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Interactive bundle pricing strategy for online pharmacies

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ABSTRACT

Online retail pharmacies usually price their products differently from traditional drugstores. Based on real-time consumer behaviors, this paper proposes a dynamic bundle pricing strategy to maximize the pharmacy's profit. Given free shipping thresholds and consumer budgets, we propose a mixed-integer nonlinear programming model and a heuristic to sequentially price customized bundles. We further conduct a numerical study using the data from a leading e-pharmacy in China. Our computational results indicate that the proposed model not only improves the e-pharmacy's profit by attracting more customers but noticeably contributes to consumer surplus. Through sensitivity analysis, our model is proved to be robust under various scenarios.

1. Introduction

Nowadays, shopping online has been welcomed by consumers all around the world, with global online sales predicted to exceed $4 trillion by 2020 (eMarketer, 2016). This trend makes online pharmacy, also called Internet pharmacy or e-pharmacy, become increasingly popular worldwide. By 2023, the global online pharmacy market is estimated to reach around $128 billion (Statista, 2018a) with a compound annual growth rate of 14.2% from the year 2018 to 2023 (Statista, 2018b). The development of online retail pharmacy (hereafter referred to as "e-pharmacy") in China has boomed these years. By April 2018, approximately 7500 pharmacy outlets provided services on Ping An Good Doctor, China's biggest online healthcare platform (Mordor Intelligence, 2018).

In practice, Internet retailers often motivate customers by adopting online recommendation systems (ORS). ORS recommend products to customers based on customers' online purchase behaviors, together with expert evaluations and analysis of product/customer characteristics. They often provide consumers with product bundles at lower prices (Ansari et al., 2000; Bakos and Brynjolfsson, 2000). Those ORS are especially important for e-pharmacies since customers who purchase pharmaceutical products need more professional recommendations than any other categories. Different from products in other online retailer platforms, pharmaceutical products also have various relationships with each other (i.e. substitutes, independence and complements), and various combinations of drugs for different diseases intensify the importance of professional recommendations. However, there is a limited number of research on e-pharmacy, this paper focuses on the e-pharmacy bundle pricing problem, which can not only satisfy consumers' pharmaceutical recommendation needs but can also improve e-pharmacy's profit and consumer surplus. Nowadays, ORS has been put into use by some e-pharmacies, but their bundle prices had not been optimized yet. For example, when a customer browses a supplement containing NMN (a molecule that boosts NAD+ levels and supports cellular health), Amazon suggests other

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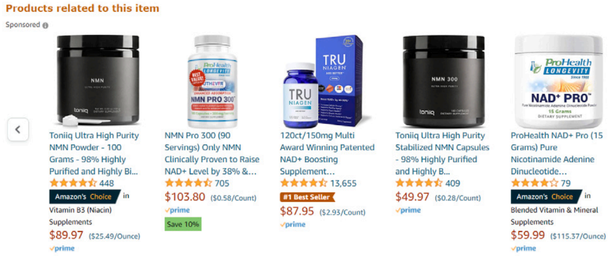


(a) Recommendation.

(b) Bundled price.

Fig. 1. E-pharmacy's recommendation system and bundle pricing strategy.

products with similar features (see Fig. 1(a)). Besides, it also offers some prepared bundles and shows their bundle prices (see Fig. 1(b)).

It is well known that customer preferences and product prices are the two main factors influencing consumers' purchasing decisions (Keeney, 1999). However, the current ORS tends to focus on a customer's purchase history, and recommend relevant products with little consideration on the profitability of Internet retailers or customer savings (Jiang et al., 2011). For example, the most common way for Amazon is to offer customers to"buy A and get B at an additional 10% off", where you only enjoy the discounts if certain products are chosen. This phenomenon is also widely observed in online pharmacies, where the bundle sizes and prices are predetermined and customers cannot create their own bundles.

In this paper, we propose an Interactive Bundle Pricing Strategy (IBPS) for e-pharmacies to optimally price their bundles. Following Xu et al. (2022), to successfully apply this strategy to e-pharmacies, we create a novel heuristic for our nonlinear mixed-integer programming model. Finally, we offer e-pharmacies an interactive pricing scheme that considers both free shipping policy and customer budget and provides a customized price to maximize the profits of e-pharmacy, customers' surplus also has a remarkable improvement in response to the pricing scheme. According to Häubl and Trifts (2000), customers' online shopping behavior can be regarded as a multistage process in that customers browse products sequentially, add the ones they like to the shipping cart, and delete some from it if they find better alternatives later. Meanwhile, the IBPS determines the bundle price of each possible product combination in the shopping cart, and it also captures the real-time events of adding or deleting items in the shipping cart to generate new bundle prices. Because the bundle price will be cheaper than the sum of the individually posted prices shown on the e-pharmacy's website, customers are encouraged to buy more products in one transaction.

Based on the data collected from a leading e-pharmacy in China (we henceforth refer to as company A) and through a numerical study, we find that the proposed approach is a "win-win" strategy because the IBPS yields more profits for e-pharmacies and extra surplus for customers. The contributions of the proposed IBPS are as follows:

(1) Most of the traditional strategies ignore customer surplus and the e-pharmacy's profitability. For example, although Jiang et al. (2011) consider the e-pharmacy's profitability, they do not involve the maximization of consumer surplus. Our model considers both, and we also incorporate the free shipping policy and consumer budget into the proposed IBPS.

(2) Different from the relevant literature that treats customers' purchasing behavior as a buy-or-not-buy one-stage decision process, our model provides real-time bundle prices and allows customers to explore as many times as they wish in terms of the number and variety of products.

(3) Our model and the corresponding heuristic developed in this paper contribute to the implementation of online pricing, which helps e-pharmacies obtain near-optimal solutions efficiently that match the real-time interactive environment.

The remainder of this article is organized as follows. In Section 2, we review the relevant literature. In Section 3, we propose a nonlinear mixed-integer programming model and a heuristic to solve it. Numerical results and sensitivity analysis are conducted in Sections 4 and 5, respectively, followed by conclusions and further research.

2. Literature review

Our research belongs to the stream of price discrimination, which has been widely adopted in several industries. Tthere are three degrees of price discrimination. The first degree is based on consumer identification. Although the online shopping environment provides the most convenient way for this price discrimination, Internet retailers would not adopt it since it may be discordant with current views on privacy. Second-degree price discrimination relies on product versions or quantities, which is a relatively common acceptable method. For example, consumers usually enjoy a big discount when they purchase mobile phones together with service plans (Yang and Ng, 2010), and strategic consumers can harm the profits of firms by purchasing their products until a discounted price occurs (Farshbaf-Geranmayeh and Zaccour, 2021). Another publicly acceptable practice, i.e., third-degree price discrimination, separates the market into segments based on observable group characteristics, e.g., hotels usually divide their customer groups into business class and leisure class. All those degrees of price discrimination have been well studied in the literature. For example, Spulber (1979) studies first-degree price discrimination, and finds that marginal cost pricing strategy contributes to the social welfare. Armstrong and Vickers (2001) shows that the adoption of third-degree price discrimination will improve the retailer's profit when the shipping cost is infinitely close to zero. He and Chen (2018) investigate the optimal pricing strategies for a platform when consumer reviews occur. Xiao et al. (2020) compare the conventional differential price strategy with the uniform price strategy. In our model, we consider the bundling strategy that is one of the most commonly used second-degree price discrimination methods.

Our research is on a bundle pricing problem based on online retailers. Internet retailers usually adopt price discrimination across customers or products by dynamically updating the posted prices or by offering quantity discounts. Bundling strategy is commonly used by Internet retailers to provide a discount when two or more products are sold together (Lin et al., 2020). Indeed, bundling can also be used as a strategic tool for the inventory-control purpose to bundle a popular product with a less popular one (Gökgür and Karabati, 2019). Actually, the practice of bundling can be regarded as one of second-degree discrimination (Kannan and Praveen, 2001). For example, Stigler (1963) observes that bundling can increase sellers' profits when consumers' reservation prices for two goods are negatively correlated, Salinger (1995) finds that under certain circumstances even positively correlated reservation prices may increase the incentive to bundle. The bundle pricing problem for more than two goods is considerably more challenging, and often considers three forms: pure component (only individual products), pure bundling (only bundle), and mixed bundling (individual and bundle) (Adams and Yellen, 1976; Stremersch and Tellis, 2002). Bakos and Brynjolfsson (1999) show that pure bundling is optimal when marginal costs are negligible and consumer valuations are independently distributed. Chung and Rao (2003) also focus on the pure bundling case and develop a product attribute model of consumer utility for bundling. When product values may be related, Jedidi et al. (2003) study the corresponding bundling strategies and find that a uniformly high-price strategy is optimal when the heterogeneity is high. In terms of mixed bundling, Chuang and Sirbu (1999) show that mixed bundling can dominate either pure bundling or individual sale alone for digital information goods. Bhargava (2013) further calculates the exact analytical solution for mixed bundling strategy of two information goods. Bajwa et al. (2016) incorporate capacity constraints, setup costs, and dynamic demand in multiple products' pricing problem. Honhon and Pan (2017) study mixed bundling strategy to maximize a firm's profit when its products are vertically differentiated. Zhou (2021) proposes a framework to study competitive mixed bundling with an arbitrary number of firms. In our model, we introduce a mixed bundling model and aim to improve customer satisfaction and the e-pharmacy's profit by optimizing the price for each bundle. In particular, we allow customers to interactively select the products of their choice, and provide them with a dynamic price menu in real-time.

