed SaaS firms is observed at approximately 110% across multiple quarters. Consequently, 110% is used as a primary threshold.

From a substantive standpoint, the threshold distinguishes firms that generate clear expansion within their existing customer base from those with only limited net growth. A threshold at 105%, would include firms with relatively modest expansion, where they are mainly retaining their installed base without demonstrably growing above the aforementioned median, whereas a threshold at 115% would impose a stricter performance criterion and substantially reduce the number of firms classified as high NRR, rendering the high NRR-set too sparse for meaningful a QCA. Within this range, 110% provides a balanced separation between unimpressive and rare retention outcomes.

The empirical distribution supports this calibration. The sample contains 27 firms with available NRR data for Calendar Year 2025. Of these, 13 firms report NRR at or above 110%, while 14 firms report NRR below this level. This distribution provides a sufficiently balanced split between outcome categories.

Alternative thresholds are used as robustness checks. At a threshold of 105%, the Calendar Year 2025 distribution is 17 firms at or above and 10 firms below the cutoff. At a threshold of 115%, the distribution is 8 firms at or above and 19 firms below the cutoff. Relative to these alternatives, the 110% threshold yields the most even distribution of cases across outcome categories without expanding the high-NRR set excessively or restricting it to a small number of cases.

Table 4. Distribution of Firms across Alternative Calibration Thresholds

Threshold (%)	Calendar Year 2025
105	17 at or above / 10 below
110	13 at or above / 14 below
115	8 at or above / 19 below

Calibration of conditions

The conditions in this study are calibrated using a crisp-set approach, where each firm is classified as either ‘in’ the set or ‘out’ of the set for each condition. Calibration follows theoretically grounded decision rules, based on prior literature on SaaS pricing model designs’ theoretical mechanisms and complemented by input from two industry experts in SaaS pricing. These rules are operationalised using publicly observable pricing model characteristics. To ensure consistency, a hierarchical coding logic was applied across all cases and documented for each firm, with ambiguous cases resolved through iterative engagement with the source material.⁴

⁴ A detailed overview of the coded conditions for all firms in the sample is provided in the Appendix (Table 11).

C1. *Value metric type* captures how firms structure pricing to align revenue with customer usage and realized value. Firms are coded as being in the set (1) if usage-based pricing constitutes the primary mechanism through which revenue expands within existing customer accounts, and out of the set (0) if pricing is primarily seat-based or flat-rate, requiring an active purchasing decision for expansion.

Coding is based primarily on company pricing pages as of year-end 2024, supplemented by investor materials and financial disclosures where necessary. Classification is determined by assessing whether usage is presented as the dominant pricing logic and whether customer growth leads to automatic increases in billing. Where firms employ hybrid pricing models, coding is based on the mechanism that primarily drives expansion within existing accounts. In such cases, investor communications are used to assess whether the firm positions its model as usage- or consumption-based, as this is typically emphasized when central to revenue generation. In cases where enterprise tiers are listed as 'contact sales,' these are assumed to follow the same underlying value metric as adjacent tiers, on the grounds that such tiers typically represent large-volume arrangements rather than a structurally different pricing model. Where such sources provided evidence of a different enterprise pricing structure, that evidence took precedence. Expert validation confirmed this decision rule as a reasonable default in the absence of contrary evidence. In the final sample, 12 firms are classified as in the set and 15 as out.

C2. *Self-serve expansion* captures the extent to which firms enable customers to increase spending without direct sales involvement. Firms are coded as being in the set (1) if existing customers can expand usage, upgrade tiers, or purchase additional functionality entirely through the product interface without sales interaction, and out of the set (0) if the primary expansion path requires engagement with a sales function.

Coding is based on publicly available pricing pages as of year-end 2024, supplemented by investor materials and financial disclosures. A key criterion is whether a customer can meaningfully increase their spending without interacting with a salesperson. Firms are coded

as out of the set where all expansion paths are routed through sales contact, for example, through “contact sales” upgrade requirements, absence of in-product purchasing functionality, or sales-led pricing for higher tiers. In cases where no public pricing page is available, the absence of self-serve infrastructure is treated as indicative of a sales-led expansion model. Where firms display mixed signals, classification is based on whether a customer can increase their spending with the firm without interacting with a salesperson, rather than on whether a self-serve option exists anywhere in the product. In the final sample, 15 firms are classified as in the set and 12 as out.

C3. *Land-and-expand entry* captures whether firms employ low-friction entry mechanisms that facilitate initial adoption and subsequent expansion. Firms are coded as being in the set (1) if they offer either a permanent free tier or a free trial of at least 14 days without requiring a credit card, and out of the set (0) if neither condition is met.

Coding is based on company pricing pages as of year-end 2024, complemented by investor materials and financial disclosures. If a permanent free tier exists that provides functional access to core product features, not merely account creation or read-only access, it is coded as present. Free trials are coded as present only if they extend for at least 14 days and do not require a credit card upfront, as credit card requirements introduce a level of commitment that alters the entry dynamic. Trials shorter than 14 days, requiring upfront payment details, or accessible only through sales interaction are coded as absent. The 14-day threshold reflects a period commonly intended to give users sufficient time to onboard and evaluate the product’s value, consistent with prior research on free-trial conversion dynamics (Cheng, Li, & Liu, 2015), and supported by expert validation. In the final sample, 18 firms are classified as in the set and 9 as out. The distribution is slightly skewed toward set membership, but is still well within the 80/20 threshold recommended by Oana et al. (2021).

To assess the stability of the findings, several robustness checks are conducted and reported in Section 4.4. These include rerunning the full analysis at alternative NRR calibration thresholds of 105% and 115%, varying the consistency threshold between 0.75 and 0.85.

4. Results

4.1 Necessity analysis

A necessity analysis was conducted to assess whether any single pricing model element is always present when the outcome occurs.

Table 5: Necessity analysis, high NRR

Condition	Consistency
C1	0.462
C2	0.769
C3	0.769
~C1	0.539
~C2	0.231
~C3	0.231

Table 6: Necessity analysis, low NRR

Condition	Consistency
C1	0.429
C2	0.356
C3	0.571
~C1	0.571
~C2	0.643
~C3	0.429

No condition is present in every case that exhibits the outcome in either analysis, and therefore no necessary conditions were identified. No single element of the pricing model, as delimited in this study, is always present when NRR is high or always present when NRR is low.

