Managing Software-as-a-Service: Pricing and Operations

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Software-as-a-Service (SaaS) applications have experienced a decade of explosive growth, eliminating barriers in reaching users and enabling real-time interchanges and intelligence. Using business analytics, SaaS applications are increasingly embedded in the day-to-day activities of businesses and consumers with competition and innovative pricing. Due to the evolution in cloud business models, new issues are surfacing to challenge practitioners and scholars. A number of issues encountered in the practice have not been properly addressed or even recognized. In this paper, we attempt to fill this important gap. We propose a framework of recent business research on SaaS in light of wide adoption of the SaaS business model. This framework broadly classifies SaaS research into two basic themes. For each theme, we review past work that has been instrumental in setting the direction of this line of research and discuss how emerging research opportunities can be addressed. For each research opportunity, we also propose an initial model and the applicable methodology. Further, in order to aid researchers, we identify the data sources wherever applicable, and even present some of the initial results. We conclude by describing promising directions on a roadmap for future research and explain why an integrative perspective of operations, marketing, and information systems is critical to SaaS. In this paper, we bridge the gap between research and practice by identifying the relevant industry problems that would help researchers who are interested in working in this area both to get a starting point and to address important theoretical and practical challenges.

Key words: business analytics, pricing, service operations, Software-as-a-Service

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1 Introduction

Gartner (2021) predicts the revenue of worldwide SaaS services reaching \$145 billion by 2022 at a compound annual growth rate of 18.9% since 2020, and IDC (2018) predicts that by 2025, 46% of the world's stored data will reside in clouds. These economic indicators and the rapid growth signal the importance for the academic community to adequately study the management of SaaS to guide the future development of these services. However, there has been limited research in SaaS management. For instance, what pricing and operational policies should a SaaS provider adopt under heterogeneous user concerns on security and privacy? Why would SaaS usage patterns influence pricing and quality decisions? Research on industry problems has gaps in certain themes, and bridging these gaps is the eventual goal of this paper.

The National Institute of Standards and Technology (NIST) defines SaaS as the capability provided to the consumer of using the provider's applications running on a cloud infrastructure where the applications are accessible from various client devices and interfaces and the consumer generally does not manage or control the infrastructure (Mell and Grance 2011). According to this definition and extant studies (e.g., Feng et al. 2018), key differences between SaaS and traditional software are Internet delivery and multi-tenancy, which distinguishes SaaS research from traditional information systems analysis. We thus summarize unique features of SaaS into two categories:

- Those derived from Internet delivery: No geographical constraint, ease of monitoring user behavior, congestion, and integration with third-party application programming interface (API).
- Those derived from multi-tenancy: Security and privacy concerns, ease of deployment and updates, limited user control on the application, and the possible outsourcing of infrastructure.

These unique features lead to six special business characteristics of SaaS:

1. The variety of pricing options, low prices, and free trials.
2. Internet marketing, fierce competition, and viability of specialized services.
3. Integration with platforms, social networks, and user devices.
4. Analytics and improvements based on user-generated data.
5. Scalability, rapid elasticity, but challenging customization.
6. Service quality, security, and privacy issues could impact all users.

1.1 The Framework

To identify relevant themes in SaaS research, we have conducted a literature search in leading operations management and information systems journals between January 2011 and August 2021 and found 31 relevant papers listed in Table EC.7. The sources are outlined in Figure EC.1, and the trend of the papers found is shown in Figure EC.2. It can be seen that the number of SaaS papers increased gradually in the last decade. Using the abstracts of these 31 papers, we have identified multiple topics using topic modeling, and the results are shown in Figure 1: Topic 1 is about the general business model, Topics 2 and 4 are about operations, and Topic 3 is about pricing. We also verify the pricing and operations schemes by checking the key words and key findings of these papers (see Table EC.8 in the E-Companion). Therefore, in this paper, we focus on pricing and operations aspects of SaaS.

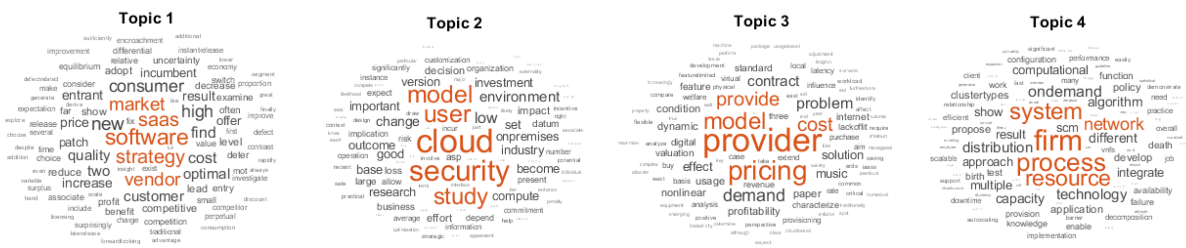

Figure 1 Themes in SaaS-related research

Johnson et al. (2008) define a business model as interlocking elements that create and deliver value together: customer value proposition, profit formula, key resources, and key processes, where the *customer value proposition* means a way to help customers solve a fundamental problem in a given situation, and the *profit formula* defines how the company creates value for itself while providing value to customers. According to this definition, we argue that at the tactical level, pricing and operations characterize the provider's profit formula (revenue and cost) by utilizing key resources and implementing key processes. Like any business, customers perceive the value of a SaaS offering through fees paid (pricing) and benefit received (operations). Based on the definition of business model and motivated by our topic modeling results, we focus on two themes shown in Figure 2 with further subdivision into eight topics shown in Figure 3.

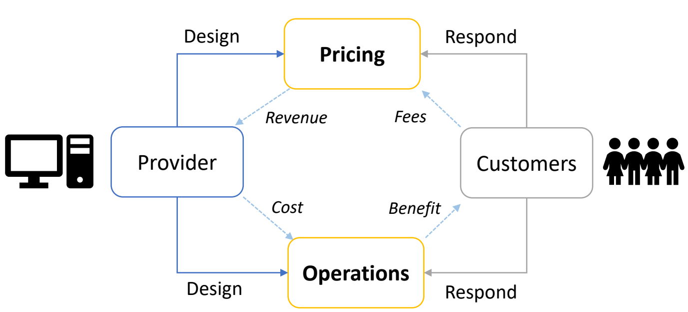

Figure 2 Areas of SaaS research

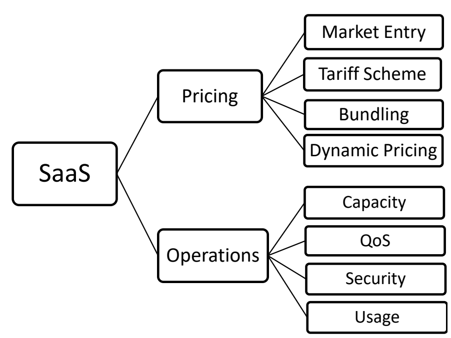

Figure 3 Topics of SaaS research

1.2 Methodologies

Diverse research methodologies can be found in SaaS research, such as queuing (e.g., Li and Kumar 2018, Saha et al. 2021), econometrics (e.g., Chu and Manchanda 2016), and mixed methodologies (e.g., Mookerjee et al. 2017). These methodologies facilitated the Federal Communications Commission's successful auction of wireless spectrum since 2010 (Kiddoo et al. 2019, Kumar 2021).

Rooted in the Internet and cloud computing, SaaS may aggregate diverse data sources to create "data lakes" for business analytics. For example, ZJ Technology, a hotel management SaaS provider, features multi-tenant data architecture where most customers share the same database and tables (except for some large enterprise clients). Its co-founder, Hilda Lo, said (Lo 2021), "*We record data from payments, room records, staff schedules, and CRM (customer relationship management) tools. We then benchmark performance metrics across hotels.*" Having learned that such data architecture is common in the SaaS industry, we conclude that data supporting SaaS research is abundant but challenging to obtain due to privacy and confidentiality concerns.

Following Gartner's analytics ascendancy model, we classify business analytics methodologies used in SaaS research to four broad categories: businesses identity what happened with *descriptive analytics*, uncover the reasons via *diagnostic analytics*, make predictions via *predictive analytics*, and pinpoint possible interventions via *prescriptive analytics*, as shown in Figure 4. These four categories ascend with both more value and more challenges (Chandler et al. 2011). In Sections 2 to 4, we discuss past studies in each area and propose emerging research problems followed by a discussion of the actual models and data sources.

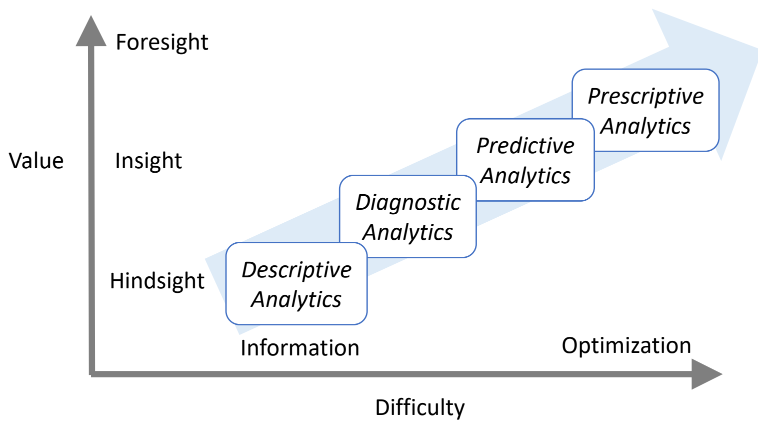

Figure 4 Gartner's 4-Level Analytics Ascendancy Model (Adapted from Chandler et al. 2011)

2 SaaS Pricing

In this section, we begin with an example of SaaS pricing challenges driven by competition, cost structure, and customer preferences. We then discuss a likely cause of new pricing decisions (entering a new market) to underline the strategic delicacy of SaaS pricing beyond optimizing revenue alone. After showing the importance and complexity of SaaS pricing, we zoom in on the pricing schemes under various scenarios. For many SaaS offerings, the price is static (Steele and Mickle 2019). Based on the industry practice, we categorize these static pricing schemes into individual pricing for homogeneous services (tariff) (Iyengar et al. 2011) and aggregate pricing for heterogeneous services (bundling) (Jones 2013), depending on the variety of services. For some SaaS offerings, prices change temporally (i.e., they have dynamic pricing) (Spann et al. 2015). We discuss what may drive this deviation from static pricing. We conclude by illustrating three research opportunities.