The complexity of the bundling problem grows exponentially as more and more factors are taken into consideration, such as limited capacities (Banciu et al., 2010), different channels (Cao et al., 2022), reservation price (Hanson and Martin, 1990; Chung and Rao, 2003; Wu et al., 2008; Lee and Sarkar, 2017), shipping cost (Sahay et al., 2015), budget constraint (Ansari et al., 1996; Zhang et al., 2014), and cost ratio (Jiang et al., 2011). In the past, researchers provide a general structure for solving simple bundling problems in closed form by mathematical method (Armstrong, 1996; Rochet and Choné, 1998; Giri et al., 2017). However, due to the increase in product variety and influence factors, it is difficult to solve complex bundling problems analytically. An alternative approach is to solve the problem directly using numerical methods. Hanson and Martin (1990) propose a mixed-integer programming model and bundle pricing algorithm to determine the optimal bundling strategy. By using empirical tests, Chung and Rao (2003) develop a product attribute model to generate market segments and optimal bundle prices. Xue et al. (2016) further study the pricing strategies for personalized product bundles through an empirical approach, with respect to the factors of bundle features and consumer attributes. Mayer et al. (2013) adopt a simulation-based approach and develop a VNS-based metaheuristic to solve mixed bundling problem with capacity constraints. Cataldo and Ferrer (2016) develop a mixed-integer nonlinear program and a novel two-phase solution approach to generate the optimal bundles. Considering complementary products, Taleizadeh et al. (2017) develop an integrated pricing inventory model and propose an algorithm to solve this problem. Zhang et al. (2023) use numerical analysis to optimize mixed bundle pricing strategy considering consumer regret. In our mixed bundling model, we consider reservation price, shipping cost, free shipping policy, and consumer budget. Moreover, we propose a heuristic solution approach to optimize each bundle price efficiently.

3. The bundling and pricing model

3.1. Problem description and model assumptions

In this section, we formulate the IBPS problem as a nonlinear mixed-integer programming model for e-pharmacies. The model is developed from the seller's perspective. Given that customers are allowed to choose any number of goods to form personalized bundles, how to price these bundles in real-time to maximize the total profit of the e-pharmacy, subject to a set of consumer participation and incentive compatibility constraints? Following Stigler (1963), we first assume that consumer demand information is captured by a vector of reservation prices of the items that go into a bundle. We also assume that consumers maximize their

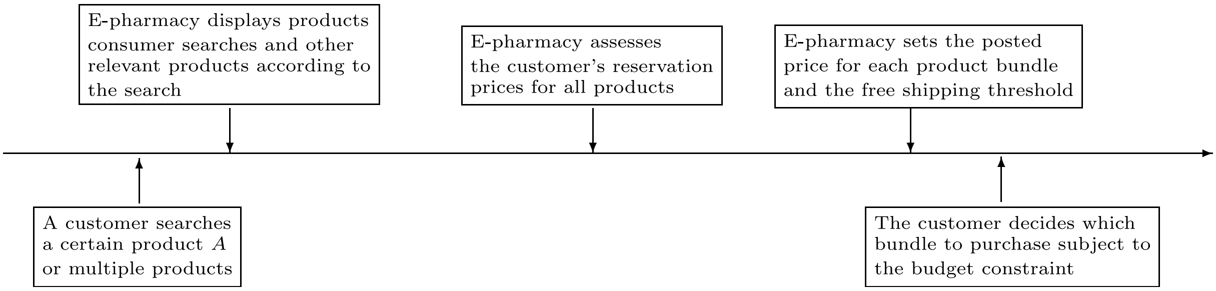


Fig. 2. Timing of the IBPS model.

Table 1
The nominations.

Nomination	Descriptions
I	Product index denotes the ith product
J	Customer index denotes the jth customer
K	Bundle index denotes the kth bundle
S	Scenario index denotes the sth scenario
n	The number of products the e-pharmacy sells
m	The number of potential customers in market
c_i	Cost of the ith product
w_i	Posted price of the ith product
$x_{i,k}$	A binary that shows whether the kth bundle includes the ith product
$\boldsymbol{G}_k$	The vector of the kth bundle
f_k	Shipping cost of the kth bundle
b_j	Budget constraint of the jth customer
$\boldsymbol{R}_j^s$	The vector of consumer j's reservation prices for all products under scenario s
$r_{j,i}^s$	Reservation price for the ith product of the jth customer under scenario s
L_0	free shipping threshold level
$S_{j,k}^s$	Consumer surplus of the kth bundle to the jth customer under scenario s
k_j^s	Bundle k as customer j's optimal bundle decision under scenario s
X_k^s	Posted price of the kth bundle under scenario s
$\boldsymbol{G}_{k_j}$	The best bundle the jth customer chooses at last
I_k^s	A binary that shows whether customer pay the shipping fees when bundle k is chosen under scenario s
$y_{j,k}^s$	A binary that shows whether customer j chooses the optimal bundle k under scenario s

surplus based on the difference between the total reservation prices for items in a bundle and the posted price they pay. The seller has to account for consumers' optimal choice behavior given their preferences and the reservation prices for product offerings, which appears as constraints in the seller's optimization problem. Fig. 2 illustrates the sequence of our model.

Before delving into the model, we outline several assumptions related to the process of consumers buying medicines online. Firstly, we assume that customers are rational in their purchasing decision, and prioritize the highest consumer surplus — which is the difference between the reservation price and the posted price. We estimate the reservation price of a bundle by summing up the reservation prices of individual items in the bundle, as proposed by Jiang et al. (2011). To determine the reservation prices of consumers, we can use various practical methods, such as Wertenbroch and Skiera (2002), Jedidi et al. (2003) and Bitran and Ferrer (2007). Additionally, we assume that each customer has a unique budget, which can be estimated based on their past purchase history using sales data, as suggested by Ulkumen et al. (2008). These budgets will limit their purchasing power. From the perspective of e-pharmacy, we assume that free shipping is provided if a customer's order meets or exceeds a specified threshold, denoted by L_0 and that orders will not be split into multiple sub-orders. Finally, we assume that the e-pharmacy adopts second-degree price discrimination, whereby customers receive a discount when they purchase more, resulting in the price of a bundle being lower than the sum of the posted prices of the individual sub-bundles.

3.2. The interactive bundle pricing systems

Here we consider an e-pharmacy that sells n products through an online website to m potential customers. Each customer demands at most one unit of each good. The costs of the products are defined as a vector $\boldsymbol{C} = \begin{pmatrix} c_1 & c_2 & \cdots & c_n \end{pmatrix}$, where $c_i (i = 1, 2, \ldots, n)$ represents the unit cost of the ith item. The posted prices of the products are defined as a vector $\boldsymbol{W} = \begin{pmatrix} w_1 & w_2 & \cdots & w_n \end{pmatrix}$, where $w_i (i = 1, 2, \ldots, n)$ is the corresponding posted price of the ith item. These n products make up 2^n different bundles $k, k = 1, 2, \ldots, 2^n$. We use a binary vector to define this sequence, i.e., $\boldsymbol{G}_k = \begin{pmatrix} x_{1,k} & x_{2,k} & \cdots & x_{n,k} \end{pmatrix}$, where $x_{i,k}$ is a binary variable that $x_{i,k} = 1$ if the customer chooses the ith item and $x_i^k = 0$ otherwise. Thus, the cost of the kth bundle is $\boldsymbol{C} \cdot \boldsymbol{G}_k^T$. Let f_k as the shipping cost of the kth bundle, and $b_j (j = 1, 2, \ldots, m)$ as the budget constraint of the jth customer. The notations are summarized in Table 1.