4.2 Sufficient conditions for high NRR

Table 7: Truth table, high NRR

C1	C2	C3	N	Consistency	Outcome
0	0	0	5	0.600	0
0	0	1	2	0.000	0
0	1	1	8	0.500	0
1	0	0	4	0.000	0
1	0	1	1	0.000	0
1	1	1	7	0.857	1

Note: configurations 010 and 110 are empirically empty and treated as logical remainders. Rows numbered according to binary ordering of conditions.

Only configuration 111, the combination of *usage-based pricing*, *self-serve expansion*, and *land-and-expand entry*, passes the 0.80 consistency threshold, with 6 out of 7 firms displaying high NRR (Datadog, Fastly, Cloudflare, Jfrog, Klaviyo, Snowflake). Amplitude is the single inconsistent case within this configuration, displaying low NRR despite having all three conditions present.

Table 8: Sufficient conditions, high NRR

Configuration	Consistency	Raw coverage	Unique coverage	Cases (N)
C1C2C3	0.857	0.462	0.462	7

Note: intermediate solution reported as primary.

Following minimization, the sufficient configuration is expressed as C1C2C3 (intermediate solution). The conservative and intermediate solutions converge on C1C2C3. The parsimonious solution simplifies to C1C2, achieved by treating the unobserved configuration 110 as a positive counterfactual outcome, effectively assuming that C1 and C2 together would be sufficient even without C3. This counterfactual is excluded from the intermediate solution because the positive directional expectation for C3, grounded in the theoretical premise that all three elements jointly enable expansion revenue, renders a C3=0 simplification theoretically unjustified.

The overall solution consistency is 0.857 and coverage is 0.462, meaning the configuration accounts for 46% of all high NRR cases in the sample. As noted by Aversa et al. (2015), coverage values of this magnitude are consistent with published QCA studies in management research, though they also indicate that idiosyncratic or unmeasured factors account for a substantial share of the outcome.

The remaining 54% of high NRR firms, specifically Crowdstrike, Gitlab, Workiva, Monday, Figma, Zscaler, and Intapp, achieve high NRR through configurations that do not meet the sufficiency threshold. Workiva, Zscaler, and Intapp are located in configuration 000 (no *usage-based pricing*, no *self-serve expansion*, no *land-and-expand entry*) which has an inclusion score of 0.600 across its five members. Crowdstrike, Gitlab, Monday, and Figma are in configuration

011 (no *usage-based pricing*, but *self-serve expansion* and *land-and-expand entry* both present), which has an inclusion score of 0.500 across eight members. Specifically, that three firms achieve high NRR with none of the three conditions present is notable. This confirms that the pricing model elements examined here are neither necessary individually nor jointly exhaustive of the pathways to high NRR, and that other mechanisms outside this model's scope are operative for a meaningful share of the sample.

4.3 Sufficient conditions for low NRR

Table 9: Truth table, low NRR

C1	C2	C3	N	Consistency	Outcome
0	0	0	5	0.400	0
0	0	1	2	1.000	1
0	1	1	8	0.500	0
1	0	0	4	1.000	1
1	0	1	1	1.000	1
1	1	1	7	0.143	0

The low NRR truth table reveals three configurations that pass the 0.80 consistency threshold, all with perfect consistency of 1.000: configuration 001, containing Okta and Hubspot; configuration 100, containing CS Disco, Braze, Bandwidth, and Vertex; and configuration 101, containing N-able. Every firm in each of these configurations displays low NRR without exception.

Table 10: Sufficient conditions, low NRR

Configuration	Consistency	Raw coverage	Unique coverage	Cases (N)
C1~C2	1	0.357	0.286	5
~C2C3	1	0.214	0.143	3

Note: all converge on a single solution, indicating full robustness.

Following minimization, all three solution types converge on a single solution: C1~C2 + ~C2C3. The first term, C1~C2, captures firms with *usage-based pricing* and absence of *self-serve expansion*. These firms have a pricing architecture that structurally scales with consumption but require sales involvement at every expansion event, creating a friction point that suppresses revenue growth within existing accounts. The second term, ~C2C3, captures

firms with absence of *self-serve expansion* combined with the presence of *land-and-expand entry*. These firms allow low-friction entry through a free tier or freemium but then require sales interaction to convert that initial adoption into expansion revenue, undermining the mechanism that *land-and-expand entry* is theorized to enable.

The absence of *self-serve expansion*, $\sim C2$, appears in every term of the solution. This makes it the most consistent predictor of low NRR across all configurations, appearing regardless of what the other conditions are doing. This directly mirrors the high NRR finding where C2 is required, establishing self-serve expansion as a pivotal condition in the model in both directions. Unlike the high NRR finding, which produces single sufficient configuration regardless of solution type, the low NRR solution exhibits equifinality, two distinct configurations are each independently sufficient for the outcome.

The role of C3 across both solutions is worth noting separately. C3 is present in the high NRR configuration, C1C2C3, where it operates alongside C2. It also appears in the low NRR term $\sim C2C3$, where it operates alongside the absence of C2. C3 is therefore not directionally consistent in isolation: its association with the outcome depends entirely on whether C2 is present or absent. This is a clear instance of conjunctural causation, the same condition contributes to opposite outcomes depending on its combinational context, and is consistent with the theoretical premise that pricing model elements operate jointly.

The overall solution consistency is 1.000 and coverage is 0.500, meaning the solution accounts for 50% of all low NRR cases. The remaining 50% of low NRR firms are not explained by any configuration in this model, suggesting that mechanisms beyond the three pricing model elements examined here, such as enterprise sales-led dynamics, market-specific factors, or product characteristics, contribute substantially to low retention outcomes. This is consistent with the scope of the model, which was designed to capture externally observable pricing structure rather than the full range of factors affecting NRR.

Importantly, the low NRR configurations are not the mirror image of the high NRR finding. The primary sufficient configuration for high NRR combines all three conditions, while low

NRR is consistently associated with the absence of self-serve expansion combined with other conditions, reflecting causal asymmetry. Together, the high and low NRR analyses provide a configurational picture of how pricing model elements combine differently across firms, which the following sections examine further through qualitative evidence and robustness testing.

