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A Queuing Approach to Pricing Strategy in B2B Markets

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ABSTRACT

Business-to-business (B2B) pricing strategies are intentionally complex and crucial levers of profitability and competitive advantage because of differences in temporal preferences, operational constraints, and multi-stakeholder decision-making. Static segmentation also neglects behavioral subtleties that correspond with service urgency; meanwhile, traditional models provide an inadequate representation of time-sensitive variables, such as delivery lead time and capacity utilization. This paper addresses such shortcomings by establishing a new and holistic framework that combines queuing theory and value-based pricing for the revenue optimization of a capacity-constrained B2B system. Related models combine game-theoretical frameworks, data-driven predictions with algorithms, and adaptive capacity control, through which firms can modulate prices in real time whenever requests, service times, and competitors' behaviors deviate. The results show that pricing, which considers temporal preferences and operational efficiency, reduces the conflict between service speed and profitability and offers insights into tiered pricing and resource allocation. Uniting queuing dynamics with segmentation strategies, the framework bolsters intellectual dialogue in calls for the creative development of B2B pricing literature. It allows managers to build customer loyalty, exploit time-sensitive demand, and mitigate margin erosion due to panic discounting.

1. Introduction

Transactions between organizations characterize Business-to-business (B2B) markets for purposes that range from production to resale to operational activity. They are a cornerstone of economic activity at a global level. Such B2B markets are distinct from business-to-consumer (B2C) markets since they are more often characterized by bidding and proposal processes, long-term contractual relationships, and high transaction values [1-3]. As mentioned, pricing strategies directly impact profitability, competition, and customer loyalty. Pricing that is fit for purpose must go further than mere cost recovery; it should be seen not just as a lever to communicate, negotiate, and pre-empt dissipation of value but rather as a fundamental mechanism for maintaining sales relationships

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in the face of mass purchasing, customized purchasing agreements, and often, multi-stakeholder decision-making [4-6].

Multiple stakeholders with divergent perceptions of value and operational priorities complicate the negotiations [7, 8]. This is compounded by the complexity of integrating a balanced perspective among cost structures, competitive intelligence, and relationships [9, 10]. Furthermore, competition in the B2B markets is more commonly based upon value co-creation, so firms differentiate through innovation, service quality, and tailored solutions rather than via simple price [1, 4, 11]. Despite the risk of price wars undermining their profitability, firms that align pricing to perceived value can set premium pricing and develop loyalty [6, 12].

To cater to these particularities, B2B companies increasingly draw on customer segmentation, i.e., regarding clients according to industry, size, purchasing behavior, or needs to tailor pricing strategies [2, 3]. Segmenting customers according to their behavior and needs is one way to do this; it is the basis for tiered pricing models, which align price points with the customer's willingness to pay and subsequently help maximize revenue by conditioning perceptions of fairness [5, 13]. This might imply that either prompt services start to ask for a more fantastic price or section tailoring turns into a market-rate product for value splits on worth pricing, leveraging the segmentation case to cement worth pricing [10, 14].

One important aspect that the current top models ignore is the influence of time on B2B buying decisions. Most traditional pricing methods fail to consider the wait time dimension, a significant dimension of customer satisfaction, especially in the division of shares in group buying auctions and capacity-constrained environment settings [15] .Queueing theory has long been established in operations management, and here, it offers a new lens for pricing optimization through the application of waiting time as a facet of perceived value. For instance, capacity planning to permit shorter lead times can order price premiums to balance income targets and high-quality customer service targets [16].

AI (artificial intelligence) uses actual time data well and responds to demand-side shifts by adjusting supply and responding to competitive actions, thus improving dynamic pricing [17, 18].

This study develops a unified framework that links queuing theory with value-based pricing techniques, surmounting temporal and operational intricacies often involved in B2B markets. We propose a dynamic pricing model to maximize revenue with minimal costs regarding service speed vs. profitability by combining the insights of game theory with those of AI-driven forecasting and capacity planning. This responds to the call for more innovative pricing strategies within diverse industries [19]. Provides firms with actionable insights to deal with increasing competitive pressures, better integrate customer loyalty, and time-sensitive demand.

