Online Business and Marketplaces

by

Yun Fong Lim
yflim@smu.edu.sg

Lee Kong Chian School of Business
Singapore Management University

July 26, 2020

To my family

Acknowledgments

The author thanks Xin Fang and Yini Gao for their comments on the initial draft of this book. Special acknowledgment must go to Qiyuan Deng and Ruijie Zhang for creating some of the figures in the book. This book is used as a textbook for *OPIM633 Online Business and Marketplaces*, a graduate-level course at Singapore Management University. The author thanks the students for many stimulating questions and constructive comments.

Contents

List of Tables

List of Figures

Chapter 1

Online Retailing

1.1 Introduction

As the Internet technology and mobile devices develop rapidly, more consumers opt for online shopping. This results in a boom of online retail sales during the past decades. For example, in 2019 the global e-commerce sales grew at a rate of 20.7% and reached US$3.535 trillion, making up 14.1% of the total retail sales (eMarketer, 2019). By 2023, the online retail sales will amount to US$6.542 trillion, which is equivalent to 22.0% of the total retail sales. In Southeast Asia, the e-commerce market is projected to grow up to US$88 billion in 2025 as shown in Figure 1.1, according to Google and Temasek Holdings. Retailers may see their sales shrinking if they ignore e-commerce as customers continue to shift to purchasing products online. The strong growth in sales makes online retailing a significant industry to study.

A common way for online retailers to boost their revenue is to run *online seasonal sales*, which have become one of the most popular online promotional events. For example, Alibaba generated more than 163.8 billion yuan (approximately US$25.3 billion) of revenue on the "Singles' Day" in 2017, whereas JD.com reported a revenue of 127.1 billion yuan (approximately US$19.14 billion) on the same day (Russel, 2017). In contrast,

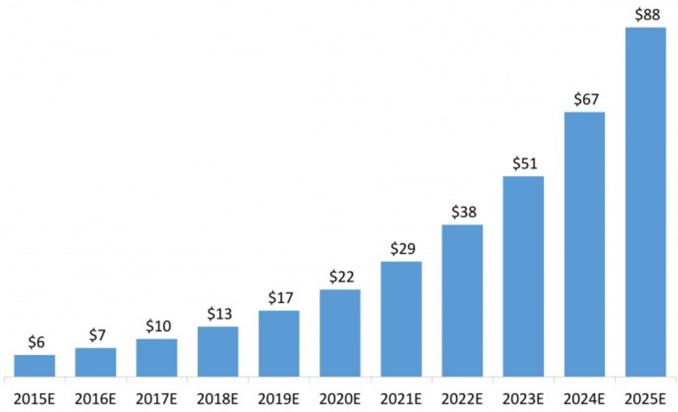


Figure 1.1: Size of Southeast Asia's e-commerce market (in billions USD) [Source: Google and Temasek Holdings, 2016.]

US online consumers spent US$5.03 billion on Black Friday and spent US$2.87 billion on Thanksgiving Day (Jones, 2017). Is online retailing really that lucrative? What are the major challenges for the online retailers? To answer these questions, we need to see how the online retailers differentiate themselves from their traditional counterparts.

1.2 Brick-and-mortar retailing versus online retailing

How is online retailing different from the traditional *brick-and-mortar* retailing? In terms of distribution of products, both brick-and-mortar and online retailers need to replenish their products from suppliers and store the products in warehouses (see Figure 1.2). For the brick-and-mortar retailers, they distribute their products from the warehouses to a number of retail stores (for example, one store per neighborhood). Customers visit the stores to choose the products. After purchasing the products, the customers bring the products home. The retailers do not need to bear the transportation costs of the customers (except bulky items such as furniture and home appliances, for which the retailers may provide free home delivery service).