In this paper, customers' reservation prices are stochastic factors, a common method is to use scenarios to represent the uncertainty since stochastic factors are really hard to be applied in computational process. We follow Hu and Hu (2016) to use S scenarios to represent customer j's reservation price. The reservation prices of the products under scenario s are defined as a vector $\boldsymbol{R}_j^s = \begin{pmatrix} r_{j,1}^s & r_{j,2}^s & \cdots & r_{j,n}^s \end{pmatrix}$, where $r_{j,i}^s$ is the reservation price of the jth customer for the ith product under scenario s. $R_j = \left\{ R_j^1, R_j^2, \ldots, R_j^s \right\}$ with each scenario's probability to be $Prob(R_j^s) = p_s$. Therefore, every scenario is a discrete value of reservation price for customer j, and discrete values with their corresponding probabilities can be generated to represent continuous distribution. The stochastic programming model is formulated as follows:

Under scenario s, the e-pharmacy decides the posted price X_k^s of bundle k chosen by the customer. In particular, $X_1^s = 0$ represents that the shopping cart of the customer is empty, and $X_{i+1}^s = w_i$ refers to the customer who only selects the i th item into the shopping cart, and the recommend price is the posted price of this item. Like most e-pharmacies do, such as Ali Health, they operate the online business under the free shipping policy that the shipment cost is covered by the e-pharmacy if the total sale of a consumer is above a certain threshold L_0. Therefore, we denote $S_{j,k}^s$ as the surplus for customer j of bundle k in scenario s.

$$S_{j,k}^s = \begin{cases} R_j^s \cdot \boldsymbol{G}_k^T - X_k^s - f_k \cdot I_k^s, & X_k^s + f_k \cdot I_k^s \le b_j \\ 0, & X_k^s + f_k \cdot I_k^s > b_j. \end{cases} \tag{1}$$

where I_k^s is an indicator function that $I_k^s = 1$ if $X_k^s < L_0$ and $I_k^s = 0$ otherwise. If the total spending of the product set excesses customer j's budget, we defined $S_{j,k}^s$ to be 0 because of the negative consumer surplus. This assumption guarantees that customers prefer the option of buying nothing rather than the option that the total spending is above the budget. The e-pharmacy pays the shipment cost f_k if the posted price X_k^s is larger than L_0, where L_0 is defined as the free-shipment threshold. We denote k_j^s as the optimal bundle decision of customer j chooses bundle k, then we have

$$k_j^s = \begin{cases} \arg\max_k \{S_{j,k}^s\}, & \max_k \{S_{j,k}^s\} \ge 0 \\ 1, & \max_k \{S_{j,k}^s\} < 0. \end{cases} \tag{2}$$

The e-pharmacy takes into account the customer reservation price, customer budget and product data, and obtains the optimal posted prices of each bundle that maximizes the total profit given by Eq. (3).

$$\max_{X_k^s, y_{j,k}^s, I_k^s} \sum_{s=1}^{S} p_s \cdot \left\{ \sum_{j=1}^{m} \sum_{k=1}^{2^n} y_{j,k}^s \left[X_k^s - \boldsymbol{C} \cdot \boldsymbol{G}_k^T - f_k \cdot (1 - I_k^s) \right] \right\} \tag{3}$$

$$\text{s.t.} \quad \boldsymbol{C} \cdot \boldsymbol{G}_k^T \le X_k^s, \forall k, s \tag{4}$$

$$X_k^s \ge X_a^s - X_b^s, a, b = \{a, b | \boldsymbol{G}_a - \boldsymbol{G}_b = \boldsymbol{G}_k\}, \forall k, a, b, s \tag{5}$$

$$I_k^s = 0\, or\, 1, \forall k, s \tag{6}$$

$$y_{j,k}^s = 0\, or\, 1, \forall k, j, s \tag{7}$$

The above constraints are explained as follows. Constraints (4) demonstrates that the sum of the costs of the bundled products should be less than the sum of the corresponding posted prices. Constraints (5) indicates that the posted price of each bundle should not exceed the total posted prices of the sub-bundles. That means, if customers split a bundle into several sub-bundles, the sum of all sub-bundles' posted prices is greater than the original bundle's posted price. Finally, there are two binary variables in the model, i.e., Constraints (6) and (7), where I_k^s equals 1 means the customer needs to pay the shipping fee if bundle k is chosen, and $y_{j,k}^s$ equals 1 means the customer j decides to buy bundle k.

As more products are added to the product list, the number of bundles grows exponentially, which makes the model hard to solve. To handle this large-scale case, we propose a heuristic algorithm based on Constraints (5), that we can calculate the optimal price of each bundle more efficiently from the larger bundle to the smaller one because each small bundle can be viewed as the subset of the large one, thus the upper and lower bound of each small bundle can be narrowed according to Constraints (5), and we describe our heuristic steps in detail in Section 3.3, also we prove that our heuristic can improve e-pharmacy's profit by 9.97% and improve consumer surplus by 32.64% in Table 5, in Section 4.2.

3.3. Heuristic algorithm

In the IBPS model, the e-pharmacy makes decision to maximize the total profit, while consumers choose bundles that maximize their own surplus. In this section, we propose a heuristic solution approach to optimize the price of each bundle. Note that the posted prices of bundles that contain only one product are not optimized and are equal to the posted price of the single product. For each scenario s, the optimization process is in the order of large bundles to small bundles is presented as follows.

Step 1. Divide all the bundles, $k = 1, 2 \cdots, 2^n$, into three groups:

Group 1: $\boldsymbol{G}_1$ is the vector of bundle with no product;
Group 2: $\boldsymbol{G}_2, \boldsymbol{G}_3, \ldots, \boldsymbol{G}_{n+1}$ is the vector of bundles which contain only one product;

Group 3: $\boldsymbol{G}_{n+2}, \boldsymbol{G}_{n+3}, \ldots, \boldsymbol{G}_{2^n}$ is the vector of bundles that contain multiple products.

We only need to calculate bundle price in Group 3 whose bundles have multiple products.

Step 2 For each bundle k, sum the posted prices and costs of all products within the bundle as the upper and lower bounds of the initial posted price, referred to as U_k and $L_k^{(1)}$, respectively. Initialize the posted bundle price to the upper bound of the initial posted price, i.e., $X_k^s = U_k$.

Step 3 Keep the posted prices of Group 2 constant, while optimizing the posted prices of Group 3 starting from $k = 2^n$.

Step 4 Under budget B_j, each consumer chooses a bundle considering products' reservation prices, bundles' posted prices, and shipping fee which will generate the highest surplus, and then calculate the initial e-pharmacy's profit, referred to as Π'.

Step 5 Find all the pairs $(\boldsymbol{G}_a, \boldsymbol{G}_b)$ which fit $\boldsymbol{G}_a - \boldsymbol{G}_b = \boldsymbol{G}_k$. Get a new lower bound for bundle k, referred to as $L_k^{(2)} = max\{X_a^s - X_b^s | \boldsymbol{G}_a - \boldsymbol{G}_b = \boldsymbol{G}_k\}$, which can sufficiently narrow the gap between the upper bound and lower bound.

Step 6 Set the lower bound price of bundle k as $L_k = max\{L_k^{(1)}, L_k^{(2)}\}$.

Step 7 Reduce the kth bundle price by a small reduction step Δ_w, i.e., $X_k^s = X_k^s - \Delta_w$.

Step 8 Under budget B_j, each consumer then selects a bundle under each X_k^s with the highest surplus as Step 4 does, and calculate the new total profit Π.

Step 9 Observe the posted price of bundle k, which contains two cases:

Case 1: The posted bundle price is larger than the lower bound, i.e., $X_k^s > L_k^s$. If $\Pi > \Pi'$, reset profit Π' as Π and posted price $X_k^{s'}$ as X_k^s, and keep profit Π' and posted price $X_k^{s'}$ unchanged otherwise. Go back to Step 7;

Case 2: The posted bundle price is less than or equal to the lower bound, i.e., $X_k^s \le L_k$. Turn to Step 10 if $k = n+2$, and set $k = k-1$ and go back to Step 5 otherwise.

Step 10. Output the optimal profit Π' and the optimal posted price set $\left\{X'_{1,s}, X'_{2,s}, \ldots, X'_{2^n,s}\right\}$.

Instead of starting with bundles containing a small number of products, we calculate bundle prices in an opposite way. In Step 5, the larger bundle can be divided into several smaller bundles, which can narrow the gap between the upper bound and lower bound for each smaller bundle, thus saving calculation time considerably. In our numerical test, our heuristic algorithm can save at least half of the calculation time compared with that of the traditional method, and as the bundles grow larger, the more calculation time it can save.

The reduction step is the key factor that will influence the performance of the heuristic algorithm, when the reduction step is relatively low, the heuristic can find better solutions but also need longer computation time, thus it is important to balance the efficiency and effectiveness by choosing a suitable reduction step. In our paper, we set the reduction step to 0.1 to get a near-optimal solution, which can efficiently improve e-pharmacy's profit by 9.97% and improve consumer surplus by 32.64%.

3.4. The performance of the heuristic

To explore the performance of the algorithm, we then study the upper and lower bounds of the algorithm. The proposed heuristic algorithm aims to maximize the profit of the e-pharmacy by iteratively testing the optimal bundle prices of each bundle in a finite number of steps. In cases where the algorithm does not optimize the bundle price, the posted price of each bundle is calculated based on the posted prices of its individual products. This yields a lower bound for the model, which serves as a benchmark for subsequent numerical studies. The benchmark is a special case of our model, which does not consider the existence of bundles. The model can be formulated as follows:

$$\max_{y_{j,k}^s, I_k^s} \sum_{s=1}^{S} p_s \cdot \left\{ \sum_{j=1}^{m} \sum_{k=1}^{2^n} y_{j,k}^s \left[(\boldsymbol{W} - \boldsymbol{C}) \cdot \boldsymbol{G}_k^T - f_k \cdot (1 - I_k^s) \right] \right\} \tag{8}$$

s.t. (6)–(7)

Compared to Eq. (3), Eq. (8) considers the sum of prices of products within a bundle as its posted price, as there is no need to price the bundles when the bundling strategy is not taken into account.