4.4 Robustness tests

Robustness tests were conducted to assess the stability of the primary findings under alternative analytical specifications. The first varied the NRR calibration threshold, rerunning the full analysis at 105% and 115%. The second varied the consistency threshold between 0.75 and 0.85. All tables are provided in the appendix.

First, the full analysis was rerun at thresholds of 105% and 115%, bracketing the primary threshold of 110%. At 105%, the high NRR solution changes substantively. A second sufficient path emerges alongside C1C2C3, the absence of usage-based pricing and absence of land-and-expand ($\sim C1^* \sim C3$), driven by firms such as Workiva, Zscaler, and Intapp, which have moderate NRR (105-113%) and neither usage-based pricing nor land-and-expand present. The low NRR solution collapses to a single case, N-able, with a raw coverage of 11%. These changes reflect that lowering the threshold changes the composition of the high NRR set. At 115%, no configuration reaches the 0.80 consistency threshold for high NRR, as the stricter outcome definition reduces the high NRR set to 8 firms distributed across multiple configurations with insufficient density for any to qualify as sufficient. For low NRR, all three solution types converge on $\sim C2$ alone (with a consistency score of 91.7%, and a raw coverage at 57.9%).

The second full analysis, investigating scenarios of alternative consistency thresholds, was rerun with the thresholds set at 0.75 and 0.85, bracketing the standard 0.80 threshold applied in the primary analysis. At both alternative thresholds, the truth table row codings remain unchanged for both the high and low NRR analyses, and all three solution types produce identical solutions to those reported in the primary analysis. The high NRR solution C1C2C3 and the low NRR solution $C1^* \sim C2 + \sim C2C3$ are fully robust to variation in the consistency threshold within this range.

Across all tests, the primary findings demonstrate partial stability. The solutions are fully stable to variation in the consistency threshold, while the NRR threshold checks confirm that 110% occupies a substantively meaningful position, producing qualitatively different solutions when lowered to 105% and failing to yield identifiable sufficient configurations when raised to 115%. The sensitivity of configurational findings to outcome calibration underscores the importance of substantively grounded threshold selection. At 105%, the outcome definition shifts from strong expansion to adequate retention, and the configurations that emerge reflect a different population of firms where the threshold fails to meaningfully distinguish high performers from the rest of the sample. At 115%, the failure to identify sufficient configurations reflects the fact that firms achieving this level of NRR represent a small minority of firms, where no single configuration contains sufficient cases to reach the consistency threshold, a direct consequence of the rarity of achieving such a performance level.

5. Qualitative complement

This section serves two purposes beyond what the QCA analysis alone can establish. It traces how the sufficient configuration C1C2C3 produces high NRR in practice, and investigates why the same configuration fails to produce the outcome in one of the cases. Both cases are analyzed using publicly available sources, consistent with the evidence standard applied in the calibration of conditions.⁵

5.1 Case selection rationale

Snowflake is chosen as the illustrative case from the six consistent firms in configuration 111. In addition to reporting one of the highest NRR figures in the sample, Snowflake's SEC filings, earnings call transcripts, and pricing documentation are unusually explicit about how consumption drives expansion revenue within existing accounts, making the theoretical mechanism more directly traceable than other consistent cases allow. Amplitude, by contrast, serves as the natural deviant case because it is the only firm in configuration 111 that does not display high NRR.

⁵ Further details on data sources for Qualitative complement cases are provided in the Appendix (Table 13).

5.2 Illustrative case: Snowflake

Snowflake is a cloud data platform providing data storage, processing, analytics, and AI-related workloads as a cloud service. As of Q4 FY2025, the firm served more than 10,600 customers, with 580 contributing more than one million dollars in trailing twelve-month product revenue. Its business model is built around consumption rather than seat licenses or flat-rate subscriptions: customers are charged for compute, storage, and data transfer, and can either commit upfront to a volume of use in exchange for discounts or consume on demand and be billed monthly in arrears.

The three conditions are all present and traceable to public filings. Snowflake clearly displays C1 value metric type. The firm's October 31, 2024 10-Q describes the model as consumption-based, stating that customers are only charged for the resources they use and that revenue is recorded as customers consume compute, storage and data transfer resources. Revenue therefore is tied to actual platform use rather than seat count or contract duration. Their Q1 FY2025 8-K reinforces this, as it states that product revenue is a key metric precisely due to it being based on platform consumption rather than contract value. This shows that the ongoing use of the platform by the customers is the revenue driver.

C2, *self-serve expansion*, follows directly from this structure. On-demand customers are billed automatically for usage each month, and capacity-contract customers who exceed their committed volume are billed at on-demand rates for overage consumption. Expansion is therefore not necessarily blocked by a new sales process when usage grows.

The presence of C3, *land-and-expand entry*, is also evident. Snowflake's 10-K states that many organizations initially adopt the platform through a self-service trial on the company's website, and its pricing documentation confirms a 30-day free trial with \$400 in usage credits and no credit card requirement. This gives prospective customers access to actual compute, storage, and transfer resources, allowing them to run a real workload before committing financially. The October 2024 10-Q connects this entry path to later expansion, noting that once the platform is adopted, Snowflake focuses on increasing the migration of additional customer

workloads to drive increased consumption. The initial trial serves as the first workload anchor, with additional data, teams, and use cases migrating onto the platform over time.

The mechanism behind Snowflake's NRR is visible in these same filings. The third quarter 10-Q, ending in October 2024, links workload migration, increased consumption, and NRR directly: expansion comes from customers moving more data, identifying new use cases, and adding product categories such as AI and machine learning workloads. Because customers pay for resources consumed, the pricing model converts this activity into revenue without requiring a discrete sales event at each step. However, the case also reveals a boundary. Consumption-based pricing is elastic in both directions, it allows revenue to grow when customers use more, but also allows revenue to fall when customers drastically reduce workloads or manage usage more tightly. Snowflake's 10-Q filing, for the quarter ending on October 31 2024, notes that many customers have sought to rationalize budgets and optimize consumption, which helps explain why NRR declined from 131% in January 2024 to 126% in January 2025, even though the firm remained well above the high-NRR threshold.

