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A pricing optimization modelling for assisted decision making in telecommunication product-service bundling

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ABSTRACT

Product service bundle (PSB) is a marketing strategy that offers attractive product-service packages with competitive pricing to ensure sustained profitability. However, designing suitable pricing for PSB is a non-trivial task that involves complex decision-making. This paper explores the significance of pricing optimization in the telecommunication industry, focusing on product-service bundling (PSB). It delves into the challenges associated with pricing PSB and highlights the transformative impact of big data analytics on decision-making for PSB strategies. The study presents a data-driven pricing optimization model tailored for designing appropriate pricing structures for product-service bundles within the telecommunication services domain. This model integrates customer preference knowledge and involves intricate decision-making processes. To demonstrate the feasibility of the proposed approach, the paper conducts a case study encompassing two design scenarios, wherein the results reveal that the model offers competitive pricing compared to existing telecommunication service providers, facilitating PSB design and decision-making. The findings from the case study indicate that the data-driven pricing optimization model can significantly aid PSB design and decision-making, leading to competitive pricing strategies that open avenues for new market exploration and ensure business sustainability. By considering both product and service features concurrently, the proposed model provides a pricing reference for optimal decision-making. The case study validates the feasibility and effectiveness of the approach within the telecommunication industry and highlights its potential for broader applications. The model's capability to generate competitive pricing strategies offers opportunities for new market exploration, ensuring business growth and adaptability.

1. Introduction

In the fast-paced and competitive landscape of the telecommunication industry, the art of pricing optimization has emerged as a crucial factor in securing market leadership, user satisfaction and maximizing profitability (Kar, 2021, Anaam et al., 2021). With the advent of big data analytics, the paradigm of decision-making in telecommunication Product-Service Bundling (PSB) has undergone a transformative shift. This introduction delves into the significance of big data in pricing optimization for PSB, while exploring the existing challenges, the importance of bundling strategies, and exemplifying other instances where PSB has been successfully employed.

The pricing of telecommunication product-service bundles is a complex endeavour, amplified by the wealth of data available through big data analytics (Kar et al., 2023). One of the primary challenges lies in comprehending the intricate interplay of various bundled components and their value to customers (Anaam et al., 2020). Extracting meaningful insights from the vast and diverse data sets becomes paramount, as telecommunication providers strive to understand customer preferences, consumption patterns, and the perceived value of individual products and services within the bundles (Susanto et al., 2023). Additionally, determining the optimal pricing strategy that ensures competitiveness and profitability poses a formidable challenge. Big data provides access to real-time market trends, but synthesizing this information to make well-informed pricing decisions in a dynamic environment is no easy task. Providers must navigate the delicate balance between offering enticing promotions to attract customers while safeguarding profitability in the long run.

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In the era of big data, product-service bundling has emerged as a strategic imperative for telecommunication providers. Bundling not only enhances customer satisfaction but also capitalizes on the wealth of insights offered by big data analytics. By combining multiple products and services into cohesive packages, telecommunication companies create offerings that resonate with specific customer segments. This personalization increases customer loyalty and engagement, as the bundles cater to unique needs and preferences. Moreover, PSB allows telecommunication providers to differentiate themselves in a crowded marketplace. With big data, companies can identify cross-selling and upselling opportunities, presenting customers with attractive packages that offer compelling value propositions. By leveraging customer data, providers can fine-tune bundles, ensuring they align with current trends and evolving customer demands.

Furthermore, in business context, companies often encounter difficulties in accurately predicting customer behaviour and anticipating demand patterns (Chen & Lin, 2021, Yang & Wong, 2022, Lin et al., 2023). Seasonality, evolving market trends, and rapidly changing technologies add further complexity to the pricing decision-making process. A misstep in pricing can lead to suboptimal revenue generation, customer dissatisfaction, and even market share erosion. PSB holds paramount importance in the telecommunication industry due to its multifaceted benefits. Firstly, PSB enables providers to create tailored solutions that cater to diverse customer needs and preferences. By combining various services, such as voice, data, internet, and value-added offerings like streaming services or cloud storage, providers can offer unique, all-inclusive packages that attract a wider customer base (Sullivan & Kim, 2018). Secondly, PSB enhances customer satisfaction and loyalty by simplifying the overall buying experience. By offering a single, consolidated package, customers can enjoy the convenience of a unified billing system and the assurance of receiving comprehensive service from a single provider. This fosters long-term relationships with customers, reducing churn rates, and increasing customer lifetime value. Moreover, PSB strategies can unlock new revenue streams for telecommunication companies. By enticing customers to adopt higher-tier bundles, providers can upsell and cross-sell additional services, further boosting their revenue potential.

Big data has extended the scope of PSB beyond the telecommunication sector, revolutionizing pricing optimization strategies in various industries. For instance, in the hospitality sector, hotels bundle accommodation with additional services such as dining, spa facilities, and recreational activities. Big data analytics enable hotels to understand guest preferences, refine bundled offerings, and deliver personalized experiences that foster customer loyalty (Zarezadeh et al., 2022). Besides, the hospitality sector, hotels often bundle accommodation, dining, and leisure activities, providing guests with all-inclusive vacation experiences at competitive prices (Padma & Ahn, 2020). Likewise, software companies offer bundled packages that combine essential applications, thereby offering enhanced functionality to users at reduced costs compared to purchasing individual licenses. In the context of entertainment, streaming platforms leverage PSB to deliver comprehensive content libraries that encompass movies, TV shows, and exclusive original productions, attracting subscribers seeking diverse entertainment options (Nam et al., 2023).

In conclusion, pricing optimization modelling for assisted decision making in Telecommunication Product-Service Bundling presents a promising avenue to address the challenges associated with pricing bundles effectively. By understanding the importance of PSB and exploring successful examples from various industries, telecommunication companies can develop pricing strategies that maximize customer value, bolster revenue, and solidify their position in the competitive marketplace.

2. Research question

The absence of such a model hinders telecommunication providers from effectively determining optimal pricing structures for bundled offerings, leading to suboptimal revenue generation and potentially unsatisfactory customer experiences. The research seeks to develop a systematic and data-informed approach that can accurately model base pricing and product-service features, allowing for better estimation of PSB cost pricing points. Additionally, the study aims to devise a methodology for generating new PSBs based on consumer data analytics, enabling telecommunication companies to create personalized bundles that align with customer preferences and enhance overall market competitiveness. By addressing this research problem, the study seeks to contribute to the advancement of pricing optimization strategies in the telecommunication industry, ultimately driving better decision-making and customer-centric PSB offerings. The following are the research questions:

i. How can a data-driven, systematic approach be developed to model base pricing and product-service features in telecommunication Product-Service Bundling (PSB)?
ii. How can the proposed approach enable a more accurate estimation of PSB cost pricing points, leading to improved decision-making for telecommunication providers?
iii. How can consumer data analytics be utilized to discover customer preferences and insights, and how can this information be harnessed to generate new and attractive PSBs?
iv. What are the key factors and variables that should be considered when developing the methodology for generating new PSBs based on consumer data analytics?

3. Related work

3.1. Product-service bundle design

Product-service bundling, also known as service bundling or solutions bundling, is a marketing strategy employed by businesses to package multiple products and services together as a unified offering. In this approach, a company combines complementary or related products and services into a single package, creating a comprehensive solution that meets the diverse needs of customers. The bundled offering typically includes a mix of tangible products, such as physical goods or software, and intangible services, such as maintenance, support, training, or additional features. The goal of product-service bundling is to enhance the overall value proposition for customers, providing them with convenience, cost savings, and a seamless experience by acquiring multiple offerings from a single source.

Product-service bundling enables businesses to differentiate themselves in the market, increase customer satisfaction and loyalty, and potentially generate higher revenue. By presenting customers with a complete solution that addresses various aspects of their needs, companies can cater to a broader customer base and simplify the purchasing process, making it more appealing to potential buyers (Capponi et al., 2021). This bundling strategy is commonly employed in various industries, including telecommunications, technology, software, entertainment, travel, and healthcare, among others. However, the success of product-service bundling hinges on the company's ability to understand customer preferences, design attractive bundles, and effectively communicate the added value of the comprehensive offering to its target audience.

Besides, product-service bundling dynamic and strategic approach that harnesses the power of data analytics to create compelling product-service combinations and optimize pricing strategies. By leveraging the vast amounts of data available in the digital age, businesses can gain valuable insights into customer preferences, behaviour, and market trends (Kar et al., 2023). This data-driven intelligence enables them to design tailored product-service bundles that meet the specific needs of individual customers, thereby enhancing overall customer experience and loyalty (Kar & Dwivedi, 2020). Moreover, with predictive analytics, companies can anticipate demand fluctuations, identify pricing trends, and adjust prices in real-time to align with market conditions, customer preferences, and competitive dynamics. The result is an agile and responsive pricing strategy that maximizes revenue generation while ensuring customer satisfaction.

