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Location-based pricing and channel selection in a supply chain: a case study from the food retail industry

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Abstract

Many retailers nowadays operate in an Internet-enabled dual-channel supply chain setting, referred to as "click and mortar". In such a structure, products and services are delivered through both online B2C (business-to-consumer e-tail) and offline B2C (traditional brick and mortar retail) channels. In this paper, we develop and present a unified modeling approach that reflects a real-world dual-channel supply chain in the food retail industry. Motivated by the actual business operations of a case study, we incorporate the spatial locations of customers, as well as other logistics and operational costs, into the service provider's pricing and the customers' channel choice decisions. We develop two models, namely the benchmark and proposed models, and conduct extensive numerical experiments with parameter values centered on actual values. The results reveal that the ratio of online and offline profit to the total dual-channel profit vary significantly, depending on the locations of customers and the values of the logistics costs. In addition, our statistical and visual analysis suggest that by jointly optimizing the logistics and operational processes, the service provider can achieve a considerably high profit through both channels, without necessarily expanding the size of its geographical service areas.

Keywords Location-based pricing · Channel selection · Dual-channel supply chains · Food retail industry · E-commerce logistics

1 Introduction

The food industry is a critical sector within the world economy, as well as any nation's economy. In 2016, the total value of the global food and agricultural industry was estimated to be USD eight trillion (Plunkett Research 2017).

The food and beverage, grocery (including non-food) and fresh produce sectors in Australia—where our case study is based—had an annual turnover of AUD 127.4 billion, and

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Abstract

Many retailers nowadays operate in an Internet-enabled dual-channel supply chain setting, referred to as “click and mortar”. In such a structure, products and services are delivered through both online B2C (business-to-consumer e-tail) and offline B2C (traditional brick and mortar retail) channels. In this paper, we develop and present a unified modeling approach that reflects a real-world dual-channel supply chain in the food retail industry. Motivated by the actual business operations of a case study, we incorporate the spatial locations of customers, as well as other logistics and operational costs, into the service provider’s pricing and the customers’ channel choice decisions. We develop two models, namely the benchmark and proposed models, and conduct extensive numerical experiments with parameter values centered on actual values. The results reveal that ratio of online and offline profit to the total dual-channel profit vary significantly, depending on the locations of customers and the values of the logistics costs. In addition, our statistical and visual analysis suggest that by jointly optimizing the logistics and operational processes, the service provider can achieve a considerably high profit through both channels, without necessarily expanding the size of its geographical service areas.

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1 Introduction

The food industry is a critical sector within the world economy, as well as any nation's economy. In 2016, the total value of the global food and agricultural industry was estimated to be USD eight trillion (Plunkett Research, 2017).

The food and beverage, grocery (including non-food) and fresh produce sectors in Australia – where our case study is based – had an annual turnover of AUD 127.4 billion, and employed over 310,000 (Australian Food & Grocery Council, 2017). In 2017, the average Australian household spent approximately AUD 4900 per year on eating out (Intermedia, 2018). The online food service spend of AUD 1.38 billion made up 6.4% of the total Australian e-commerce expenditure of AUD 21.65 billion. From 2015 to 2016 online food sales was the fastest growing category within Australian e-commerce, with a 30.6% growth rate (Kressmann, 2017).

According to a recent business report, 36% of Australian small to medium businesses took online orders and 47% of them accepted online payments (Sensis, 2017). For the restaurant studied, considerable additional sales revenue was achieved through the online channel by increasing its food production capacity, and improving the logistics operations. This suggests that for food service providers, it can make business sense to add an online channel to their operations, converting their traditional offline (brick and mortar) operations into dual-channel *click and mortar* operations (Loiacono, 2007).

Establishing the online B2C channel (e-tail) in addition to the offline channel enables service providers to increase sales revenue with minimal investment in assets (Hsiao and Chen, 2014). An inefficient delivery service, however, being directly executed or managed by a third-party logistics provider, would result in time delays in serving customers and possibly degraded food quality (Morganti et al., 2014). While considering the logistics performance in online delivery, customers choose the channel with the lowest total channel cost to them, where the total cost of a channel depends on both operational and logistics costs.

Given the size of the food and agriculture industry, and the growing importance of e-tail (electronic retail), in this paper we report a case study from the food retail industry and analyze the operations of a service provider (restaurant) in Melbourne, Australia. Our case study allows us to develop an analytical solution to the pricing decisions of the service provider, operating through dual-channels, namely *offline* (traditional dine-in) and *online* (delivery for B2C e-tail orders). The *delivery charge* of an online channel is a marginal fee charged by the supplier in addition to the price of the product, while the *travel cost* of an offline channel is a function of the distance between the customer's location and the restaurant.

Under the dual-channel setting, customers' channel preference and the sensitivity of their demand to price have been identified as influential factors that drive a service providers' sales revenues and profits (Wang et al., 2017; Xu et al., 2017; Yao and Zhang, 2012). While our research has overlap with some existing studies, certain contributions which distinguish our study from the rest of literature include:

1. Developing a mathematical representation of the service provider's pricing and the customers' channel choice in a dual-channel supply chain. Our study is motivated by a *real-world case* and our proposed models are driven by actual operations. Hence, the parameter values in our experiments and our model assumptions reflect the realities of the analyzed case study.

2. Despite the significance of customers' spatial location in shaping their demand (Fernández et al., 2017), to the best of our knowledge, the value of a service provider's *location-based pricing* and its impact on a customer's channel preference have not been previously studied within a unified framework and in a real-world setting.
3. Experimental analyses for the models developed in this paper are among the most practical and extensive studies in this line of research. In addition, to the best of our knowledge, our study is the first in this field where the significance of the effects of both operational and logistics parameters on performance measures have been tested through formal statistical methods.

To address the industry needs and bridge the gap in extant studies, our research seeks to analyze the location-based pricing policies that make dual-channel supply chains more efficient, both for the service providers and the end customers. Our premise is that by developing and implementing policies that incorporate the customers' locations and the varying delivery costs into price decisions we can significantly improve the service provider's revenue.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature and highlights the research gaps. Section 3 describes the case study, the planning problem, and the mathematical notation. Section 4 presents the benchmark and proposed mathematical optimization models. Section 5 provides the analysis and discusses the results. Section 6 concludes this paper, describing limitations and suggests future work.

2 Literature review

This section begins with a review of research on dual-channel pricing under deterministic demand, which is the topic of our research. We then discuss the various logistical determinants of price that have been considered in earlier studies and describe research on location-based pricing. Finally, we compare our proposed models with existing models and illustrate the research gaps that are addressed in this paper.

2.1 Dual-channel supply chain pricing

Building upon earlier supply chain research, dual-channel pricing and its impact on customer purchasing behavior have been studied extensively in recent years (Amrouche and Yan, 2016; Chen, 2015; Choi et al., 2012; Matsui, 2017).

Table 1 summarizes notable studies where pricing in a dual-channel supply chain is analyzed. Among the categories listed, our research falls into category B, where dual-channel pricing is analyzed in a *single-stage* supply chain through mathematical modeling and extensive experimental analysis (Guo and Zheng, 2017; Zhang and Wang, 2017).

We next review studies that mainly focus on location-based pricing and the challenges involved. As further reference, interested readers can refer to recent related papers (Asian and Nie, 2014; Faghih-Roohi et al., 2016; Giri et al., 2017; Lu et al., 2018a; Lu et al., 2018b; Paul et al., 2017; Somarin et al., 2018; Yeo et al., 2017), and the references therein.

2.2 Logistical determinants of price

As confirmed by de Kervenoael et al. (2015) and other studies (Hayel et al., 2016; Mangiaracina et al., 2015; Werner et al., 2002; Xiao and Qi, 2016; Yeung et al., 2011), logistics is one of the most critical drivers of success in dual-channel supply chains.

In developing and analyzing an empirical model to study customers' channel preferences under different conditions, de Kervenoael et al. (2015) show that while product price is the main driver of customers' shopping intentions, logistics operations also have a significant impact on customers' channel preferences and overall satisfaction.

Table 1 Selected studies from the literature on optimal dual-channel pricing with deterministic demand

ID	Category	Research paper	Technique	Closed form	Extensive analyses	No. of stages	Demand nature	Distinguishing aspects
1	A	Cai et al. (2009)	Optimization	✓	✓	2	Deterministic	Price-discount contracts
2		Wang et al. (2016)	Optimization	✓	✓	2	Deterministic	Operating costs
3		Chen et al. (2017)	Optimization	✓	✓	2	Deterministic	Quality decisions
4		Li et al. (2016)	Optimization	✓	✓	2	Deterministic	Green channel
5		Wang et al. (2017)	Optimization	✓	✓	2	Deterministic	Consistent and inconsistent pricing
6		Zhang and Ma (2016)	Optimization	✓	✓	2	Deterministic	Fairness in the profit distribution
7		Pu et al. (2017)	Optimization	✓	✓	2	Deterministic	Consumer free-riding
8		Yu et al. (2015)	Optimization	✓	✓	2	Deterministic	Product substitutability
9	B	Guo and Zheng (2017)	Optimization	✓	✓	1	Deterministic	Multiple restaurants and a single third-party website
10		Zhang and Wang (2017)	Optimization	✓	✓	1	Deterministic	Inventory level of the product, Timing of when to introduce the online channel
11	C	Chen (2015)	Optimization	✓	✗	2	Deterministic	Cooperative advertising
12		Chen et al. (2016)	Optimization	✓	✗	2	Deterministic	Power structure
13		Giri et al. (2017)	Optimization	✓	✗	2	Deterministic	SC with forward & reverse flows
14		Hsiao and Chen (2014)	Optimization	✓	✗	2	Deterministic	Parameter ranges for optimal channel strategies
15		Huang et al. (2016)	Optimization	✓	✗	2	Deterministic	Power structure
16		Matsui (2017)	Optimization	✓	✗	2	Deterministic	Timing of when to declare wholesale price & direct price
17		Cai (2010)	Optimization	✓	✗	2	Deterministic	Conditions for introducing a direct (ex: online) channel
18		Lu and Liu (2015)	Optimization	✓	✗	2	Deterministic	Efficiency & acceptance of the online channel
19		Xu et al. (2012)	Optimization	✓	✗	2	Deterministic	Channel structure & delivery time decisions
20		Soleimani et al. (2016)	Optimization	✓	✗	2	Deterministic	Demand and production cost disruptions
21		Han et al. (2016)	Optimization	✓	✗	2	Deterministic	Alternative e-commerce channels

In line with the findings of de Kervenoael et al. (2015), Wang et al. (2017) suggest that companies would rather apply consistent pricing for online and offline channels and create a price differentiation through delivery charges.