Snowflake therefore illustrates the C1C2C3 mechanism in a direct form. C1 connects product use to revenue, C2 allows use to expand without every increase being blocked by a sales event, and C3 lowers the barrier to initial adoption while anchoring the first workload that subsequent expansion builds on. These three present conditions create a low-friction path from initial use to expanded consumption to retained revenue growth.

5.3 Deviant case: Amplitude

Amplitude is a Nasdaq-listed digital analytics company headquartered in San Francisco. Its platform helps firms analyze how users interact with digital products through event tracking, cohort analysis, funnel analysis, experimentation, session replay, and in-product guidance. Its business model is subscription-based and Monthly Tracked User-oriented (MTU): customers pay according to the number of tracked users or events included in their plan, with a permanent free Starter tier, a self-serve Plus tier, and sales-led Growth and Enterprise tiers.

All three conditions are present, but each with qualifications that matter for the interpretation of the deviation. The presence of C1, *value metric type*, can be further corroborated through

Amplitude's pricing page which states that customers commit to a certain volume of MTUs and that all plans are available on this basis, with automatic overage billing on Plus plans when customers exceed included MTUs. However, the marginal price per MTU declines as volume increases, meaning usage growth raises total spend but not proportionally. More importantly, Amplitude's NRR definition, stated consistently across SEC filings, explicitly excludes overage charges from the calculation. MTU overages are the most direct revenue output of the C1 and C2 mechanisms combined, as a customer expanding tracked users triggers both automatic billing and self-serve revenue growth simultaneously, yet this revenue does not flow into the outcome variable being studied. Amplitude's 10-K for CY2025 states that “*Historically, overage charges have not made up a significant portion of our revenue*”, which limits but does not eliminate the significance of this exclusion. This signifies a notable gap between what the pricing model produces and what NRR captures. C2, *self-serve expansion*, is present for the Plus tier, where a direct self-serve checkout path and automatic overage billing allow expansion without sales contact. However, Growth and Enterprise tier upgrades require sales engagement, narrowing the effective scope of self-serve relative to the consistent cases. Further, C3, *land-and-expand entry*, is also confirmed, with a permanent free Starter tier at 50,000 MTUs requiring no credit card, present on the pricing page.

Despite the presence of all three conditions, Amplitude's NRR was 104% as of December 31, 2025, below the 110% threshold. The trajectory is informative, NRR was 101% in 2023, declined to 97% in 2024, and recovered partially to 104% in 2025, reflecting a protracted multi-year compression rather than a single-period anomaly.

Two factors are most relevant to explaining the deviation. The first is condition instantiation, as described above, C1 and C2 are present but their most direct expansion mechanism is excluded from the outcome metric, and the self-serve path is somewhat confined. The second is competitive substitution. Amplitude operates in product analytics, a category with credible free alternatives. Google Analytics provides event-based analytics at no cost, and PostHog offers product analytics, session replay, feature flags, and experimentation through an open-source model with a generous free tier, directly overlapping with Amplitude's core product set. For budget-constrained customers, particularly startups and smaller technology firms, these substitutes reduce willingness to expand paid usage and increase churn risk. Snowflake, in comparison, does not face equivalent substitution pressure. Replacing enterprise-scale data

warehousing with a free tool is not a realistic path for most customers, whereas in product analytics it is.

Of the explanations examined, competitive substitution carries the strongest evidentiary support. The overage exclusion adds a secondary measurement contribution. The C1C2C3 configuration appears to function mechanically as designed, but the expansion is neutralized.

5.4 Synthesis

The two cases clarify what the QCA finding does and does not claim. Snowflake shows the C1C2C3 configuration operating as theorized: customers enter through a low-friction trial, adopt real workloads, consume more resources over time, and generate expansion revenue as a structural consequence of increased use. The pricing model converts customer activity into revenue without requiring a discrete sales event at each expansion step. Amplitude shows the same configuration present but the mechanism producing a different outcome. MTU-based billing scales with usage, self-serve expansion is available, and a free entry tier exists. Yet NRR remained below the threshold across multiple years, driven primarily by competitive substitution pressure in a category where credible free alternatives exist, amplified by a customer base concentrated in segments most exposed to that substitution risk.

The contrast points to a scope condition on the C1C2C3 finding that connects to the theoretical framing established in Section 2.4. The mechanisms theorized there assume a baseline level of validated customer value, that customers derive sufficient value from the product that continued and expanded use is the natural path. When that assumption holds, as it does for Snowflake, the configuration creates a direct channel from consumption to revenue. When it is contested by competitive substitution, the channel exists structurally but is undermined by customers contracting, consolidating tools, or moving to free alternatives rather than deepening their engagement with the paid product.

6. Discussion

This study examined which configurations of pricing model design are associated with high and low levels of NRR among US-listed B2B SaaS firms in the sample. The aim was not to isolate one pricing feature and treat it as a stand-alone driver of retention. The study instead began from a configurational argument: in recurring software markets, pricing model design is theorized to matter because it is associated with how customer use, account growth, and value capture are connected over time.

The discussion interprets the QCA results through that theoretical position. Rather than treating usage-based pricing, self-serve expansion, and land-and-expand entry as separate pricing choices, it examines how these elements combine into a revenue path linking capture, use, and entry.

6.1 Main findings

The research question asked: Which configurations of pricing model design are associated with high or low levels of firm NRR? The results provide a bounded answer. High NRR is associated with the joint presence of all three conditions: usage-based pricing, self-serve expansion, and land-and-expand entry. This configuration, C1C2C3, is consistent with six of seven firms in the configuration displaying high NRR. As reported in Table 8, the intermediate solution remains C1C2C3. This finding fits the theoretical position developed in Section 2.4.

On the other hand, low NRR follows a separate pattern. As reported in Table 10, the solution $C1\sim C2 + \sim C2C3$ indicates that the low-NRR solution is composed of configurations where self-serve expansion is absent. In the first term, firms have usage-based pricing but lack self-serve expansion. In the second, firms have land-and-expand entry but lack self-serve expansion. Signifying that both usage-based pricing and free entry may fail to support high retention if the primary expansion path appears to require sales involvement. The customer can use the product, and the customer may even enter easily, yet the movement from product value to higher recurring spend remains blocked.