On the other hand, the telecom industry employs various pricing strategies to attract and retain customers, optimize revenue generation, and remain competitive in the market. These pricing strategies are tailored to suit the diverse needs and preferences of customers while taking into account market dynamics, competition, and technological advancement (Ahmad et al., 2019). Pricing plays a significant role in resolving product uncertainty in social commerce. Consumers are more likely to purchase from sellers offering competitive prices, as it may be perceived as a sign of value and authenticity. Pricing strategies, such as offering discounts or limited-time offers, can attract hesitant buyers and incentivize them to make a purchase (Al-Adwan & Yaseen, 2023).

3.2. *Pricing decision making*

Pricing of product or service offers is usually one of the most critical decisions for companies, as it has direct implications for product or service growth and profitability. Pricing strategies are commonly applied in various marketing situations, including new product pricing, competitive pricing, and product line situations. These strategies play a central role in marketing and can differ based on industry applications. They are crucial for businesses to effectively craft and optimize their pricing strategies in alignment with consumer behaviours, regulatory constraints, data-driven challenges, and considerations for sustainability and social responsibility (Gao, 2023). Generally, the increasing number of product and service offerings in the markets will increase the complexity of pricing decision-making, which affects market factors such as product and service costs, market growth (Wang et al., 2017). From the literature, there are a number of studies that have investigated various pricing strategies for products and services. Among the related works are: a novel approach to developing product bundles within a retail channel setting, where they consider demand dependencies between product bundles and individual categories in a nested optimization of retail prices that accounts for the increasing influence of retailers in the market (Williams et al., 2010). A significant relationship between customer perceived values (i.e., satisfaction, dissatisfaction) and the actual prices of products offered (Codini et al., 2012). They found that there are no significant findings that explain the reason for the misalignment between price and customer value in the domain of their study. Besides, the pricing and service problems of complementary products in dual channel sales by comparing the consistent and inconsistent pricing (Wang et al., 2017). In general, most of the previous studies are mainly focused on individual product or service pricing domains, with only a few researchers focused on bundling pricing decisions.

In line with the focus of this study, we found that there are not many studies that have researched the pricing design of product service bundles (PSBs). A related study in which they investigated the pricing decision faced by a seller of product service bundles on a subscription basis using a two-part tariff scheme (Ferrer et al., 2010). A multinomial logit model was applied together with reservation prices in their study, and it was assumed that an increase of one unit in the bundle's quality would represent an increase of one monetary unit in the reservation price. From their study, optimal pricing policies were determined for bundles of products and services of different qualities (i.e., different attributes of service) considering the substitution across different alternatives. It has been concluded that customer loyalty can bring profits to a company through introducing a fee for subscribed customers to deter them from switching from one bundle to the other.

Another key piece of research, where study investigated a mixed product-service bundling problem in the wireless telecommunication business. The optimal bundle pricing was determined using non-linear mixed-integer programming to maximise service providers' long-term total profit (Yang & Ng, 2010). A case study was conducted with an actual telecommunications provider that offers 22 types of cellular phones and 22 types of service contracts to customers. Customers were divided into 12 categories, with their reservation prices (i.e., the maximum price a customer is willing to pay) for each bundle recorded through a survey. Based on this and a number of assumptions (e.g., no options for free mobile phones and fee rebates), they were able to come up with good estimates for reservation pricing and subsequently suggest bundle pricing for service providers, which helps in the decision-making for suitable profit margins for each service contract.

In relation to the telco industry, the user's perception of the utility of mobile service bundles was analysed using conjoint analysis (Klein & Jakopin, 2014). Their data was collected online from 116 respondents to allow the estimation of reservation prices. Through conjoint analysis, there was a full profile set of 384 stimuli that respondents were expected to rank order sixteen service bundle cards according to their preferences, and their ranks were transferred into limit ranks. Their findings revealed that the pricing aspect is the most important criterion in a mobile service bundle, and elements such as minutes and Internet access play a vital role in the consumers' evaluation of mobile telecommunication offers. The bundling strategies of individual products and services as one unit to derive the optimal price for the bundle and components (Banciu & Ødegaard, 2016). They have proposed the price independence concept to provide pure bundling that considers the exact limit of lower and upper bound profit. The pricing strategies for hybrid bundles in which service quality variability is positively or negatively associated with optimal bundle price or profit (Meyer & Shankar, 2016). A bundle pricing decision model for multiple products was developed using a non-linear mixed integer program with the objective of optimizing the seller's profit, based on the framework of the Stackelberg game (Fang et al., 2017). Solved by Cplex solver, their outcomes indicate that a bundle strategy can improve both the retailer's profit and the customer's savings when the number of individual products is increased

Previously, researchers have explored multiple approaches to solve the PSB configuration problem that are based on different assumptions, targeted goals, modelling and solution algorithms (Ferrer et al., 2010, Yang & Ng, 2010, Klein & Jakopin, 2014, Banciu & Ødegaard, 2016, Meyer & Shankar, 2016, Fang et al., 2017). For instance, there are studies that are focused on formulating bundles based on customer segmentation for existing cellular phones and service contract offers (Yang & Ng, 2010) using customer ranking and price estimation to derive feasible mobile service bundles (Klein & Jakopin, 2014), and hybrid bundling pricing that is dependant on service quality variability (Banciu & Ødegaard, 2016). The majority of these studies used computational models like non-linear mixed integer programming (Yang & Ng, 2010, Fang et al., 2017) and conjoint analysis to find the best solutions (Klein & Jakopin, 2014). It can be discovered that previous studies have incorporated pricing into their modelling for PSB design with profitability as their optimization goal.

Previous studies have also highlighted the importance of incorporating customer requirements during the decision-making process. For instance, there are studies that have gathered direct customer feedback on given PSBs (Yang & Ng, 2010, Klein & Jakopin, 2014). Such an approach is less practical in modern days as companies are able to discover implicit customer needs through multiple ways, including membership, past sales records, social network applications, and market surveys. There is a call to include consumers' willingness-to-pay (Klein & Jakopin, 2014), and competition across firms (Ferrer et al., 2010), in PSB research. The challenge of PSB pricing design remains, which is to achieve a balance between customer perceived values and long-term profitability with increased company revenue.

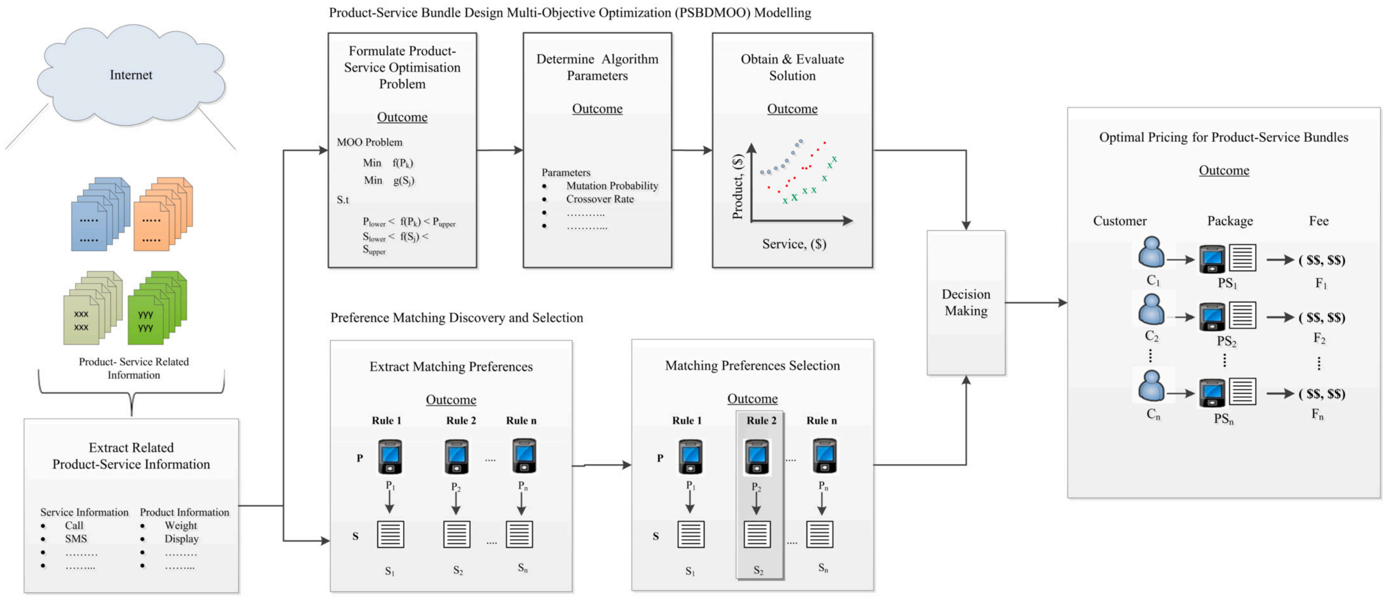

Fig. 1. A framework of assisted PSB pricing decision in PSB.