The rest of this paper is organized as follows. In Section 2, a brief review of the literature on queueing theory business-to-business pricing strategies is provided. Section 3 discusses and reveals the research problem and shortcomings in the field of time-sharing and pricing in businesses. Section 4 presents the mathematical formula related to the queuing theory. Section 5 presents the parameter evaluation, the analysis of the reported data, and the computational results of the research. Section 6 presents the explanations and conclusions, theoretical contributions, and implications for future research.

2. Literature review

Finding out how far the client order goes throughout a company's supply chain is vital for selecting the appropriate strategy. Nowadays, marketing innovation has placed new price-setting strategies beside other traditional aspects of marketing, such as the development of new services, new advertising promotions, new distribution channels, and marketing information systems (20), it shows the importance of pricing decisions at the strategic level.

Compared to the other marketing mix components, price seems to be a less likely area of innovation. However, our analysis suggests that organizations worldwide are experimenting with new pricing approaches to attract customers' attention and build new ties with them. Hinterhuber and Liozu [21] highlight that 'Innovation in pricing introduces new-to-the-industry approaches to pricing strategies, pricing techniques, and pricing organization to boost consumer happiness and corporate profits' [22].

Most of the research undertaken on creative pricing strategies focuses on B2C rather than B2B environments [23]. Several possible avenues for innovation in B2C pricing include bundling (selling two or more products or services as a package), individualized pricing (charging different prices for identical products or services based on individual customer data), flat fee (allowing unlimited consumption for a fixed fee), creative discounting techniques (e.g., steadily decreasing discounts whereby discounts are gradually phased out), and participative pricing mechanisms (e.g.' name your price'; [24, 25]). The limited B2B pricing strategies we observed include pay-for-performance [21], contingency pricing, profit sharing, coordinated pricing across different channels [26], and, to some extent, advanced payment systems [27]. Innovation surrounding pricing strategies has the potential to disrupt entire industries and introduce fresh ideas to tackling traditional problems while enhancing consumer satisfaction and organizational revenues.

This interaction becomes even more complex since B2B sales and pricing involve long-term contracts, service-level agreements (SLAs), and supply chain dependencies. Thus, competitive actions must also consider the needs of various stakeholders over the length of a contract. While price sensitivity is generally driven by consumer perception in B2C markets, in B2B markets, competition is centered on value propositions associated with reliability, customization, and strategic partnerships.

Research by Lin and Wang [28] highlights that in oligopolistic market settings, such as those for IT services, firms pursue price differentiation strategies based on differences in service availability and expected response times. IT service providers, for instance, can cater to heterogeneous client needs by launching "gold," "silver," and "bronze" tiers of service with diminishing prices and levels of guaranteed uptime. Based on queue theory, such a cumulative discount lets firms short the market and close gaps relative to their available capacity. The inverse price segmentation also occurs in the parking garage industry, as seen where higher rates are charged for reserved spots with guaranteed parking, thus pricing visibility typifying the intersection of competition and queuing theory [28]. These tactics speak to the important interplay of price, supply, and competitive position.

In a competitive relationship with the B2B market, the price strategy is a comprehensive variable of production planning. Flexibility also allows companies to synchronize production schedules with demand forecasts and pricing to sway consumer behavior. A notable application of LRM modeling is JIT delivery models in manufacturing, where queuing theory empirically informs production flows to eliminate waiting while easily accommodating varying order flows [29].

A fully flexible price system that quickly adapts to real-time capacity will force firms to smooth demand during non-peak periods or focus on high-margin orders during capacity constraints. Take semiconductor manufacturers, for example; they charge high prices for high-demand chips in peak periods to reserve capacity for premium customers and discount lower-tier products to keep up minimum production levels [30]. Indeed, dynamic pricing improves revenue and smooths production planning, thus minimizing overstocks or stockouts.

In combination, queuing theory predicts improvements in operational efficiency, which further proves the viability of competitive pricing strategies. Finding a bottleneck in service processes can help to minimize the waiting time. This can be an undermanning of a line or having too many machines; in these cases, the firm would change its resources to shorten production times. In other words, it would reduce the waiting times for customers. Here, the time-and-motion study can be analyzed as reducing production cycles, but it shortens the customer's wait for service.