Hua et al. (2010) investigate the promised delivery lead time of a direct channel and its impact on pricing decisions. Yao and Zhang (2012) develop an analytical model to study the pricing policy of an online supplier and show that the supplier may subsidize free delivery by increasing the price of a product. Yu et al. (2015) develop a model where offline and online pricing depends on transportation and processing costs, as well as product substitutability. The authors find that, to increase their profits, suppliers may set their online prices lower than offline prices, while charging the customers a higher delivery cost.

While the above studies take some logistical determinants into consideration, none incorporate the location of customers and its impact on dual-channel pricing and customers' choice of channel. Most prior models view the logistics costs as non-existent or fixed, while we recognize the logistics costs as variable and incorporate them explicitly into our models.

2.3 Location-based pricing

While an extensive body of literature on dual-channel pricing exists, the impact of spatial distribution of customers on logistics costs, customers' channel preferences, and service providers' pricing have received limited attention.

Saarijärvi et al. (2014) explore various business models in online food delivery services and propose a framework for understanding retailers' use of mobile services. They consider the two dimensions of stage of interaction (pre-purchase, in-store, post-purchase) and the nature of interaction (utilitarian vs hedonic). Saarijärvi et al. (2014) find that online food orders can result from both utilitarian motivations, such as saving time and money, and hedonic motivations.

Our research fits in the research stream where the focus of analysis is on the utilitarian pre-purchase process of deciding whether to order online or offline.

Another research stream related to our study is on location and pricing, where firms decide on their locations and prices to achieve competitive advantage. As an example, He et al. (2016) investigate the impact of customers' spatial location on joint pricing-location decisions of competing suppliers, assuming that information sharing is allowed among suppliers. Our study is different from that of He et al. (2016) as we consider a single service provider with a fixed location and explore the effect of operational and logistics costs on dual-channel pricing and customers' channel preferences.

Our literature survey shows that while a large body of literature on dual-channel pricing exists, there is scant literature considering the locations of customers and the logistical determinants of price in a real-world environment. To address this research gap, we study the location-based pricing of a food retail company and jointly analyze the customers' channel preferences and the service provider's dual-channel sales performance.

3 Case study, problem description and mathematical notations

The motivation for this study was a Joint Industry Project initiated by a local

Australian food retail company, Roza's Kitchen, which was established in 2017 by an entrepreneur who has more than 25 years of experience in the food service industry. It offers its customers a fresh food menu, via its *online* (delivery of online orders) and *offline* (dine-in) channels. Roza's Kitchen is a pizza and burger restaurant located in Southbank, in the heart of Melbourne, Victoria. Close to the Central Business District (CBD), Southbank has a mixture of businesses, including tertiary education facilities, an entertainment precinct and apartment buildings.

In the offline channel, customers bear a travel cost to enjoy a dine-in experience. Alternatively, customers can place orders via a third-party e-commerce website[1] or similar mobile applications. Through the online channel, the restaurant delivers the ordered products and passes the incurred logistics costs on to the customers within their delivery charge.

To capture the actual business operations of our industry partner case study we consider a single-stage, dual-channel service supply chain. Analysis on the firm's sales transactions data revealed that online demand accounted for approximately 15% of the restaurant's total sales, while offline demand accounted for the remaining 85%. Since the opening of the restaurant in 2017, both offline and online prices have been set by the manager, based on his industry experience and market conditions.

Customers decide on their preferred channel to minimize their total cost (effective price). The service provider must make optimal decisions regarding its online and offline product prices, taking into consideration operational and logistics costs, as well

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[1] Foodora (https://www.foodora.com.au)

as how prices affect customers' channel preferences.

Table 2 Mathematical notation for the developed models

Notations	Definitions
A_{on}	Potential demand of online customers
A_{off}	Potential demand of offline customers
S_{on}	Size of online area (potential area over which online customers demand service)
S_{off}	Size of offline area (potential area over which offline customers demand service)
b_{on}	Sensitivity of online demand to online price
b_{off}	Sensitivity of offline demand to offline price
ρ	Intensity of price competition between online and offline channels
$p_{\min}$	Effective price (total cost) to the customer below which the potential customer will order from the service provider
$p_{\max}$	Effective price (total cost) to the customer above which the potential customer will *not* order from the service provider
$\theta(p)$	Purchase proportion (proportion of potential customers whose demands are actualized) at an effective price (total cost) of p
D_{on}	Demand of online customers
D_{off}	Demand of offline customers
p_{on}	Price of online product
p_{off}	Price of offline product
p_d	Fixed product delivery charge, per unit of online product
C_p	Production cost, per unit of product
C_{off}	Offline service cost, per unit of offline product
C_d	Unit delivery cost, per online product unit, per unit distance (i.e. kilometer)
C_t	Customer's travel cost per unit distance (i.e. kilometer)
C_{off}^t	Total travel cost of the customers in the offline channel
$T_{\text{on}}(l)$	Delivery cost to a customer for a distance of l
$\bar{T}_{\text{on}}(S_{\text{on}})$	Average delivery cost in area S_{on} for the online channel
$T_{\text{off}}(l)$	Travel cost of a customer for a distance of l
$\bar{T}_{\text{off}}(S_{\text{off}})$	Average travel cost in area S_{off} for the offline channel
l	Distance between the customer and the service provider (restaurant in this study) in unit distance (kilometers)
l_e	The distance where customer's online payment equals offline payment
l_m	The distance where online product marginal revenue is 0 (i.e. the online price of product and delivery equals the cost of product and delivery)
l_f	The fixed distance of online delivery radius
l_u	The distance where the purchase proportion for the offline channel is 0
Π_{on}	Online profit
Π_{off}	Offline profit
Π_t	Dual-channel total profit

Table 2 provides the mathematical notation used throughout the paper.

In the past, the service provider operated under a restricted dual-channel setting, only offering an online service to customers residing close to the restaurant. The online delivery service was internally managed with a fixed flat-rate per delivery[2]. Although this policy enabled the service provider to control its delivery costs and logistics investment, it significantly limited access to a wider range of potential online customers.

Following a growth strategy to expand its online offering, the service provider decided to update its online delivery operations and revise its dual-channel pricing strategy. The goals were to cope with the logistics complexity introduced by increased online sales and to maintain business profitability with minimal investment. As a solution, the service provider decided to outsource its online delivery service to professional third-party logistics providers. This decision expanded the delivery of online orders into a broader geographical region and changed the delivery cost structure from fixed flat-rate (per delivery) to a variable distance-based structure.

Collaborating with the service provider, we initiated a project to establish a location-based dual-channel pricing model, where the logistical determinant of price and the customers' channel preference are linked to the location of customers[3].

4 Mathematical models

4.1 Customers' channel choice

In a general dual-channel setting with deterministic demand, customers' online

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[2] This case is represented by the benchmark model and discussed in detail in Section 4.3.

[3] This case is represented by the proposed model and discussed in detail in Section 4.4.

and offline demand functions are represented in Equations (1) and (2):

$$D_{\text{on}} = A_{\text{on}} - b_{\text{on}} \cdot p_{\text{on}} + \rho \cdot p_{\text{off}} \tag{1}$$

$$D_{\text{off}} = A_{\text{off}} - b_{\text{off}} \cdot p_{\text{off}} + \rho \cdot p_{\text{on}}, \tag{2}$$

where D_{on} and D_{off} represent the customers' realized online and offline demand. This type of demand function is widely accepted and used in economics and operations management literature, and is confirmed by empirical evidence (Hua et al., 2010; Lu and Liu, 2015; Yao and Liu, 2005). Discussions with the restaurant manager established support for the simplicity and practicality of using demand functions with this structure.

Customers' channel preferences are affected mainly by the effective price, comprising the product price (p_{on} or p_{off}) and the associated logistics costs. In the online channel, the effective price is the sum of the product price and the delivery charge $p_{\text{on}} + p_d$, as set by the service provider. On the other hand, the customers' total payment in the offline channel is the sum of the product price and their travel cost $p_{\text{off}} + T_{\text{off}}(l)$, where $T_{\text{off}}(l)$ denotes the travel cost and l indicates the distance of the customer from the restaurant.

We assume that a customer prefers the online channel (when such service is available) only if the online channel costs less than the offline channel, i.e., $p_{\text{on}} + p_d < p_{\text{off}} + T_{\text{off}}(l)$. The offline channel, on the other hand, will be preferred when $p_{\text{on}} + p_d > p_{\text{off}} + T_{\text{off}}(l)$. When the effective price in online and offline channels is equal, $p_{\text{on}} + p_d = p_{\text{off}} + T_{\text{off}}(l)$, the customer may select either channel.

Figure 1 demonstrates how the channel price, delivery charge, and travel cost affect customers' channel preferences.