In an overview, pricing decision strategies in the literature can be summarised into three main general perspectives: (1) a well-perceived pricing decision can have an impact on after-sales profit (Wang et al., 2017, Codini et al., 2012), (2) long-term profitability, defined as the ability to maintain profits throughout the product-service life cycle despite constantly changing customer demand and purchasing behaviour (Banciu & Ødegaard, 2016) and (3) profit maximisation in which a company attempts to maximise the profit of a product-service bundle offered (Meyer & Shankar, 2016). In the context of the telco industry, service items normally have very low marginal costs. This is because most of the service-related costs are fixed equipment or IT system investments (Yang & Ng, 2010, Klein & Jakopin, 2014). As such, an upfront investment is heavy, and companies will try multiple ways to get a faster return on investment. One method is through signed contracts, in which customers commit to monthly payment commitments that can last up to 24 months (Klein & Jakopin, 2014), complemented by offers such as lower mobile phone ownership costs and better service options.

From the customers' perspective, deciding on a suitable PSB is often a difficult decision that results in a longer commitment period. Therefore, customers usually do their own research to look for the best PSB that is attractive to them while catering to their needs. From the company's perspective, such a decision is beyond a simple pricing discount (Klein & Jakopin, 2014). Previous researchers have also mentioned that the traditional research method of solely market survey is no longer suitable to explore customers' complex decision-making. Due to fast moving competition (e.g., fast turnover rate of new smart phones), a valid measurement of consumers' willingness-to-pay is necessary (Klein & Jakopin, 2014). It was suggested that further research on competition across firms or companies should be taken into account, with consideration of two or more market segments and the introductory cost of a newly designed bundle (Ferrer et al., 2010). In addition, Klein and Jakopin (2014) have also suggested that data analytics needs to be incorporated into pricing models to improve the practicability of the pricing models with more efficient algorithms to be able to solve a large-scale pricing problem.

In relation, it was noticed that recent literature is beginning to focus on customer data-driven dynamic bundling problems. For instance, the dynamic bundle pricing of two independently valued products with the aim of clearing inventories was studied (Gökgür & Karabatı, 2019). A revenue model is developed with dynamic and targeted bundle discounts, and a computational study is presented. The results of their study indicate that discounted bundles are most effective when the initial inventory of the promotional item is high, and dynamic discounts are more effective if the inventory level is low. A data-driven approach towards personalized bundling of products in an online shopping scenario (Ettl et al., 2020). A model is suggested to dynamically select, price, and recommend a bundle of related products to a consumer during their online shopping session, where the consumer can then choose to accept the bundled discounted offer before checkout. Their model considers the trade-off between profit maximisation and inventory management, while catering to consumers' preferences simultaneously. While these studies have promising proposals to solve the dynamic bundling problem with inventory consideration, they are mainly focused on product bundles during one-time purchases (either retail or online) for maximised profit. This differs from the focus of this paper, where the service element is emphasised in the context of long-term commitment (i.e., contracted services).

In a nutshell, from the context of a product-service bundle, the challenge of PSB pricing remains: to achieve a balance between customer perceived values in PSB (that lead to purchasing decisions), maximising company revenue and profit in a sustainable manner, and long-term customer commitment (i.e., loyalty). The aforementioned discussion indicates that PSB design methodology is a significant research issue, which is still less explored in previous studies. In this regard, we reckoned the need for a market and customer data-driven approach to PSB design that can assist companies in developing market-competitive PSBs. Such an approach would assist companies to design PSBs with better profit margins and market sustainability. We shall detail our ideas in the following sections.

4. A methodology for assisted pricing decision

Fig. 1 shows a framework of our proposed modelling approach towards assisted pricing modelling and optimization for PSB design. Our groundbreaking proposal unfolds in four pivotal steps, each crucial to the success of our research. The first step involves meticulous data collection, laying the foundation for our investigation. Moving forward, step 2 encompasses the discovery and selection of customer preferences, an essential element in our pursuit of excellence. In step 3, we delve into the core of our study, where we undertake PSB optimization modelling. This phase is pivotal in uncovering valuable insights and refining our approach. Finally, step 4 encompasses the decisive process of making well-informed choices. Moreover, our current work is in direct continu-

Table 1
Nomenclature for product price with service bundle.

Parameter	Description	Constraints
i	Product item	
j	Product category item	
$n_p^{(j)}$	Total number of products in the $j-th$ product category	
n_{cp}	Total number of product category	
$RP_i^{(j)}$	Product price per month (with service bundle)	
$D_{rp}^{(i,j)}$	Product price (retail)	$D_{rp(l)}^{(a)} \le D_{rp}^{(a)} \le D_{rp(u)}^{(a)}$
$D_p^{(i,j)}$	Product price (with service bundle)	$D_{p(l)}^{(a)} \le D_p^{(a)} \le D_{p(u)}^{(a)}$
$D_u^{(i,j)}$	Product first/upfront payment (with service bundle)	$D_{u(l)}^{(a)} \le D_u^{(a)} \le D_{u(u)}^{(a)}$
$D_r^{(i,j)}$	Product price rebate (with service bundle)	$D_{r(l)}^{(a)} \le D_r^{(a)} \le D_{r(u)}^{(a)}$
D_T	Service contract period	
$RS_i^{(j)}$	Service package price per month	
$C_k^{(i,j)}$	Price rate for k-th service item per month	$C_{k(l)}^{(b)} \le C_k^{(b)} \le C_{k(u)}^{(b)}$
$N_k^{(i,j)}$	Number of k-th service item	$N_{k(l)}^{(b)} \le N_k^{(b)} \le N_{k(u)}^{(b)}$
$N_{rk}^{(i,j)}$	Rebate for k-th service item	$N_{rk(l)}^{(b)} \le N_{rk}^{(b)} \le N_{rk(u)}^{(b)}$
$n_s^{(j)}$	Total number of services in the $j-th$ category	
n_{cs}	Total number of service category	
a	Product category indicator	
b	Service category indicator	
l	(suffix) Lower limit	
u	(suffix) Upper limit	
RCP_a	Averaged monthly product category price ($/Month)	
RCS_b	Averaged monthly service category price ($/Month)	
$D_{rp}^{(a)}$	Product retail price (or manufacturer suggested retail pricing (MRSP)) ($)	
$D_p^{(a)}$	Product price (with service bundle) ($)	
$D_u^{(a)}$	Product upfront payment (or “Down payment”, with service bundle) ($)	
$D_r^{(a)}$	Rebate Price (with service bundle) ($)	
D_T	Service contract period (months) ($)	
$N_c^{(b)}$	Call duration (minutes)	
$N_m^{(b)}$	Number of messaging service (number)	
$N_d^{(b)}$	Internet data maximum limit (Gigabyte, GB)	
$N_{cr}^{(b)}$	Free call duration (minutes)	
$N_{dr}^{(b)}$	Free Internet data quota (Gigabyte, GB)	

ity with the previous publication, particularly building upon the strides made in steps 1 and 2 (Zakaria & Lim, 2016). This paper, however, will be exclusively dedicated to the in-depth exploration of PSB optimization modelling. By focusing solely on this aspect, we aim to shed new light on its implications and potential, significantly advancing the field.

4.1. Step 1: data collection and preprocessing

A PSB design multi-objective optimization (MOO) problem presents an opportunity to create a well-tailored solution for diverse market segments. This problem involves modelling a variety of product and service categories to cater to the specific needs of customers. In general, a PSB design problem comprises variables related to either products or services. For instance, selected products can be organized into distinct product categories, while services can be grouped into separate service categories. This classification is typically based on product and service specifications and pricing, which results from a meticulous market segmentation exercise. A detailed product and service related features information, such as service packages offering and product reviews, were downloaded. Besides, information from marketing brochures by telecommunication companies also used. Generally, there are a number of product and service packages that can be obtained from telecommunication providers. Product related features are usually based on their technical or price specification, i.e. camera resolution, weight, and retail price, while service-related features may differ depending on the type of product offered, such as duration of voice call, Internet data, and subscription period. In addition, device retail price, contract period, and call rebates are also important features. These features for product, service, and product-service bundle are commonly considered during a purchasing decision.