After obtaining the lower bound using the benchmark, we focus on analyzing the upper bound of the algorithm. We start by examining Eq. (3), which is the profit function of the e-pharmacy. This equation consists of three parts: the revenue generated by bundles chosen by customers under different scenarios, the cost of the products included in the bundles, and the possible shipping fees. The key to finding the upper bound is to determine how to make the most of the information available regarding customers' reservation prices for each product and total budgets in order to maximize profits. Constraints (4) ensures that the minimum price of a bundle is not lower than its cost, setting a lower bound for the pricing of each bundle and thereby narrowing the search space of feasible solutions without affecting optimality. Constraints (5) guarantees that the prices of bundles do not violate second-degree price discrimination, which means that consumers who purchase more products are entitled to greater price discounts. However, second-degree price discrimination does not utilize consumers' private information. To increase profits, we can consider further adjusting the posted prices of the bundles while keeping the consumers' choices constant. Consider the example of pricing bundles for three products: under the determinate scenario s, refer to the previous naming rules for bundles, one bundle contains products A and B with a posted price of X_5 while another bundle contains products A, B, and C with a posted price of X_8. If a consumer

Table 2
Scenarios for customer's reservation price.

Scenario number	Probability	Reservation price for scenario s
1	0.2	$\{40.4, 46.1, 18.8\}$
2	0.2	$\{31.5, 49.6, 17.9\}$
3	0.2	$\{35.0, 61.6, 17.6\}$
4	0.2	$\{37.6, 40.7, 11.1\}$
5	0.2	$\{44.4, 44.0, 17.9\}$

chooses the latter bundle, it means that both bundles are within their budget and the latter provides a greater consumer surplus. If we can estimate the consumer's reservation price for each product in advance, we can set the price of the second bundle to be the price of the former plus the consumer's reservation price for product C, that is $X_5 + r^s_{j,3}$, where $r^s_{j,3}$ represents consumer j's reservation price on product C under scenario s.

The literature has extensively studied various methods for evaluating consumer reservation prices, including conjoint analysis (Jedidi and Zhang, 2002), incentive-compatible elicitation (Wang et al., 2007), and semi-compensatory approaches (Kaplan et al., 2011). Thus, it is feasible to estimate customers' reservation prices for bundles. We aim to leverage this information to enhance the profitability of e-pharmacies by finding the upper bound of the algorithm based on known or predicted customer reservation prices. Building on this concept, our objective is to optimize bundle pricing strategies to obtain an upper bound. To do so, we first run the previous heuristic algorithm and obtain a set of initial bundle prices X^{s0}_k and consumer choices $y^{s0}_{j,s}$, which is the basis for subsequent optimization of the bundle price. Then we relax Constraints (5) and adjust the pricing of the bundles. For all bundles, let $\boldsymbol{J}_k = \left\{ j_k \in J_k | y^{s0}_{j,k} = 1, k = n+1, n+2, \dots, 2^n \right\}$, which records all consumers' original choices. k starts from $(n+1)$ to 2^n because first n bundles represent either empty bundles or bundles consisting of individual products. Then starting from the (n + 1)th bundle, we add some constraints to formulate the upper bound model and optimize the prices as follows:

$$\max_{X^s_k, I^s_k} \sum_{s=1}^{S} p_s \cdot \left\{ \sum_{j=1}^{m} \sum_{k=1}^{2^n} y^{s0}_{j,k} \left[(X^s_k - \boldsymbol{C} \cdot \boldsymbol{G}^T_k - f_k \cdot (1 - I^s_k)) \right] \right\} \tag{9}$$

s.t. (6)–(7)

$$X^s_k \le X^s_a + R^s_j \cdot G^T_b, a, b = \left\{ a, b | G_a + G_b = G_k \right\}, \forall k, s, j \in \boldsymbol{J}_k \tag{10}$$

$$X^s_k + f_k \cdot I^s_k \le b_j, \forall k, s, j \in \boldsymbol{J}_k \tag{11}$$

$$X^s_k \ge X^{s0}_k, \forall k, s \tag{12}$$

Constraints (10) states that the price of any bundle should not exceed the price of any of its sub-bundles plus the customers' reservation prices for the remaining products, resulting from a consumer's current choice must be greater than that of other choices when bundle prices change, where R^s_j represents the vector of consumer j's reservation prices for all products under scenario s. Constraints (11) indicates that the adjusted bundle price must remain within the customer's budget. Constraints (12) demonstrates that the adjusted bundle prices should be higher than the initial prices. Together, Constraints (11) and (12) ensure that customers will maintain their choices while also obtaining greater consumer surplus. As a result, the profit serves as an upper bound for the heuristic algorithm. Our experimental results demonstrate that the proposed heuristic algorithm can reach an upper bound of 99.6%, indicating its high effectiveness.

4. Numerical study

In this section, the proposed approach will be tested and evaluated using the real operation data from company A. All the experiments are implemented on a Windows10 workstation with two Intel Core i5-2410M CPUs and 4G RAM.

4.1. Data description

Posted Price and Product Cost. Chen et al. (2008) suggest that consumers, in general, order no more than eight items in one transaction. Thus, we collect the data of the top-8-ranked healthcare products from company A, including product titles and posted prices, in June 2018. Since we were not able to obtain the real information of product costs even though company A knows the exact costs of their products, we follow Sampson (2007) and assume the product costs are uniformly distributed at $U(0.6, 0.8)$ of the posted price.

Reservation Price. Following Li et al. (2013), we assume the reservation prices of all the consumers are independent and follow uniform distribution. We follow Hu and Hu (2016) to use scenarios to represent customer j's reservation price, we assume each customer's reservation price has 5 scenarios that can be estimated from his purchasing history (Jedidi et al., 2003). Thus we have customer j's reservation price to be $R_j = \left\{ R_{j1}, R_{j2}, \dots, R_{js} \right\}$ with each scenario's probability to be $Prob(R_{j,s}) = p_s$. Table 2 shows a customer's reservation price scenarios on 3 products to represent their uniform distribution.

Table 3
Comparison of two heuristic algorithms.

Bundle size	Execution time (s)		E-tailer's profit improve		Consumer surplus improve	
	Method A	Method B	Method A	Method B	Method A	Method B
3	7.61	3.18	1.77%	1.77%	10.21%	10.21%
4	22.38	4.54	2.25%	2.32%	8.61%	8.05%
5	73.81	10.04	3.43%	5.09%	14.68%	11.55%
6	291.29	33.44	5.18%	7.03%	20.73%	15.82%
7	1077.19	88.97	2.89%	7.21%	22.36%	14.77%
8	3920.47	169.91	3.74%	6.98%	16.41%	8.97%

Shipping Cost. As for the shipping cost, it is calculated based on the real operation of company A as follows: shipping cost = ¥7.50 + ¥2.50 × number of products, and the free shipping threshold level is assumed to be ¥69.

Consumer Budget. We assume the customer budgets follow the normal distribution $N(u_b, \sigma^2)$, and we set square coefficient of variation to be 0.2, which is $\sigma^2 = 0.2 * u_b^2$. In the following analysis, we set $u_b = 100$.

4.2. Comparison of heuristic algorithms

Considering the search process of the heuristic algorithm, we might calculate each bundle price starting with the smaller bundles, labeled as method A, and calculate bundle price in an opposite way, labeled as method B. Jointly considering the effectiveness of the above two types of heuristic algorithms and the calculation time, a better one would be chosen through a numerical study. In particular, we analyze the impact of the two optimization directions on e-pharmacy's profit and consumer surplus. As we mentioned before, consumer orders, in general, contain no more than eight items in one transaction, thus we assume the bundle size follows $U(3, 8)$. We use second (s) as the unit of execution time and percentage (%) as the measurement of the improvement rate. The testing results are shown in Table 3.

From Table 3, we find that, although method A can improve consumer surplus, from the perspective of e-pharmacies, considering the timeliness in bundle price and the profitability, method B has a shorter execution time and more significant profit improvement. We thus adopt method B to conduct our numerical study.