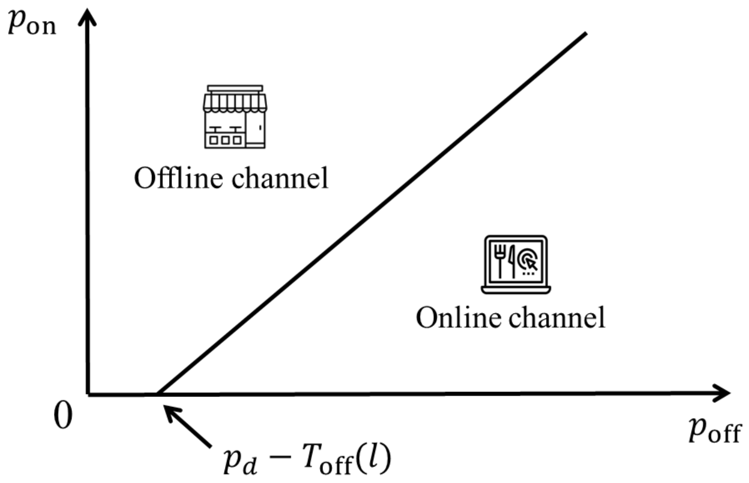

Figure 1. Customers’ channel choice when the distance from the service provider is l

Let A_{on} and A_{off} denote the potential demand of the offline and online channels, and let S_{on} and S_{off} denote the sizes of online and offline areas (potential areas over which online and offline customers demand services), respectively.

Hence, Equations (1) and (2) can be rewritten as follows:

$$D_{\text{on}} = A_{\text{on}} \cdot \left(1 - \frac{b_{\text{on}}}{A_{\text{on}}} \cdot p_{\text{on}} + \frac{\rho}{A_{\text{on}}} \cdot p_{\text{off}}\right) = S_{\text{on}} \cdot \theta(p_{\text{on}} + p_d) \tag{3}$$

$$D_{\text{off}} = A_{\text{off}} \cdot \left(1 - \frac{b_{\text{off}}}{A_{\text{off}}} \cdot p_{\text{off}} + \frac{\rho}{A_{\text{off}}} \cdot p_{\text{on}}\right) = S_{\text{off}} \cdot \theta(p_{\text{off}} + \bar{T}_{\text{off}}(S_{\text{off}})), \tag{4}$$

where $\theta(p)$ denotes the customer’s purchase proportion (proportion of potential customers in an area whose demands are actualized), at an effective price p.

In this research, $\theta(p)$ is formulated as a linear piecewise function of the expected price (Duffey et al., 2010; Kalyanaram and Winer, 1995; Pauwels et al., 2007). We consulted with our case study partner about maximum and minimum price thresholds to confirm accuracy and to ensure the non-negativity of the value for the effective purchase proportion.

$$\theta(p) = \begin{cases} \dfrac{p_{\max} - p}{p_{\max} - p_{\min}}, & p \le p_{\max} \\ 0, & p > p_{\max} \end{cases} \tag{5}$$

4.2 Service provider's dual-channel pricing

We now turn our attention to the service provider's pricing strategy. The restaurant's offline and online profit functions are calculated in Equations (6) and (7):

$$\Pi_{\mathrm{on}} = (p_{\mathrm{on}} + p_d) \cdot D_{\mathrm{on}} - C_p \cdot D_{\mathrm{on}} - \bar{T}_{\mathrm{on}}(S_{\mathrm{on}}) \cdot D_{\mathrm{on}} \quad (6)$$

$$\Pi_{\mathrm{off}} = p_{\mathrm{off}} \cdot D_{\mathrm{off}} - (C_p + C_{\mathrm{off}}) \cdot D_{\mathrm{off}} \quad (7)$$

In Equation (6), $(p_{\mathrm{on}} + p_d) \cdot D_{\mathrm{on}}$ denotes the sales revenue from the online channel, $C_p \cdot D_{on}$ denotes the production costs, and $\bar{T}_{\mathrm{on}}(S_{\mathrm{on}})$ denotes the average delivery cost in online area S_{on}.

In Equation (7), $p_{\mathrm{off}} \cdot D_{\mathrm{off}}$ denotes the sales revenue of the offline channel, and $(C_p + C_{\mathrm{off}}) \cdot D_{\mathrm{off}}$ denotes the sum of production costs and offline service costs.

We next introduce and study a benchmark model and a proposed model[4]. In both models, the service provider (restaurant) makes the first move and declares prices for offline and online channels, together with the delivery charges, taking into consideration the demand function of customers. Then the customers respond to the move, a portion of them selecting their least costly channel (Ertek and Griffin, 2002).

4.3 Restricted dual-channel with fixed delivery costs

To build a base dual-channel model (called *benchmark model* hereafter), we focus on a dual-channel setting with restrictive online delivery rules. This reflects the past practice of our case study, where the service provider only offered its online service to

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[4] For the sake of brevity and to concentrate on the dual-channel setting, the resulting properties of two basic models (offline-only and online-only), where either in-store or online service is active, are provided in Appendix A.

customers located within a fixed and limited radius (l_f) around the restaurant. The online service within this region was internally managed through a fixed flat-rate per delivery system (i.e. considering the maximum delivery cost $C_d \cdot l_f$ to the farthest online customer).

A customer's travel cost in the offline channel is given in Equation (8):

$$T_{\text{off}}(l) = C_t \cdot l \tag{8}$$

To formulate the benchmark model, we expand Equations (3) and (4) to derive the online and offline demand functions:

$$D_{\text{on}}^b = \int_{l_e}^{l_f} \theta(p_{\text{on}} + p_d) \cdot 2\pi \cdot l \cdot \mathrm{d}l \tag{9}$$

$$D_{\text{off}}^b = \int_0^{l_e} \theta(p_{\text{off}} + T_{\text{off}}(l)) \cdot 2\pi \cdot l \cdot \mathrm{d}l + \int_{l_f}^{\infty} \theta(p_{\text{off}} + T_{\text{off}}(l)) \cdot 2\pi \cdot l \cdot \mathrm{d}l \tag{10}$$

Equation (11) represents the channel choice of customers within a radius of l_f around the restaurant. Equation (12) indicates the distance l_u where the purchase proportion $\theta(p)$ is 0.

$$p_{\text{off}} + T_{\text{off}}(l_e) = p_{\text{on}} + p_d \tag{11}$$

$$\theta(p_{\text{off}} + T_{\text{off}}(l_u)) = 0 \tag{12}$$

In this benchmark model, the restaurant optimizes its dual-channel pricing decisions through the following mathematical programming model:

$$\text{Max} \quad \Pi_t^b = \Pi_{\text{off}}^b + \Pi_{\text{on}}^b \tag{13}$$

$$\text{s.t.} \quad u \geq l_f - l_e \tag{14}$$

$$u \geq 0 \tag{15}$$

$$D_{\text{on}}^{b} \leq \int_{l_f-u}^{l_f} \theta(p_{\text{on}} + p_d) \cdot 2\pi \cdot l \cdot \mathrm{d}l \tag{16}$$

$$\begin{aligned} D_{\text{off}}^{b} = & \int_{0}^{l_e} \theta\big(p_{\text{off}} + T_{\text{off}}(l)\big) \cdot 2\pi \cdot l \cdot \mathrm{d}l \\ & + \int_{l_e+u}^{\infty} \theta(p_{\text{off}} + T_{\text{off}}(l)) \cdot 2\pi \cdot l \cdot \mathrm{d}l \end{aligned} \tag{17}$$

$$p_{\text{on}} + p_d - p_{\text{off}} = C_t \cdot l_e \tag{18}$$

$$p_{\text{off}} \geq 0, p_{\text{on}} \geq 0 \tag{19}$$

Substituting Equations (9) and (10) into Equations (6) and (7), the service provider's dual-channel profit under benchmark setting, Equation (13), can be calculated as follows[5]:

$$\begin{aligned} \Pi_t^b & = \Pi_{\text{off}}^b + \Pi_{\text{on}}^b \\ & = \big(p_{\text{off}} - C_p - C_{\text{off}}\big) \cdot D_{\text{off}}^b + \big(p_{\text{on}} + p_d - C_p - C_d \cdot l_f\big) \cdot D_{\text{on}}^b \\ & = \pi \cdot \frac{\big(p_{\text{off}} - C_p - C_{\text{off}}\big)}{p_{\max} - p_{\min}} \left(p_{\max} \cdot l^2 - p_{\text{off}} \cdot l^2 - \frac{2}{3} C_t \cdot l^3\right)\Bigg|_{0}^{l_e} \\ & + \pi \cdot \frac{\big(p_{\text{off}} - C_p - C_{\text{off}}\big)}{p_{\max} - p_{\min}} \left(p_{\max} \cdot l^2 - p_{\text{off}} \cdot l^2 - \frac{2}{3} C_t \cdot l^3\right)\Bigg|_{l_f}^{l_u} \\ & + \pi \cdot \big(p_{\text{on}} + p_d - C_p - C_d \cdot l_f\big) \cdot \frac{p_{\max} - p_{\text{on}} - p_d}{p_{\max} - p_{\min}} \cdot l^2 \Bigg|_{l_e}^{l_f} \end{aligned} \tag{20}$$

In Constraints (14) and (15), an auxiliary variable u is used to ensure the positivity of the online and offline demands, represented in Constraints (16) and (17). Constraint (18) calculates l_e, based on the online and offline prices, and unit travel cost. Constraint (19) guarantees the non-negativity of the decision variables.