Next, the corresponding features values for each product and service were extracted. In this study, feature values are price related for pricing decision modelling. Based on collected information, the corresponding features for each product and service were extracted by determining common or typical features offered in market as in Table 1. Upon the completion of extraction process, selected product feature values were used to categorise the selected products into categories, $CP_j = \{CP_j \mid j = 1, 2, ...n_{cp}\}$, with n_{cp} represents total number of product category; e.g. high-end, mid-end and low-end. On the other hand, services were also categorised into three different categories, e.g. basic, standard and premium using similar approach, $CS_j = \{CS_j \mid j = 1, 2, ...n_{cs}\}$, with n_{cs} represents total number of service category (see Table 2). Furthermore, the feature value refers to the value assigned to a specific parameter within a given range. When we mention the ‘lower range of the parameter,’ we are referring to the minimum possible value that the parameter can take. Conversely, the ‘upper range of the parameter’ in-

Table 2
Selected product and service offerings.

Selection	Category			
	Low-End (CP_1)	Mid-End (CP_2)	High-End (CP_3)	Total (n_p)
Product (P)	2	2	2	6
	Basic (CS_1)	Standard (CS_2)	Premium (C_3)	Total (n_s)
Service (S)	3	3	3	9

dicates the maximum possible value that the parameter can reach. In this context, where a represents a product category indicator and b represents a service category indicator, with suffixes l and u represents the lower and upper limit of the parameter value range.

4.2. Step 2: problem formulation and objective definition

To offer the best pricing bundle of product and service, companies have the flexibility to tailor their approach based on varying customer needs. They can opt for multiple categories, particularly when they have similar products that can be grouped together under specific classifications. This enables them to create diverse bundles that cater to distinct customer preferences. Conversely, in scenarios with limited product choices, companies may choose a single category to consolidate all available options. This approach simplifies the pricing structure, making it easier for customers to select from the bundled offerings. By customizing their categories based on product characteristics and customer demands, companies can craft optimal pricing bundles that maximize customer value and satisfaction.

Mathematically, the product price per month (with service bundle) can be defined as in Equation (1). The equation considers the pricing when a product is purchased with bundled service, which may include product price with service bundle (which are usually discounted), first or down payment, and total rebates (which can be performed over a few months to maintain customer loyalty). The average product pricing per month in the j-th product category is defined in Equation (2). The descriptions for each parameter are given in Table 1.

$$RP_i^{(j)} = \frac{D_{rp}^{(i,j)} - \left[D_p^{(i,j)} - D_u^{(i,j)} + D_r^{(i,j)}\right]}{D_T}, i = 1,2,...,n_p^{(j)}, j = 1,2,...n_{cp} \quad (1)$$

$$RCP_j = \frac{\sum_i RP_i^{(j)}}{n_p^{(j)}}, i = 1,2,3...,n_p^{(j)}, j = 1,2,3,..n_{cp} \quad (2)$$

On the other hand, a service package is designed to compliment the device purchasing plan under a PSB. The service fee function is formulated similarly to the device pricing function. Using service feature information, the monthly service package price for the i-th service package in the j-th service category with m service items can be calculated as shown in Equation (3). Equation (4) shows the average monthly service package price for the j-th category. The parameters described for the two equations are described in Table 1.

$$RS_i^{(j)} = \sum_{k=1}^{m} C_k^{(i,j)}(N_k^{(i,j)} - N_{rk}^{(i,j)}),$$
$$i = 1,2,...,n_s^{(j)}, j = 1,2,3,..n_{cs}, k = 1,2,..m \quad (3)$$

$$RCS_j = \frac{\sum_i RS_i^{(j)}}{n_s^{(j)}}, i = 1,2,...,n_s^{(j)}, j = 1,2,..n_{cs} \quad (4)$$

Based on the available product and service information such as price values, the main objective is to generate the optimal configuration of each product and service feature subject to design constraints. This problem can be formulated as a MOO problem. MOO deals with optimising more than one objective function subject to the value constraints of product-service features. In this study, we have formulated the general Product-Service Bundle Design Multi-Objective Optimization (PSBDMOO) problem as follows:

$$max \quad RCP_a, a = 1,2,3,...,n_{cp} \quad (5)$$

$$min \quad RCS_b, b = 1,2,3,...,n_{cs} \quad (6)$$

subject to:
Constraint described in Table 1.

As found in the common mathematical formulation for optimization, the formulation in its general mathematical form is to minimise the objective functions. As the formulation is formulated based on pricing (not operating cost), companies may formulate multiple mixes of minimization and maximisation according to specific needs. For instance, a company may maximise the service package price coupled with a minimised product price when the PSB profit comes mainly from the service aspect (e.g., in the case of a service providing company) or a minimised service package price coupled with a maximised product price (e.g., in the case of product companies). Both objectives can also be minimised to examine how minimum product and service package prices can be achieved to maintain profitability.

4.3. Preference matching discovery and selection

The goal of this step is to determine customer preferences on PSBs based on their demographic information by matching their demographic information to possible PSB combinations. Normally, companies would determine the demand or preference of customers from available previous sales records, customer inquiries, or extensive customer surveys. Upon obtaining this information, data mining can be performed to determine the possible preference and PSB match, based on metrics such as highest sales record, inquiries, or other technical metrics (e.g. support, frequency, etc.). The authors wish to note that this is not the focus of this study. This study follows the methodology of Zakaria and Lim (2016).

Mathematically, there are two steps involved. The first step is to obtain a matching product-service combination, taking into account customer demographics and preferences. To determine preference, there are a number of ways to obtain this information, which include sales transaction records, customer big data analytics, surveys, etc. Mathematically, consider a set of customers demographic profile set with n_{dm} profiles $DM = \{dm_k | k = 1,2,...n_{dm}\}$. Each dm_k is a set of values that represent a customer's demographic information such as age, income, etc. Next, a profile dm_i and $p_i^{(j)}$ are matched to $s_i^{(j)}$. Upon matching, a way to determine the relative importance of each match is required. Assume that a rule is formed by matching profile DM and i-th product category to the j-th service category, where $\left(DM, P^{(i)}\right) \mapsto S^{(j)}$, resulting in a set rules R where $R = \{r_i \mid i = 1,2,...,n_r\}$. In the second step, selection of matching rules is performed based on the metrics of each rule (that indicate the relative importance of each rule), such as support value (e.g., frequency of occurrence). This can be determined through machine learning techniques such as association rule mining and classification. Upon selection, interesting matching rules can be selected to aid the decision-making process.

4.4. Decision making

For decision-making, the discovered knowledge of customer preference (as in the previous chapter) can be used as a basis to design new PSB packages. Upon the availability of the optimised solution and the selected matching product-service rules, the decision-making process involves the selection of the best pricing reference for PSBs. Under different requirements that have multiple combinations of product, service, and user preferences, the competitive pricing reference of PSBs can be determined based on optimised results and selected matching rules. For instance, a PSB package can be designed for a specific customer group that takes into account the group's preferences. Then, suitable

Table 3
Product and service feature range values.

Product	Low-End (CP_1)		Mid-End (CP_2)		High-End (CP_3)	
	Lower (l)	Upper (u)	Lower (l)	Upper (u)	Lower (l)	Upper (u)
D_{rp} ($)	1000	2000	2001	3000	3001	4000
D_p ($)	100	500	500	1000	600	1200
D_u ($)	100	400	400	800	500	900
D_r ($)	50	100	101	150	151	200
Service	**Basic (CS_1)**		**Standard (CS_2)**		**Premium (CS_3)**	
	Lower (l)	Upper (u)	Lower (l)	Upper (u)	Lower (l)	Upper (u)
N_c (Minutes)	100	300	300	600	500	1000
N_m	300	500	300	500	500	1000
N_d (GB)	2	10	8	15	10	20
N_{cr} (Minutes)	100	200	100	200	100	200
N_{dr} (GB)	1	3	3	5	5	10

D_T = 24 months.

solution points that match the criteria can be selected to provide a reference of optimised pricing for design decision-making. In the case study section, we shall illustrate how this can be feasibly performed.

5. Case study and discussion

5.1. Data collection

In order to showcase our approach, two PSB design scenarios were illustrated in the context of mobile smart phones and the accompanied telecommunication services. Firstly, a few existing PSB packages in the market, i.e., mobile devices and accompanied service plans, were selected. Based on the selected packages, all product information such as model, manufacturer, and specifications was extracted from the Internet. This information was gathered from the fonoApi mobile phone database[1] and the ultrazone database,[2] which is accessible through a database API.[3] Furthermore, service-related information such as the number of SMS, voice calls, Internet data, and rebates on these services per package were obtained from a number of local service providers.