4.3. Experiment procedure

To evaluate the effectiveness of IBPS, we first use a regression model. Xue et al. (2016) use an exponential regression model to assess the value of each component in a bundle package, as they encountered the issue of multicollinearity in their regression. Through the variance inflation factor method, we found no multicollinearity among the independent variables in our model, and thus we directly used a linear model for regression. In this model, we use $PROFIT$ to represent the e-pharmacy's profit, while $SURPLUS$ represents the total consumer surplus, both of which are the dependent variables of interest. We also include CUS_NUM to denote the number of consumers who purchase a bundle, $THRESHOLD$ to represent the value required for free shipping, and $SHIP\_COST$ as the fixed cost for each shipment. Additionally, we incorporate BUD_MEAN and BUD_SCV to represent the mean and squared coefficient of variation of the budget, respectively. Finally, $IBPS$ is included as a binary variable to indicate whether the IBPS strategy has been adopted and ε is represents the stochastic error. In order to investigate the impact of IBPS on profit and consumer surplus, we establish two models:

$$\begin{aligned} PROFIT = \theta_0 + \theta_1 CUS\_NUM + \theta_2 THRESHOLD + \theta_3 \\ BUD\_MEAN + \theta_4 BUD\_SCV + \theta_5 SHIP\_COST + \theta_6 IBPS + \varepsilon \end{aligned} \tag{13}$$

$$\begin{aligned} SURPLUS = \theta_0 + \theta_1 CUS\_NUM + \theta_2 THRESHOLD + \theta_3 \\ BUD\_MEAN + \theta_4 BUD\_SCV + \theta_5 SHIP\_COST + \theta_6 IBPS + \varepsilon \end{aligned} \tag{14}$$

The fitting results in Table 4 show that our linear model has a good fit and reveal that the coefficient on $IBPS$ is positive and statistically significant in two of the models. Specifically, the results indicate that the adoption of IBPS leads to an average increase of 1130.243 in profit and 2164.439 in consumer surplus.

In our numerical study, we let the market size m equal 1000. In general, we have done 80 groups of experiments with 20 groups each time, to test the optimal amount of samples. In order to identify the significance of the difference between 10 groups and 20 groups, we randomly choose 10 groups of data out of every 20 groups to run t-test and show the results in Table 5. We find that the significance of difference decreases with increased sample size, and a sharp reduction in t-value appears when the sample size is 1000. Thus, 1000 might be the most appropriate amount if we take the running time into account. We then collect three best-sellers from company A, the posted prices of which are ¥40, ¥49, and ¥15, respectively.

In the numerical experiment, the consumers' purchase behavior is as follows : First, the optimal price of each bundle is obtained by running this model. Then each customer independently chooses the bundle that maximizes its consumer surplus based on post

Table 4
Regression results.

Variables	$PROFIT$	$SURPLUS$
Constant	939.206***	−5018.417***
	(228.932)	(188.131)
CUS_NUM	6.757***	11.787***
	(0.232)	(0.190)
$THRESHOLD$	36.469***	9.223***
	(0.988)	(0.812)
BUD_MEAN	84.995***	22.715***
	(0.810)	(0.665)
BUD_SCV	−118.008	−104.035
	(128.306)	(105.439)
$SHIP\_COST$	−793.679***	11.336
	(10.588)	(8.701)
$IBPS$	1130.243***	2164.439***
	(42.115)	(34.609)
Observations	3270	3270
R-squared	0.870	0.874

Note:
***Indicates the significance at the 1%. The standard errors are in parentheses.

Table 5
Difference of significance with different market sizes.

Market size	100	500	1000	10 000
t-value	7.379	6.286	3.226	3.157
p(sig)	<0.001	<0.001	0.011	0.016

Table 6
Sales data, consumer surplus, and e-pharmacy's profit.

	Benchmark	IBPS	Improvement rate
Customer number	502	603	20.12%
Sales volume	1067(=500 + 499 + 68)	1530(=587 + 571 + 372)	43.39%
Sales revenue (¥)	45 471	55 365	21.76%
E-pharmacy's profit (¥)	6817.81	7497.67	9.97%
Consumer surplus (¥)	4619.49	6127.07	32.64%
Average consumer surplus (¥)	9.2	10.16	10.42%

prices, their own budget, and the reservation prices of the products. Finally, we calculate the profit of the e-pharmacy as an indicator to evaluate our algorithm efficiency.

According to Chernev (2003), customer selection made from large numbers of assortments leads to weaker preferences. In fact, extending the size of choice set may confuse customers, which increases the probability of delaying their choice or not choosing at all (Dhar, 1997; Greenleaf and Lehmann, 1995; Iyengar and Lepper, 2000). In most categories, the recommended bundle size on the website of company A is no more than three items. Thus we choose at most three products as a bundle in our model.

Then, we can calculate the optimal posted price of each bundle by the proposed heuristic algorithm within two minutes. We compare the sales data, consumer surplus, and e-pharmacy's profit under the IBPS with those under the strategy without the bundling policy (hereafter referred to as "benchmark strategy"). The results are listed in Table 6, where "customer number" refers to the number of consumers who purchase the product, and we henceforth use "number of customers" to represent the above meaning.

Table 6 shows that, compared to the benchmark strategy, the IBPS has a number of desirable effects: it improves the sales volume and sales revenue by 43.39% and 21.76%, respectively; it enhances e-pharmacy's profit by 9.97%, even though e-pharmacy enjoys less profit margin; it also improves the consumer surplus and customer number by 32.64% and 20.12%, respectively, where every customer get a 10.42% higher consumer surplus. Thus we conclude that the IBPS is not only beneficial to e-pharmacy but also contributes to consumer surplus. Moreover, the IBPS contributes more to the consumer surplus than to e-pharmacy's profit.

Further, we analyze the sales of each bundle, the results are shown in Table 7. We use three circles to represent the three products, respectively, and different markings of the circle to show the customer's purchasing decision. In particular, the symbol "∘" stands for the customer who do not purchase the product and the symbol "•" refers to the customer who buys the product. For example, "• • ∘" means that the customer chooses the bundle that contains the first product and the second one but without the third one.

As shown in Table 6, compared to the benchmark strategy, the IBPS has a positive effect on attracting customers: It reduces the number of customers who purchase nothing by 20.3%, i.e., (498-397)/498; it increases the number of consumers who buy the bundle of all three products by 406.3%, i.e., (324-64)/64. In particular, almost half of the customers who choose to buy the first and the second products together under the benchmark case buy all three products under the IBPS. Moreover, compared with purchasing the product individually, each of the posted bundle price reduce by ¥4.5 except that of the bundle with the first and the second

Table 7
The purchase decisions of 1000 customers.

Purchasing choice		Benchmark strategy			IBPS		
No.	Products	Profit margin (¥)	Posted price (¥)	Customer number	Profit margin (¥)	Posted price (¥)	Customer number
1	∘∘∘	0	0	498	0	0	397
2	•∘∘	9.56	40	0	9.56	40	0
3	∘•∘	16.08	49	1	16.08	49	0
4	∘∘•	5.72	15	0	5.72	15	0
5	••∘	13.13	89	433	13.13	89	231
6	•∘•	15.28	55	3	10.78	50.5	32
7	∘••	21.8	64	1	17.3	59.5	16
8	•••	16.36	104	64	11.86	99.5	324

Table 8
Impact of consumer budget's average value on e-pharmacy's profit, consumer surplus, and customer number.

Budget	E-pharmacy's profit (¥)			Consumer surplus (¥)			Customer number		
	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve
70	2947.20	5733.76	94.55%	523.89	4104.33	683.43%	183	619	238.25%
80	3456.05	6121.56	77.13%	594.74	3333.43	460.49%	201	562	179.6%
90	5310.65	6783.20	27.73%	2879.45	3746.59	30.11%	374	526	40.64%
100	6817.81	7497.67	9.97%	4619.49	6127.07	32.64%	502	603	20.12%
110	7932.26	8207.57	3.47%	5221.73	5851.87	12.07%	537	578	7.64%
120	8172.47	8346.06	2.12%	5340.99	5861.72	9.75%	544	579	6.43%
130	8172.47	8346.06	2.12%	5340.99	5861.72	9.75%	544	579	6.43%
140	8172.47	8346.06	2.12%	5340.99	5861.72	9.75%	544	579	6.43%

Table 9
Impact of consumer budget's SCV on e-pharmacy's profit, consumer surplus, and customer number.

SCV	E-pharmacy's profit (¥)			Consumer surplus (¥)			Customer number		
	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve
0.1	6641.69	7237.73	8.97%	4186.42	5361.68	28.07%	466	559	19.96%
0.2	6817.81	7497.67	9.97%	4619.49	6127.07	32.64%	502	603	20.12%
0.3	5894.84	6107.24	3.60%	3626.87	3912.07	7.86%	399	429	7.52%
0.4	5577.43	5878.84	5.40%	3279.82	3586.40	9.35%	373	404	8.31%
0.5	4910.23	5103.79	3.94%	3096.38	3524.89	13.84%	328	366	11.59%

products, which remains unchanged. This is because customers can enjoy free shipping service, another form of price promotion provided by the e-pharmacy when they purchase the first and the second products together (¥40 + ¥49 = ¥89 >¥69). Thus the e-pharmacy has no incentive to further reduce the posted price of the bundle.