2.1 Apple Music: Revamping Pricing Schemes for Digital Services

Since 2003, Apple Inc. has operated an iTunes Store that unbundles songs from physical albums and distributes digital music to iPods and iPhones with a price for each song (often 99 cents), replacing Napster as the market leader for acquiring music legally online and becoming the biggest music retailer worldwide in 2010 (Ingraham 2013). Despite the iTunes Store's success, on June 30, 2015, Apple Inc. launched the Apple Music streaming service in over 100 countries (Apple Inc. 2015). At launch, Apple Music charged a $9.99/month subscription fee for an individual user and $14.99/month for a family (up to six family members). Apple Music quickly gained market advantages over incumbent digital music providers by re-bundling previously-unbundled iTunes songs (Steele and Mickle 2019). This suggests that revamping SaaS pricing schemes can create competitive advantages and lead to new research opportunities.

2.2 Pricing for Market Entry

As SaaS providers grow, they enter new markets with better products and sales efforts, often with competitive pricing. Apple's entry into the music subscription market is one example. As another example, Steve Pratt, CEO and founder at Noodle.ai, suggests seizing the recent supply chain chaos opportunity to market their supply chain analytics solutions in SaaS (Amazon AWS 2021): *"Global CPG (consumer packaged goods) leaders spent decades capturing and organizing data (e.g., data lakes), building capabilities, and feeding planning systems that blew up in an instant in 2020.... We firmly believe CPG industry leaders are willing to invest in technologies that can help solve critical challenges."*

With business customers, Benlian and Hess (2011) analyze a survey of 349 German IT executives and find that cost advantages affect perceptions of SaaS opportunities heavily, whereas uncertainties in cost savings and quality improvements keep potential adopters at bay. To resolve these uncertainties, potential SaaS customers want to evaluate the software prior to purchase, and proving the value via demos (e.g., Zendesk) and pricing can facilitate the purchase and migration (Grieve 2021). Towards adoption, many business customers start from a basic SaaS application before moving to sophisticated SaaS applications following the LAER (Land, Adopt, Expand, Renew) model proposed by The Technology & Services Industry Association (2017). Hence, SaaS providers may offer some basic services with attractive pricing first to facilitate customer success and then expand the service portfolio, as Rhett Glauser (an executive at ServiceNow) puts it (2checkout 2012): *"We've been successful because we have successful customers, a rabid fan base. These guys tell their friends, these guys take us with them to their next gig."*

For many software markets, incumbents remain providers of off-the-shelf (OTS) software that is often customized for heterogeneous clients, whereas SaaS is not, meaning that an unfit disutility is attributed to SaaS. OTS and SaaS differ in revenue structure (one-time vs. usage-based per billing period), cost structure (high initial cost vs. usage-based), and customer value (without/with unfit disutility) in addition to delivery method and architecture. For example, Ma and Seidmann (2015) examine competition between customized commercial OTS software and un-customized SaaS where the user firm faces stochastic demand and customers learn their fit after making their OTS/SaaS choice with exit and switching permitted. They find that both providers may co-exist, but reducing lack-of-fit costs intensifies competition and pushes SaaS to dominance; Li et al. (2018) echo this. With a related setting where the SaaS provider conducts continuous quality improvements and an OTS provider offers upgrade, Guo and Ma (2018) find that prices of OTS upgrades can be low to attract upgrades or in response to an SaaS entrant or possibly deter weak SaaS entrants under continuous quality improvement. Zhang et al. (2022) find that an entrant could gain foothold of a quality-differentiated information goods market with subscription pricing.

Incumbent providers' responses vary. Some, such as Adobe Systems Inc., stop selling boxed-software and become SaaS providers. By doing so, Adobe was able to continue its dominance of the market (Jones 2013). For a pure-SaaS market, Feng et al. (2018) show that a high-quality entrant to a SaaS market dominated by an incumbent prefers instant-release of the service with high pricing under within-product and cross-product network effects, whereas a low-quality entrant prefers late-release with low pricing. Xiao et al. (2020) define SaaS churn as "premature termination of the use of the current SaaS system and replacement of it with an alternative" and establish how commitment to the SaaS product and commitment to the cloud computing technology impact churns. Going a step further, a provider could strengthen such commitments by outstanding customer service and cost reimbursement (see, for example, RO3 and Xiao et al. 2020), which deserves further research. See Table EC.1 for a summary of the aforementioned studies.

2.3 Tariff Schemes

Tariff choice for homogeneous services is generally a nonlinear pricing problem where subscription pricing (a.k.a., flat-fee), two-part tariff (2PT), and three-part tariff (3PT) are ubiquitous choices. In the remainder of this subsection, we delineate the assumptions and findings using a coherent set of notations. 2PT contains an access fee (denoted as a) and a per-unit usage fee (denoted as u) where the service quantity (usage) is denoted as q. Subscription pricing (i.e., $u = 0$) and pay-per-use (i.e., $a = 0$, also known as pay-as-you-go) are special cases of 2PT (Jain et al. 2020). 3PT contains a base fee (denoted as b), an allowance of free units, and an additional fee for overage. Table EC.2 offers a summary of popular tariff schemes (where P denotes payment to the provider). We observe that SaaS providers sometimes adopt subscription pricing and sometimes use tiered (nonlinear) pricing and pay-per-use pricing to account for usage. One could find 2PT and 3PT in SaaS, too. As a variant of the subscription pricing scheme adopted by Apple Music, some SaaS applications charge by the number of users (e.g., Apple Music family plans) with possible quantity discounts. Xin and Sundararajan (2020) find that this nonlinear pricing problem can be decomposed into a set of simpler subproblems under inelastic individual usage. In addition to these, complex contracts could be found (Susarla and Barua 2011) and sometimes enforced (Zhao et al. 2021). Many providers such as Twilio even have several options for their customers to choose from (e.g., pay-per-use and subscription). Features of these SaaS tariff models are tabulated in Table EC.3.

2.3.1 Comparing tariff schemes

Generally, a SaaS application administers the same pricing within a country (e.g., Netflix Inc. 2020), and such pricing is sometimes a function of usage. Note that specific discussions about usage can later be found in Section 3.5. Another popular pricing scheme, per-user pricing, has compliance challenges. For access services, Iyengar et al. (2011) discover that consumers prefer pay-per-use to two-part tariffs. Bagh and Bhargava (2013) show that 3PT is superior to 2PT in efficiency and find that a small menu of 3PTs designed with less information can be more profitable than a menu of 2PTs of any size. Observing consumer switching between 2PT and 3PT, Lambrecht et al. (2007) show that higher usage variation steers customers toward high allowances under 3PT. Bhargava and Gangwar (2018) find that when demand has an increasing price elasticity, the optimal 3PT has an equivalent optimal 2PT. Despite these advantages, 3PT is not often adopted in SaaS, partly due to negligible usage costs for some high-value SaaS and the presence of switching costs. By comparing varioius tariff schemes, Fibich et al. (2017) find that a fixed fee is usually necessary, but an overage fee is optimal only if usage is costly and consumers are homogeneous. Different from studies involving 2PT/3PT, Li et al. (2020) incorporate an additional ad-supported option for digital music and find that subscription pricing (e.g., Apple Music) is preferred to a fee per song (e.g., iTunes) when usage cost and advertisement revenue are low. There remain considerable research gaps in optimizing SaaS subscription pricing as shown in RO3.

2.3.2 Impact of capacity on tariff scheme

Leveraging on the general theory about tariffs, researchers incorporate real-world considerations such as capacity-related delays (more in Section 3.2) to evaluate tariff schemes. Essegaier et al. (2002) examine a choice among subscription pricing, usage pricing, and two-part tariff. They assume a capacity limit K and binary heavy/light users where heavy (light) user segments constitute α $(1-\alpha)$ fraction of the market and use q_H (q_L) units of capacity. Consumers feature a reservation price v and vary in fit (represented by the position x on a Hotelling line). The capacity constraint is $(1-\alpha)x_l q_l + \alpha x_h q_h \leq K$, where x_l and x_h are fractions of subscribers for each service. They conclude that when capacity is plentiful, market penetration should be the strategy with subscription pricing being the tactic. The takeaway is that when capacity utilization is low (true for most SaaS), subscription pricing is preferred.

2.3.3 Impact of usage on tariff scheme

Usage is crucial for tariff scheme choice. In an early study, Sundararajan (2004b) finds that introducing subscription pricing is always profit-improving with transaction costs associated with administering usage-based pricing in quantity-price pairs. In another early study, Jain and Kannan (2002) consider search-based pricing, subscription-fee pricing, and connection-time-based pricing and derive general conditions under which subscription-fee pricing is optimal. They find that undifferentiated online servers may co-exist and that higher server costs and consumer valuation heterogeneity may encourage differentiation. Recent studies reaffirm the preference towards subscription pricing. Bala and Carr (2010) consider per-use valuation heterogeneity and usage heterogeneity, compare fixed-fee and usage-fee, and do not include capacity considerations. They model each customer's utility from service as vqu where $v \in [0,1]$ is single-use utility, $q \in [0,1]$ is frequency of use, and u is service quality, analogous to customer fit. A customer purchases the service if $vqu - p_f > 0$ for fixed-fee (p_f) and if $q(vu - p_u) > 0$ for usage-based pricing (p_u per unit usage). They find that light users acquired via usage-based pricing are unlikely to compensate for the monitoring costs incurred. Hence, SaaS managers should be cautious about implementing usage-based pricing in a competitive setting. More studies related to usage will be discussed in Section 3.5.