Products with higher prices are generally products with better technical specifications, such as screen resolution, camera resolution, and internal storage. On the other hand, among the salient service features are Internet data quota, the number of call minutes, and SMS for telecommunication services. Service offerings were also sorted based on monthly commitment fees that correspond to features such as call rebates, extra Internet quota, streaming service and etc. In this study, a total of 12 products and 16 service packages from four local telecommunication service providers with a fixed contract period of 24 months were gathered, followed by product sorting based on their corresponding device retail price. Finally, 6 products with 9 service packages were classified into different categories as summarised in Table 2. The sorting of products based on their corresponding device retail price provides a meaningful classification criterion. Categorizing the products and services based on this parameter enables the study to analyze and understand how pricing influences bundling decisions.

Generally, product and service feature values are used to classify products and services into different categories, based on range values (i.e., lower and upper value limits) as shown in Table 3. To define our pricing model, we begin by investigating the existing and common price range of PSB packages in the market. To determine the possible pricing of PSB packages taking into account different product and service categories, a simple cost-based pricing technique can be used Avlonitis and Indounas (2005). These limits are determined based on typical feature values provided by service providers in the market.

In this study, our basic assumption about how service providers design PSBs is that they should forecast the pricing demand for PSBs and possible pricing that customers are willing to pay. Based on gathered intelligence and company related factors (e.g. company market positioning) and specialised service features, they will be able to design the best subscription or promotional PSBs. Usually, service providers will offer several attractive pricing options with different combinations of product and service offerings corresponding to multiple customer segments. With reference to objective functions in Equation (5) and (6), and constraints (i.e., parameter with feature value range in Table 1) from parameters description for our PSBDMOO problem is as detailed in Table 1, where for service, there are three ($m = 3$) service items: call, short message service (SMS) and Internet. While costs related to telecommunication services, such as operational costs and maintenance costs, vary among different telcos, all the related costs are assumed to be the same across different telcos for simpler base comparison.

5.2. Product-service bundle design multi-objective optimization (PSBDMOO) modelling

The main objective of the PSBDMOO problem is to determine the optimal pricing reference for decision making during the PSB design process. Product features such as product retail price, contract period, and upfront payment are commonly considered by customers during a package purchasing decision. Similarly, service features such as pricing for calls, SMS, and Internet quotas are also important decision elements. Because telcos do not manufacture mobile phones, service pricing accounts for a larger portion of their PSB pricing. Thus, to offer attractive pricing with better service offerings and overall profitability (service-focused), two design objectives are considered in this paper: minimising product pricing (Equation (5)) and maximising service pricing (Equation (6)). This is possible because, depending on the product category, the device price offered with service can typically be reduced to 60% to 70% of the original retail price (Kameshwaran et al., 2007). The purpose of Equation (5) is to determine the lowest device price and whether it fits within the limits of the aforementioned discounted price, whereby this result shall help telco to determine a more competitive device price point.

For our PSBDMOO modelling, the upper and lower value limits for the two objectives are obtained from minimum and maximum price from each product and service category. For each product category, the price range from four different existing telcos was taken into consideration. The average price for each product category is considered as existing reference price for each category. Both product and service pricing constraints are as indicated as feature value range with con-

[1] https://fonoapi.freshpixl.com.
[2] https://smartphone.ultra-zone.net/en/.
[3] https://github.com/openstf/stf-device-db.

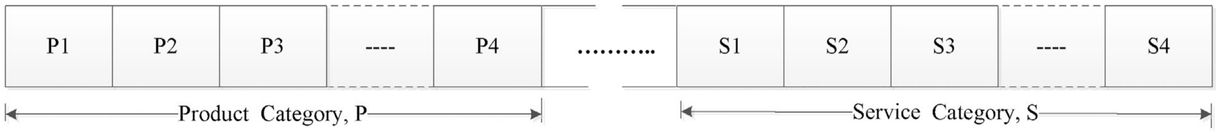

Fig. 2. Chromosome representation.

Table 4
Products and Service Price Range Values.

Product Category	Price ($)	Service Category	Price ($)
Low-End (CP_1)	10–30	Basic (CS_1)	0–60
Mid-End (CP_2)	30–60	Standard (CS_2)	50–80
High-End (CP_3)	60–100	Premium (CS_3)	70–100

Table 5
Selected experimental settings for multi-objective evolutionary algorithm.

Parameter	Parameter Values	Selected Value
Population Size	100, 1000, 2000, 4000, 5000	2000
Maximum Evaluation	100, 2000, 4000, 5000, 8000	4000
Crossover Probability	0.2, 0.4, 0.6, 0.8,1.0	0.4
Mutation Probability	0.2, 0.4, 0.6, 0.8,1.0	1.0

straint values for each product and service category as summarised in Table 4.

In order to represent the optimization problem, Fig. 2 shows in general the chromosome representation of the PSBDMOO problem. The chromosome can be viewed in two sections, where each section represents the product or service feature levels of each product or service category. Each gene on the chromosome represents one product or service feature for each product and service category. As the problem is formulated as a MOO problem, there can be a number of possible solutions to solve the PSBDMOO problem. In this study, an evolutionary algorithm, fast Non-Dominated Sorting Genetic Algorithm Version II (NSGA-II), is adopted as a solution strategy (Deb et al., 2000). From previous studies, NSGA-II is found to be a suitable solution strategy as compared to other genetic algorithms because it is able to handle higher dimensional and conflicting multi-objective problems in a variety of situations, such as service-design (Goodale et al., 2003), supply chain (Chen et al., 2006), and product family design (Liu et al., 2013).

Implementation wise, an open-source package for MOO using an evolutionary algorithm, jMetal (Durillo & Nebro, 2011) was applied to solve the PSBDMOO problem. The experimental results were examined with a combination of parameter metrics in order to obtain the best parameter settings. For this purpose, a total of 625 combinations of parameter metrics were generated to obtain spread value. Out of these 625 combinations, the top ten parameter combinations that have the lowest spread value were acquired. In order to select the best parameter setting, crossover rate was considered as the first selection criteria, as it controls the capability of the evolutionary algorithm in exploiting the population to reach the local optima. A higher crossover rate results in quicker exploitation. However, if the crossover rate is too large, it can disrupt the speed of exploitation (Lin et al., 2003).

Results from initial runs suggest that the average crossover rate was typically in the range of 0.4 – 0.6 among the ten parameter metric combinations with the lowest spread values. Within the average crossover rate, the speed of the exploitation can be balanced. As a result, three out of ten combinations with a mid-range crossover rate were selected. Finally, based on the lowest spread value as a performance metric, the selected experimental parameter combinations are as indicated in Table 5. The algorithm achieved convergence at a crossover rate of 0.4, a population size of 2000, and a maximum evaluation of 4000. However, with longer computation times, the population can be increased to obtain more diversified optimal solutions. In this paper, our aim is to explore a larger search space to the convergence of the population to the global optimum. Thus, a mutation probability of 1.0 was selected as a higher mutation rate can increase the probability of solution searching in a larger solution space.

Upon solving a MOO problem with selected experimental settings, suitable performance metrics are also essential in determining solution quality. Typical performance metrics in a MOO problem are spread (Δ), generational distance (GD) and hyper-volume (HV). For our PSBD-MOO problem, there are no previously available benchmark or reference solutions as the problem itself is unique. Due to this limitation, the GD is not suitable as a performance metric in this context. Similarly, hyper-volume (HV) is not used as selection criteria as it is constructed between each solution point and the reference point. Thus, we have applied spread value (S) in this study as the performance metric to select the best combination of parameter metrics. The spread value is generally used to measure the extent of spread achieved among the obtained solutions, where finding a smaller value of spread helps to determine a more diverse set of non-dominated solutions.

The Pareto solution sets for optimal product and service pricing are obtained and plotted for the low-end, mid-end, and high-end, as shown in Fig. 3, 4, and 5, respectively, based on the selected experimental parameter values. The solution sets were compared against every service category, such as basic, standard, and premium. From the results, an optimal solution set can serve as the best price reference for PSB. For example, for high-end product-service packages, the maximum price reference for the high-end product category is $95.58 with corresponding premium service at $60.95 while the minimum price reference for the high-end product category is $63.25 with premium service at $99.60. These indicate that an optimal price reference for each product-service package can be provided to designers in a sensible manner. Based on these values, telcos can further customise their product-service package pricing to be better suited to customer preferences. We shall showcase how these outcomes can be useful for PSB design in subsequent sections using two illustrative decision-making cases.