Hence, the findings answer the research question in configurational terms. High and low NRR are not associated with mirror-image conditions. Nor are they explained by any single element. High NRR is associated with a configuration that reduces commercial intervention across entry, usage, and expansion. The low-NRR solution, by contrast, consists of configurations where the primary expansion path remains mediated by sales intervention. This supports the study's core premise.

6.2 Pricing configuration as a value-capture architecture

The theoretical contribution of the high-NRR result lies in how C1C2C3 connects value creation and value capture. Baden-Fuller and Haeffliger (2013) frame business models as systems through which firms engage customers and monetize value, and Teece (2010) similarly treats the business model as the architecture through which firms create, deliver, and capture value. The present study applies that logic to SaaS pricing design. Pricing is not only the final step after value has been created. In recurring revenue markets, it shapes how value is captured over the life of the customer relationship.

Importantly, each condition present in C1C2C3 reduces commercial intervention at a different stage. C3 reduces intervention at entry by allowing the customer to test the product before paying. C1 can reduce the need for a separate commercial event between increased use and increased billing. C2 reduces intervention during expansion by allowing customers to increase usage, upgrade, or add functionality without a separate sales process. Together, the configuration can be interpreted as a more direct route from customer activity to recurring revenue.

This theoretical interpretation also connects to the economics of pricing and transaction costs reviewed earlier. Usage-based pricing reflects the logic that consumption can be metered and monetized through the pricing metric, as suggested by the literature on assessment bases and metered pricing (Lehmann & Buxmann, 2009; Oi, 1971). Self-serve expansion draws on transaction cost logic; if every expansion event requires search, negotiation, and contract execution, then growth inside an account carries commercial friction (Coase, 1937; Susarla et al., 2009; Williamson, 1975, 1985). Land-and-expand entry draws on free-trial and freemium

research, where early product experience can reduce uncertainty before purchase and help users evaluate product fit (Cheng & Tang, 2010; Cheng, Li, & Liu, 2015; Kumar, 2014). The QCA result supports this combined reading, since none of the three conditions is necessary on its own and only their joint presence passes the sufficiency threshold for high NRR.

Snowflake exemplifies this logic at the case level. The firm allows entry through a trial, monetizes use through consumption of compute, storage, and data transfer, and permits usage growth to translate into revenue without a separate sales event at each step. The case therefore gives empirical substance to the high-NRR configuration, C1C2C3, with a working path from first use to expanded consumption and revenue.

6.3 The role of self-serve expansion in the low-NRR findings

The low-NRR findings draw sharper attention to the role of C2. Self-serve expansion is not necessary for high NRR in the formal QCA sense, since no single condition is necessary. Still, its absence appears in both sufficient terms for low NRR. That pattern suggests that the expansion path may be the point at which otherwise promising pricing structures fail.

The first low-NRR term, C1~C2, captures firms with usage-based pricing but no self-serve expansion. Usage-based pricing can create a revenue basis that scales with consumption, but if customers must engage sales to expand, the connection between use and revenue is no longer direct. Demand may be visible in product usage, yet billing growth still depends on a commercial process. The pricing metric points toward expansion, but the expansion path reintroduces commercial friction. The second term, ~C2C3, captures firms with land-and-expand entry but no self-serve expansion. This result qualifies the positive reading of free trials and free tiers. Free entry may reduce adoption friction, but adoption is separate from revenue expansion. If a customer can enter easily but later needs sales contact to grow spending, the firm has only moved friction from the entry stage to the expansion stage. In that case, C3 can increase access without creating a smooth path to higher NRR.

This would explain why C3 changes meaning across configurations. In C1C2C3, it forms part of a broader revenue path. In $\sim$ C2C3, it appears in a low-NRR configuration. The condition is therefore not directionally stable on its own. Its association with the outcome depends on what surrounds it, which aligns with the study's QCA logic and with the broader configurational argument that performance relevance may depend on combinations rather than single choices.

6.4 Baseline customer value as a scope condition

The qualitative cases also confirmed an additional theoretical point. C1C2C3 should be read as an expansion-enabling configuration, not as a guarantee of high NRR. Pricing design can structure value capture, but it cannot by itself create customer value. This insight aligns with the theoretical position in Section 2.4, which rests on a baseline customer value assumption. Michel (2014) argues that firms often focus on creating customer value without paying enough attention to value capture. Yet the reverse is also true for this study, value capture mechanisms cannot generate durable expansion unless customers first derive value from the product. Zeithaml's (1988) definition of customer value as perceived utility clarifies the point. Expansion also depends on whether customers perceive continued paid use as worthwhile.

Snowflake and Amplitude make this distinction visible. Snowflake shows the configuration operating under conditions where continued and expanded use appears to be a natural path. Customers migrate workloads, consume more resources, and generate additional revenue through the pricing model. Amplitude shows the same configuration under weaker product-market conditions. Its MTU-based billing, self-serve Plus tier, and free entry tier are all present, but the product analytics category exposes the firm to credible free or low-cost substitutes as discussed in Section 5.3. Customers can reduce spend, consolidate tools, or move analytics needs elsewhere rather than deepen paid use.

In sum, this clarifies the context under which the identified mechanism is likely to operate. C1C2C3 can be interpreted as a channel through which customer use may become revenue expansion, but that channel only produces expansion revenue if customers continue to see enough value in the product. If the baseline value assumption is weakened by substitution, shallow adoption, weak product fit, or budget pressure, the configuration may remain present

without producing high NRR. Thus, Amplitude should not be discarded as an anomaly, its case clarifies the limits of the mechanism.

6.5 Contributions

This thesis makes three key contributions. Theoretically, it extends configurational business model thinking into SaaS pricing design. Prior literature treats business models as systems for value creation and value capture (Baden-Fuller & Haefliger, 2013; Teece, 2010), and Aversa, Furnari, and Haefliger (2015) show why combinations of business model elements may matter for performance. This thesis applies that logic to B2B SaaS by treating pricing model design as part of the business model's value-capture architecture. More specifically, the thesis specifies pricing model design as a staged value-capture architecture, with C3 governing entry, C1 governing the monetization of use, and C2 governing the conversion of account growth into revenue. Usage-based pricing, self-serve expansion, and land-and-expand entry are associated with higher NRR when they form a connected path from entry to use to expansion.