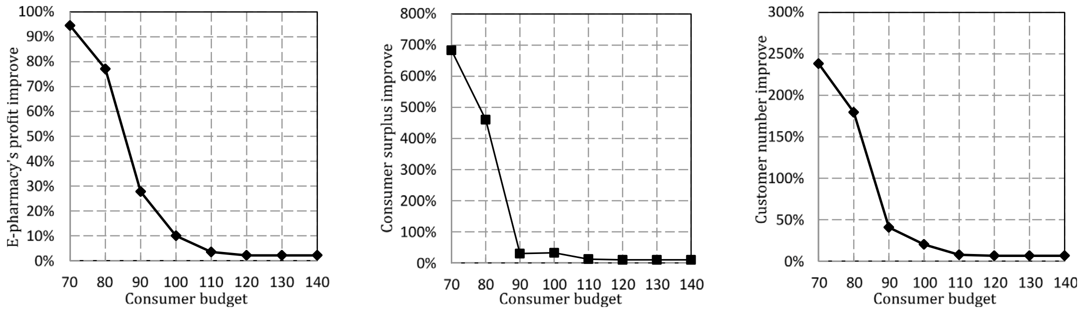
5. Sensitivity analysis

In this section, we further analyze the impact of consumer budget, product cost, shipping cost, and free shipping strategy on the IBPS performance by three indicators, i.e., the e-pharmacy's profit, consumer surplus, and customer number.

5.1. Impact of consumer budget on IBPS performance

From customers' perspectives, the budget is an important factor that affects their purchasing decisions. This section examines the e-pharmacy's profit, consumer surplus, and customer number under different levels of consumer budget. As mentioned before, we assume that the consumer budget follows the distribution $N(u_b, \sigma^2)$. Here, we further assume the average value u_b changes from 70 to 140 and SCV changes from 0.1 to 0.5. The results are shown in Tables 8 and 9, illustrated in Fig. 3.

Tables 8 and 9 both imply that IBPS outperforms the benchmark when consumer budget varies. Table 8 shows that e-pharmacy's profit, consumer surplus, and customer number reach the highest when $SCV = 0.2$, Table 9 shows that e-pharmacy's profit, consumer surplus and customer number all increases at first and stays stable after then with the increasing consumer budget, under both the IBPS and the benchmark strategy. In particular, their increase rates plunge sharply as the budget increases at a low level (see Fig. 3). This is because the budget plays a significant role in determining the customer's purchasing behavior when it is low, causing most customers buy nothing even though they have preferences for the products under the benchmark strategy. When the IBPS is adopted, customers have extra choices of purchasing bundles with lower prices compared to the case of the benchmark strategy, which contributes to large improvements in customer number, consumer surplus, and e-pharmacy's profit. However, the above effects are weakened with the increase in budget, since the majority of the demand has already been satisfied by the IBPS under low budget levels. When the budget is high enough, exceeding 120 in our test, customers have already got rid of budget constraints and achieve optimal choices which will maximize their surplus. Thus e-pharmacy's profit, consumer surplus, and customer number

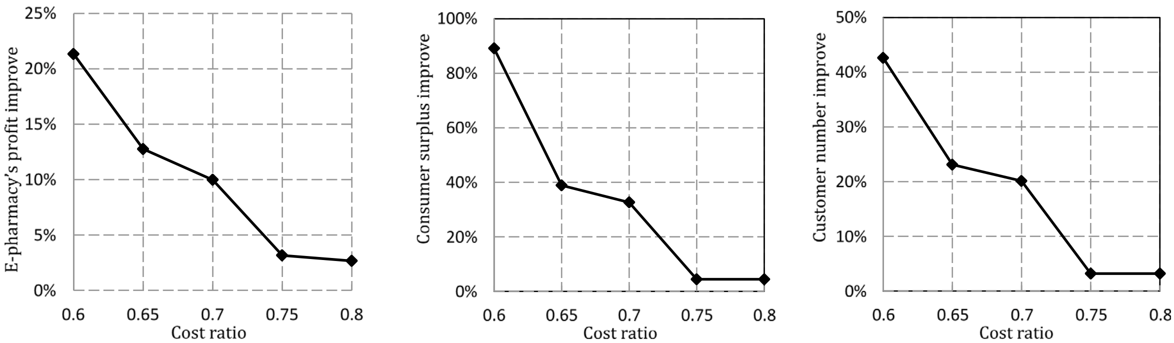


(a) e-pharmacy's profit. (b) Consumer surplus. (c) customer number.

Fig. 3. Impact of consumer budget on IBPS performance.

Table 10
Impact of cost ratio on e-pharmacy's profit, consumer surplus, and customer number.

Cost ratio	E-pharmacy's profit(¥)			Consumer surplus(¥)			Customer number		
	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve
0.60	11 364.91	13 789.80	21.34%	4619.49	8738.19	89.16%	502	716	42.63%
0.65	8204.49	9251.46	12.76%	4619.49	6415.94	38.89%	502	618	23.11%
0.70	6817.81	7497.67	9.97%	4619.49	6127.07	32.64%	502	603	20.12%
0.75	5203.78	5367.60	3.15%	4619.49	4824.21	4.43%	502	518	3.19%
0.80	3428.34	3519.44	2.66%	4619.49	4824.21	4.43%	502	518	3.19%



(a) e-pharmacy's profit. (b) Consumer surplus. (c) customer number.

Fig. 4. Impact of cost ratio on IBPS performance.

all remain unchanged with the continuous increase of the budget. In general, the IBPS is better than the benchmark strategy with respect to e-pharmacy's profit, consumer surplus, and customer number, especially when the consumer budget is tight.

In addition, from Fig. 3(b) and (c), we observe that the improvement rate of consumer surplus decreases faster than that of customer number, indicating that e-pharmacy raises the posted prices for the bundles when consumer budget increases. In this way, e-pharmacy squeezes more consumer surplus which contributes to his own profit.

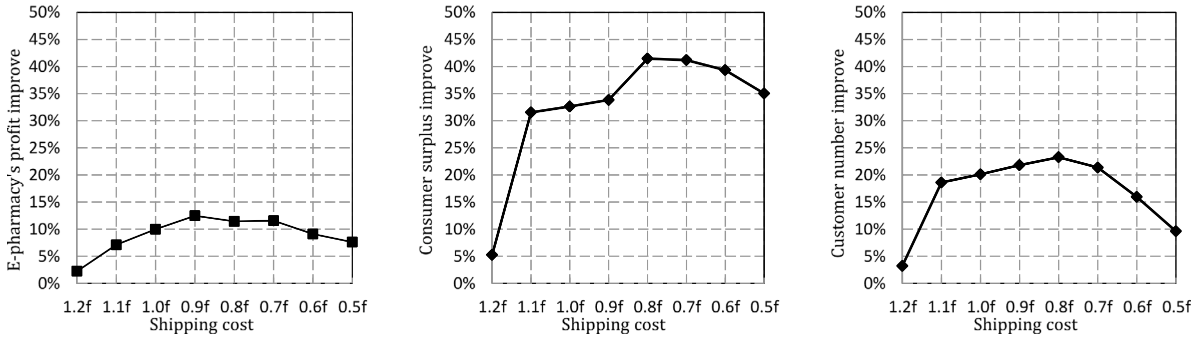
5.2. Impact of cost ratio on IBPS performance

For e-pharmacies, product cost determines their marginal profits. We define the "cost ratio" as the percentage that the product cost makes up in the posted price of a bundle, and set its value from 0.6 to 0.8. The cost ratio reflects e-pharmacy's potential profit margin regardless of the shipping cost. Since the posted price is determined by the market rather than e-pharmacy itself, we thus assume the posted price is an exogenous variable, and then the change of cost ratio is mainly reflected by the change in product cost. Table 11 shows the impacts of cost ratio on e-pharmacy's profit, consumer surplus, and customer number under both IBPS and benchmark strategy. Fig. 4 illustrates the above impacts under the IBPS.

From Table 10, we find that e-pharmacy's profit, consumer surplus and customer number all decrease with the increased cost ratio under the IBPS; while under the benchmark strategy, e-pharmacy's profit decreases but consumer surplus and customer number both remain unchanged as the cost ratio increases. The reason behind is, the posted prices are fixed under the benchmark strategy, while the posted bundle prices are adjusted according to the cost ratio under the IBPS. When cost ratio rises to more than 0.75,

Table 11
Impact of shipping cost on e-pharmacy's profit, consumer surplus, and customer number.

Shipping cost	E-pharmacy's profit (¥)			Consumer surplus (¥)			Customer number		
	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve
$1.2f$	5483.59	5605.40	2.22%	4616.57	4858.43	5.24%	499	515	3.21%
$1.1f$	6139.66	6575.81	7.10%	4616.98	6073.48	31.55%	500	593	18.60%
$1.0f$	6817.81	7497.67	9.97%	4619.49	6127.07	32.64%	502	603	20.12%
$0.9f$	7550.83	8492.17	12.47%	4630.47	6197.42	33.84%	509	620	21.81%
$0.8f$	8525.88	9499.76	11.42%	4672.40	6609.86	41.47%	533	657	23.26%
$0.7f$	9378.95	10 462.77	11.56%	4757.03	6716.88	41.20%	552	670	21.38%
$0.6f$	10 517.10	11 473.27	9.09%	4892.64	6817.38	39.34%	590	684	15.93%
$0.5f$	11 608.09	12 490.54	7.60%	5106.35	6895.32	35.03%	645	707	9.61%



(a) e-pharmacy's profit. (b) Consumer surplus. (c) customer number.