5.3. Preference matching discovery and selection

In this step, the C4.5 classification algorithm is applied as the metric for decision tree pruning and rule selection, with reference to the proposed methodology and results in Zakaria and Lim (2016). Conjoint analysis was applied to obtain survey results, and a total of 113 matching rules between product and service features with consideration of demography profiles were generated. In order to optimise classification accuracy of the model, a sub-tree replacement pruning method is applied to reduce the complexity and possible over-fitting of matching products and services. At this stage, all generated rules undergo the redundant rules elimination process to search for interesting matching rules. The redundancy issue is reduced by using set union theory, where rules from the same category are merged together as a single rule with duplicated features removed. To discover interesting matches, classification rules are selected based on information gain (IG) as the metric. From the results, 22 filtered matching rules out of 113 rules are obtained. Significant rules are further selected based on the information gain (IG) metric. Product-service matching rules that gain a higher IG represent the more preferred feature combination. That helps telcos focus on pricing design for highly-rated packages. Table 6 shows 15 matching rules with high IG values that can be used to help design

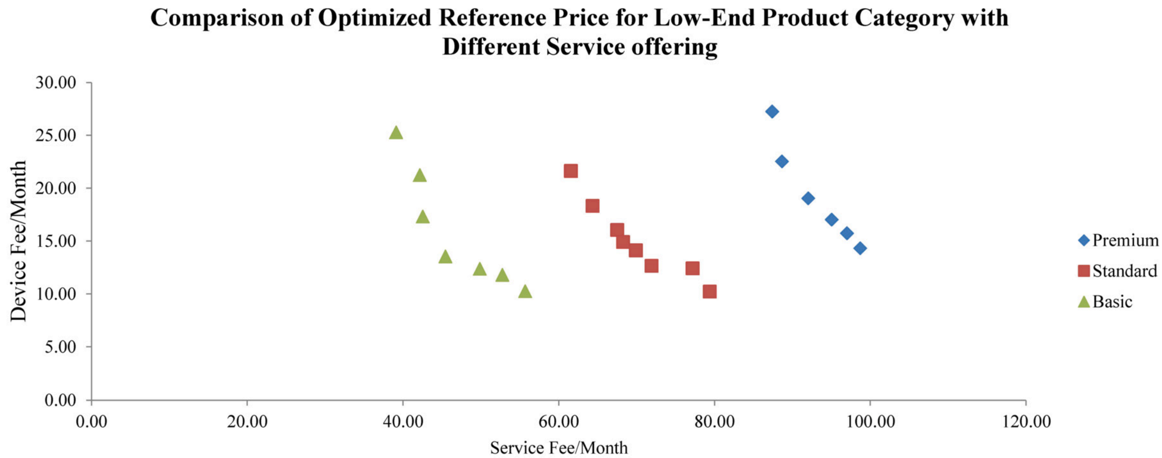

Fig. 3. Non-dominated Pareto solution sets for low end product category.

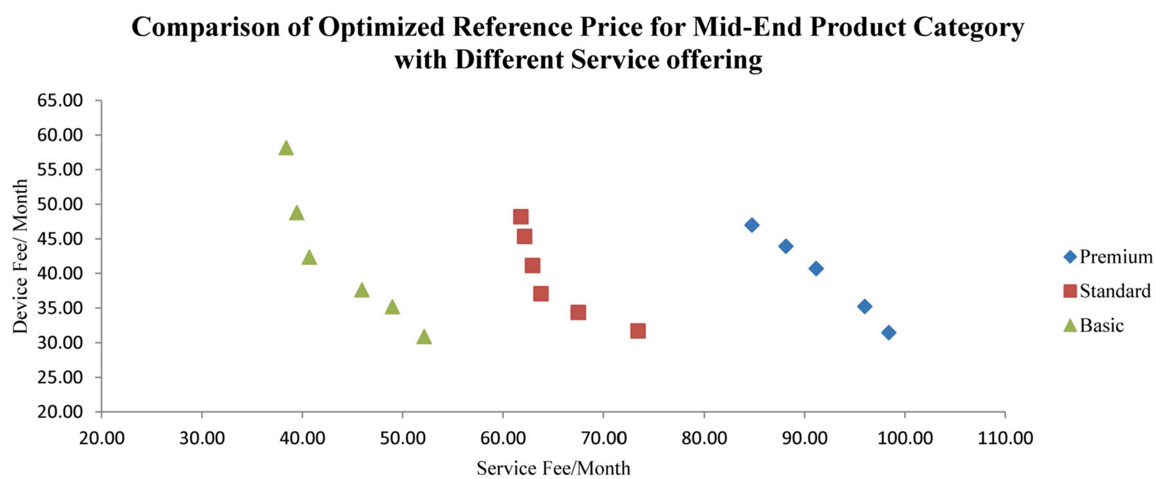

Fig. 4. Non-dominated Pareto solution sets for mid end product category.

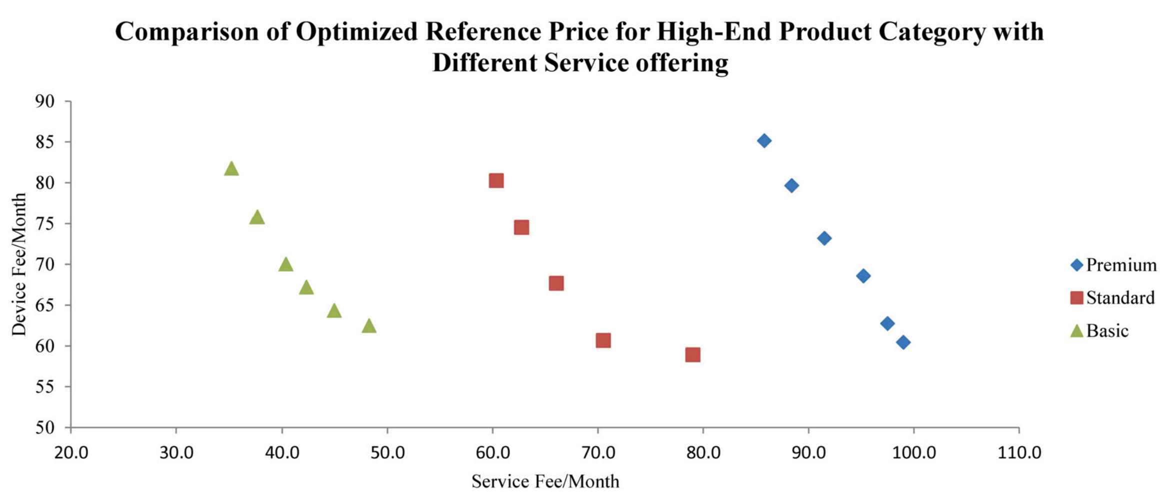

Fig. 5. Non-dominated Pareto solution sets for high end product category.

Table 6
Summary of selected matching rules (Zakaria & Lim, 2016).

Rules, R	Product, P	Demography, DM	Service, S	IG
LE1	$\boxed{p^{(1)}\text{: Low-End}}$	$dm_1 = \{A = 33 - 49, O = W, G = M\}$	$s^{(3)}$: Premium	0.5210
LE2	Device Price = 1000-2000	$dm_2 = \{A = 26 - 32, I =< 1000\}$	$s^{(3)}$: Premium	0.5210
LE3	RAM < 2 GB	$dm_3 = \{A = 33 - -49, O = W, G = M\}$	$s^{(3)}$: Premium	0.5210
LE4	Weight = 190	$dm_4 = \{A = 19 - 25, E = Bc\,Dg, G = F\}$	$s^{(2)}$: Standard	0.5044
LE5	Display = 4, 4.5 inch	$dm_5 = \{A = 33 - 49, O = S, G = M\}$	$s^{(1)}$: Basic	0.5007
ME1	$\boxed{p^{(2)}\text{: Mid-End}}$	$dm_6 = \{A = 33 - 49, I => 4000, O = W, G = M\}$	$s^{(3)}$: Premium	0.5185
ME2	Device Price =2001-3000	$dm_7 = \{I = 3001 - 4000, O = W, G = M\}$	$s^{(2)}$: Standard	0.5293
ME3	RAM > 2 GB	$dm_8 = \{A = 26 - 32, G = F, O = S, I = 1001 - 2000\}$	$s^{(2)}$: Standard	0.5293
ME4	Camera = 12,10 MP	$dm_9 = \{I => 4000, O = W, G = M\}$	$s^{(2)}$: Standard	0.5293
ME5	Battery life = 2300-2500 mAH	$dm_{10} = \{A = 33 - 49, O = W, G = F, E = Post\,Dg\}$	$s^{(1)}$: Basic	0.5307
HE1	$\boxed{p^{(3)}\text{: High-End}}$	$dm_{11} = \{A = 26 - 32, I => 4000, O = W\}$	$s^{(3)}$: Premium	0.4715
HE2	Device Price = > 3000	$dm_{12} = \{I = 2001 - 3000, G = F, E = Post\,Dg\}$	$s^{(2)}$: Standard	0.5287
HE3	RAM ≥ 2	$dm_{13} = \{I = 1001 - 2000, G = F, A = 26 - 32, O = S\}$	$s^{(2)}$: Standard	0.5287
HE4	Weight = 120 g	$dm_{14} = \{I = 2001 - 3000, G = M\}$	$s^{(1)}$: Basic	0.5303
HE5	Camera = 20, 16MP	$dm_{15} = \{I = Below1000, A = 19 - 25\}$	$s^{(1)}$: Basic	0.5303

*IG = Information Gain, A = Age, O = Occupation, W = Working, S= Studying, G= Gender, F= Female, M = Male, I = Income, E= Education level, Bc Dg = Bachelor degree, Post Dg = Post graduate degree.