Empirically, the study analyzes 27 US-listed B2B SaaS firms using externally observable pricing model conditions and disclosed NRR data. This study provides usefulness and value to the academic field since academic work on SaaS pricing remains fragmented relative to the practitioner side, especially on usage-based pricing, product-led growth, and NRR (Saltan & Smolander, 2021). By employing QCA, the thesis provides a structured cross-case account of which pricing model configurations are associated with retention outcomes, rather than relying on single cases or practitioner benchmarks alone.

Practically, the findings suggest that SaaS managers should evaluate pricing model design as a revenue path. A free trial may help customers enter, but it does not secure expansion. Usage-based pricing may connect consumption to billing, but it can still fail if growth requires repeated sales contact. Finally, self-serve expansion may reduce friction, but only if it applies to the customers and product areas that account for most recurring revenue. The key question is whether these elements work together to move customers from product value to paid

expansion. Managers should therefore examine and diagnose where the expansion path may break.

It should be noted that this practical contribution follows certain boundaries. Several high-NRR firms fall outside C1C2C3, including firms in configurations 000 and 011, indicating that other routes of pricing model design are also associated with high NRR. Enterprise account management, customer success, product criticality, switching costs, and customer segment structure most probably remain relevant for supporting high retention, even when the pricing configuration studied here is absent. The central point is not that every SaaS firm should adopt C1C2C3, but rather that C1C2C3 is one identifiable pricing configuration associated with high NRR, and the thesis provides a theoretically grounded account of why that configuration may work.

6.6 Scope of the finding

The findings should be read as associations within a defined sample, not as evidence that pricing model design alone causes NRR. The claim made in this study is specific: among the firms studied, C1C2C3 is associated with high NRR, and the low-NRR solution is composed of configurations in which self-serve expansion is absent. This does not infer that pricing model design determines retention by itself. Additionally, because the sample is restricted to firms that voluntarily disclose NRR, it likely skews toward firms with more mature pricing infrastructure than the broader B2B SaaS population, further limiting the generalizability of the identified configurations. Further it should be noted that the finding is conditional on defining high NRR at 110%, a threshold anchored in benchmark evidence and empirical distribution, but one that shapes which firms constitute the outcome set.

The coverage values make this constraint visible. The high-NRR solution accounts for 46% of high-NRR cases, and the low-NRR solution accounts for 50% of low-NRR cases. Pricing model configuration therefore captures one part of the revenue expansion process, not the whole process. Product criticality, switching costs, customer success, customer segment mix, competitive intensity, and macroeconomic conditions likely explain part of the remaining variation.

These boundaries motivate the limitations discussed below, particularly those related to sample selection, crisp-set calibration, public-source measurement, NRR comparability, and timing.

7. Limitations

This study has several limitations. First, the sample is restricted to US-listed B2B SaaS firms that disclose NRR or a comparable retention metric. This improves comparability, but it also biases the sample by, likely, creating a directional selection mechanism. It excludes private SaaS firms and public firms for which comparable retention data are not readily available. Firms that voluntarily begin disclosing NRR may systematically differ from those that never disclose it: they tend to be larger, more mature, and more established in investor relations. The findings should therefore not be assumed to apply equally to earlier-stage firms, private companies, or SaaS firms in all regions. However, the selection concern is weaker for continuing disclosures than for initial entry into disclosure. Once a firm has begun reporting NRR, discontinuing it carries a negative signalling cost that creates a lock-in effect, keeping firms reporting the metric even when performance deteriorates. This is consistent with the presence of several low-NRR firms in the sample, including firms reporting NRR below 100% indicating that the disclosing population spans a meaningful range of retention outcomes rather than being filtered exclusively toward top performers.

Second, the study uses crisp-set calibration. This makes the analysis transparent and suitable for a small-N QCA design, but it also simplifies variation within each condition. Firms differ in how central usage-based pricing is to revenue generation, how broadly self-serve expansion applies across customer segments, and how meaningful a free tier or trial is for later conversion. This also means that firms close to the 110% NRR threshold may be sensitive to calibration

choices, even when the threshold is theoretically and empirically justified. The qualitative case analysis partly addresses this issue by showing that Amplitude displays all three conditions, but that the strength and scope of those conditions differ from Snowflake.

Third, the study relies on externally observable pricing model features. This is appropriate given the research design, but it limits what can be observed. Public pricing pages, SEC filings, product documentation, and investor communications do not reveal all customer-specific contract terms, negotiated discounts, internal customer success processes, or account-level expansion motions. As a result, the analysis captures the visible structure of pricing models rather than the full commercial process behind customer expansion.

Fourth, NRR is not defined identically across all firms. Although the study uses functionally comparable retention metrics and documents the source used for each case, differences remain in how firms treat overage charges, cohort definitions, currency effects, or revenue categories. The Amplitude case illustrates why this matters, its NRR definition excludes overage charges, even though overages are one way in which usage growth can become revenue. The crisp-set calibration provides partial mitigation: because firms are coded above or below 110% rather than ranked by precise NRR levels, small definitional differences are unlikely to shift outcome codings except for firms at the threshold. Fastly and Klaviyo which both qualify as firms with the C111 configuration, reported at 110.1% and 110% respectively, are therefore the firms most sensitive to this limitation, as a hypothetical definitional difference resulting in a, minor, reduction of their NRR percentage would affect their coding.

Fifth, the study's employment of temporal lag helps separate the pricing configuration from the outcome, but it assumes that firms did not materially change the relevant pricing model features during the outcome period. Because value metrics and self-serve infrastructure are usually strategic design choices rather than short-term tactical changes, this assumption is reasonable, but it cannot be verified perfectly from public sources. Entry mechanisms may change more easily, but such changes are still observable through archived pricing pages where available. This assumption was checked directly: archived pricing pages retrieved via the Wayback Machine were reviewed across the observation window for each of the 27 sample firms, comparing the pricing state coded at year-end 2024 against year-end 2025 captures. No

firm was found to have moved into or out of usage-based pricing, self-serve expansion, or land-and-expand entry during this period. Thus, we deem it unlikely that any company would have changed structure during the calendar year.

8. Conclusion

This thesis examined which configurations of pricing model design are associated with high and low Net Revenue Retention among US-listed B2B SaaS firms. Using crisp-set QCA on 27 firms, the study found no single pricing model condition to be necessary for either outcome. High NRR was associated with $C1C2C3$, the joint presence of usage-based pricing, self-serve expansion, and land-and-expand entry. Low NRR was associated with $C1\sim C2 + \sim C2C3$, where the absence of self-serve expansion appeared in both sufficient terms.