In contrast, the online retailers need to first pick the products ordered by customers in the warehouses. The *order-picking* process, which can be manual or automated, is often

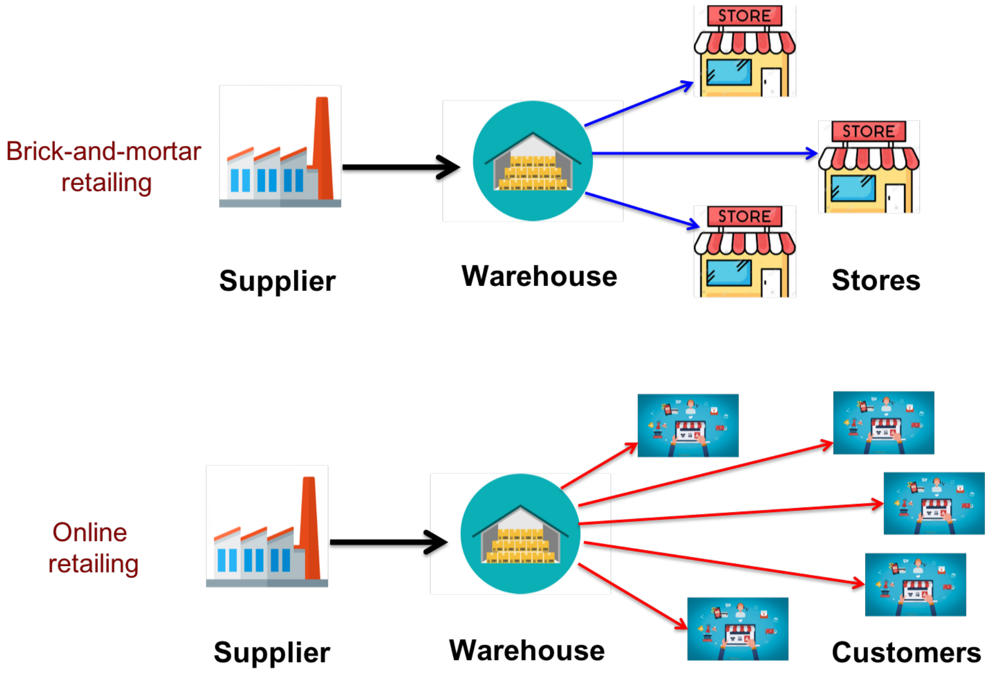


Figure 1.2: Brick-and-mortar retailing versus online retailing

considered the most costly operation within a warehouse. The online retailers incur a *fulfillment cost*, which includes the costs of operating and staffing warehouses and customer service centers as well as payment processing costs. The retailers then deliver the products from the warehouses to numerous, individual customers, which are significantly more than the brick-and-mortar stores. For example, Amazon receives more than 400 customer orders *every second* during a typical cyber Monday. Each of these customer orders requires a delivery. Thus, the online retailers also need to bear a *shipping cost* to get the products to the customers. Figure 1.2 illustrates the main difference between brick-and-mortar retailing and online retailing.

The fulfillment cost and the shipping cost constitute the major operating cost of most online retailers. Figure 1.3 shows that the sum of the fulfillment and the shipping costs of Amazon increased over time from 2010 to 2017. Reducing these costs becomes the main challenge for the online retailers in this cut-throat industry.