Table 7
Summary of results for scenario I.

Package	Features	Existing Offers		Our Approach		Existing Offers		Our Approach	
		Telco A	Telco B	Optimal Result I	Suggested Pricing I	Telco C	Telco D	Optimal Result II	Suggested Pricing II
Product: Low-End (CP_1)	D_{rp} ($)	1225	1229	1187	1299	1399	1409	1302	1399
	D_p ($)	395	488	393	400	599	489	416	45
	D_u ($)	465	388	259	300	299	299	248	250
	D_r ($)	–	–	72	80	–	–	66	70
Service: Basic (CS_1)	N_c (Minutes)	300	300	102	100	100	80	105	100
	N_m*	300	(0.12)	313	300	(0.05)	(0.02)	319	200
	N_d (GB)	8	8	4	4	8	6	8	6
	N_{cr} (Minutes)	–	–	115	100	–	–	106	60
	N_{dr} (GB)	3	2	1	1	4	–	2	2
Customer's Perspective	Monthly Fee ($)	56	65	58.39	75	70	75	64.38	85
	1st Payment ($)	916	941	–	775	968	863	–	785
	Total Payment ($)	2234	2436	–	2420	2578	2588	–	2670

D_T = 24 months. *Value in brackets represents charges per SMS ($/SMS).

a new PSB. We shall apply these findings to the next step of decision making.

5.4. Decision making

5.4.1. Scenario I: designing service pricing with given product category

The first illustrative scenario involves the PSB design being given a pre-determined product category. Specifically, the decision involves determining the overall PSB pricing if a product category is pre-selected, hence service parameter design is given more attention. In this context, the focus is on how to determine the best service pricing (and its corresponding service element values). To illustrate our approach, assume that we are designing a product-service package for a low-end device. Table 7 shows a summary of possible pricing structures based on our optimization results with a detailed comparison of product-service feature values from four Telcos. Four different Telcos that offered products at retail prices within the price range of $1200–$1500 were selected (corresponding to low product category). Among the four Telcos, we have categorised Telco A and Telco B into the same group set (set I), with another set (set II) consisting of Telco C and Telco D. Telco offerings within the same set are similar in terms of product retail price, monthly commitment fee range, and product technical specifications.

From optimization results (as in Fig. 3), we have obtained two solution points based on the information contained in Telco's offer, generally considering the boundaries of device retail price range ($1200–$1500) and package monthly commitment fee range ($50–$80). Set I was chosen at a point between ($19.29 and $39.10), where the sum of the two values (monthly device fee and service fee) represents a monthly commitment fee of $58.39. This number is also comparable to the total monthly commitments of Telco A ($56) and also Telco B ($65). Similarly, solution points ($23.83 and $40.55) were chosen for set II, with a total monthly commitment of $64.38, comparable to Telco C ($70.00) and Telco D ($75.00). From the two solution points and their corresponding values for product-service features, we are able to propose possible pricing schemes as indicated in Table 7. As the solution points already represent the minimised product feature values and maximised service feature values, possible pricing can be proposed where product feature values are generally higher than the optimised values, while for service feature values are lower than optimised values (e.g., additional service charges if certain feature values are exceeded).

From the customers' point-of-view, the first payment (the summation of device price, device upfront, and first month's commitment fee) and the monthly commitment fee are usually the two factors that mainly influence the PSB purchasing or sign-up decision. For Set I, our optimization results showed that the device price and upfront can be designed significantly lower than Telco A and B with a lower first payment at $775. Although the monthly commitment fee is higher at $75, the price can be offset by device rebate where it can be offered within a certain period of time. For instance, from the marketing standpoint, if $80 is proposed, the rebate can be offered as a rebate of $10 per month over a period of 8 months, which indicates a monthly commitment fee of $65 (same as Telco B) for the first 8 months. When considering the payment over the overall contract period (24 months), the total payment by customer is $2420, which is almost similar to the offers from Telco A and B. In addition, the optimal result I also offered flexibility for service elements, such as free calls that can be provided at different time periods (e.g., capped at a maximum of 100 minutes per month only during weekends or weekdays) and free Internet (e.g., 250 MB per week for four weeks, or 500 MB for two weeks, etc.).

On the other hand, the possible pricing for Set II is similar to that of Set I. Although a higher package commitment fee ($85) is suggested when compared to Telco C and D, the first payment is significantly lower at $785. This package also comes with a total device rebate of $70 over the contract period and enhanced service elements such as free calls (60 minutes), free internet (2 GB), and a SMS bundle (200 SMS) that are lower than maximum values. While features such as free call minutes, Internet quotas, etc. are optionally configured, the promotion of such a service feature can be an attractive factor in closing PSB deals in a fiercely competitive telco industry.

In an overview, the proposed two sets of pricing in this case are based on solution points for basic services as in Fig. 3. Pairing up a low-end device with another service pricing scheme (such as premium) is also possible by choosing other solution points from other service categories. While the possible pricing resulted in a generally comparable total payment with other Telcos over the contract period, the optimal results provide a useful pricing reference for designers to potentially adjust product-service pricing structures based on their own business objectives and profitability requirements. This indicates that our approach is able to offer flexibility for designers to propose competitive pricing and service element values when designing product-service packages, without compromising the overall profitability (over the contract period).

Based on the finding, this study have shown that the interplay between service pricing and product choice is a complex and crucial aspect that significantly influences business success. We explore the importance of carefully designing service pricing strategies concerning specific product choices. The strategic design of service pricing in the context of product choice is a multifaceted endeavour that has far-reaching implications for businesses across industries (Nemmaoui et al., 2023). It involves a sophisticated understanding of customer preferences, perceived value, and market dynamics. Customer preferences significantly impact service pricing strategies. Products elicit varying degrees of desirability and utility among consumers, leading to divergent perceptions of service value. A thorough analysis of customer preferences enables businesses to tailor pricing structures that resonate with target markets, fostering a deeper connection between customers and the services they see.

Besides, the perceived value of a service is intrinsically linked to the chosen product (Zhang et al., 2020). Customers often associate specific products with certain attributes, quality levels, or status symbols. As a result, the perceived value of a service tied to a luxury product, for example, will differ significantly from one related to a mass-market item. By accurately assessing and leveraging this perceived value, telecommunication companies can justify premium pricing and differentiate themselves from competitors. Consumers' willingness to pay a price premium for a product or service is closely linked to their perception of its value. When individuals believe that a particular offering provides superior quality, unique features, or fulfills their specific needs exceptionally well, they become more inclined to invest in it, even if it comes with a higher price tag. A product and service's reputation, brand image, customer reviews, and perceived exclusivity contribute to this perception. Moreover, the emotional and psychological aspects of ownership, such as prestige and status, further enhance its perceived value. As businesses understand and effectively communicate the advantages of their offerings, consumers are more likely to embrace the idea of paying a premium, forging a mutually beneficial relationship where customers find genuine value in the products or services they acquire.

Moreover, there are number of challenges can be found for designing service based on the product. One of the challenges is price sensitivity varies across different products and service categories. Setting the right price for a service linked to a product with elastic demand requires caution, as customers may be highly responsive to even minor price fluctuations (Ansari & Binninger, 2022). Conversely, inelastic products demand careful evaluation to avoid undervaluing services that enjoy relatively stable demand irrespective of price changes. Secondly, dynamic market trends, which can be found during the selection of matching product and service category. Product choices and market trends are subject to constant change. New products emerge, while others may lose their appeal over time. Price wars and aggressive discounting can erode profit margins, necessitating a thorough understanding of competitors' pricing strategies and value propositions to strike a balance between competitiveness and financial sustainability. Navigation the balance complexities of designing service pricing with product choice, data-driven decision making is imperative. Telecommunication companies should leverage customer data, market research, and pricing analytics to gain insights into customer behaviour, product preferences, and pricing elasticity. This information empowers informed pricing decisions that optimize customer satisfaction and profitability.