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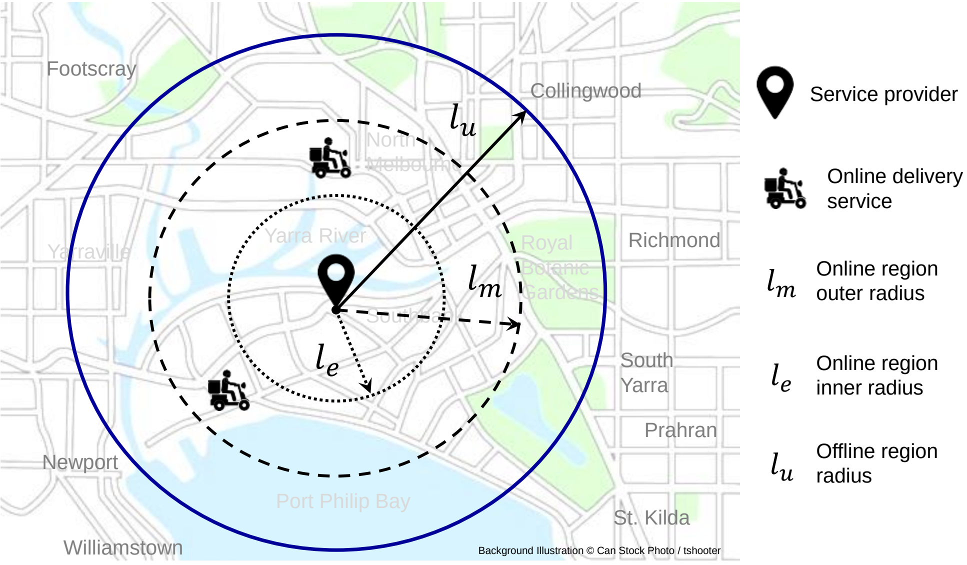
[5] Here, the mathematical symbol shown as the long vertical line refers to evaluation of the expression at the two given points and taking their difference.

4.4 Dual-channel with spatial distribution of customers' consideration

We now introduce our proposed dual-channel setting, where the restrictive online delivery rule and the fixed delivery cost assumption are relaxed. In this environment, online deliveries are undertaken by a professional third-party logistics provider that charges the restaurant a variable delivery cost, depending on customer location and distance from the restaurant.



Background Illustration © Can Stock Photo / tshooter

Figure 2. Online and offline service regions under the proposed model

The service provider's online delivery cost (per delivery) is calculated in Equation (21):

$$T_{\text{on}}(l) = C_d \cdot l \tag{21}$$

Let l_m denote the longest distance range, under which the online channel is the customers' desirable option:

$$p_{\text{on}} + p_d = T_{\text{on}}(l_m) + C_p \tag{22}$$

Figure 2 illustrates the online and offline service regions under the proposed model, established from customer channel choice.

As Figure 2 shows, customers located closer than l_e and farther than l_m from the service provider will choose the offline channel. Customers residing between l_e and l_m radius distance from the service provider, however, prefer the online channel.

Using Equation (3), the actualized *online* demand in this area is calculated in Equation (23):

$$D_{\text{on}} = \int_{l_e}^{l_m} \theta(p_{\text{on}} + p_d) \cdot 2\pi \cdot l \cdot \mathrm{d}l \tag{23}$$

$$= \pi \cdot \left(\frac{p_{\text{on}} + p_d - C_p}{C_d}\right)^2 \cdot \theta(p_{\text{on}} + p_d) - \pi \cdot \left(\frac{p_{\text{on}} + p_d - p_{\text{off}}}{C_t}\right)^2 \cdot \theta(p_{\text{on}} + p_d)$$

Next, using Equation (4), the actualized *offline* demand is presented in Equation (24). This is calculated through integration over the inner circle in Figure 2, with radius of l_e, plus integration outside the outer circle with radius of l_m:

$$D_{\text{off}} = \int_0^{l_e} \theta\big(p_{\text{off}} + T_{\text{off}}(l)\big) \cdot 2\pi \cdot l \cdot \mathrm{d}l + \int_{l_m}^{\infty} \theta\big(p_{\text{off}} + T_{\text{off}}(l)\big) \cdot 2\pi \cdot l \cdot \mathrm{d}l \tag{24}$$

The restaurant can optimize its dual-channel pricing decisions through the following mathematical programming model:

$$\text{Max} \quad \Pi_t = \Pi_{\text{on}} + \Pi_{\text{off}} \tag{25}$$

$$\text{s.t.} \quad D_{\text{on}} \leq \theta(p_{\text{on}} + p_d) \cdot S_{\text{on}} \tag{26}$$

$$D_{\text{off}} \leq \theta(p_{\text{off}} + \bar{T}_{\text{off}}(S_{\text{off}})) \cdot S_{\text{off}} \tag{27}$$

$$p_{\text{on}} + p_d \geq C_p + \bar{T}_{\text{on}}(S_{\text{on}}) \tag{28}$$

$$p_{\text{off}} \geq 0, \; p_{\text{on}} \geq 0 \tag{29}$$

Substituting Equations (23) and (24) into Equations (6) and (7), the service provider's dual-channel profit under the proposed model can be calculated as follows:

$$
\begin{aligned}
\Pi_t &= \Pi_{\text{off}} + \Pi_{\text{on}} \\
&= \pi \cdot \frac{\left(p_{\text{off}} - C_p - C_{\text{off}}\right)}{p_{\max} - p_{\min}} \left(p_{\max} \cdot l^2 - p_{\text{off}} \cdot l^2 - \frac{2}{3} C_t \cdot l^3\right)\Big|_0^{l_e} \\
&+\pi \cdot \frac{\left(p_{\text{off}} - C_p - C_{\text{off}}\right)}{p_{\max} - p_{\min}} \left(p_{\max} \cdot l^2 - p_{\text{off}} \cdot l^2 - \frac{2}{3} C_t \cdot l^3\right)\Big|_{l_m}^{l_u} \\
&+\pi \cdot \left(p_{\text{on}} + p_d - C_p\right) \cdot \frac{p_{\max} - p_{\text{on}} - p_d}{p_{\max} - p_{\min}} \cdot l^2 \Big|_{l_e}^{l_m} \\
&-\frac{2}{3} \pi \cdot C_d \cdot \frac{p_{\max} - p_{\text{on}} - p_d}{p_{\max} - p_{\min}} \cdot l^3 \Big|_{l_e}^{l_m},
\end{aligned}
\tag{30}
$$

where $l_e = (p_{\text{on}} + p_d - p_{\text{off}})/C_t$ and $l_m = (p_{\text{on}} + p_d - C_p)/C_d$.

Constraints (26) and (27) ensure the customers' actualized demand is always lower than the potential demand. Constraint (28) guarantees the online price and the delivery price can cover the product and average delivery costs. Constraint (29) ensures the non-negativity of the decision variables.

5 Analysis and Discussion

5.1 Data

In this sub-section we implement and test our developed mathematical models using real-world data from our industry partner. A logical step-by-step method was developed and applied to validate the collected data and to make accurate estimates[6].

The estimated values for the input parameters are as follows:

$$(l_f, p_d, C_t, C_d, C_{\text{off}}, C_p, p_{min}, p_{max}) = (5, 10, 0.8, 1.5, 6, 12, 10, 30)$$

To obtain further managerial insights, we include a range of values for each

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[6] Details on parameters' values can be provided by the corresponding author upon request.

parameter in our experiments[7].

Customer locations were based on historical sales transaction data, coming from the restaurant's information system and its online food ordering platforms. The locations of offline and online customers gave us the fixed online radius L_f for the benchmark model. Unit travel cost C_t was calculated using numerical values from a research paper (Lagura et al., 2011), public transport data from Expatistan[8], as well as living cost statistics from Numbeo[9]. Unit delivery cost C_d was calculated by systematically combining estimates for fuel and labor costs[10].

The value for the current delivery charge p_d (for the online channel in both models), the offline service cost C_{off}, and production cost per unit of product C_p were obtained from the restaurant manager as point estimates. Two critical parameters that significantly affect demand are p_{min} and p_{max}, which determine the price range over which purchases actualize and the purchase proportion $\theta(p)$. Again, the values for these parameters were determined through discussions with the manager.

Finally, the current values for online and offline prices were obtained for validation purposes, through weighted averaging of product prices using each product's demand as its weight. The current product prices were not used in the model but are compared against the optimal prices obtained through our experiments for validation purposes.

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[7] These value ranges are given in Appendix B (Tables B1 and B3), where the estimated values for the input parameters are shown as central values in **bold**.

[8] https://www.expatistan.com/price/public-transport/melbourne

[9] https://www.numbeo.com/cost-of-living/in/Melbourne

[10] http://www.abc.net.au/news/2016-05-31/minimum-wage-how-does-australia-compare/7461794

5.2 Experiments for comparing benchmark and proposed models

We now report the results of comparative experiments (Haridy et al., 2011) to analyze the effects of logistics parameters on the location-based pricing decisions and the performance – measured by the profits – of the optimization models.

The value ranges for the fixed online delivery radius l_f (used only in the benchmark model), the delivery charge p_d, and the logistics parameters (unit travel cost C_t and unit delivery cost C_d) are listed in Table B1, Appendix B. In these experiments, fixed values are assigned for the remaining parameters as follows:

$$(C_{\text{off}}, C_p, p_{\min}, p_{\max}) = (6, 12, 10, 30)$$

Optimal prices and profits for both the online and offline channels, as well as the total profit in both models (benchmark and proposed), were computed. Furthermore, the *percentage improvement in total profit* $\Delta\Pi$ was calculated as the primary measure for comparing the performance of the two models (proposed vs benchmark), and $\Delta\Pi$ was calculated as $\Delta\Pi = 100 \times (\Pi_t^* - \Pi_t^{b*}) / \Pi_t^{b*}$, where Π_t^* and Π_t^{b*} represent the total profit in the proposed and benchmark models, respectively, under respective optimal prices of each model.