2.4 Bundling

Bundling is a popular scheme for quantity-based pricing for heterogeneous goods. This scheme is not uncommon in SaaS: Apple Music is a collection of music pieces, Adobe combines its popular products in their Adobe Creative Cloud (Jones 2013), and Box Inc. bundles their storage with enterprise applications (Barret 2013). Bundling of information goods is a challenge for firms but may produce substantial economic benefits (Adams and Yellen 1976), such as the Microsoft Office Suite, when consumer valuations of the components in the bundle are positively correlated (Gandal et al. 2018). In a seminal paper, Bakos and Brynjolfsson (1999) denote the valuation of good i out of a total of n goods as $U_{ni}(\omega)$ for customer $\omega \in \Omega$ where $U_{ni}(\omega)$ are independent for any given n. Using the weak law of large numbers that facilitates prediction of customer valuation, Bakos and Brynjolfsson (1999) show that the benefits of large bundles of unrelated information goods persist even under positive correlation between goods' valuations. However, their pricing method may produce a very high bundle price for large bundles (Geng et al. 2005). Bundling fits SaaS applications nicely due to their low marginal cost and vast variety. For example, Bakos and Brynjolfsson (1999) find that unified bundling by a collection of single-good monopolists selling the goods to a single distributor is preferred, which partially explains the success of subscription-based online content providers.

However, bundling too much may not be optimal. In two-sided networks, the network externality coupling encourages unbundling and subsidizing one side to increase transactions volume (Parker and Van Alstyne 2005). In the presence of positive marginal costs, Abdallah (2019) compares pure bundling mechanism to theoretical profit bounds and provides analytics to quantify the allocation inefficiency created by large-scale bundling where user valuation of certain bundled goods is lower than the marginal production cost. Geng et al. (2005) analyze the price of a bundle, rather than the price of a good in a bundle (e.g., Bakos and Brynjolfsson 1999) and show that bundling's degree of optimality is generally high if consumers' values do not decrease too quickly. Unlike Bakos and Brynjolfsson (1999), Geng et al. (2005) model the value of a bundle to the customer as $Y(\omega) = \sum_{i=1}^{\infty} c_i X_i(\omega) = \lim_{n\to\infty} \sum_{i=1}^{n} c_i U_{ni}(\omega)$ and assume the series $(c_1, c_2, \cdots, c_i, \cdots)$ to eventually decrease to 0 for customer $\omega \in \Omega$. For the finite mean (μ) and finite variance (σ^2) of $Y(\omega)$, when σ/μ is small, pure bundling achieves the majority of the profit of a perfectly-discriminating monopolist.

Mixed bundling (i.e., selling both bundles and individual goods) is challenging to analyze, and researchers respond by reducing the problem space. Hitt and Chen (2005) show that out of a total of N goods, the complex mixed-bundle problem ($2^N - 1$ possibilities) can be reduced to the cardinality-bundle problem (N possibilities). They also propose a computational pricing strategy that Wu et al. (2018) improve later by having fewer restrictions and an efficient combinatorial solution approach for both discrete and continuous problems. With the discovered advantages and drawbacks of bundling, we conclude that SaaS bundling (and core bundling) deserves further research, especially for flagship SaaS products with superior valuations that may sell separately from a bundle (e.g., RO2). See Table EC.4 for a classification of bundling studies.

2.5 Dynamic Pricing

Dynamic pricing such as Uber's surge pricing is common in retail, travel, and on-demand services, and less so for manufactured products (Spann et al. 2015). However, pure dynamic pricing in SaaS is still uncommon, partly due to the ease of product differentiation in SaaS (e.g., the exclusive albums on Apple Music). As another reason, enterprise customers seek predictable operating costs by using SaaS, but dynamic pricing adds a layer of unpredictability to financial planning.

Even if retail prices remain stable, it is possible to use limited-time discounts and promotion codes to change real prices dynamically and try A/B testing for different prices. Some commodity SaaS services, for example, VPN (virtual private client) services, are in a price war where providers often discount their services (VPN Overview 2021). Moreover, a provider could run promotions at the end of quarters to meet growth plans and attract clients dealing with new budgets.

Separate from sales, the need for dynamic pricing may emerge from cloud computing providers adjusting prices for computing instances in different regions due to demand fluctuations in these spot markets, and Passacantando et al. (2016) provide an algorithm for SaaS providers to manage multiple cloud computing providers in real time. This is despite the fact that there are reservations and preemptible instances (e.g., Chen et al. 2021) for customers preferring cost stability. For the cloud computing market, Cheng et al. (2015) find that larger latency effects result in larger pricing differentials by analyzing the pricing dynamics of Amazon EC2 U.S. East and West markets. For the providers, Dierks and Seuken (2021) develop a condition under which a cloud computing provider may prefer to offer a spot market using idle resources to both increase profit and enhance user welfare. Due to spot market fluctuations, SaaS providers may want to charge users differently based on time and server location. We conclude that dynamic pricing research in SaaS is scarce but necessary to understand the related factors and the feasibility of dynamic pricing tactics, and we will present an example in RO1.

Adding to the challenges of dynamic pricing, network effects are not uncommon in SaaS and information services at large. For example, Apple Music and Spotify allow listeners to learn from the tastes of each other based on social networks (Hagiu and Wright 2020), which in turn would dynamically impact usage and willingness-to-pay for a music streaming subscription. The formulation of network effects in SaaS can be classified into four categories: linear in network size (Niculescu et al. 2012), nonlinear in network size (Chu and Manchanda 2016), two-sided network (Chu and Manchanda 2016, Parker and Van Alstyne 2005), and industry-wide network (Nair et al. 2018).

2.6 New Research Opportunities in SaaS Pricing

SaaS applications often introduce new pricing plans that connect the provider and the market, as shown in Figure 2. We propose two ROs listed in Table 1 based on emerging industry practices.

Table 1 Future research opportunities in SaaS pricing

	RO1	**RO2**	**RO3**
Summary	Dynamic pricing in SaaS	Building a core bundle	Pricing for SaaS market penetration
Methodology	Diagnostic / Predictive / Prescriptive Analytics	Diagnostic / Predictive / Prescriptive Analytics	Descriptive / Diagnostic / Predictive Analytics
Research Questions	*Should SaaS providers adopt dynamic pricing?*	*Should SaaS providers offer a core bundle of individual services?*	*Could reimbursing or reducing lack-of-fit costs help penetrating a SaaS market?*
Industry Examples	Netflix	Microsoft Office	Noodle.ai
Examples of Data Source	Latka (2021)	Poyar (2020)	Wharton Customer Analytics (2012)

2.6.1 RO1: Dynamic pricing in SaaS

When economic conditions evolve, an SaaS application may want to change prices over time. Netflix is a classic example of penetration pricing: entering the market at a low price and increase it thereafter. Prophet, a leading supply chain planning SaaS, designs dynamic pricing plans that are tied to client metrics that evolves over time due to demand growth and supply chain reconfigurations (Kennedy 2016). A natural research question follows: *Should SaaS providers adopt dynamic pricing?* To understand when and why dynamic pricing is adopted and sustained in a SaaS market, similar to Spann et al. (2015), one may conduct an empirical study on price changes in SaaS subscription plans. For this study, one could use lists of SaaS companies, say the Golden Research Engine (Golden Recursion Inc. 2021), and GetLatka (Latka 2021), to track the pricing tactics of companies. Moreover, GetLatka contains business metrics and podcasts about the SaaS companies and their CEOs. On the cost side, the Amazon EC2 spot pricing data (Amazon Web Services 2021) can be used to analyze cost dynamics.

The following model classifies the pricing tactics of SaaS services into latent classes.

$$\log p_{it} = \sum_s \pi_s h_s(\alpha_0 + \alpha_{1s} + \alpha_{2s}\log ProductAge_t + \alpha_{3s}\log ProductAge_{it} + \boldsymbol{\beta PI_i} + \boldsymbol{\gamma Dummies_t})$$

where p_{it} is the retail price of SaaS product i in year t, π_s is the probability of class membership, h_s is class-specific density function, $ProductAge_{it}$ is the SaaS-service-specific service age (elapsed months since launch), $ProductAge_t$ is the average of $ProductAge_{it}$, PI_i are the indicator variables for integration with various platforms, and $Dummies_t$ are the time and service attribute dummies. There are two possible results from this econometric model:

1. Coefficient estimates on whether factors such as user-generated data and platform integration matter: CRM might be more likely to use penetration pricing than a document tool.
2. Firm-level data could be added to explore how π_s (and the use of penetration pricing) depends on business factors such as product differentiation. For example, extant studies argue that undifferentiated products encourage penetration pricing.

To derive normative predictions, one may analyze equilibrium outcomes for the choice among skimming pricing and penetration pricing using a two-period game-theoretic model. Consider a SaaS provider entering a new market. Let the value of service be k_0 at time $t = t_1$ and $k_0 + f(n_1)$ at time $t = t_2$, where n_1 is the number of subscribers at t_1, and $f(n_1)$ is the value of user-generated data at t_2. Let $f(\cdot)$ be increasing and concave. Denote the number of potential subscribers by A_i, $i = 1, 2$. The $\beta(n_1)$ subscribers that stay with the service will be charged the minimum of p_1 and p_2 in period-2. The number of subscribers are $n_1 = g_1(k_0, p_1, A_1)$ and $n_2 = \beta(n_1) + g_2(k_0 + f(n_1), p_2, A_2)$. The problem of maximizing the expected profit of the SaaS provider is therefore

$$\min_{\{p_1,p_2\}} \pi(p_1, p_2) = p_1 n_1 + \min\{p_1, p_2\} \cdot \beta n_1 + p_2(n_2 - \beta n_1).$$

The predictions of the game theory model (prices) could then be compared with empirical findings (predicted prices and coefficients) and jointly answer the research question. It is possible to perform finer customer segmentation after gaining knowledge about customer behavior.