In conclusion, designing service pricing with given product choice is a vital component of business strategy that significantly impacts customer satisfaction and financial success. By understanding customer preferences, leveraging perceived value, and adopting data-driven approaches, businesses can overcome challenges and strike the delicate balance between meeting customer expectations and maintaining profitability. Continuous adaptation to dynamic market trends and a keen awareness of the competitive landscape will ensure telecommunication companies remain resilient in the face of ever-changing product choices and customer demands. By tailoring service pricing to match the chosen product, telecommunication companies can optimize customer satisfaction, enhance brand loyalty, and secure a competitive edge. However, this pursuit is not without its challenges, as businesses must navigate complex pricing decisions that balance profitability and customer-centricity.

5.5. Scenario II: product-service design based on customer preference knowledge

In general, customer purchasing decisions and behaviour are generally related to several factors, such as age, income level, education level, gender, marital status, etc. However, their purchasing pattern can be difficult to predict when considering different combinations of these factors. For instance, the purchasing preferences of a middle-aged, low-income person may be very different from those of a young-aged, mid income person. In this information age, we are able to sensibly predict customer preference from customer data, where their demography, preferences, purchasing habits, etc. can be captured and analysed. In this second scenario, our aim is to illustrate how PSB design can be approached with the presence of customer preference knowledge.

Consider the case where we are designing a product-service package with a low-end device and premium service, corresponding to the discovered matching rules LE1, LE2 and LE3 as in Table 6. The three rules indicate that the targeted users are working males in the age range of 26–32 or 33–49, with a monthly income of below $1000. We obtained a solution point ($18.5, $93.05) from our optimization results (as shown in Fig. 3) by comparing with a similar existing telco's offer, generally considering the boundaries of low device retail price ($1000–$2000) and package monthly commitment fee range ($100–$150). Similar to

Table 8
Summary of results for scenario II.

Rules Used	Customer Profile	Package	Parameters	Existing Package (Telco A)	Optimized Result	Suggested Pricing
LE1 LE2 LE3	Age = 33–49 or 26–32 Working = Yes Gender = Male Income = <$100	Product: Low-End (CP_1)	D_{rp} ($)	1499	1383	1399
			D_p ($)	599	635	640
			D_u ($)	399	397	400
			D_r ($)	–	93	120
		Service: Premium (CS_3)	N_c (Minutes)	500	502	500
			N_m	300	504	400
			N_d (GB)	12	16	15
			N_{cr} (Minutes)	–	103	100
			N_{dr} (GB)	–	5	5
		Customer's Perspective	Monthly Fee ($)	128	111.55	120
			1st Payment ($)	1126	–	1160
			Total Payment ($)	4070	–	3800

$^*D_T = 24$ months.

scenario I, the solution point also corresponds to a monthly commitment of $111.55. For the basis of comparison, Telco A offers a low-priced device package with premium service elements at a comparable monthly commitment fee of $128. The details of package offerings are as summarised in Table 8.

Table 8 shows the comparison of a detailed possible pricing structure based on optimised results with the existing offer by Telco A. From the table, we noticed that Telco A is offering a package with a low first payment, but with a high monthly commitment fee. In contrast, our approach can suggest a PSB package with a generally lower device retail price, a device rebate, and better service offers. Based on the optimised results, a PSB can be introduced with a comparable first payment ($1160) and monthly commitment fees ($120). The proposed package is able to offer a total device rebate of $120 over the contract period, with better service element offerings such as higher Internet quotas (15 GB), free Internet (5 GB) and free call minutes (100 minutes). Although positioned at a lower overall payment of $3800 compared to Telco A, such a price is deemed competitive for new market penetration with added feature values. In short, a new PSB can be created based on discovered customer preference knowledge. This allows companies to sensibly design new product-service offerings, explore possible new markets and strengthen existing customer loyalty.

Based the aforementioned finding, in the context of pricing optimization for product-service bundle, customer data is essential. Customer preference knowledge provides valuable insights into customers' needs and desires. By analyzing data on customer behaviour, feedback, and preferences, companies can identify pain points and unmet needs, allowing them to design products and services that address specific customer requirements effectively. Besides, armed with customer preference knowledge, businesses can offer customization and personalization options for their products and services. Tailoring offerings to individual preferences enhances the customer experience, leading to higher satisfaction and loyalty. Moreover, data-driven product-service design enables an iterative approach, companies can collect feedback, observe usage patterns, and make continuous improvements based on customer insights, ensuring that the offerings evolve to meet changing preferences and expectations.

Furthermore, customer preference knowledge can spark innovation by identifying untapped opportunities in the market (Yang & Chang, 2012). Companies can leverage this data to create unique features and functionalities, differentiating themselves from competitors and gaining a competitive edge. Designing products and services based on customer preference knowledge allows businesses to optimize the user experience. By understanding how customers interact with their offerings, companies can make informed decisions to improve usability and overall satisfaction.

On the other hand, data-driven pricing begins with thorough market research and competitor analysis (Yang et al., 2023). By gathering data on pricing trends, customer spending behaviours, and competitor pricing strategies, businesses can make informed decisions about their own pricing structures. Besides, data-driven pricing allows for dynamic adjustments based on real-time data and market conditions. Through algorithms and analytics, businesses can optimize prices to match demand, seasonal fluctuations, and competitor pricing changes.

In conclusion, product-service design and pricing based on customer preference knowledge from a data-driven perspective are powerful tools for businesses to stay competitive and meet customer expectations. By leveraging data analytics and customer insights, companies can create tailored offerings, optimize pricing strategies, and enhance the overall customer experience. Data-driven decision-making ensures that businesses remain agile, adapting to changing market dynamics and customer preferences effectively. As technology advances and data analysis capabilities improve, data-driven approaches will continue to play a crucial role in driving business growth and success.

6. Practical implications

In this study, we have exemplified our approach using the PSB in the telecommunication domain. Besides this common application instance, the approach can also be usefully applied in other domains where products need to be paired with services. For instance, in the context of an automotive purchase, pricing and specifications of a product (e.g. car, truck, etc.) may be different across different automotive variants (or specification) with multiple customizable parts / accessories (e.g. premium head lights, audio entertainment system, etc.), and service pricing elements that may include discounted parts and labour charges for subsequent periodic servicing. Service in this context may also come with different promotional pricing and a possible extended warranty to attract customers to sign up. From the perspective of the automotive company, they may consider the modular costing for each customizable parts or accessories (e.g. cushion covers, floor mat, car recorder), service elements (e.g., labour inspection fee, replaceable parts, external/internal washing), and warranty period coverage (e.g., yearly inspection, licence renewal) to be included in the PSBDMOO modelling to assist in designing the best PSB package for potential customers. Another similar example is a water filtering system (either for home or commercial) where periodical service packages can be bundled together during the product subscription. In this context, the service part may consist of replaceable parts (e.g., water filters, hose and tubing parts, water machine spare parts) and device warranty (e.g., periodic inspection), to name a few. Our proposal should be able to assist the aforementioned companies in designing competitive PSBs while maintaining profitability and customer loyalty in the long term.

7. Conclusion

In this study, we have proposed an approach for PSB price decision-making based on optimization modelling and customer preference knowledge. A PSB pricing optimization model that considers both product and service features simultaneously is proposed to provide a pricing reference for an optimal pricing decision. We have showcased the feasibility of our approach by using a case study that details two case scenarios in the context of a telecommunication service provider. We have also discussed the possible applications of such an approach besides the discussed telecommunication domain. Generally, the merit of our approach is that, through the knowledge of existing market offers and the categorical product-service pairing, optimised product-service pricing can be suggested to support the PSB decision-making process. While we have only performed customer preference analysis using a small-scaled collection of customer profiles we do believe that our approach can be a useful reference, particularly in the era of big customer data analytics, where the availability of large-scaled customer preference and purchasing behaviour data can provide the basis for more sophisticated exploratory analysis and knowledge discovery. In this regard, dynamic changes in product categories, customer segments, customer preference uncertainty, and the customization of product-service package offerings tailored for specific customer groups or individuals, among other things, will be important areas of PSB-related research. Similarly, it is worth exploring how all of these issues can be linked and researched to benefit decision-making in relevant industry and academic focus in the future.

CRediT authorship contribution statement

Anies Faziehan Zakaria: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Resources, Visualization, Writing – original draft, Writing – review & editing. **Soon Chong Johnson Lim:** Supervision. **Muhammad Aamir:** Methodology.

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.

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