Fig. 5. Impact of shipping cost on IBPS performance.

e-pharmacy tends to hold their bundle prices still due to the low-profit margin, resulting in the stability of consumer surplus and customer number. Moreover, compared to the benchmark strategy, the IBPS has the following effects: it significantly improves e-pharmacy's profit; it contributes to consumer surplus; it increases customer number.

From Fig. 4, we find that, with the increase in cost ratio, the improvement rates of e-pharmacy's profit, consumer surplus, and customer number decrease largely. However, the improvement rates of consumer surplus and customer number both remain unchanged when cost ratio rises from 0.75 to 0.8. This somehow reflects the fact that the IBPS at least guarantees improvements on consumer surplus and consumer number no matter how high the cost ratio is.

5.3. Impact of shipping cost on IBPS performance

The shipping cost cannot be ignored in an online transaction, and the only difference is who pays for it, i.e., the e-pharmacy or the customer. In practice, e-pharmacies often induce consumers to buy more products by providing free-shipping policy. This section examines the impacts of reducing shipping cost on e-pharmacy's profit, consumer surplus, and customer number. We assume the shipping cost varies from half of the original shipping cost ($0.5f$) to 1.2 times of the original shipping cost ($1.2f$). The results are shown in Table 11, and illustrated in Fig. 5.

Table 11 shows that e-pharmacy's profit, consumer surplus and customer number all increase with the reduction of shipping cost under both strategies. In particular, e-pharmacy's profits almost doubled when the shipping cost reduces by half. This explains why many big e-pharmacies, such as ehaoyao.com, spend a large amount of money on improving the efficiency of their logistics systems, which aims to reduce the shipping costs and improve consumer experience at the same time. Compared to the benchmark strategy, the IBPS exhibits the following performance: it enhances e-pharmacy's profit by at least 2.22% to at most 12.47%; it improves the consumer surplus by at least 5.24% to at most 41.47%; it increases customer number by at least 3.21% to at most 23.26%.

Fig. 5 shows that the above improvement rates of e-pharmacy's profit, consumer surplus, and customer number have similar changing patterns that they almost increase at first and decrease after then with the reduction of the shipping cost. Thus we conclude that the IBPS is especially useful for improving e-pharmacy's profit, consumer surplus and customer number when the shipping cost is intermediate.

In the following part, we further consider the effect of free shipping strategy on e-pharmacy's profit, consumer surplus, and customer number when different levels of shipping cost are adopted. We set the free shipping threshold at ¥60, ¥30, ¥0, and list the results in Table 10.

From Table 12, we conclude the following observations. First, with the decrease of the free shipping threshold value, e-pharmacy's profit decreases while the consumer surplus and customer number increase. This reflects the fact that, for e-pharmacy, the profit earned from the increasing customer numbers cannot offset the losing profits caused by lowering the free shipping threshold, which

Table 12
Impact of free shipping threshold under different shipping cost.

Shipping	Free	E-pharmacy's profit (¥)			Consumer surplus (¥)			Customer number		
cost	threshold	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve	Benchmark	IBPS	Improve
1.0f	60	6767.86	7472.04	10.40%	5619.44	6409.38	14.06%	581	616	6.02%
	30	5538.01	6139.17	10.86%	7345.46	8493.07	15.62%	808	812	0.50%
	0	4735.91	5364.87	13.28%	7596.30	8797.08	15.81%	871	873	0.23%
0.75f	60	5536.94	5822.42	5.16%	5674.06	6680.04	17.73%	618	667	7.93%
	30	3135.16	3300.91	5.29%	7345.46	8705.74	18.52%	808	813	0.62%
	0	2263.79	2475.31	9.34%	7596.30	9001.29	18.50%	871	873	0.23%
0.50f	60	4146.52	4291.58	3.50%	5893.91	6955.83	18.02%	688	711	3.34%
	30	3970.09	4167.79	4.98%	7346.74	9804.04	33.45%	811	833	2.71%
	0	3362.27	3609.31	7.35%	7596.30	10 022.32	31.94%	871	880	1.03%

reduces e-pharmacy's profit at last. Second, compared to the benchmark strategy, IBPS improves e-pharmacy's profit, consumer surplus and customer number under all shipping cost levels and free shipping thresholds. In particular, comparing the above improvement rates under free shipping threshold 60 with those under 0, the improvement rates of e-pharmacy's profit all increase. Thus, compared to the benchmark strategy, the IBPS is especially useful for enhancing e-pharmacy's profit when free shipping threshold is low.

Moreover, comparing the improvement rates of the same free shipping threshold under different shipping cost levels, the improvement rate of e-pharmacy's profit gradually reduces as the shipping cost decreases, indicating that the IBPS outperforms the benchmark strategy in enhancing e-pharmacy's profit especially when the shipping cost is high. With respect to the consumer surplus, we find that the improvement rate of consumer surplus increase with the rise of the free-shipping threshold (or shipping cost). Thus, we conclude the adoption of the IBPS greatly improves consumer surplus when the logistics cost and the free shipping threshold are both low.

6. Conclusion

Product bundling is a commonly adopted method for Internet pharmacies to attract customers and make more profits. However, the traditional pricing strategies used by online pharmacies usually prespecify bundle sizes and prices, which largely limit customer choices. To solve this problem, this paper provides a new approach to offering interactive bundling and pricing for e-pharmacies. We allow customers to put any goods into the shopping cart as a bundle, and provide real-time online pricing so as to maximize the e-pharmacy's profit. We incorporate free shipping policy and consumer budget into our proposed mixed-integer nonlinear programming model and designed a heuristic algorithm to solve this interactive bundling pricing problem. Through numerical study using the data from company A, we find that the proposed IBPS outperforms the benchmark strategy with respect to e-pharmacy's profit, consumer surplus, and customer number. The intuition behind this lies in that, the IBPS takes full advantage of the bundling strategy to attract customers and raise sales by reducing profit margins. In this way, compared with the benchmark strategy, the IBPS contributes more to the consumer surplus than to e-pharmacy's profit. Moreover, we analyze the effects of consumer budget, cost ratio, shipping cost, and free shipping threshold on e-pharmacy's profit, consumer surplus, and the number of customers, respectively. We find that, compared to the benchmark strategy, the IBPS is especially useful for improving e-pharmacy's profit and consumer surplus when one of the following conditions is satisfied: (1) consumer budget is tight, (2) cost ratio is low, (3) shipping cost is intermediate, and (4) free shipping threshold is low.

The proposed IBPS model provides a starting point for exploring bundle pricing in the context of e-pharmacy. However, we make several assumptions in our model such as the expressions of reservation price and shipping cost, which can be further studied. For example, considering the reservation price can largely influence e-pharmacy's pricing decision, the estimation of the consumer reservation price can be further improved. Another direction for future research is to incorporate the inventory level into our IBPS model to help e-pharmacies manage their inventories.