Fakokunde et al., [31] show that manufacturers who adopt a queuing-based scheduling approach reduce their lead times by 20% to offer competitive prices without losing delivery time. Manufacturers also price production slots according to urgency and production capacity, ensuring their margins are maintained even when demand spikes [29]. This operational fine-tuning, based on queuing theory, is now an end-to-end feedback loop in which operational efficiency enables better pricing strategies (probably more aggressive), reinforcing demand and revenue growth.

There is no doubt that technology is a helping hand behind these strategies. Ultimately, the latest data analytics and artificial intelligence (AI) progress allow companies to implement advanced dynamic or flexible pricing strategies that massive information sets encompass, supply and demand in markets, and what competitors are up against and available production capabilities. Levin et al., [32] show that industrial suppliers are leveraging AI-enabled tools to customize their prices down to the individual client level to extract the maximum margin possible while still preserving value on a relational level. For example, predictive analytics enables freight logistics companies to adjust real-time shipping rates based on road congestion levels, fuel prices, and customer need for speed [3]. Not only does this technological integration eliminate pricing mistakes, but it also increases customer loyalty with pricing in line with perceived worth.

However, dynamic pricing and discount strategies can sometimes be hard to fathom. While discounts can immediately stir up consumption and increase customer loyalty (and appreciation of customers), too heavy reliance on them can lead to the perception of benefits, devalued costs, and marketing wars. Beyond the steel sector, Ozcelik and Ozdemir [33] show that economic downturns negatively impacted the steel industry's margins, as there is aggressive discounting and commoditization that ultimately eroded long-term profitability. On the other hand, volume or long-term contracts tied to customized discounts can reinforce relationships between buyers and sellers [17], as is the case with the automotive parts market.

On the horizon, integrating sustainability goals into pricing models is an emerging frontier of B2B research. With rising pressure on firms to decarbonize, pricing strategies could include environmental costs as a part of production processes as a competitive advantage. For example, renewable energy suppliers work with manufacturers to devise price structures that reflect carbon-neutral production metrics, where risks and rewards are shared between the two [34]. The capabilities and features of AI to help adjust queuing models, for example, and forecast demand, also require further research. Refining forecasting capabilities with machine learning methods will help companies proactively adjust pricing in response to anticipated market changes [32].

3. Statement of the problem

The construction of a plan based on the concept that distinct groups of customers attach different levels of priority to diverse benefits supplied by a product or service type is called market segmentation [35]. For instance, the same car model may be proposed in multiple variations (two-door or four-door, different engine powers, different finishing levels, etc.), and each version may attract a particular sort of customer [36].

This method applies to a type of item in a monopoly market. It consists of segmenting the market and charging a different price for each segment, depending on the desire of these customers to spend more or less to purchase the item. Indeed, some "rate fences" should be created to ensure that the clients of a segment will pay the price allotted to the section. These "rate fences" can be the advertising of some perks that attract the clients of a specific niche or by delivering some particular services to the customers of a distinct group. Again, the customers belonging to a given segment should be similar or, in other words, characterized by the same parameters and dissimilar from the customers of others. Similarity and dissimilarity are related to purchase habits [35].

This study seeks to fill these gaps by answering the research question: How can we combine queuing theory with market segmentation to generate dynamic pricing strategies for B2B firms that maximize revenue considering temporal preferences, operational constraints, and competitive pressures? This study attempts to develop a unified framework that overcomes the trade-offs of service speed, capacity utilization, and profitability in multilayer B2B ecosystems by bridging value-based segmentation with queuing-driven operational insights [35].

4. Problem formulation

We consider a B2B industry in which each customer can order any product, which means 1 to infinite boxes of products. The order quantity for each product may follow any PDF (Probability density function). The probability of ordering i units is p_i (the model is general) so

$$\sum_{i=1}^{\infty} p_i = 1 \tag{1}$$

We have two kinds of products, called new products and routine products.