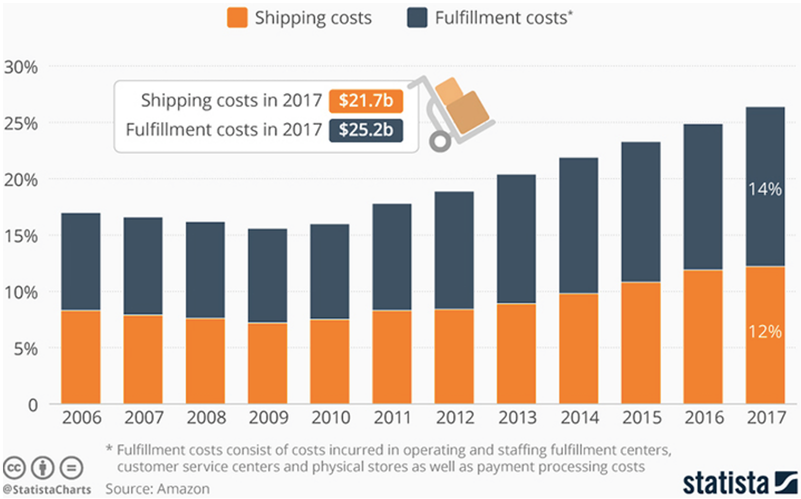


Figure 1.3: Fulfillment and shipping costs

It is also worth noting that the pace of distribution of brick-and-mortar retailing is much slower than that of online retailing. For example, the brick-and-mortar retailers may deliver a set of products (in bulk quantities) from the warehouses to each of their stores once a week according to a regular schedule. In contrast, the online retailers process customer orders in an almost continuous, real-time manner. For example, after an order is received from a customer, it may be picked and packed in a warehouse within 30 minutes and ready for shipping. As a result, compared to the brick-and-mortar retailers, the online retailers require very different processes, technologies, corporate culture and mindset, and employee skillsets. We discuss the pros and cons of online retailing below.

1.3 Advantages of online retailing

Compared to brick-and-mortar retailing, online retailing has the following advantages.

1. **No stores:** Since there are no brick-and-mortar stores, online retailers can save inventory, customer-facing staff, rental costs, utility fees, and other costs related to physical assets. Instead, the online retailers just operate a few centralized distribution centers (warehouses). This allows retailers to invest in better marketing and

customer experience on their e-commerce sites.

2. **Access to market is easier:** Through the Internet, the access to market for sellers has become easier. Many online marketplaces such as Alibaba, Amazon, eBay, Flipkart, Lazada, and Taobao allow sellers to set up an online shop and sell products in a short period of time. See how to sell through an online marketplace in Chapter 2.

3. **Less inventory:** With all the regions (countries) served by a few distribution centers, the online retailers' inventory can be pooled. Thus, less safety stock is necessary. This saves space for the online retailers.

4. **Attractive cash conversion cycle:** Some online retailers adopt the "stock less" fulfillment model that allows them to achieve remarkable inventory turnover. This results in an attractive cash conversion cycle. For example, Figure 1.4 shows that Amazon receives payments from customers 19 days before it pays its supplier. In contrast, a typical book retailer pays its supplier 78 days before it receives payments from customers (Netessine, 2009).

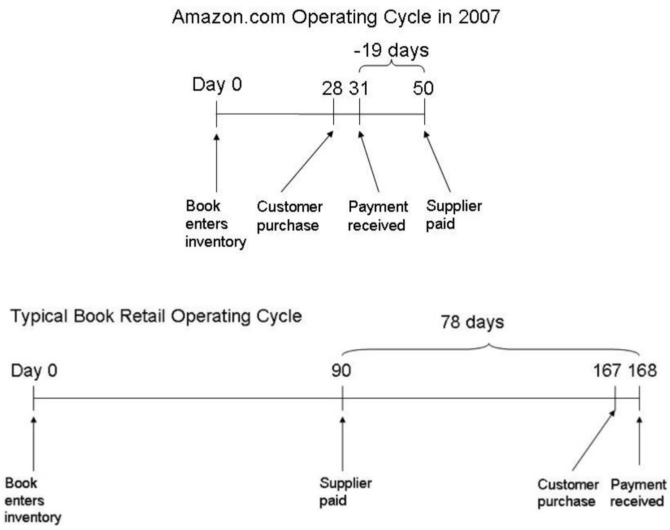


Figure 1.4: Cash conversion cycles [Source: Data compiled from the presentation by Tom Szkutak, CFO of Goldman Sachs Group Inc., Eighth Annual Internet Conference, May 24, 2007, and "Amazon.com-going public," HBS No. 899-003.]