This RO provides a new opportunity for providers to generate more revenue from customers and align pricing with customers' perceived value of the service, which is crucial both to the bottom-line and to adoption by potential customers. For dynamic pricing under cost uncertainty, this RO contributes to the link between pricing and operations in SaaS. For dynamic pricing under market uncertainty, this RO contributes to the link between pricing and customer characteristics in SaaS.

This RO expands the current literature which is primarily about static pricing (tariff and bundling) and adapt dynamic pricing research on cloud computing to the business models of SaaS and to its customers. Since bundling may incorporate more uncertainties in cost and market than standalone offerings, it is also possible to create bundles that adopts dynamic pricing.

2.6.2 RO2: Building a core bundle

The first version of Microsoft Office Suite for Windows included Word, Excel, and PowerPoint back in 1990 (Da Costa 2018). A few years later, Microsoft added Mail (Outlook) and OneNote to the bundle. Some applications such as Frontpage and PhotoDraw were once in the bundle but later discontinued or removed, but several popular Microsoft business applications such as Project and Visio (with the exception of Visio Viewer) were not in the Microsoft Office Suite. Since 2011, a subscription option called Microsoft Office 365 is offered and includes SaaS applications such as OneDrive, Teams, and SharePoint, in addition to cloud versions of classical applications such as Word. Microsoft Office 365 has different versions tailored to enterprises, educational institutions, and individuals (Da Costa 2018).

Accounting for usage uncertainty in SaaS, a provider may build a core bundle of popular services that is not sold separately (e.g., the Microsoft Office 365 Suite) and complement the core bundle with standalone offerings. Evidenced by Microsoft Office, this strategy may suit providers that operate several leading services. Typically, the price of a core bundle of SaaS applications is for a monthly, yearly, or permanent license. Hence, a research question is: *Should SaaS providers offer a core bundle of individual services?* If a core bundle is deemed necessary, the next steps are examining how to assemble and price such a bundle, which we will address in this RO.

To answer this research question on building a core bundle, the first step is to understand the value of each software component. SaaS providers collect usage information easily. The dataset in Poyar (2020) indicates that 38% of SaaS companies adopt pricing plans based on usage (transactions, storage, computing, servers). It would be meaningful to collect information on usage (say, during a free trial) and estimate willingness-to-pay (WTP) for unit usage in unbundled services to design a core bundle. It is also possible to use surveys and case studies to document and analyze how SaaS providers bundle their services with usage considerations. Table 2 summarizes key variables that can be collected and used in the subsequent optimization model (e.g., usage is a critical factor in determining the core bundle). Ideally, a panel dataset could be formed to develop a dynamic understanding about the core bundling strategy.

After estimating the value of each service, the core bundling optimization problem can be solved. Consider a SaaS provider offering I services where each service is indexed by i. The provider creates a single core bundle from the I services. The prices for the core bundle and an individual service are p_b and p_i, respectively. The bundling decision $x_i = 1$ if service i is in the core bundle, and $x_i = 0$ otherwise. Denote the value of each service by $v_i \sim F_i(\cdot)$. Let $\mathbf{x} = (x_1, x_2, \cdots, x_I)$ and $\mathbf{p} =$

Table 2 Variables in RO2

Name	Type	Source (apart from user data)
Mean usage	numerical	survey
Variance of usage	numerical	survey
Fee per unit usage	numerical	survey
Bundled	binary	survey or case study
Price of bundle	numerical	survey or industry dataset

$(p_1, p_2, \cdots, p_I)$. Denote the value of the core bundle by $v_b \sim \Gamma(\cdot)$ which depends on $\mathbf{x}$. For the case of independent $F_i(\cdot)$s, one may derive exact expressions of $\Gamma(\cdot)$ if $F_i(\cdot)$s are uniform, exponential, or normal; otherwise, one could approximate $\Gamma(\cdot)$ using its first two moments. Denote the expected revenue of the provider by $\Pi(\mathbf{x}, \mathbf{p}, p_b)$. The revenue maximization problem is

$$\max_{\mathbf{x},\mathbf{p},p_b} \Pi(\mathbf{x}, \mathbf{p}, p_b) = [1 - \Gamma(p_b)]\, p_b + \sum^{i \in I} (1 - x_i)\,[1 - F_i(p_i)]\, p_i$$
$$s.t.\ x_i = 0 \ \ or\ \ 1, \forall i;\ p_i, p_b > 0, \forall i.$$

Possible results derived from solving this model (i.e., membership of the core bundle, price of the core bundle, and prices for the standalone services) answer the proposed research question and are readily applicable to SaaS providers. It is possible to extend this model to a competitive setting to explore whether a core bundle strategy should be universally adopted by players in a market. After obtaining the qualitative results of the proposed analytical model, researchers may test them and develop new theories based on the empirical findings (e.g., offering a core bundle with a higher price may increase user perception of value for light users).

This RO about core bundling adds to the information services bundling literature (e.g., Geng et al. 2005) by optimizing a core bundle that is not sold separately, which is frequently found in the industry. In addition to the connection to the bundling perspective of heterogeneous goods, this RO could pave ways to adding auxiliary services with usage caps or usage fee discounts to the core bundle due to easy usage tracking in SaaS, which relates to the tariff literature (e.g., Bala and Carr 2010).

2.6.3 RO3: Subsidy for SaaS market penetration

Founded in 2016, Noodle.ai offers AI-as-a-Service to help firms improve their operations and supply chains (Makinen and Burgelman 2018). When disruptions hit supply chains, its machine learning algorithm could adjust the sales and operations plan immediately to account for factors such as weather, holidays, traffic conditions, and customer feedback. Noodle.ai trains its algorithm in its own data centers and once trained, it is hosted on AWS for clients. To facilitate ingesting customer data, they build a feature library and data streams that could help interpret and digest customer data and hire consultants to work with clients for major projects. For example, when working with XOJET, a large private jet firm, a Noodle.ai team consisting of managers and engineers worked with XOJET employees to develop a quotation tool (Makinen and Burgelman 2018).

The practice of Noodle.ai to provide extensive customer support aligns with the recommendations of Floerecke (2018) that over the whole SaaS service lifecycle, it is fundamental to provide extensive support on usage, operation, and selection of SaaS services and work closely with customers: Many clients appreciate personal contacts and could pay extra for being able to call if a problem occurs. This is partly because SaaS services must often integrate the customers' business processes and information technology (IT) systems, so many problems may appear and bring lack-of-fit costs. One possible solution is to reduce lack-of-fit costs to facilitate market penetration (Ma and Seidmann 2015), for example, by providing high-quality customer service and technical support for customer problems. Hence, a research question is: *Could reimbursing or reducing lack-of-fit costs help penetrating a SaaS market?* The findings from answering this question could shed light on the relationship between usage, service quality, and service fit in the context of SaaS and extend previous studies such as Ma and Seidmann (2015).

To answer this research question, one might explore the dataset Wharton Customer Analytics (2012) that contains a random sample of customers of satellite radio services pre-installed on new vehicles. Table 3 summarizes key variables that can be generated from this dataset. Let the outcomes be no-subscription and subscription of various lengths (monthly, quarterly, semi-annually, annually, and two year). The following multinomial-logit model could be used to estimate the likelihood of each outcome (denoted by Y_i) and test if high-quality customer service could improve the fit between user needs and the service and in turn enhance user conversion. One could write

$$\beta_c \cdot X_i = \beta_{c0} + \beta_{c1} X_{usage} + \beta_{c2} X_{quality} + \beta_{c3} X_{fit},$$

where β_c is an array of coefficients of the independent variables $X_i = \{1, X_{usage}, X_{quality}, X_{fit}\}$ for outcome c out of a total of K outcomes, and hence $\Pr(Y_i = c) = \frac{\exp(\beta_c \cdot X_i)}{\sum_{k=1}^{K} \exp(\beta_k \cdot X_i)}$. The independent variables array X_i includes usage (data available), service quality (from customer care calls, free-text available), and service fit (from technical support calls, free-text available), the latter two of which can be converted into indices using text analytics to estimate user-experienced service quality. For example, text categorization (supervised machine learning) can classify technical support calls about the fit between the application and customer needs, and sentiment analysis (e.g., using naive Bayes classifiers) could assess whether the issue is resolved. Other applicable text analytics approaches include thematic analysis. An alternative to the proposed multinomial-logit model is survival analysis. For example, we present a Cox model where $h_0(t)$ is the baseline hazard function for customer churn and $h_i(t)$ is the conditional hazard: $h_i(t|X_i) = h_0(t)\exp\{\beta_c X_i\}$.

By estimating these models, the possible results would quantify impacts of usage, service quality, and service fit on renewal decisions and justify measures to improve service fit (e.g., by streamlining features or adding documentation) for market penetration, which answers the research question. Delineating the influence of service fit and its interactions with other factors could provide guidance for possible improvement efforts to increase retention rates. This RO examines levers that would

Table 3 Variables in RO3

Name	**Type**	**Source**
Subscription	binary	user data
Length of Subscription	numerical	user data
Usage	numerical	user data
Service quality (customer care)	numerical	user data
Service fit (technical support)	numerical	user data

make a market entry successful, and the results would facilitate SaaS practitioners to disrupt existing markets or enter new markets with an appropriate strategy to reduce lack-of-fit. This RO is also related to studies on quality of service by studying whether improving service fit in addition to quality could enhance customer retention.