The findings matter given that NRR in SaaS concerns a broader issue than only keeping customers. It also concerns whether existing accounts continue to grow after adoption. In that setting, pricing model design appears to be associated with the route through which customer activity becomes retained and expanded revenue. Usage-based pricing, self-serve expansion, and land-and-expand entry together form a staged value-capture architecture that is associated with recurring revenue growth within the same cohort.

The qualitative cases define the scope of this argument. Snowflake exemplifies how the configuration can support retention when deeper product use translates into additional consumption and revenue. On the other hand, Amplitude shows why the same structure may be insufficient when the usage-to-revenue link is weaker, self-serve expansion is conditionally confined, and customers face credible free or low-cost substitutes. The central point is therefore that $C1C2C3$ can enable expansion within the retained customer base, but it depends on customers continuing to perceive enough product value to stay, use, and expand.

The thesis contributes to SaaS pricing research by specifying pricing model design as part of the firm's value-capture architecture. It also offers an empirical account of how observable pricing model conditions combine across public B2B SaaS firms with disclosed retention metrics. The study is bounded by its sample, crisp-set calibration, and public-source data. Future research could extend this study in several ways. A larger sample could test whether the identified configurations hold across a broader SaaS population. A fuzzy-set design could capture degrees of membership in usage-based pricing, self-serve expansion, and land-and-expand entry. Customer-level or contract-level data could examine whether the mechanisms identified here operate within accounts, rather than only at the firm level. Future research could also examine whether the configuration remains associated with high NRR after accounting for product category, customer segment, and enterprise exposure. Finally, future studies could add conditions outside pricing model design, such as product criticality, switching costs, customer success intensity, competitive substitution, and customer segment mix, to explain why some firms achieve high NRR outside C1C2C3 and why some firms with that configuration do not.

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AI disclosure

In accordance with Stockholm School of Economics' guidelines on the use of generative AI, we disclose how AI tools were used during the thesis process.

ChatGPT and Claude were used as supporting tools for review, critique, and technical assistance. Their role was limited to evaluating selected parts of the thesis and suggesting possible improvements in structure, clarity, consistency, and argumentation. The tools were also used to suggest and troubleshoot R code for the QCA analysis.

AI tools were not used to write the thesis text. Any suggestions concerning wording, structure, or argumentation were treated as feedback only. The authors decided independently whether and how to revise the text, and all final formulations were written, reviewed, and approved by the authors.

AI was not used to formulate the research question, collect the data, code the sample firms, set calibration thresholds, interpret the empirical results, or draw conclusions. AI was also not used as a source of factual, theoretical, or academic authority. All company information, source interpretations, coding decisions, R outputs, empirical findings, and conclusions were checked by the authors against the underlying material.

The main value of using AI was that it provided an additional source of feedback and supported the technical implementation of the QCA in R. The main risks were inaccurate suggestions, vague feedback, and undue reliance on generated output for R. These risks were addressed by treating all AI input as advisory and by retaining full authorial control over the thesis.

The authors remain fully responsible for the content, analysis, conclusions, and academic integrity of the thesis.

Appendix

Table 11. All firms in sample and their corresponding condition codings

Firm	C1	C2	C3
Crowdstrike	0	1	1
Okta	0	0	1
Box	0	1	1
Gitlab	0	1	1
Workiva	0	0	0
Sprout social	0	1	1
Datadog	1	1	1
Fastly	1	1	1
Amplitude	1	1	1
CS Disco	1	0	0
Braze	1	0	0
Cloudflare	1	1	1
N-able	1	0	1
Asana	0	1	1
Yext	0	0	0
Jfrog	1	1	1
Bandwidth	1	0	0
Pagerduty	0	1	1
Blackline	0	0	0
Monday	0	1	1
Hubspot	0	0	1
Figma	0	1	1
Klaviyo	1	1	1
Vertex	1	0	0
Zscaler	0	0	0
Intapp	0	0	0
Snowflake	1	1	1

Tables for robustness tests

Screenshots from R.

ROBUSTNESS CHECK 1A: THRESHOLD 105%

High NRR:

	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	1	5	0.800	0.800	5,15,19,25,26
2	0	0	1	0	2	0.500	0.500	2,21
4	0	1	1	0	8	0.500	0.500	1,3,4,6,14,18,20,22
5	1	0	0	0	4	0.500	0.500	10,11,17,24
6	1	0	1	0	1	0.000	0.000	13
8	1	1	1	1	7	1.000	1.000	7,8,9,12,16,23,27

Intermediate:						
From C1P1:						
M1: ~C1*~C3 + C1*C2*C3 -> NRR_105						
		inclS	PRI	covS	covU	cases
1	~C1*~C3	0.800	0.800	0.222	0.222	5,15,19,25,26
2	C1*C2*C3	1.000	1.000	0.389	0.389	7,8,9,12,16,23,27

M1		0.917	0.917	0.611		

Low NRR:

	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	0	5	0.200	0.200	5,15,19,25,26
2	0	0	1	0	2	0.500	0.500	2,21
4	0	1	1	0	8	0.500	0.500	1,3,4,6,14,18,20,22
5	1	0	0	0	4	0.500	0.500	10,11,17,24
6	1	0	1	1	1	1.000	1.000	13
8	1	1	1	0	7	0.000	0.000	7,8,9,12,16,23,27

```

Intermediate:

From C1P1:

M1:      C1*~C2*C3 -> NRR_105_low

              inclS    PRI    covS    covU    cases
-----
1  C1*~C2*C3  1.000    1.000    0.111    -      13
-----
              M1  1.000    1.000    0.111

```

ROBUSTNESS CHECK 1B: THRESHOLD 115%

High NRR:

	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	0	5	0.200	0.200	5,15,19,25,26
2	0	0	1	0	2	0.000	0.000	2,21
4	0	1	1	0	8	0.375	0.375	1,3,4,6,14,18,20,22
5	1	0	0	0	4	0.000	0.000	10,11,17,24
6	1	0	1	0	1	0.000	0.000	13
8	1	1	1	0	7	0.571	0.571	7,8,9,12,16,23,27

Note: no configuration reaches the 0.80 consistency threshold, so no minimization output is produced.