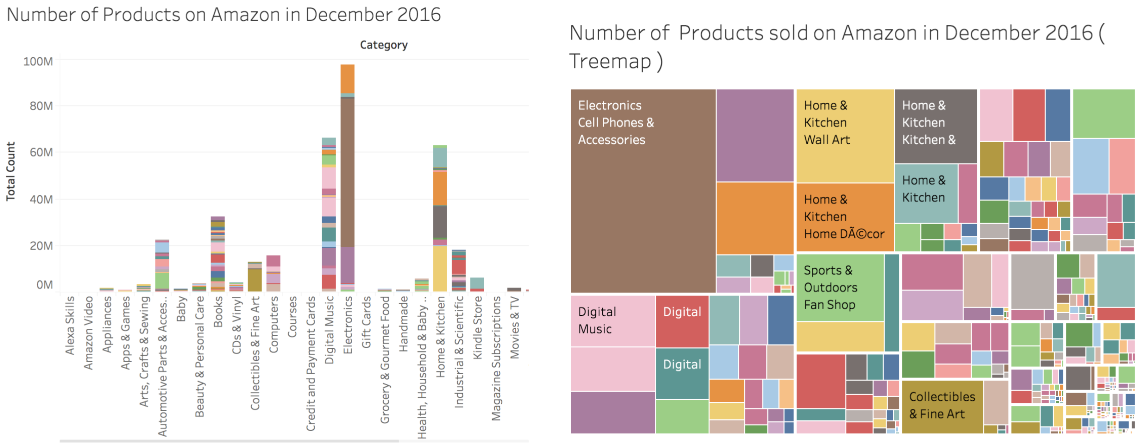


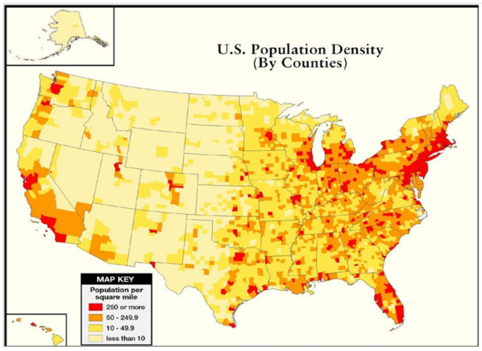
Figure 1.5: As of December 1, 2016, Amazon sells 368,876,590 items. [Source: https://www.scrapehero.com/how-many-products-does-amazon-sell-december-2016/]

5. **Product assortment decision is easier:** The online retailers only need to decide what to sell on their websites. This is much simpler compared to the assortment decisions for individual brick-and-mortar stores that are located in different markets with different demands. Figure 1.5 shows the assortment of Amazon.

6. **Can capture demand data, not just sales data:** Since the online retailers can capture the click-stream data, they can track what the consumers are looking for (which products they click). They can even analyze the shopping patterns of consumers on their websites and leverage this information to maximize their revenue. For example, if the consumers usually buy products A and B in the same order, then the retailers can put these two products next to each other on the websites. The online retailers can also use online marketing tools to target new customers and website analytics tools to gain insights into their customers' needs.

7. **Can provide personalized service:** Many online retailers require consumers to sign in before they place an order. As the shopping pattern is captured at an individual level, an online retailer can customize the shopping experience for each individual consumer. Such a customized experience includes personalized product assortment,

(a)



(b)

Figure 1.6: (a) The locations of fulfillment centers of an online retailer in the USA. (b) The population distribution of the USA.

shipping and pick-up options, promotions, and pricing.

8. **Ability to locate in "convenient" states:** The online retailers can build their fulfillment centers (warehouses) at strategic locations such that their main markets can be served economically and efficiently. Figure 1.6(a) shows the locations of fulfillment centers of an online retailer in the USA, which are strategically chosen to serve populated areas of the country shown in Figure 1.6(b).

9. **Flexible in fulfillment:** In contrast to brick-and-mortar retailing, a significant characteristic of online retailing is that the retailers have the flexibility to satisfy the demands of a zone (say, a city or a country) from any fulfillment center that holds the inventory. Figure 1.7 shows an example. This fulfillment flexibility improves service levels, but may also increase the retailers' outbound shipping cost, which is a main operating cost of the online retailers (Dinlersoz and Li, 2006). This fulfillment flexibility further complicates the allocation of inventory to the fulfillment centers and the replenishments of the products from the suppliers (see Figure 1.7). To address these issues in an effective manner, the retailers need to make the replenishment, allocation, and fulfillment decisions *jointly*.