To extend this analysis, one may examine whether extensive usage could interact with customer service quality to reduce uncertainty in service valuation and induce users to choose a longer subscription length or try add-on services. Since many SaaS start-ups go global at their early age (e.g., Serena Capital 2020), how they penetrate diverse global markets is intriguing, and combining firm-specific data (e.g., RO6), surveys, and experiments (e.g., Gao et al. 2022) may facilitate addressing RO3.

3 SaaS Operations

This section reviews SaaS studies with operational decisions, moving gradually from making key decisions in SaaS delivery to incorporating customers' preferences. For any type of service, it is fundamental to meet customer needs on both the quantity of service capability (capacity) and the quality of the service (Li and Kumar 2018). However, the automatic remote delivery and the multi-tenancy structure of SaaS make it challenging to do so optimally while manipulating and securing customer data (Allyn 2020), as evidenced by an industry example later in this section. Addressing this challenge demands an understanding of customer usage behavior that impacts both revenue and operational performances.

3.1 ServiceNow — Building Operational Excellence

ServiceNow, a SaaS provider of customer service automation (e.g., incident management) is known among competitors and clients for its excellent offering. In 2019, ServiceNow housed its SaaS on Microsoft Azure in addition to its own private cloud (Microsoft 2019a). Released in 2010, the Azure service features computing instances that are known for its security and affordable prices, creating a sourcing decision to be made by users (e.g., ServiceNow) who may want to integrate public cloud with their own data centers. SaaS services are sensitive to delays, and Microsoft addresses this need by reducing latencies (The New York Times 2012). To ServiceNow, the partnership will allow it to "more fully leverage and integrate our platform and products with Microsoft's leading enterprise technology and capabilities," which translates to improved security and compliance of its SaaS offering (Microsoft 2019a). Meanwhile, ServiceNow adds private data centers in UK, Ireland, and

Netherlands to serve European customers (ServiceNow 2020). Hence, for a SaaS application like ServiceNow, building operational excellence with private and public clouds could yield resilient and efficient cloud operations, which creates many research opportunities outlined in this section.

3.2 Capacity

We have just shown that SaaS providers such as ServiceNow must manage and source their capacities appropriately. SaaS is unique in its capacity infrastructure since the capacity is shared between many individual users (i.e., multi-tenancy) with demand fluctuations and may need to be adjusted in an on-demand or scheduled manner, which differs from intranet server applications and OTS software. The demand for capacity is satisfied by three different types of clouds: (i) private cloud, (ii) public cloud, and (iii) hybrid cloud, which we will outline separately. According to NIST (Mell and Grance 2011), *private cloud* is a cloud infrastructure for exclusive use by a single organization, *public cloud* is a cloud infrastructure open to the general public, and *hybrid cloud* is a combination of distinct cloud infrastructures (private, public, etc.) exampled by ServiceNow. Many SaaS providers evolve from building private capacity, to incorporating cloud computing infrastructure to form a hybrid system, and to completely relying on public cloud vendors. Another trend is moving from treating capacity as a constraint to making it endogenous (e.g., Li and Arreola-Risa 2022). The studies in this subsection follow these trends and are summarized in Table EC.5. These studies suggest a need to understand the infrastructure sourcing decisions and the impact of other factors such as security (see RO5).

3.2.1 Private cloud

Huang and Sundararajan (2011) classify costs of SaaS provision into infrastructure costs and service costs, and show that the periodic fixed costs of IT capacity can be substituted by a virtual constant variable cost when economies or dis-economies of scale in capacity are absent, which facilitates analytical modeling. In other words, the cost of capacity (μ) is $\gamma\mu$, where γ is a coefficient. When capacity addition is not instantaneous, demand (q) may overwhelm capacity and thus impair customer utility. According to Huang and Sundararajan (2011), there is a utility loss Δu for the value per transaction for OTS transactions under over-capacity ($q \leq \mu$) with respect to under-capacity ($q > \mu$), which gives rise to a threshold solution for optimal capacity to balance the costs of over-capacity and under-capacity. Similarly, Ma and Seidmann (2015) consider lower service value under insufficient capacity for OTS but no capacity constraint for SaaS.

3.2.2 Hybrid cloud

Chen and Wu (2013) model a market with two identical firms and two technologies: Proprietary infrastructure with a high per-period fixed cost (with capacity constraint) and on-demand services with a low per-period fixed cost (without capacity constraint) that is found to benefit differentiated products. Coping with demand uncertainty, Jain and Hazra (2019) show that higher average demand favors a private cloud, but higher demand uncertainty favors a public cloud. On-demand services also feature a variable usage cost in both studies.

3.2.3 Public cloud

Managing capacity can be a challenge for public cloud giants: The Azure service in the UK struggled to meet rising demand in using owned and rented data centers and in 2019, it had to increase its UK capacity by more than 15 times its 2016 capacity (Microsoft 2019b). It is possible to mitigate demand uncertainty using backup virtual machines (VMs) in a dynamic manner called (Guo et al. 2019) which may impact pricing and market entry (Fazli et al. 2018). Another method to mitigate demand uncertainty is allowing reservations, which is popular among public cloud computing services. In this regard, Chen et al. (2019) analyze competition among Infrastructure-as-a-Service (IaaS) providers and find that low-demand-variability customers prefer reservation-based pricing and that high-demand-variability customers prefer usage-based pricing. However, reservations are not always actually used, which creates opportunities for IaaS providers to over-commit. To address this opportunity, Cohen et al. (2019) propose algorithms for over-committing cloud computing services appropriately under job-size uncertainty to save unused computing resources in capacity requests, suggesting a cost reduction of 1.5% to 17%. In the upstream, IaaS providers face the challenge to manage multiple computing resources. To explore this challenge, Arbabian et al. (2021) analyze a two-resource capacity-expansion problem where a cloud infrastructure provider adopts two server configurations with different CPU/RAM ratios, which differs from the single-resource capacity model in many studies.

3.3 Quality of Service

In addition to the quantity of service capacity just discussed in Subsection 3.2, the quality of service capacity, namely quality of service (QoS), is frequently studied in information services research. Low quality SaaS could be costly: 23% of small and medium businesses surveyed said the per-hour cost of IT system-related downtime for their business was more than $40,001 (Help Net Security 2020). Working with leading SaaS providers such as ServiceNow reduces such risk. Sitesbi, a Polish SaaS provider, had problems with backups, database nodes, and support with their cloud provider, which hurts their business performance. After migrating to a different cloud provider, they have a good service level agreement (SLA) and improved server performance (UpCloud 2021), which underscores the importance of measuring the quality of and procuring online services. In this section, we start from quality differentiation and then discuss various aspects of QoS in SaaS.

3.3.1 Quality differentiation

To attract and retain segmented customers, quality differentiation is a natural choice for providers (Afeche et al. 2017, Guo and Ma 2018). For example, in the online payments market, Stripe succeeds with its developer-friendly API that eases integrating payments on websites, and Braintree became popular thanks to its transparency and enabling data portability (Braintree 2012, Bu 2020). In academic research, Fan et al. (2009) examine pricing decisions with asymmetric information about SaaS capacity cost and investigate quality improvement where customer defection rates depend on market players' quality. Modeling quality as a binary costly decision (high/low), Ma and Kauffman (2014) consider pricing strategies and quality choices in duopoly competition of SaaS providers where customers sample (free-trial), learn their true fit, then switch or stay in the presence of lock-in costs. They find that higher switching cost benefits users via fiercer price competition, and hence may not always benefit both providers. With multiple services available, bundling can pair differentiated services. Zhang et al. (2016) consider two firms serving customers with heterogeneous tastes where each firm offers either a free basic service plus an additional charge for a premium service or a bundle of both. They derive conditions for free service outperforming bundling and prove that exogenous quality advantage in the basic service leads to bundling under certain conditions, which is analogous to the capacity cost differentials in Li and Kumar (2018). All these studies consider how quality differentiation could leverage customer heterogeneity for better quality.

3.3.2 QoS measurements

Beyond the SERVQUAL scale (Parasuraman et al. 1988), Benlian et al. (2011) identify two new essential factors (security and flexibility) for measuring SaaS service quality, where *flexibility* covers the degrees of freedom customers have to change contractual or functional/technical aspects in the relationship with a vendor. In practice, public cloud vendors routinely use SLAs to guarantee service levels to customers (Yuan et al. 2018). Another important dimension of SaaS service level is service delay, since users could be highly sensitive to delays (The New York Times 2012). To profit from heavy users and quality-sensitive users, providers may monetize service quality (e.g., Netflix Premium Plan). However, it is unclear from extant studies what business consequences providers may face when violating SLAs, say compliance to relevant regulations (see RO4).

3.3.3 QoS meets the market

Frequently, service providers differentiate their offerings in QoS to cater to heterogeneous customers. Let the cost of low QoS be γd per unit of time, where d is a QoS metric (e.g., average delay, maximal delay) and γ is a parameter potentially heterogeneous among users. In many studies, the user's problem is to maximize $v - p - \gamma d$ where v is the unit service value and p is the unit service price paid by the user. As an early study, Zhang et al. (2007) consider a monopoly model with queuing formulation and provide justification for using a stationary model rather than a dynamic-arrival-rate model with single- and dual-classes of service under various QoS guarantees. Going a step further, Zhang et al. (2009) consider a sequential duopolistic market where the providers choose service levels (high or low) and prices simultaneously. Considering heterogeneity in customer usage, Li and Kumar (2018) discuss the implications of subscription pricing for SaaS with premium and standard services differentiated by expected delay. In their model, a user's problem is to maximize $vm - p - \gamma dm$, where m is the usage level of the user and p is a subscription fee. Investigating market entry and deterrence, they show that investments in deterrence are viable, especially when new entrants face other significant barriers to entry such as cost disadvantage or QoS disadvantage. With results showing the importance of QoS in market competition, how QoS of SaaS and online platforms work together (e.g., RO7) is an enticing question.