The time between two consecutive arrivals of customers follows exponential PDF with parameter λ. If customers arrive with Poisson and the probability of ordering i units is p_i then the demand quantity of number i follows Poisson with the parameter:

$$\lambda_i = \lambda p_i \tag{2}$$

We define the probability that a customer orders a new product as q; therefore, the probability of ordering a routine product will be 1-q.

The demand quantity of i unit for each type of product is:

For new product:

$$\lambda_i = \lambda p_i \mathrm{q} \tag{3}$$

For routine products:

$$\lambda_i = \lambda p_i (1 - \mathrm{q}) \tag{4}$$

So, the rate of demand for the system is:

$$\Lambda = \sum_{i=1}^{\infty} [\lambda p_i q + \lambda p_i (1 - q)] = \sum_{i=1}^{\infty} \lambda p_i \tag{5}$$

The transition diagram of this part of the model is shown in Figure 1.

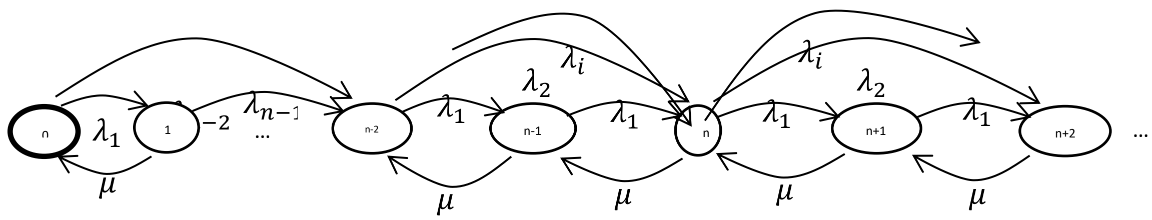

Fig. 1. The transition diagram of demand

System states are the demand entered into the system.

$$\lambda\pi_0 = \mu\pi_1 \tag{6}$$

$$(\lambda+\mu)\pi_n = \mu\pi_{n+1} + \sum_{k=1}^{n}\lambda_k\pi_{n-k}\,; n = 1,2,\ldots \tag{7}$$

Solving the system of these equations, we have:

$$\pi_0 = 1 - \frac{\lambda\sum_{i=1}^{\infty} ip_i}{\mu} \tag{8}$$

If $\mathcal{N}$ is the number of demands of each amount, the average of that is:

$$E(N) = \sum_{i=1}^{\infty} ip_i \tag{9}$$

Considering the product groups, we have:

$$E(N_1) = \sum_{i=1}^{\infty} ip_i\, q \tag{10}$$

$$E(N_2) = \sum_{j=1}^{\infty} jp_j(1-q) \tag{11}$$

$$E(N) = E(N_1) + E(N_2) \tag{12}$$

The average of demands entering the system during the time unit equals the average of each customer's demand by the number of customers entering the system:

$$\lambda.E(N) = \lambda\left[\sum_{i=1}^{\infty} ip_i q + \sum_{j=1}^{\infty} jp_j(1-q)\right] \tag{13}$$

Then Eq. (8) can be rewritten as:

$$\pi_0 = 1-\rho = 1 - \frac{\lambda E(N)}{\mu} \tag{14}$$

Now by Eq. (7) all the π_n can be calculated.
L= the steady state average of demand in the system.

$$L = \sum_{n=0}^{\infty} nP(existence\ of\ n\ customers\ in\ system) = \sum_{n=0}^{\infty} n\pi_n = \frac{\rho}{1-\rho} + \frac{\rho.\left[\frac{E(N^2)}{E(N)}-1\right]}{2(1-\rho)} \tag{15}$$

Where $\rho = \frac{\lambda E(N)}{\mu}$

A closed form of the model can be written as follows:

$$Max\ z = \nu_1(\lambda\sum_{i=1}^{\infty} ip_i q - B_1) + \nu_2(\lambda\sum_{j=1}^{\infty} jp_j(1-q) - B_2) - C_1(\lambda\sum_{i=1}^{\infty} ip_i q - B_1) - C_2(\lambda\sum_{j=1}^{\infty} jp_j(1-q) - B_2)$$

$$\begin{aligned} &Sub\ to: \\ &E(N) - (B_1 + B_2) \le C \\ &B_1 + B_2 \le E(N) \\ &0 \le p_i \le 1 \\ &0 \le q \le 1 \end{aligned}$$

The objective function calculates the total profit of the system. The first phase gives the income of the new product, the second phase gives the income of the routine product, and the next two phases give the costs of the new and routine products, respectively. And the constraints define the production capacity. The notation of used symbols is defined in Table 1.