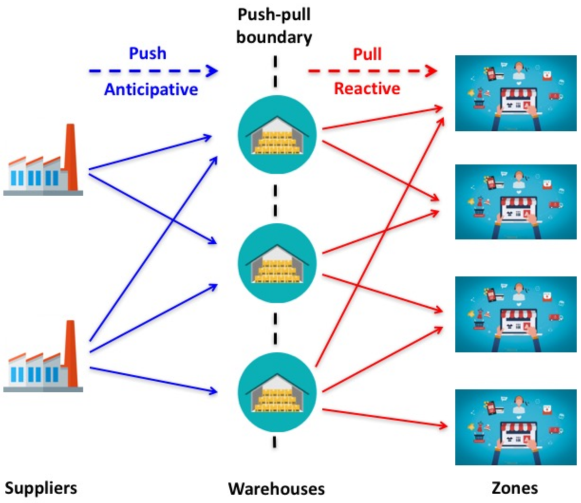


Figure 1.7: An online retailer can satisfy the demands of a zone from any warehouse that holds the inventory.

10. **Tracking and locating inventory is easier:** Since all the inventory is kept in a few distribution centers, it is easier to track and locate the inventory compared to doing so at many brick-and-mortar stores.

11. **Inventory is less likely to be damaged:** It is easier to manage (protect) the inventory in a few distribution centers than at many brick-and-mortar stores.

12. **Can diversify the products:** The online retailers can diversify their product assortment on their websites with almost the same business process. However, this causes additional investment in back-end fulfillment for possibly lower-margin products with very different inventory turns. The retailers may no longer be able to use the same equipment for packaging and assembling shipments. Furthermore, expanded product variety leads to more inventory.

13. **Can diversify beyond a country:** A major advantage of online retailing over brick-and-mortar retailing is the ability to expand the market beyond local customers relatively faster. The online retailers can sell their products to other countries or duplicate the same business model in other regions or countries by targeted marketing,

offering their websites in different languages, or perhaps partnering with an overseas company. However, this causes other problems such as more inventory due to more stocking points. Furthermore, complex trade rules and custom regulations for cross-border e-commerce may lower the profit margins.

14. **Sales taxes:** The online retailers can choose to build their distribution centers at locations with tax advantages. For example, Delaware in USA did not charge sales tax on items shipped to consumers located outside the state (Netessine, 2009).

1.4 Disadvantages of online retailing

Compared to brick-and-mortar retailing, online retailing has the following disadvantages.

1. **Fulfillment costs:** The online retailers require a lot of manual labor as well as automated technologies for the operations within their distribution centers and the last-mile delivery to the receivers. The operations in the distribution centers include receiving, storing, order-picking (most costly), checking, packing, and shipping. The last-mile delivery of online retailing is notoriously costly because it requires delivery to each individual consumer. Furthermore, the online retailers also need to deal with returns from the customers.

2. **Website and marketing costs:** It is not cheap to plan, design, create, host, secure, and maintain a professional e-commerce website, especially if the sales volumes are large and growing. Furthermore, the online retailers require a generous budget for online marketing to get the right customers for their products. This is especially so for a crowded sector with popular keywords.

3. **Technology development costs:** The online retailers need to invest in fulfillment software to connect with a variety of suppliers. They also need sophisticated software to constantly change shipping prices and options, track products, and update

receiving and shipping. In addition, the significant growth of the online retail market has induced sophisticated criminal activities. The online retailers must invest in the latest security systems to protect their websites and transaction processes.

4. **More susceptible to seasonal fluctuations:** Online retailing is like “make-to-order” because the online retailers cannot pre-pack their shipments. Thus, it requires very accurate forecasts and an extremely efficient fulfillment process to absorb demand spikes.

5. **Customer trust and legal issues:** Without a physical store with a track record and face-to-face interactions with the customers, it can be challenging to build a trusted brand name. Setting up a good online customer service system can be costly. The online retailers also need to cope with legal issues associated with customer rights that are attached to online sales.

1.5 Problems

1. Suppose a retailer, such as Barnes & Noble, decided to better integrate its online and offline (physical) channels. What would be the advantages of better integration?

2. Suppose a retailer, such as Barnes & Noble, decided to better integrate its online and offline (physical) channels. What are the operational challenges to achieve that integration?