3.3.4 QoS in acquiring computing resources

The importance of QoS to end users prompts SaaS providers to incorporate QoS in their procurement decisions of cloud computing services. For example, Anselmi et al. (2017) model a marketplace with users purchasing services from SaaS providers, which in turn acquire computing resources from infrastructure providers such as Amazon Web Services (AWS) with a distinction between shared and dedicated latency in the cloud. For applications sensitive to downtime, Guo et al. (2020) have proposed a method to estimate transient downtime in virtual network function, which facilitates service provisioning to ensure availability. A summary of studies discussed in Section 3.3 can be found in Table EC.6.

3.4 Security

A SaaS application is insecure when information is obtained without consent. For SaaS users and providers, security is a valid concern, and hence we single it out among service quality factors. In this section we also explore closely related issues like piracy and privacy in addition to security, all of which are related to unauthorized data access. While ServiceNow seeks to improve security with the Microsoft Azure partnership, some providers such as Zoom are at risk. Despite the fast growth of Zoom, it failed to use end-to-end encryption, and its popularity has attracted "Zoombombing" by hackers and created security, privacy, harassment, and other concerns, leading to business losses and legal challenges (Allyn 2020). Providers therefore should rationalize their security and privacy protection to facilitate user adoption under competition, which RO5 seeks to address.

The spread of the IoT (Internet of Things), the emergence of the Darknet, and scandals such as Cambridge Analytica may impede the adoption of SaaS. Regarding the trade-off between SaaS and OTS, August et al. (2014) find that a SaaS version is generally preferred in low security-loss environments in the presence of an on-premises version. In addition, customers might have concerns about transparency and compliance of SaaS due to its multi-tenant architecture. These worries are magnified under competition which may drive providers to collect and sell customer information at the expense of privacy. On the contrary, Casadesus-Masanell and Hervas-Drane (2015) find that competition fosters services with a high level of privacy, but higher competition intensity need not improve privacy when consumers are reluctant to pay. Since an owner of consumer data sells information optimally to only one firm in a market, policymakers should promote equal access to consumer data rather than merely protecting consumer privacy (Montes et al. 2018). Zhang et al. (2020b) explore the competition between SaaS and OTS under security risk and find that SaaS could be preferred when customer may suffer greatly under attacks.

In addition to the effects of competition, enhancement measures are also costly. August et al. (2019) suggest that providers could reduce vulnerabilities by offering different patching schemes. Sundararajan (2004a) analyzes a market with digital piracy where sellers can influence the degree of piracy by implementing digital rights management (DRM) systems and a pirated good is an inferior substitute for the legal good. Appropriately granting digital rights and choosing the level of protection are found to maximize profit with trade-offs among pricing schedules and technological deterrence. Similarly, Nan et al. (2018) explore the trade-off between the effect of decreasing uncertainty and that of cannibalization and find that stronger piracy enforcement may actually hurt the firm. Further to the intricacy of security enhancement, Yang et al. (2021) find that a provider may profitably free-ride on customers' security efforts by cutting corners on its own effort.

3.5 Usage

A crucial link between pricing and operations, usage impacts renewals. One case in point is Netflix. Netflix's increasing offering of original shows benefits from customers sharing and discussing them with friends, because if one knows that her/his friends are also watching Netflix, one may trust and value the service more (Gilchrist and Luca 2017). In addition, the data collected from subscribers enables Netflix to cater to their tastes and add new shows to leverage on network effects, which would attract more subscribers or allow higher pricing (Taylor 2018). Founded in 1997, Netflix now has successfully amassed roughly 158 million users (Netflix Inc. 2019). With tools to track clicks, swipes, fills, and pageviews automatically, usage analytics allow SaaS providers like Cloudfare and Twilio to segment their users and to pinpoint opportunities to improve user engagement (Heap 2021), and ServiceNow leverages user community for customer support, gathering feedback, and expertise sharing (Imroz 2019).

Many studies on subscription services treat usage as either exogenous (e.g., Li and Kumar 2018) or irrelevant. To that end, Danaher (2002) considers subscription service with a field experiment and finds that access price has limited effect on usage, partially supporting the frequently-made assumption that usage is independent of access price. However, it is possible to influence SaaS usage. On the one hand, Lambrecht and Skiera (2006) provide evidence that many Internet service users prefer a flat fee even though their billing rate would be lower with pay-per-use pricing (i.e., flat-rate bias) and that these users are less likely to churn. On the other hand, proactive customer education may increase perceived usefulness, and thus increase usage and reduce churning (Retana et al. 2015). It can be concluded that SaaS usage behavior deserves further investigation (e.g., RO6 to identify methods to influence usage) and may influence purchases and operations (Mallipeddi et al. 2022, Zhao et al. 2022).

3.6 New Research Opportunities in SaaS Operations

In this subsection, we elaborate on four ROs related to SaaS operations in Table 4.

Table 4 Future research opportunities in SaaS operations

	RO4	**RO5**	**RO6**	**RO7**
Summary	Competition and privacy for apps	Managing user security preferences	Factors and strategies to influence usage	Quality interplay of platform and SaaS
Methodology	Diagnostic / Predictive / Analytics	Predictive / Prescriptive Analytics	Diagnostic / Predictive / Prescriptive Analytics	Diagnostic / Predictive / Prescriptive Analytics
Research Questions	*Does higher competition intensity improve SaaS privacy when consumers pay nothing?*	*How should a SaaS provider maximize its profit under user security-preference heterogeneity?*	*How can a SaaS provider influence usage and content creation in consideration of service quality and social impacts?*	*What is the interplay of service quality between the platform and SaaS and how does it impact customers?*
Industry Examples	Facebook	Zoom	NetEase Cloud Music	Salesforce.com
Examples of Data Source	Zimmeck et al. (2019)	N.A.	Zhang et al. (2020a)	KeyCorp (2020)

3.6.1 RO4: Competition and privacy for apps

Customer privacy proves to be a significant challenge for platforms such as Facebook, which owns its private data centers, but allows third-party developers to host their applications on services such as AWS (Metz 2014). Despite having an internal authorization process for data collection, Facebook was negligent in the Cambridge Analytica scandals where tens of millions of Facebook profiles were harvested without their consent and used for political advertising (Ballhaus and Gross 2018). Notwithstanding its increased efforts to boost security and privacy, in 2019, more than 540 million records about Facebook users were publicly leaked on AWS, consisting of 146 gigabytes of Facebook user data with account names, IDs, and details about comments and reactions to posts, after which Facebook upgraded user privacy settings to allow users to clear their location data, turn off facial recognition, and stop data collection by Facebook's partners (Silverstein 2019).

In light of online data breaches and hacks, it is crucial for providers to identify, measure, benchmark, and improve SaaS privacy. However, providers cannot eliminate privacy concerns since they have significant incentives to harness data from users to improve customization and functionality. Nevertheless, such a practice must be accompanied by appropriate privacy disclosure to raise awareness of the users. A helpful resource is Zimmeck et al. (2019) which provides a dataset containing 1,035,853 Android apps from the Google Play Store with URLs to their privacy policies. Due to laws such as General Data Protection Regulation (GDPR) in the European Union (EU) and the Children's Online Privacy Protection Act (COPPA) and the California Online Privacy Protection Act (CalOPPA) in the U.S., app stores (such as the Android App Store) require developers to disclose how their apps collect, use, and share user data. However, media coverage and research (e.g., Zimmeck et al. 2019) show that many apps exhibit potential privacy compliance issues such as not disclosing certain data collection practices.

These issues call for a thorough understanding of factors affecting privacy practices through the analysis of privacy policies and the business landscape. Casadesus-Masanell and Hervas-Drane (2015) predict that higher competition intensity need not improve privacy when consumers are reluctant to pay. It would be meaningful to test such a prediction in the context of Android apps, since Android apps documented in the Zimmeck et al. (2019) dataset are free. In other words, the research question is: *Does higher competition intensity improve SaaS privacy when consumers pay nothing?* Understanding this question allows better implementation of public policies and the design of SaaS applications to enhance privacy in many mobile apps.

To answer this question, researchers may complement the privacy policies by collecting data on the competition intensity of apps (e.g., the number of downloads of each app in the same category). Following the method outlined in Zimmeck et al. (2019), it can be identified whether an app declares that it will collect (or not collect) certain user information and share it with third parties from the app's privacy policy. To determine whether an app attempts to collect privacy-sensitive information (such as calling a Facebook API to obtain user IDs), one can monitor the app in a manual experiment or trust the prediction of a well-trained machine learning algorithm. See Table 5 for a list of variables useful for the model outlined below.

$$logit_i(p_{breach}) = \beta_0 + \beta_1 \cdot child_i + \beta_2 \cdot updatefreq_i + \beta_3 \cdot competitionintensity_i + \gamma \cdot category_i + u_i$$

where the subscript i represents each observation and u_i denotes the random error. The possible results, namely the empirical parameter estimates, could pinpoint the effect of competition intensity on the likelihood of privacy breach and answers the research question. Going a step further, it is possible to study the implications of privacy on SaaS competition, particularly users' response to privacy disclosure transparency in SaaS applications, with surveys or lab experiments.

This RO connects to the security perspective and in a broad way to the quality-of-service perspective. Findings of this RO contribute to the SaaS competition literature (e.g., Li and Kumar 2018) and the SaaS privacy literature (e.g., Montes et al. 2018) since the impact of competition on privacy will be analyzed. Moreover, the findings could elaborate on the link between privacy disclosure, privacy practice, and usage, if additional data could be collected and analyzed.