CRediT authorship contribution statement

Jianbin Li: Conceptualization, Methodology, Supervision, Revision. **Lang Liu:** Software, Validation, Revision. **Xiaomeng Luo:** Data curation, Writing – original draft, Revision. **Stuart X. Zhu:** Writing – review & editing, Methodology, Supervision, Revision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Adams, W.J., Yellen, J.L., 1976. Commodity bundling and the burden of monopoly. Q. J. Econ. 90 (3), 475–498.
Ansari, A., Essegaier, S., Kohli, R., 2000. Internet recommendation systems. J. Mar. Res. 37 (3), 363–375.
Ansari, A., Siddarth, S., Weinberg, C.B., 1996. Pricing a bundle of products or services: The case of nonprofits. J. Mar. Res. 33 (1), 86–93.
Armstrong, M., 1996. Multiproduct nonlinear pricing. Econometrica 64 (1), 51–75.
Armstrong, M., Vickers, J., 2001. Competitive price discrimination. Rand J. Econ. 4, 579–605.
Bajwa, N., Sox, R.C., Ishfaq, R., 2016. Coordinating pricing and production decisions for multiple products. Omega 64, 86–101.
Bakos, Y., Brynjolfsson, E., 1999. Bundling information goods: Pricing, profits, and efficiency. Manage. Sci. 45 (12), 1613–1630.
Bakos, Y., Brynjolfsson, E., 2000. Bundling and competition on the internet. Mark. Sci. 19 (1), 63–82.
Banciu, M., Gal-Or, E., Mirchandani, P., 2010. Bundling strategies when products are vertically differentiated and capacities are limited. Manage. Sci. 56 (12), 2207–2223.
Bhargava, H.K., 2013. Mixed bundling of two independently valued goods. Manage. Sci. 59 (9), 2170–2185.
Bitran, Gabriel R., Ferrer, Juan Carlos, 2007. On pricing and composition of bundles. Prod. Oper. Manage. 16 (1), 93–108.
Cao, Q., Tang, Y., Perera, S., Zhang, J., 2022. Manufacturer-versus retailer-initiated bundling: Implications for the supply chain. Transp. Res. E 157, 102552.
Cataldo, A., Ferrer, J., 2016. Optimal pricing and composition of multiple bundles: A two-step approach. European J. Oper. Res. 259 (2), 766–777.
Chen, L.S., Hsu, F.H., Chen, M.C., Hsu, Y.C., 2008. Developing recommender systems with the consideration of product profitability for sellers. Inf. Sci. Int. J. 178 (4), 1032–1048.
Chernev, A., 2003. When more is less and less is more: The role of ideal point availability and assortment in consumer choice. J. Consum. Res. 30 (2), 170–183.
Chuang, C.I., Sirbu, M.A., 1999. Optimal bundling strategy for digital information goods: Network delivery of articles and subscriptions. Inf. Econ. Policy 11 (2), 147–176.
Chung, J., Rao, V.R., 2003. A general choice model for bundles with multiple-category products: Application to market segmentation and optimal pricing for bundles. J. Mar. Res. 40 (2), 115–130.
Dhar, Ravi, 1997. Consumer preference for a no-choice option. J. Consum. Res. 24 (9), 215–231.
eMarketer, 2016. Worldwide retail ecommerce sales will reach $1.915 trillion this year. www.emarketer.com/Article/Worldwide-Retail-Ecommerce-Sales-Will-Reach-1915-trillion-This-Year/1014369 Accessed on 2019-12-11.
Farshbaf-Geranmayeh, A., Zaccour, G., 2021. Pricing and advertising in a supply chain in the presence of strategic consumers. Omega 101, 1–20.
Giri, R.N., Mondal, S.K., Maiti, M., 2017. Bundle pricing strategies for two complementary products with different channel powers. Ann. Oper. Res. 1, 1–25.
Gökgür, B., Karabati, S., 2019. Dynamic and targeted bundle pricing of two independently valued products. European J. Oper. Res. 279 (1), 184–198.
Greenleaf, E.A., Lehmann, D.R., 1995. Reasons for substantial delay in consumer decision making. J. Consum. Res. 22 (9), 186–199.
Hanson, W., Martin, R.K., 1990. Optimal bundle pricing. Manage. Sci. 36 (2), 155–174.
Häubl, G., Trifts, V., 2000. Consumer decision making in online shopping environments: The effects of interactive decision aids. Mark. Sci. 19 (1), 4–21.
He, Q.C., Chen, Y.J., 2018. Odynamic pricing of electronic products with consumer reviews. Omega 80, 123–134.
Honhon, D., Pan, X.A., 2017. Improving profits by bundling vertically differentiated products. Prod. Oper. Manage. 26 (8), 1481–1497.
Hu, Zhengyang, Hu, Guiping, 2016. A two-stage stochastic programming model for lot-sizing and scheduling under uncertainty. Int. J. Prod. Econ. 180, 198–207.
Iyengar, S.S., Lepper, M.R., 2000. When choice is demotivating: Can one desire too much of a good thing? J. Personal. Soc. Psychol. 79 (6), 995–1006.
Jedidi, K., Jagpal, S., Manchanda, P., 2003. Measuring heterogeneous reservation prices for product bundles. Mark. Sci. 22 (1), 107–130.
Jedidi, K., Zhang, Z.J., 2002. Augmenting conjoint analysis to estimate consumer reservation price. Manage. Sci. 48 (10), 1350–1368.
Jiang, Y., Shang, J., Kemerer, C.F., Liu, Y., 2011. Optimizing e-pharmacy's profits and consumer savings: Pricing multistage customized online bundles. Mark. Sci. 30 (4), 737–752.
Kannan, P.K., Praveen, K.K., 2001. Dynamic pricing on the Internet: Importance and implications for consumer behavior. Int. J. Electron. Commun. 5 (3), 63–83.
Kaplan, S., Bekhor, S., Shiftan, Y., 2011. Eliciting and estimating reservation price: A semi-compensatory approach. J. Bus. Res. 64 (1), 45–50.
Keeney, R.L., 1999. The value of Internet commerce to the consumer. Manage. Sci. 45 (4), 533–542.
Lee, Y.H., Sarkar, M., 2017. Optimum pricing strategy for complementary products with reservation price in a supply chain model. J. Ind. Manag. Optim. 13 (2), 1553–1586.
Li, M., Feng, H., Chen, F., Kou, J., 2013. Numerical investigation on mixed bundling and pricing of information products. Int. J. Prod. Econ. 144 (2), 560–571.
Lin, X., Zhou, Y.W., Xie, W., Zhong, Y., Cao, B., 2020. Pricing and product-bundling strategies for e-commerce platforms with competition. European J. Oper. Res. 283 (3), 1026–1039.
Mayer, S., Klein, R., Seiermann, S., 2013. A simulation-based approach to price optimisation of the mixed bundling problem with capacity constraints. Int. J. Prod. Econ. 145 (2), 584–598.
Mordor Intelligence, 2018. ePharmacy market size - Segmented by drug type (prescription drugs, over the counter (OTC) drugs), product type (skin care, dental, cold and flu, vitamins, weight loss, others) and geography - growth, trends, and forecast (2019 - 2024). mordorintelligence.com/industry-reports/epharmacy-market Accessed on 2019-12-11.
Rochet, J.C., Choné, P., 1998. Ironing, sweeping, and multidimensional screening. Econometrica 66 (4), 783–826.
Sahay, A., Mukherjee, S., Dewani, P.P., 2015. Price discount framings on product bundles with shipping surcharges in the indian market. J. Indian Bus. Res. 7 (1), 4–20.
Salinger, M., 1995. A graphical analysis of bundling. J. Bus. 68 (1), 85–98.
Sampson, B., 2007. Sell Your Book on Amazon: Top-Secret Tips Guaranteed To Increase Sales for Print-on-Demand and Self-Publishing Writers. Outskirts Press., Parker. CO.
Spulber, D.F., 1979. Non-cooperative equilibrium with price discriminating firms. Econom. Lett. 3, 221–227.
Statista, 2018a. Global online pharmacy market size in 2014 and a forecast for 2023 (in billion U.S. dollars). www.statista.com/statistics/819754/global-e-pharmacy-drug-market-size/ Accessed on 2019-12-11.
Statista, 2018b. Number of healthcare service providers on ping an good doctor platform online in China as of April 2018, by type. www.statista.com/statistics/942554/china-number-of-healthcare-service-providers-on-ping-an-good-doctor-platform-by-type/ Accessed on 2019-12-11.
Stigler, G.J., 1963. United states v. loew's inc.: A note on block-booking. Supreme Court Rev. 152–157.
Stremersch, S., Tellis, G., 2002. Strategic bundling of products and prices: new synthesis for marketing. J. Mark. 66 (1), 55–72.

Taleizadeh, A.A., Babaei, M.S., Niaki, S.T.A., Noori-Daryan, M., 2017. Bundle pricing and inventory decisions on complementary products. Oper. Res. (8), 1–25.
Ulkumen, G., Thomas, V.G., Morwitz, M., 2008. Will I spend more in 12 months or a year? The effect of ease of estimation and confidence on budget estimates. J. Consum. Res. 35 (2), 245–256.
Wang, T., Venkatesh, R., Chatterjee, R., 2007. Reservation price as a range: An incentive-compatible measurement approach. J. Mar. Res. 44 (2), 200–213.
Wertenbroch, K., Skiera, B., 2002. Measuring consumers? Willingness to pay at the point of purchase. J. Mar. Res. 39, 228–241.
Wu, S., Hitt, L.M., Chen, P., Anandalingam, G., 2008. Customized bundle pricing for information goods: A nonlinear mixed-integer programming approach. Manage. Sci. 54 (3), 608–622.
Xiao, H., Xu, M., Yang, H., 2020. Pricing strategies for shared parking management with double auction approach: Differential price vs. uniform price. Transp. Res. E 136, 101899.
Xu, G., Zhong, L., Hu, X., Liu, W., 2022. Optimal pricing and seat allocation schemes in passenger railway systems. Transp. Res. E 157, 102580.
Xue, Z., Wang, Z., Ettl, M., 2016. Pricing personalized bundles: A new approach and an empirical study. Manuf. Serv. Oper. Manag. 18 (1), 51–68.
Yang, B., Ng, C.T., 2010. Pricing problem in wireless telecommunication product and service bundling. European J. Oper. Res. 207 (1), 473–480.
Zhang, Y., Chin, F.Y., Ting, H.F., 2014. Online pricing for bundles of multiple items. J. Global Optim. 58 (2), 377–387.
Zhang, G., Li, G., Shang, J., 2023. Optimizing mixed bundle pricing strategy: Advance selling and consumer regret. Omega 115, 102782.
Zhou, J., 2021. Mixed bundling in oligopoly markets. J. Econom. Theory 194, 105257.