In order to assess the significance of the effects that these four parameters and their pairwise interactions have on the performance of the two models, the analysis of variance (ANOVA) was applied as a formal statistical test (El-Taweel and Haridy, 2014; Haridy et al., 2012). In the ANOVA, the four parameters and their pairwise interactions (shown with a + sign between the factors in each pair) are each considered as factors and the *percentage improvement in total profit* $\Delta\Pi$ is considered as the response. Each different value of each factor was considered as a level, with 11 levels for each main factor and 121 levels for each pairwise interaction (a total of 11^4 =14,641 experiments).

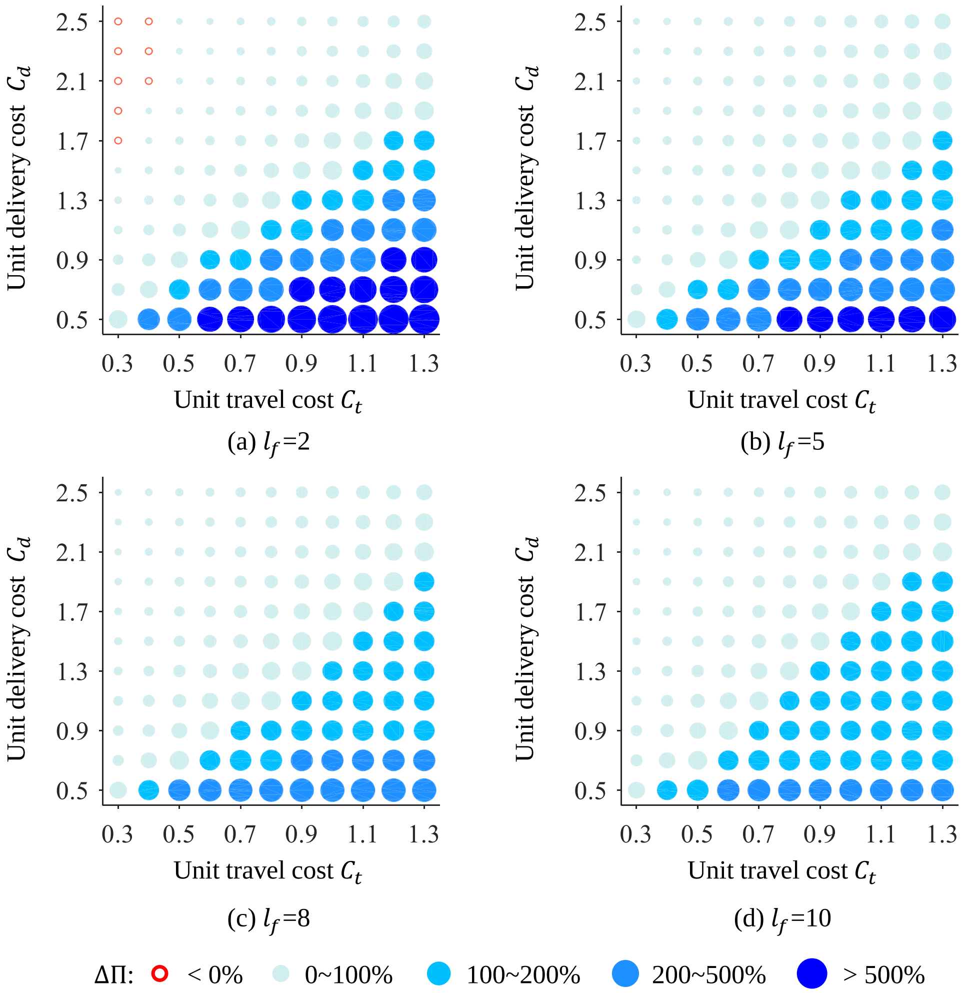
As given in the ANOVA results (see Table B2, Appendix B), the p values corresponding to all the included factors (with the exception of $p_d + C_t$) are less than 0.05, indicating that their effects on $\Delta\Pi$ are statistically significant with 95% confidence.

Having confirmed the statistically significant effects of almost all the factors, we now present visualizations that provide us with insights into our experimental results. Selected representative visualizations and their interpretations are provided to illustrate the *types* of insights that one can derive through such analysis.

Figure 3 illustrates the change in percentage improvement in profit $\Delta\Pi$ (denoted by color and size of the circles) in relation to unit delivery cost C_d, unit travel cost C_t, and fixed online radius l_f.

It can be observed that lowering the unit delivery cost C_d encourages the service provider to implement the location-based flexible delivery service in lieu of the restricted delivery service. The percentage improvement in profit $\Delta\Pi$ is especially higher (denoted by larger and darker circles) if the customers are bearing higher values of unit travel cost C_t.

Figure 3 also displays the effect of fixed online radius l_f on $\Delta\Pi$. The percentage profit improvement $\Delta\Pi$ introduced by the proposed model decreases with increasing values of l_f.



(a) l_f=2 (b) l_f=5 (c) l_f=8 (d) l_f=10

Figure 3. The impact of C_t, C_d and l_f on $\Delta\Pi$, the percentage improvement in total profit in the proposed model, compared to the benchmark model ($p_d = 10$, $C_{\mathrm{off}} = 6, C_p = 12$)

A counter-intuitive result in Figure 3(a) is that for some parameter settings (the region with small red circles, where $\Delta\Pi < 0$) switching to the proposed model decreases total profit, rather than increasing it. This occurs when unit delivery cost C_d is high, unit travel cost C_t is low, and the fixed online radius l_f is also low. Among the 14,641 experiments, $\Delta\Pi < 0$ was observed in 121 experiments in total, and the minimum value of $\Delta\Pi$ was observed to be -2.78%.

We next focus on the effect of the logistics parameters on the ratio of online channel profit to total profit (share of online profit within dual-channel profit) in the benchmark and proposed models. For given values of ($l_f = 3, C_t = 0.7, C_d = 1.5$), Figure 4 displays the impact of delivery charge p_d on the ratio of online channel profit to total profit, in the two models.

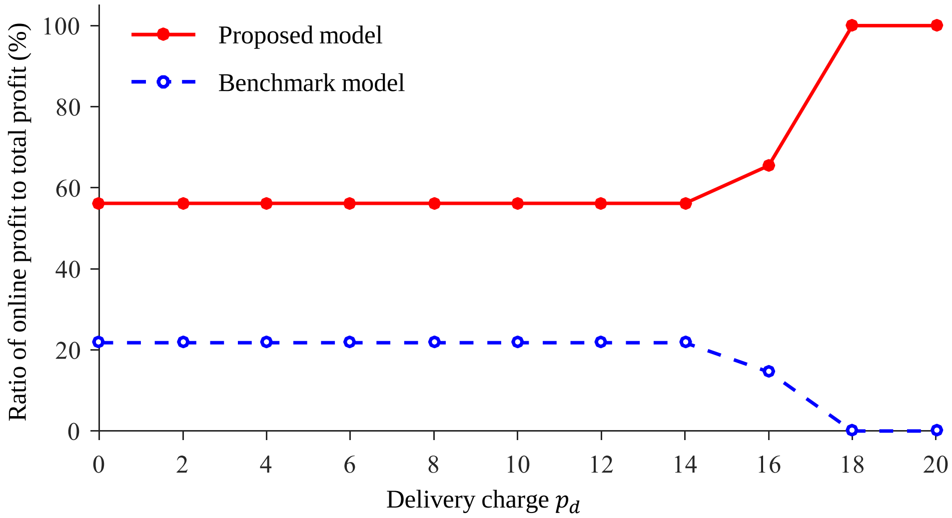


Figure 4. The impact of unit travel cost on the online profit ratios in the proposed model and benchmark model ($l_f = 3, C_t = 0.7, C_d = 1.5$)

From Figure 4, it can be observed that the ratio of online channel profit to total profit is higher in the flexible delivery service (proposed model) compared to that in the benchmark model. Another insight from Figure 4 is that the ratio of online profit to total profit moves in opposite directions in the two models, beyond $p_d > 14$. With higher values of p_d, the ratio of online profit decreases and eventually reaches zero (offline channel only) in the benchmark model, whereas it increases and eventually constitutes the total profit (online channel only) in the proposed model.

Figure 5 displays the impact of unit travel cost C_t on the ratio of online channel profit to total profit. Figure 5 shows that the online profit ratio of the proposed model is more sensitive to changes in unit travel cost C_t compared to the restricted service of the benchmark model. When $C_t \leq 0.5$, the benchmark model has a higher ratio of online profit. As C_t increases beyond $C_t > 0.5$, the ratio of online profit in the proposed model increases much faster than in the benchmark model and eventually constitutes the total profit (online channel only), at around $C_t = 0.8$.