Table 5 Variables in RO4

Name	Type	Source
Privacy-senstivie API calls	a binary array	running the app
Disclosure	binary	privacy policy
Child	binary	Google Play
Update frequency	numerical	Google Play
Number of apps in the same category	numerical	Google Play

3.6.2 RO5: Managing user security preferences

There was incredible growth for Zoom during the COVID-19 pandemic, expanding to 300 million users from about 10 million in months (Allyn 2020). However, Zoom did not use end-to-end encryption, as it had claimed, and its popularity has attracted Zoombombers, whereas Facebook and Google seized the opportunity to introduce and promote Zoom alternatives. Zoom was also asked to improve its privacy and security protections by a U.S. Senator and the New York Attorney General (Allyn 2020).

In response to the grave need to bolster security, Zoom has devoted resources to increasing security and privacy in an update: Among other changes such as requiring passwords for creating or joining a meeting by default, Zoom began to support AES 256-Bit GCM encryption to protect meeting data against hacks, report an inappropriate user, and allow business customers to choose which data center regions their meetings and webinars use for real-time traffic (Gal 2020).

Despite efforts by Zoom and other SaaS providers to enhance security, some customers are willing to trade functionality for security, since many security enhancements (extra verification steps, etc.) are a hassle for customers and incur additional computing tasks (network communication, encryption/decryption, etc.) that slow down the processing of customer requests. For example, AES 256-bit encryption consumes approximately 40% more in computing resources than AES 128-bit encryption does (Cyclonis Ltd. 2018). It is therefore important to understand the incentives for security investment of SaaS and its trade-off with performance. A question emerges: *How should a SaaS provider maximize its profit under user security-preference heterogeneity?* The results derived from answering this question could be applied to the design and update of SaaS applications with security concerns, which is a critical challenge as evidenced by the recent incidents of Zoom. Hence, we next propose a model to address this research question. Different from extant studies (e.g., Yang et al. 2021), this primitive model does not make assumptions on the probability of security breach and the cost of security efforts but incorporates the performance penalty of security enhancement.

Consider a market with one provider and many customers. The security level is denoted by a, and the sensitivity to security is denoted by δ. Let $\eta(a)$ be a discount function where $\eta(a) \leq 1$. A customer's utility is $u_s = \eta(a)v - p + \varrho(a,\delta)$ with a security enhancement option where $\varrho(a,\delta)$ denotes the utility gained through security enhancement and v denotes the value of the base SaaS offering to a customer. Let $\bar{\varrho} = \max \varrho(a,\delta)$. Without the security enhancement option, a customer's utility is $u_w = v - p$. Let $v \sim F(\cdot)$ and $v \in [0,V]$. Suppose θ proportion of customers choose the service, of which κ proportion choose the security enhancement option. Let $r(p,\kappa)$ be the provider's net revenue per user, which depends on capacity cost , QoS, and capacity mix (for hybrid cloud). The net revenue of the provider is therefore $\pi = r(p,\kappa)\theta$. Setting $u_s = 0$, we arrive at the indifference point of service value: $v^o = \frac{p-\varrho(a,\delta)}{\eta(a)}$. We consider a problem of maximizing the profit (Π) of a monopolistic provider:

$$\max_{p,a} \Pi(p) = \int_{v^o}^{V} r(p,\kappa) f(v) dv.$$
$$s.t.\ 0 \leq p \leq \delta\bar{\varrho}.$$

The optimal price and security level derived from solving this model would guide SaaS providers on designing the security level of their services and shed light on possible equilibriums and societal outcomes, hence answering the research question. As a result, findings of this RO contribute to the SaaS security literature (e.g., Zhang et al. 2020b) and the differentiation literature (e.g., Li and Kumar 2018) by advancing our understanding on the interplay between pricing, security, and capacity. This RO connects to the security, capacity, pricing, and the quality-of-service perspectives since security enhancements could increase processing time of customer requests, impact service performance and pricing, and justify additional computing capacity.

3.6.3 RO6: Factors and strategies to influence usage

SaaS providers typically crave for higher usage for value realization or advertising revenue, and meeting quality expectations could greatly enhance the chance of SaaS usage continuance (Benlian and Hess 2011). The externalities of SaaS usage, however, cannot be ignored. A question comes: *How can a SaaS provider influence usage and content creation in consideration of service quality and social impacts?* This question is important since user time spent on mobile apps and the user content-creation are not only operational outcomes for the app provider but also opportunities to benefit the society. The possible results derived from answering this research question are readily applicable to NCM, entertainment SaaS alike, and other SaaS leveraging social networks (Kumar et al. 2022, Petryk et al. 2022).

A case in point is NetEase Cloud Music (NCM), one of the most popular music streaming services in China with over 800 million registered users and 160,000 independent musicians (NetEase Inc. 2020). With personalized recommendations, NCM promotes user interaction and builds a strong social community in their daily operations. However, gaining high-quality usage, especially usage aligned with social values, is never easy. NCM has been mocked as "NetEase Depression Cloud," which refers to sentimental stories posted for likes in the comments section of songs; in August 2020, NetEase Cloud Music officially launched a campaign to provide emotional support to users who are genuinely struggling with mental health issues (Chen 2020).

One may use a NCM dataset to answer the proposed research question. Zhang et al. (2020a) provide a one-month dataset of the NCM mobile app containing six tables about users, content creators, and impressions available to members of the INFORMS Revenue Management and Pricing section. We may explore relevant factors and evaluate strategies to maximize usage per user by analyzing user demographics, user activity data on the impression level, content data, and content creator data for a music-streaming SaaS application. A card is a video or set of pictures with music created by creators in the app (who are also users). Following a recommender logic, the gradient-boosted regression trees (GBRT) algorithm (e.g., in *xgboost* and *scikit-learn* packages) can predict the likelihood of a user to be interested by a card. The GBRT algorithm could perform automatic variable selection to suit a large number of variables in this dataset and infer both the optimal functional form (allowing for interactions and nonlinearities) and the parameters of the model efficiently using a greedy algorithm (Friedman 2001). Successful recommendations could keep a user active or turn inactive users active (Cheng et al. 2020, Kumar and Qiu 2022). A GBRT example may be:

$$User\_response\_score = f\,(Impression, Card, Song, User, Creator)\,,$$

where each item in the list {*Impression, Card, Song, User, Creator*} represents a category of variables outlined in Table 6, and user response is a composite score. Alternatively, researchers may evaluate two related but potentially conflicting goals: maximizing usage (i.e., clicks/plays) in the short-term and maximizing high-quality content creation in the long-term using simulation/visualization tools (Pu et al. 2020), which may allow boosting the membership revenue later.

If content information of cards and songs is released to enable sentiment analysis, it may be socially beneficial to leverage on the "Elements of Value Pyramid" (Almquist et al. 2016) to make sure that the intended usage increase aligns with social values and avoid perpetuating negative emotions through song recommendation systems. A similar move by Amazon makes its Alexa more empathetic to identify and respond to depression, suicide, and domestic abuse.

Since customer usage is a frequent indicator of willingness-to-pay (WTP), the results obtained by empirically studying factors that influence usage (at NCM) could decipher the interactions between the providers, users, and user-turned content creators, which contributes to the SaaS purchase and usage behavior literature (e.g., Retana et al. 2015) and the network effects literature (e.g., Nair et al. 2018). The possible results could shed light on the optimal trade-off between maximizing revenue (through influencing usage) and maximizing high-quality content creation, which answers the research question in this section. This RO adds a dimension to our understanding of SaaS service quality: an emotion that drives loyalty and service quality perceptions (White 2006). This RO is also tied to customer usage behavior and how it is affected by customer interactions.

To the same end of understanding and possibly influencing user behavior, it may be valuable to analyze a publicly available dataset (Lim et al. 2015) where mobile app user behavior (app stores, app search triggers, download method, reason for abandonment, types of apps, etc.), demographics, and personality are documented. It may also be useful to explore publicly available surveys on Internet services (e.g., Pew Research Center 2021).

Table 6 Categories of variables in RO6

Name	Type	Source
User response to impression	an array of binary variables that form a score	app data
Impression information	an array of numerical and categorical variables	app data
Card information	an array of variables with daily statistics	app data
Song information	an array of numerical and categorical variables	app data
User information	an array of variables (demographics, number of follows, activity intensity, etc.)	app data
Creator information	an array variables (demographics, number of follows and followers, activity intensity)	app data
Sentiment of cards	ordinal (if free text information of cards or lyrics of songs is available)	app data

3.6.4 RO7: Quality interplay of platform and SaaS

Starting from offering SaaS in CRM, Salesforce.com transformed itself into a platform of enterprise business applications where customers could subscribe to each service to customize their IT solution (THINKstrategies 2007). The Salesforce platform differentiated from incumbents such as Oracle by encouraging developers to create third-party apps on the platform. Doing so strengthens its analytics capability and allows entry into new markets such as some financial IT sectors dominated by Bloomberg. However, despite its dominance in CRM, Salesforce.com suffered from service failures of its own Heroku (Jackson 2013) and faced recent new entrants such as Microsoft (Kim 2015). As a platform, Salesforce.com is also plagued by third-party application service issues, such as the connection service between Tableau and Salesforce (Vegi 2020). Anselmi et al. (2017) conclude that although users are both sensitive to SaaS performance and price at purchase, many of the performance metrics of a SaaS are inherited from the back-end Iaas/PaaS. Therefore, a relevant question is: *What is the interplay of service quality between the platform and SaaS and how does it impact customers?* As SaaS grows to become a major form of service and the emergence of online platforms hosting SaaS, understanding the interaction between SaaS and platform service qualities is crucial to SaaS firms in choosing platforms to operate on.