Low NRR:

	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	1	5	0.800	0.800	5,15,19,25,26
2	0	0	1	1	2	1.000	1.000	2,21
4	0	1	1	0	8	0.625	0.625	1,3,4,6,14,18,20,22
5	1	0	0	1	4	1.000	1.000	10,11,17,24
6	1	0	1	1	1	1.000	1.000	13
8	1	1	1	0	7	0.429	0.429	7,8,9,12,16,23,27

```

Intermediate:

From C1P1:

M1:      ~C2 -> NRR_115_low

              inclS    PRI    covS    covU    cases
-----
1  ~C2  0.917    0.917    0.579    -      5,15,19,25,26; 2,21; 10,11,17,24; 13
-----
              M1  0.917    0.917    0.579

```

ROBUSTNESS CHECK 2A: CONSISTENCY THRESHOLD = 0.75

High NRR:

OUT: output value								
n: number of cases in configuration								
incl: sufficiency inclusion score								
PRI: proportional reduction in inconsistency								
	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	0	5	0.600	0.600	5,15,19,25,26
2	0	0	1	0	2	0.000	0.000	2,21
4	0	1	1	0	8	0.500	0.500	1,3,4,6,14,18,20,22
5	1	0	0	0	4	0.000	0.000	10,11,17,24
6	1	0	1	0	1	0.000	0.000	13
8	1	1	1	1	7	0.857	0.857	7,8,9,12,16,23,27

Intermediate:						
From C1P1:						
M1:	C1*C2*C3 -> NRR					
		inclS	PRI	covS	covU	cases
1	C1*C2*C3	0.857	0.857	0.462	-	7,8,9,12,16,23,27
	M1	0.857	0.857	0.462		

Low NRR:

OUT: output value								
n: number of cases in configuration								
incl: sufficiency inclusion score								
PRI: proportional reduction in inconsistency								
	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	0	5	0.400	0.400	5,15,19,25,26
2	0	0	1	1	2	1.000	1.000	2,21
4	0	1	1	0	8	0.500	0.500	1,3,4,6,14,18,20,22
5	1	0	0	1	4	1.000	1.000	10,11,17,24
6	1	0	1	1	1	1.000	1.000	13
8	1	1	1	0	7	0.143	0.143	7,8,9,12,16,23,27

Intermediate:

From C1P1, C1P2:

M1: C1*~C2 + ~C2*C3 -> NRR_low

		inclS	PRI	covS	covU	cases
1	C1*~C2	1.000	1.000	0.357	0.286	10,11,17,24; 13
2	~C2*C3	1.000	1.000	0.214	0.143	2,21; 13
	M1	1.000	1.000	0.500		

ROBUSTNESS CHECK 2B: CONSISTENCY THRESHOLD = 0.85

High NRR:

OUT: output value
n: number of cases in configuration
incl: sufficiency inclusion score
PRI: proportional reduction in inconsistency

	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	0	5	0.600	0.600	5,15,19,25,26
2	0	0	1	0	2	0.000	0.000	2,21
4	0	1	1	0	8	0.500	0.500	1,3,4,6,14,18,20,22
5	1	0	0	0	4	0.000	0.000	10,11,17,24
6	1	0	1	0	1	0.000	0.000	13
8	1	1	1	1	7	0.857	0.857	7,8,9,12,16,23,27

Intermediate:

From C1P1:

M1: C1*C2*C3 -> NRR

		inclS	PRI	covS	covU	cases
1	C1*C2*C3	0.857	0.857	0.462	-	7,8,9,12,16,23,27
	M1	0.857	0.857	0.462		

Low NRR:

```

OUT: output value
n: number of cases in configuration
incl: sufficiency inclusion score
PRI: proportional reduction in inconsistency

```

	C1	C2	C3	OUT	n	incl	PRI	cases
1	0	0	0	0	5	0.400	0.400	5,15,19,25,26
2	0	0	1	1	2	1.000	1.000	2,21
4	0	1	1	0	8	0.500	0.500	1,3,4,6,14,18,20,22
5	1	0	0	1	4	1.000	1.000	10,11,17,24
6	1	0	1	1	1	1.000	1.000	13
8	1	1	1	0	7	0.143	0.143	7,8,9,12,16,23,27

Intermediate:

From C1P1, C1P2:

M1: C1*~C2 + ~C2*C3 -> NRR_low

		inclS	PRI	covS	covU	cases
1	C1*~C2	1.000	1.000	0.357	0.286	10,11,17,24; 13
2	~C2*C3	1.000	1.000	0.214	0.143	2,21; 13
	M1	1.000	1.000	0.500		

Table 12. Complementary information on data sources

Source category	Companies covered	Main use in thesis
SEC annual filings, primarily Form 10-K and, for monday.com, Form 20-F	All 27 sample firms	Collection of NRR figures, fiscal-year information, financial disclosures, and coding of conditions
SEC quarterly filings, primarily Form 10-Q	Used where annual filings did not provide the closest relevant disclosure	Verification of NRR figures, timing and company-specific retention disclosures
Archived pricing pages via the Wayback Machine	All firms where public pricing information was available	Coding of value metric type, self-serve expansion, and land-and-expand entry as of year-end 2024
Investor presentations and earnings call transcripts	Used where filings or pricing pages required corroboration	Supplementary evidence for NRR, pricing model interpretation, and qualitative case analysis

Table 13. Data sources for Qualitative Complement

Company / source	Source type
Snowflake, Inc.	Form 10-Q (quarter ended October 31, 2024)
Snowflake, Inc.	Form 8-K (Q1 FY2025 earnings release)
Snowflake, Inc.	Form 10-K (Fiscal year ending January, 31, 2025 & 2026)
Snowflake, Inc.	Pricing and free-trial documentation
Snowflake, Inc.	Q4 FY2025 earnings call transcript / investor relations material
Amplitude, Inc.	Form 10-K (Fiscal year ended December, 31, 2024)
Amplitude, Inc.	Pricing page
Google	Product documentation and product page
U.S. Securities and Exchange Commission (SEC)	SEC EDGAR database
PostHog, Inc.	Product and pricing page