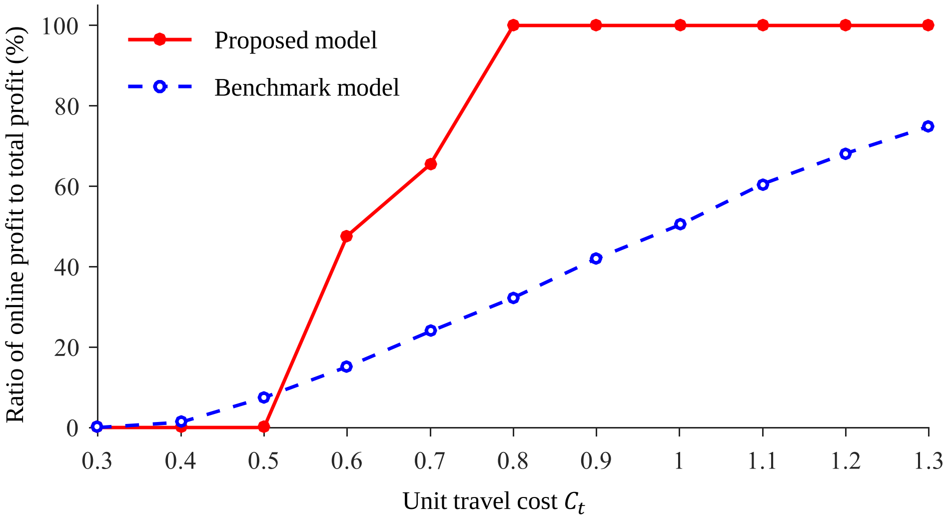


Figure 5. The impact of unit travel cost on the online profit ratios in the proposed model and benchmark model ($l_f = 5, p_d = 16, C_d = 1.5$)

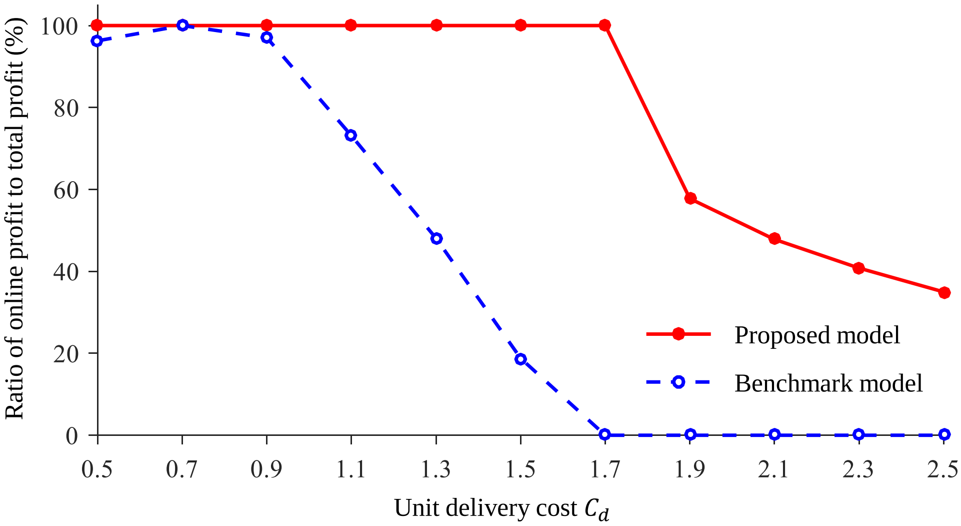


Figure 6. The impact of unit delivery cost on the online profit ratios in the proposed model and benchmark model ($l_f = 8, p_d = 10, C_t = 0.9$)

Figure 6 displays the impact of unit delivery cost C_d on the ratio of online channel profit to total profit. It exhibits that, in the benchmark model, as C_d increases the ratio of online profit increases slightly and then starts to decrease sharply at around $C_d =$

0.9, eventually hitting zero at around $C_d = 1.7$. Thus, beyond $C_d > 1.7$, the online channel becomes infeasible in the benchmark model. In the proposed model, the decrease in the ratio of online profit is at higher values of C_d (at around $C_d = 1.7$) and less drastic, compared to the benchmark model.

5.3 Experimental results for the proposed model

We now report the results of our extensive experiments for the proposed model. We examine how the logistics and operational factors influence customer channel preference and the service provider's total profit.

In addition to the input, parameters of the experiments for the proposed model are listed in Table B3, Appendix B. The extensive experiments (a total of 11^5 =161,051 cases) were conducted by considering the 11 levels of each of the five input factors p_d, C_t, C_d, C_{off} and C_p, while using fixed values of ($p_{\min}$, $p_{\max}$) = (10, 30). Performance measures computed include total profit, inner and outer boundaries for the online boundary, and a boundary for the offline area.

In order to assess the significance of the effects that these five factors and their pairwise interactions have on total profit, the analysis of variance (ANOVA) was applied again. Based on the ANOVA results (see Table B4, Appendix B), the p values corresponding to all the included factors (with the exceptions of $p_d + C_t$ and $p_d + C_{\text{off}}$) are less than 0.05, indicating that their effects on total profit Π_t^* in the proposed model are statistically significant with 95% confidence. The high p values were observed for $p_d + C_t$ and $p_d + C_{\text{off}}$, indicating that the effect of delivery charge p_d

on total profit is insignificant, when considered together with unit travel cost C_t and offline service cost C_{off}.

Now we turn our attention to how the logistics factors (unit travel cost C_t and unit delivery cost C_d) affect the supply chain structure and total profit in the proposed model, where logistics costs are location-based[11].

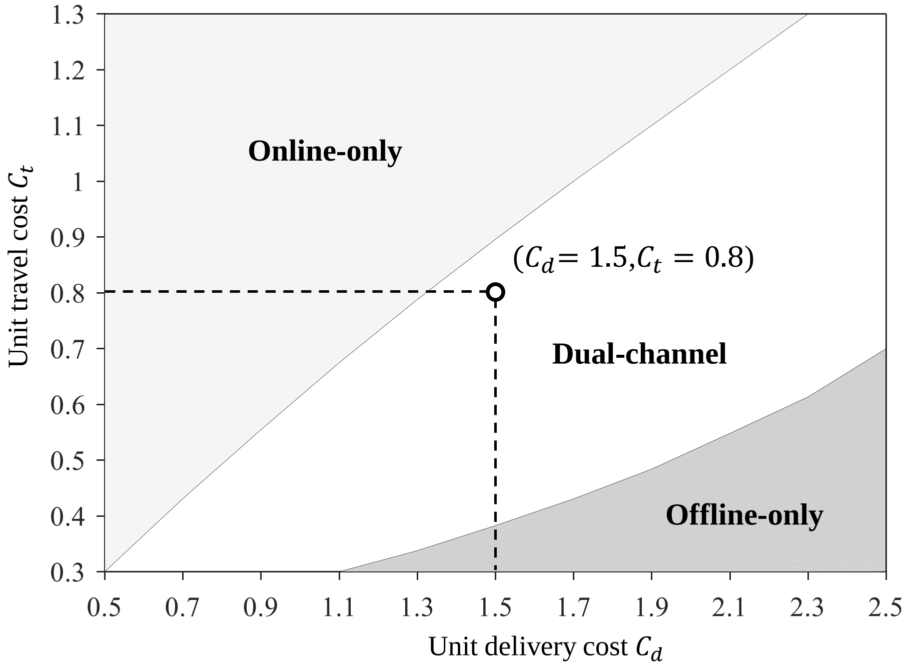


Figure 7. The impact of C_d and C_t on the supply chain structure ($p_d = 10$, $C_{\text{off}} = 6, C_p = 10$)

Figure 7 shows the preferred supply chain structures under changing values of unit delivery cost C_d and unit travel cost C_t. It can be observed that a supply chain with an *online-only channel* is preferred in the upper left region of the chart, above the curve[12] that approximately connects $(C_d = 0.5, C_t = 0.3)$ to $(C_d = 2.3, C_t = 1.3)$. On the other hand, a supply chain with an *offline-only channel* is preferred in the lower

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[11] Similar analyses were conducted to explore the effects of the delivery charge p_d and offline service cost C_{off} (together with other parameters) on the supply chain structure, and can be provided by the lead author upon request.

[12] This can be approximated by the expression $C_t > 0.0222 + 0.5555\, C_d$.

right region of the chart, below the curve[13] that approximately connects $(C_d = 1.1, C_t = 0.3)$ to $(C_d = 2.5, C_t = 0.65)$. In the remaining middle section, a dual-channel supply chain, where both the online and offline channels are active, is preferred and generates the highest profit, respectively.

Taking the estimated values for the key parameters (provided in Section 5.1) into consideration, the above results confirm that the proposed location-based pricing model is valuable to our industry partner's business, particularly when both service channels are active $(C_d = 1.5, C_t = 0.8)$.

Our next analysis focuses on the impacts of operational costs on the service areas for the online and offline channels, as well as total profit.

Figure 8 depicts the total profit and service areas for the online and offline channels for varying value combinations of production and offline service costs.

When these operational costs are both low enough, it is optimal to only serve customers through the online channel $(C_p = 8, C_{\text{off}} = 2)$. Furthermore, low operational costs, and the consequent low offline prices, encourage customers in a larger geographical area to make the trip to the restaurant for a dine-in experience.

As these operational costs increase, the online service area emerges and gradually expands. Yet, despite the introduction of the online channel, the service area shrinks and total profit decreases (depicted in Figure 8 by lighter colors for circular service areas). It means that the introduction of the online channel counters the negative impacts of higher operational costs. Eventually, when the operational costs are highest,

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[13] This can be approximated by the expression $C_t < 0.0250 + 0.2500\, C_d$.

customers are served only through the online channel ($C_p = 16, C_{\text{off}} = 10$), as the combined operational costs, especially the offline service cost, make it infeasible for the service provider to offer a dine-in experience.