Since many SaaS providers are hosted in and integrated with platforms, it is important to examine the role of platform service quality in addition to the SaaS service quality to answer the aforementioned research question. It remains to be determined how the service quality of a SaaS application interacts with the service quality of a platform, but such interaction is crucial since it impacts customer utility and informs the choice of pricing schemes. Factors such as the integration between the SaaS and the platform and users' technical abilities may matter as well.

To determine the aforementioned interaction, one possible avenue is to estimate the functional form of customer utility. Denoting the service quality of SaaS as q_s and that of the platform as q_p, it is interesting to empirically examine the decisions of SaaS providers and platform operators when the customer utility is formulated as $u = k_0 + k_1 q_s + k_2 q_p$ (additive), $u = k_0 + k_3 q_s q_p$ (multiplicative), $u = k_4 \min\{q_s, q_p\}$ (minimum of the two), or $u = k_5 (q_s)^\alpha (q_p)^\beta$ (Cobb–Douglas), where k_i (i=0, 1, 2, 3, 4, 5) are parameters. One may estimate customer utility from satisfaction surveys or price paid. We may employ the Maximum Likelihood Estimation to estimate the parameter values of these functional forms and evaluate the model fit using the Bayesian information criterion (Schwarz 1978). The estimated functional forms could pinpoint the interaction between the SaaS and the platform in the service quality dimension and answer the research question. For datasets, it is possible to use financial disclosures of public SaaS companies such as Qualtrics and ServiceNow (KeyCorp 2020); alternatively, user surveys of SaaS platforms such as Salesforce.com can be helpful: More than half of all users believing that up to 80% of their Salesforce data is not useful or reliable (Symphonic Source Inc. 2017) . Key variables aforementioned are summarized in Table 7.

Table 7 Variables in RO7

Name	**Type**	**Source**
SaaS service quality	ordinal	composite measure based on survey
Platform service quality	ordinal	composite measure based on survey
User techinical ability	numerical	survey or user data
Customer utility (satisfaction)	numerical	estimated from user data
SaaS profitability	percentage	financial data

Findings of RO7 could contribute to the SaaS service quality literature (e.g., Li and Kumar 2018) in characterizing how SaaS service quality interacts with platforms' service quality in shaping perceived value of the service which is closely related to customer purchase and usage behavior. These findings could service as steppingstones for further analysis on the relationship between SaaS and platforms. Moreover, RO7 is connected to the market entry perspective since service quality impacts customer purchases and renewals.

Another possible avenue for data analytics is to construct the antecedents and to test how the service quality of SaaS and that of the platform jointly impact customer loyalty with the mediation of customer satisfaction using the service loyalty model (Caruana 2002), since subscription pricing makes it crucial to maintain customer loyalty and renewals that contribute to revenue. For this possible avenue, Figure 5 describes a potential framework to delineate the interaction between SaaS and platform in service quality, where such interaction is moderated by their integration.

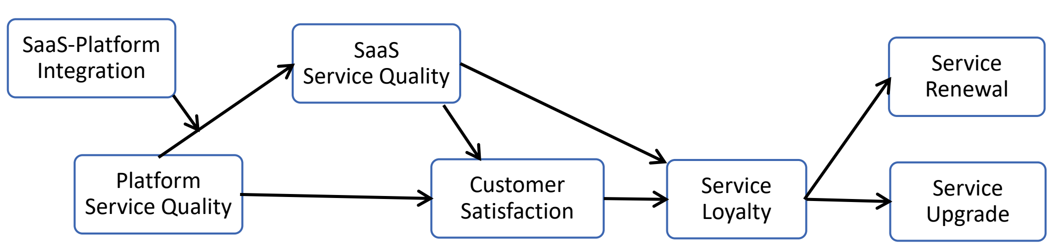

Figure 5 Service Quality Interaction Between SaaS and Platform

4 Future Roadmap for SaaS

In the fast-changing industry of software-as-a-service, the importance of a dynamic perspective can never be stressed enough. Hence, it may help to use case studies, system dynamics, and machine learning to expand the research methodology and to achieve a dynamic understanding. In subsequent subsections, we provide a future roadmap of SaaS research summarized in Figure 6.

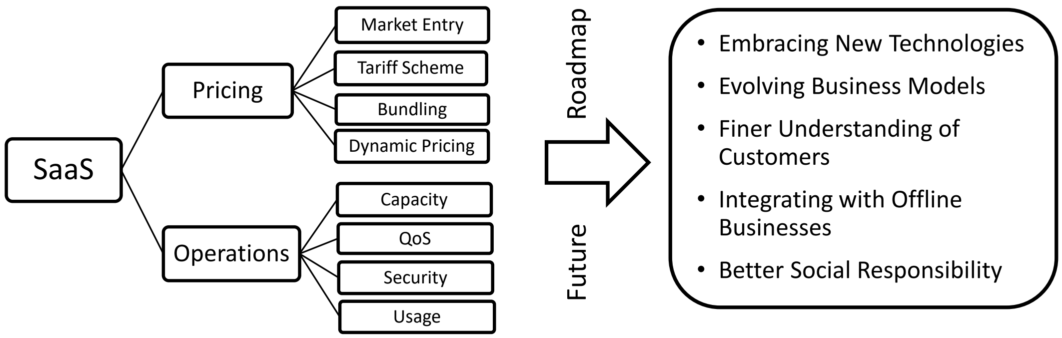

Figure 6 Future roadmap of SaaS research

4.1 Embracing New Technologies

SaaS include the acquisition, transmission, computation, visualization, and storage of data, all of which are popular targets for innovations. There is a pressing need to embed big data and artificial intelligence into the management of SaaS and cloud services in general (Choi et al. 2022, Guha and Kumar 2018, Kumar et al. 2018b), from optimizing revenues to using chatbots, thanks to cheaper computing resources and better data availability. Despite the potential to create significant value from SaaS with these techniques, generating insights from data alone is insufficient to advance the field. With IoT and edge computing, one may deliver SaaS services with cheaper data acquisition and possibly data-driven automated actions by Internet-connected devices. With 5G, data transmission is faster and more reliable, and it becomes feasible to turn connected mobile devices into a virtual and omnipresent computing system as envisioned by the InterPlanetary File System (`https://ipfs.io`). At the same time, blockchain is expected to improve SaaS security and transparency.

4.2 Evolving Business Models

A transformation towards cloud-based services may prompt an organizational overhaul to recoup lost revenue of selling high-margin OTS (Suarez et al. 2013). At Microsoft, 40,000 salespersons had to revamp how they did their jobs: From selling ready-made software to encouraging more cloud usage (The Economist 2019). To help companies like Microsoft, researchers may study what organizational changes can facilitate a cloud business model. Efforts should also be made to improve SaaS-enabled process changes in business functions such as supply chain management (Bala 2013).

Digital platforms could enable value-creating interactions between external producers and consumers (Constantinides et al. 2018). It is important for SaaS providers to choose which platforms to operate on for market access and value proposition. For example, Dropbox integrates with many platforms including Salesforce and SAP. As another example, Boomi's AtomShere product invests in technical capabilities to interoperate with Salesforce, SAP, and Taleo, different from its peers.

Despite the attractiveness of freemium, it is not always preferred (Nan et al. 2018). In light of increased privacy protection and peer-to-peer product sharing, how the freemium strategy might be implemented via product design (e.g., Ray et al. 2017) is an enticing question. Connected to freemium and often found in SaaS, tiered pricing combines tariff and bundling by offering several price points with limited usage allowance and features, which deserves further research.

4.3 Finer Understanding of Customers

The impacts of consumer behavior deserve future research. For example, Netflix's recommendation system saves the company $1 billion annually through reduced churn (Gomez-Uribe and Hunt 2016). In addition, work practices may complement SaaS investment by accelerating user learning (Avgar et al. 2018). Future work may examine how decision capacity and learning of users shape SaaS market outcomes. Due to the importance of service quality (Kumar et al. 2018a, Li and Kumar 2018), SaaS providers may explore which QoS characteristics are deemed critical by consumers and how service recovery via artificial intelligence can be worthwhile. Future work may also investigate the roles of diversification, aging, and urbanization in SaaS.

4.4 Integrating with Offline Businesses

SaaS applications may integrate with offline businesses in many ways. For example, an on-demand service platform may connect customers to offline agents. In turn, the advancements in autonomous vehicles could in turn feed offline information to SaaS for better intelligence. Moreover, since some SaaS providers advertise offline, it may be interesting to investigate the offline marketing of SaaS applications. Another promising opportunity is cloud manufacturing. In addition to managing business resources of manufacturers, SaaS providers can zero in on the production floor. For instance, Helo et al. (2019) introduce a cloud-based production scheduling system to serve distributed sheet metal manufacturing lines. However, due to the technical complexity and safety implications, it remains a crucial challenge to ensure the security and reliability of cloud-based manufacturing.

4.5 Better Social Responsibility

The societal impacts of SaaS deserve study. With anti-trust implications, Li and Kumar (2018) find that it is not necessarily beneficial to mandate the presence of multiple SaaS providers in the market when potential entrants exist. In light of urbanization and population growth in developing countries, SaaS can be used to quantify carbon footprints and improve efficiency, flexibility, and equity in public sustainability efforts. In public health, SaaS tools have been deployed to assist decision-making—for example, using Google Trends in virus outbreaks to analyze data including weather and travel patterns to predict where the virus might hit next.

4.6 Closing Remarks

In this paper, we have proposed a business research framework of SaaS and categorized related studies to serve as a reference for researchers currently working in the field, and as a starting point for those contemplating to explore it. This literature is expanding quickly, motivated by the growth of SaaS and the increasing vulnerabilities of cloud computing. For researchers, we have noted opportunities to bridge gaps and move forward. For scholars interested in such a growing research stream, there could not be a better time to join it with the help of business analytics.

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