Table 1
Notations

p_i	The probability of ordering i unit of product
λ	Arrival rate of two consecutive customers
q	The probability that a customer orders a new product
μ	The service rate of the system
$\mathcal{N}$	The number of demands for each amount
L	The steady-state average of demand in the system
ν_1	The unit price of the new product
ν_2	The unit price of a routine product
C_1	The production cost per unit of new product
C_2	The production cost per unit of routine product
C	The production capacity
B_1	The lost sale of new product
B_2	The lost sale of routine product

5. Numerical analysis

The closed-form solution presented in Section 4 enables decision-makers to refine pricing strategies and determine optimal price differentiation coefficients across product or customer segments. These insights can further guide the company's strategic planning team in resource allocation and long-term strategy formulation.

For instance, if a company observes significant price disparities between its innovative products and established product lines, coupled with higher profit margins for the former, the model suggests prioritizing investments in targeted marketing campaigns and expansion into untapped markets to maximize profitability.

The model has been solved using company-specific parameter values defined in Table 2 to demonstrate practical applicability.

Table 2
Parameter values

p_i	Uniform (1,21)
λ	400
q	0.05
μ	350
ν_1	100
ν_2	90
C_1	75
C_2	60
C	3500

Figure 2 shows the total profit function fluctuations when the probability of new product order changes. In a company with this situation and parameter values, we suggest that its managing board choose advertising campaigns to introduce their product to potential customer companies better.

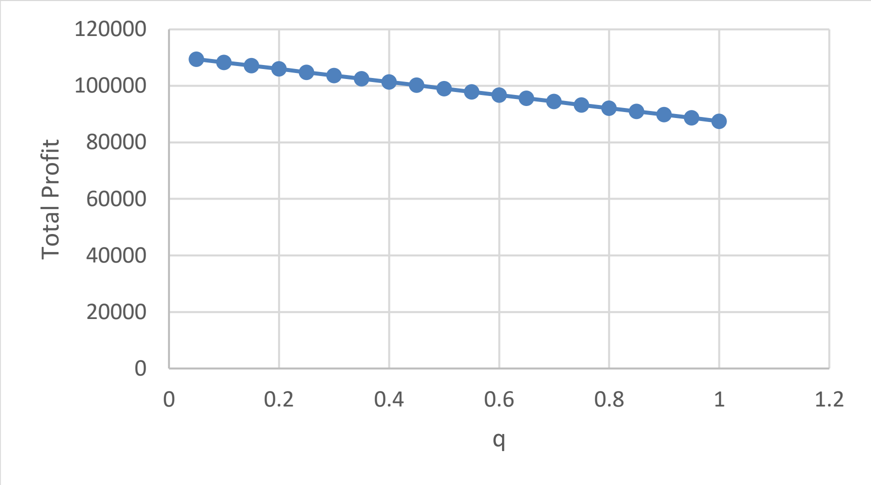

Fig. 2. Total profit for different new product order probability

6. Conclusions

Understanding and managing the impact of pricing on buyer behavior and evolving business relationships is critical for the long-run profitability of B2B sellers. More generally, this research offers B2B sellers a comprehensive decision framework to manage their buyer base using dynamic price targeting. As many B2B sellers routinely apply cost-based pricing strategies, we also assumed the same situation. Still, the generality of the proposed queueing model prepares a significant foundation for companies to check different strategies using the model. We considered two groups of products, but it can be extended to several products and several customer groups to model a more realistic situation where companies face a competitive world.

The model can suggest the best capacity assignment by calculating the lost sale amounts, where the assignment strategy can be ordered or selected by the higher level of management in the company.

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Conflicts of Interest

The authors declare no conflicts of interest.

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