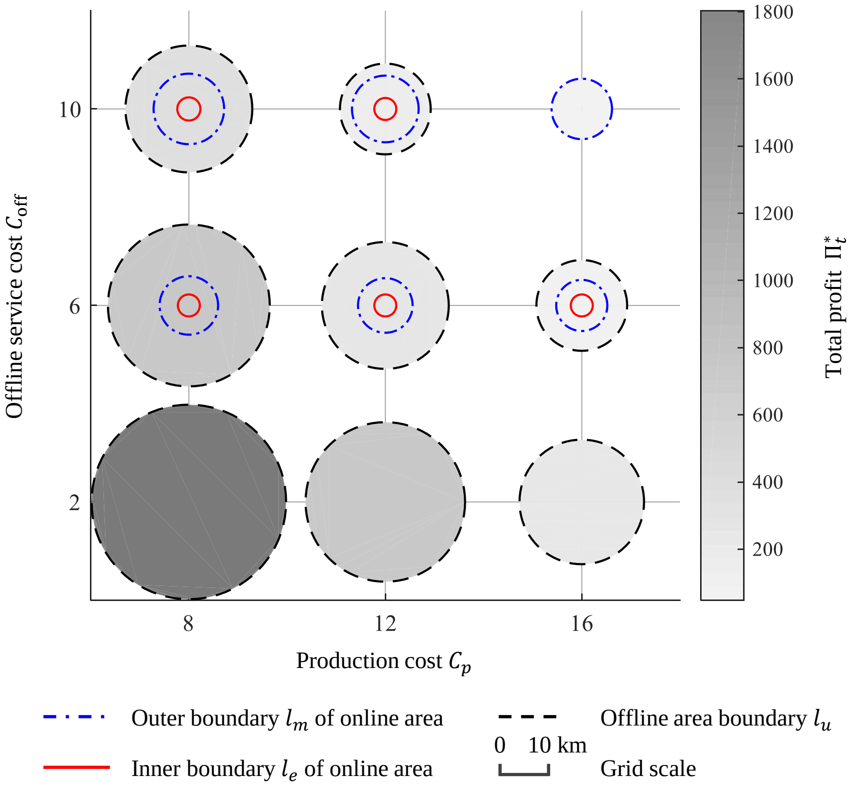

Figure 8. The impact of production cost C_p and offline service cost C_{off} on the service areas and total profit ($p_d = 10$, $C_d = 2.1$, $C_t = 0.7$)

Figure 9 jointly considers operational and logistics costs and depicts the total profit and areas of service for the online and offline channels for varying value combinations of production cost C_p and unit delivery cost C_d. It can be observed that the size of the service area increases when production cost decreases and unit delivery cost increases. As production cost becomes relatively more than unit delivery cost ($C_p > C_d$), the online area expands, eventually reaching the point ($C_p = 17, C_d = 0.7$) where customers clearly prefer the online channel over the offline channel (dine-in), and the whole delivery area is served through the online channel.

As expected, total profit decreases with increasing values of any of the operational or logistics parameters. For a given value of production cost C_p, as the unit delivery cost increases, total profit may decrease, despite an expansion of the service area.

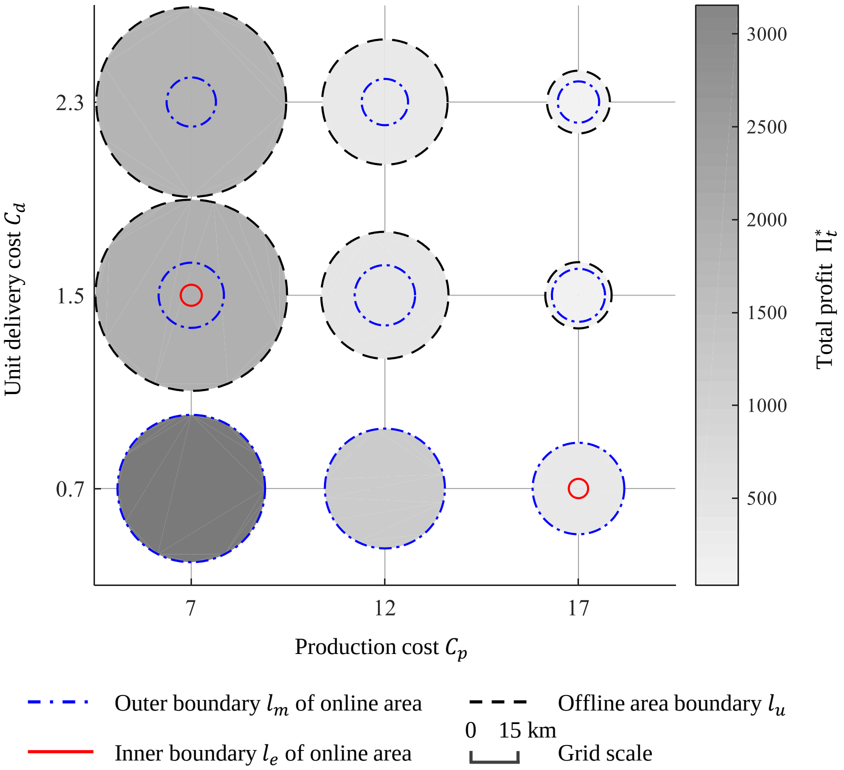

Figure 9. The impact of production cost C_p and unit delivery cost C_d on the service areas and total profit ($p_d = 10, C_t = 0.3, C_{\text{off}} = 10$)

This is a counter-intuitive result, suggesting that when both operational and logistics costs are low enough (here, $C_p = 7, C_d = 0.7$), the service provider can achieve a considerably high profit through both online and offline channels, without needing to significantly expand the size of its service area.

6 Conclusion

The motivation for this study was an industry project initiated by a newly-established local food service provider in Melbourne, Australia. We developed a real-world case based modeling approach for this dual-channel supply chain, which consists of an online and an offline channel. The key difference in the logistics of the two channels is that in the online channel the product is delivered to the customer by the service provider (a restaurant, in our case study), whereas in the offline channel, the customer travels to the service provider's location for dine-in or order collection.

We based our assumptions, models, and the experimental settings of our study on primary data and information sourced from our industry partner and its third-party e-commerce partner. We developed two models, referred to as the benchmark model and the proposed model, corresponding to the current and proposed operations of the company, respectively. The objective of our modeling is to find the optimal values of the decision variables, i.e. product prices for the online and offline channels that maximize total profit for the service provider.

Our study presents several new findings and introduces a variety of best practices to the dual-channel pricing literature on both the theoretical and practical fronts.

In regard to theory, we jointly model the customers' channel choice and the service provider's location-based pricing within a unified framework. We also provide an example of how formal statistical tests and visualization techniques can be used for the analysis of the effects of both operational and logistics parameters on key performance measures of a dual-channel supply chain.

On the practical front, to our knowledge, we develop the first model in the dual-pricing literature that is based on a real-world case study, where all the parameter values and value estimates are based on actual values obtained from primary sources.

The results revealed that the proposed model, with its flexible delivery service, performs significantly better than the benchmark model, evidenced by an overwhelming percentage of the experiments. Under the proposed model, the established supply chain structure (online-only, offline-only or dual-channel) depends on the specific values of the cost parameters. We observed that ratio of online and offline profit to the total dual-channel profit vary significantly, depending on the locations of customers and the values of the logistics costs. In addition, our statistical and visual analysis suggest that by jointly optimizing the logistics and operational processes, the service provider can achieve a considerably high profit through both channels, without necessarily expanding the size of its geographical service areas.

Taking the research limitations into account, several extensions could be conducted as future work, to strengthen the quality of our results and generalize our models:

- One of our goals in this paper was to obtain meaningful and interesting insights on the effects of different input factors through extensive experiments. While we obtained and presented a variety of results, due to the size of the experiments and large number of output parameters, there is still a need for further in-depth analyses. To this end, exploratory, descriptive, predictive and prescriptive methods of data science, including visual analytics, statistical and machine learning methods could be employed in future studies.
- In this research, we analyzed a single-stage supply chain, where a service provider directly serves its customers through only two channels. The dual-channel model, and

the related analysis can be extended to a multi-channel setting with more than two channels. For example, for the restaurant in our case study, its own website could be added as a third channel. Another possible extension is modelling price differentiation between offline customers who dine in the restaurant versus the customers who simply collect their order, where the order may have been placed either online or offline.

- In this research – based on historical sales transaction data from the restaurant's information system – we estimated that potential demand is uniformly distributed within the service area. However, to generalize our results, one could examine the effect of multiple customer segments, with different demand distributions and/or different skewness and parameters.

In conclusion, we foresee an abundance of studies in the upcoming decade where data analytics and optimization, particularly real-cases based operations research, will be applied conjointly. Our research can serve as an example, especially in the multi-channel supply chain literature, of how such a combined study can be conducted.

Acknowledgements

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Appendix A

A1: Offline-only model

Under the offline-only setting, the customer service area is modeled as a circle with the restaurant at the center. Following Equation (A1), the customer area is a circle with a radius denoted as l_u, such that the purchase proportion is equal to 0 at a distance of l_u:

$$\theta(p_{\text{off}} + T_{\text{off}}(l_u)) = 0, l_u = (p_{\max} - p_{\text{off}})/C_t \tag{A1}$$

As shown in Equation (A2), the potential demand for the offline channel can be calculated through integrating over the circle of service with radius l_u:

$$\begin{aligned} D_{\text{off}} &= \int_0^{\infty} \theta\big(p_{\text{off}} + T_{\text{off}}(l)\big) \cdot 2\pi \cdot l \cdot \mathrm{d}l \\ &= \int_0^{l_u} \theta\big(p_{\text{off}} + T_{\text{off}}(l)\big) \cdot 2\pi \cdot l \cdot \mathrm{d}l \\ &= \int_0^{l_u} \frac{p_{\max} - p_{\text{off}} - C_t \cdot l}{p_{\max} - p_{\min}} \cdot 2\pi \cdot l \cdot \mathrm{d}l \\ &= \frac{\pi \cdot (p_{\max} - p_{\text{off}})^3}{3C_t^2 \cdot (p_{\max} - p_{\min})} \end{aligned} \tag{A2}$$

The offline profit function Π_{off} for this offline-only setting then can be derived, as in Equation (A3).

$$\begin{aligned} \Pi_{\text{off}} &= p_{\text{off}} \cdot D_{\text{off}} - \big(C_p + C_{\text{off}}\big) \cdot D_{\text{off}} \\ &= \pi \cdot (p_{\text{off}} - C_p - C_{\text{off}}) \cdot \frac{(p_{\max} - p_{\text{off}})^3}{3C_t^2 \cdot (p_{\max} - p_{\min})} \end{aligned} \tag{A3}$$

To find the optimal price for the offline-only setting, we take the derivative of the offline profit function Π_{off} with respect to the offline price p_{off}, as shown in Equation (A4):

$$\frac{\partial \Pi_{\mathrm{off}}}{\partial p_{\mathrm{off}}} = \frac{\pi}{3C_t^2 \cdot (p_{\max} - p_{\min})} \cdot \left[(p_{\max} - p_{\mathrm{off}})^3 - 3(p_{\mathrm{off}} - C_p - C_{\mathrm{off}}) \cdot (p_{\max} - p_{\mathrm{off}})^2\right] \qquad \text{(A4)}$$

When this equation is solved for price, the optimal offline price p_{off}^* for the offline-only setting is found in Equation (A5), where purchase proportion is non-negative:

$$p_{\mathrm{off}}^* = \frac{1}{4} \cdot (3C_p + 3C_{\mathrm{off}} + p_{\max}) \qquad \text{(A5)}$$

The customers' travel costs can be obtained through integrating over the potentially infinite circular service area, as given in Equation (A6):

$$C_{\mathrm{off}}^t = \int_0^\infty T_{\mathrm{off}}(l) \cdot \theta\big(p_{\mathrm{off}} + T_{\mathrm{off}}(l)\big) \cdot 2\pi \cdot l \cdot \mathrm{d}l = \frac{\pi}{6C_t^2} \cdot \frac{(p_{\max} - p_{\mathrm{off}})^4}{p_{\max} - p_{\min}} \qquad \text{(A6)}$$

A2: Online-only model

In the online-only setting, customers can only order online and receive delivery of the product ordered from the service provider, but not visit the restaurant. This setting is particularly suitable for customers who have limited meal time (e.g. office staff) and prefer their meals to be delivered to their locations.

In the online-only setting, the maximum online delivery distance is limited to l_m. In other words, the online demand is 0 for customers at a distance of l_m. The value of l_m can accordingly be obtained through Equation (A7):

$$T_{\mathrm{on}}(l_m) + C_p = p_{\mathrm{on}} + p_d, l_m = (p_{\mathrm{on}} + p_d - C_p)/C_d \qquad \text{(A7)}$$

Online demand is calculated by integrating the online-only demand over the service area with a radius of l_m, as given in Equation (A8):

$$D_{\mathrm{on}} = \int_0^{l_m} \theta(p_{\mathrm{on}} + p_d) \cdot 2\pi \cdot l \cdot \mathrm{d}l = \pi \cdot \frac{p_{\max} - p_{\mathrm{on}} - p_d}{p_{\max} - p_{\min}} \cdot \left(\frac{p_{\mathrm{on}} + p_d - C_p}{C_d}\right)^2 \qquad \text{(A8)}$$

Substituting demand, price, and delivery costs into Equation (A9), the online profit can be calculated:

$$\Pi_{\mathrm{on}} = \left(p_{\mathrm{on}} + p_d - C_p\right) \cdot D_{\mathrm{on}} - \bar{T}_{\mathrm{on}}(S_{\mathrm{on}}) \cdot D_{\mathrm{on}} \qquad \text{(A9)}$$

Total delivery cost and an alternative form of online profit function are derived in Equations (A10) and (A11), respectively:

$$\begin{aligned} \bar{T}_{\mathrm{on}}(S_{\mathrm{on}}) \cdot D_{\mathrm{on}} &= \int_0^{l_m} T_{\mathrm{on}}(l) \cdot \theta(p_{\mathrm{on}} + p_d) \cdot 2\pi \cdot l \cdot \mathrm{d}l \\ &= \frac{2}{3}\pi \cdot C_{\mathrm{on}} \cdot \frac{p_{\max} - p_{\mathrm{on}} - p_d}{p_{\max} - p_{\min}} \cdot \left(\frac{p_{\mathrm{on}} + p_d - C_p}{C_d}\right)^3 \end{aligned} \qquad \text{(A10)}$$

$$\begin{aligned} \Pi_{\mathrm{on}} &= \left(p_{\mathrm{on}} + p_d - C_p\right) \cdot D_{\mathrm{on}} - \bar{T}_{\mathrm{on}}(S_{\mathrm{on}}) \cdot D_{\mathrm{on}} \\ &= \frac{\pi}{3} \cdot \frac{p_{\max} - p_{\mathrm{on}} - p_d}{p_{\max} - p_{\min}} \cdot \frac{\left(p_{\mathrm{on}} + p_d - C_p\right)^3}{C_d^2} \end{aligned} \qquad \text{(A11)}$$

Finally, the optimal online price is derived in Equation (A12), when purchase proportion is non-negative:

$$p_{\mathrm{on}}^* = \frac{1}{4} C_p - p_d + \frac{3}{4} \cdot p_{\max} \qquad \text{(A12)}$$

Appendix B

Table B1 Experimental factors and levels for the comparative experiments

Input parameter	Levels
Fixed online radius (l_f)	0, 1, 2, 3, 4, **5**, 6, 7, 8, 9, 10
Delivery charge (p_d)	0, 2, 4, 6, 8, **10**, 12, 14, 16, 18, 20
Unit travel cost (C_t)	0.30, 0.40, 0.50, 0.60, 0.70, **0.80**, 0.90, 1.00, 1.10, 1.20, 1.30
Unit delivery cost (C_d)	0.50, 0.70, 0.90, 1.10, 1.30, **1.50**, 1.70, 1.90, 2.10, 2.30, 2.50

Table B2 ANOVA results showing the significance of factors and interactions with respect to affecting $\Delta\Pi$. (SS: sum of squares; DF: degrees of freedom; MS: mean square)

Source	SS	DF	MS	F-statistic	*p* value
l_f	7.17×10^7	10	7.17×10^6	573.62	< 0.001
p_d	1.61×10^6	10	1.61×10^5	12.88	< 0.001
C_t	1.54×10^8	10	1.54×10^7	1228.99	< 0.001
C_d	5.81×10^8	10	5.81×10^7	4650.94	< 0.001
$l_f + p_d$	2.25×10^6	100	2.25×10^4	1.80	< 0.001
$l_f + C_t$	6.38×10^7	100	6.38×10^5	51.11	< 0.001
$l_f + C_d$	2.13×10^8	100	2.13×10^6	170.27	< 0.001
$p_d + C_t$	1.03×10^6	100	1.03×10^4	0.82	0.90
$p_d + C_d$	6.07×10^6	100	6.07×10^4	4.86	< 0.001
$C_t + C_d$	1.92×10^8	100	1.92×10^6	153.88	< 0.001
Error	1.75×10^8	14000	1.25×10^4		
Total	1.46×10^9	14640			

Table B3 Experimental factors and levels for the proposed model

Input parameter	Levels
Delivery charge (p_d)	0, 2, 4, 6, 8, **10**, 12, 14, 16, 18, 20
Unit travel cost (C_t)	0.30, 0.40, 0.50, 0.60, 0.70, **0.80**, 0.90, 1.00, 1.10, 1.20, 1.30
Unit delivery cost (C_d)	0.50, 0.70, 0.90, 1.10, 1.30, **1.50**, 1.70, 1.90, 2.10, 2.30, 2.50
Offline service cost (C_{off})	1, 2, 3, 4, 5, **6**, 7, 8, 9, 10, 11
Production cost (C_p)	7, 8, 9, 10, 11, **12**, 13, 14, 15, 16, 17

Table B4 ANOVA results for the proposed model, showing the significance of factors and interactions with respect to affecting Π_t^*. (SS: sum of squares; DF: degrees of freedom; MS: mean square)

Source	SS	DF	MS	F-statistic	*p* value
C_d	2.48×10^{10}	10	2.48×10^{9}	51813.29	< 0.001
C_t	2.08×10^{10}	10	2.08×10^{9}	43516.93	< 0.001
p_d	4.61×10^{7}	10	4.61×10^{6}	96.59	< 0.001
C_p	3.85×10^{10}	10	3.85×10^{9}	80665.91	< 0.001
C_{off}	1.17×10^{10}	10	1.17×10^{9}	24418.85	< 0.001
$C_d + C_t$	1.72×10^{9}	100	1.72×10^{8}	361.60	< 0.001
$C_d + p_d$	4.42×10^{7}	100	4.42×10^{6}	9.30	< 0.001
$C_d + C_p$	1.22×10^{10}	100	1.22×10^{9}	2559.21	< 0.001
$C_d + C_{\text{off}}$	1.13×10^{9}	100	1.13×10^{8}	236.82	< 0.001
$C_t + p_d$	1.96×10^{6}	100	1.96×10^{5}	0.41	1.00
$C_t + C_p$	7.89×10^{9}	100	7.89×10^{8}	1650.68	< 0.001
$C_t + C_{\text{off}}$	1.12×10^{10}	100	1.12×10^{9}	2345.82	< 0.001
$p_d + C_p$	3.29×10^{7}	100	3.29×10^{6}	6.89	< 0.001
$p_d + C_{\text{off}}$	4.18×10^{6}	100	4.18×10^{5}	0.87	0.81
$C_p + C_{\text{off}}$	3.30×10^{9}	100	3.30×10^{8}	689.69	< 0.001
Error	7.37×10^{9}	154347	4.78×10^{4}		
Total	1.33×10^{11}	155397			

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