References

Dinlersoz, E.M., Li, H. 2006. The shipping strategies of internet retailers: Evidence from internet book retailing. *Quant. Marketing Econom.* **4**(4) 407–438.

eMarketer. 2019. Global Ecommerce 2019. `https://www.emarketer.com/content/global-ecommerce-2019`.

Ferreira, K.J., Lee, B.H.A., Simchi-Levi, D. 2016. Analytics for an online retailer: Demand forecasting and price optimization. *Manuf. Serv. Oper. Manag.* **18**(1): 69–88.

Jones, C. 2017. Retailers rejoice – and Cyber Monday sales could set a record. `https://www.usatoday.com/story/money/2017/11/26/online-sales-surge-over-thanksgiving-day-weekend/892767001/`, last retrieved on Nov. 27, 2017.

Local Offer Network. 2011. The daily deal phenomenon: A year in review. Report, Local Offer Network, Chicago.

Netessine, S. 2009. Online Book Retailing: Operational Strategies. *Wharton Case* 23. The Wharton School of The University of Pennsylvania.

Ostapenko, N. 2013. Online discount luxury: In search of guilty customers. *Internat. J. Bus. Soc. Res.* 3(2):60–68.

Russel, J. 2017. *Alibaba smashes its Single's Day record once again as sales cross $25 billion.* `https://techcrunch.com/2017/11/11/alibaba-smashes-its-singles-day-record/`, last retrieved on Nov. 20, 2017.

Wolverson, R. 2012. High and low: Online flash sales go beyond fashion to survive. *Time Magazine* 180(19):9–12.

Chapter 2

Online Marketplaces

2.1 Introduction

Many online retailers run an *online marketplace* where third-party sellers list their products for sale. These products include books, video games, metal parts, soft drinks, honey, pasta sauces, etc. An example of an online marketplace can be found on Amazon.com called Sell on Amazon, where individual sellers can upload their product information (including the inventory level) to the marketplace website. The sellers' products are listed on the retailer's website with other products. After a customer places an order on the retailer's website, the seller ships the order directly to the customer. The retailer charges a percentage of the payment as a commission and then transfers the remaining balance to the seller. Figure 2.1 illustrates the business model of an online marketplace. Other examples of online retailers operating a marketplace include Lazada.com in Southeast Asia and Flipkart.com in India. There are also pure-play marketplaces, which do not own any products, such as Taobao.com and Tmall.com in China, eBay.com in USA, and Rakuten.com in Japan.

2.2 Why does an online retailer run a marketplace?

An online retailer runs a marketplace because of the following reasons.

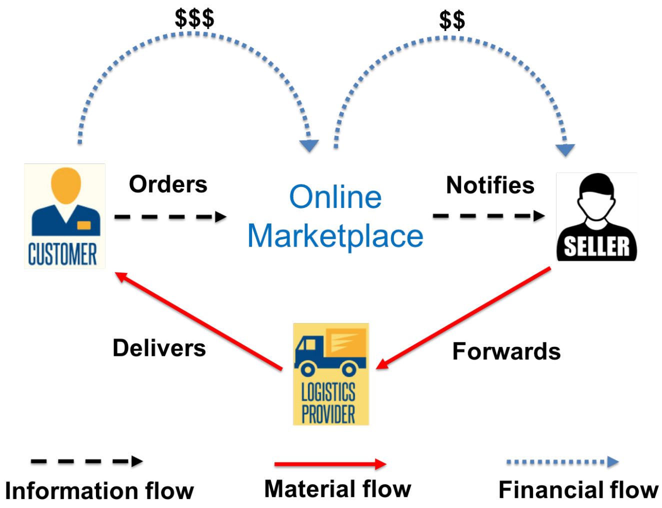


Figure 2.1: The business model of an online marketplace

1. **To provide a one-stop shopping experience:** Almost all online retailers want their customers to shop for everything on their websites. Providing one-stop shopping experience creates convenience for the customers and will attract the customers to revisit their websites. However, selling a broad assortment of products requires an online retailer to hold a lot of inventory. The demands for different products in retailing typically follow a distribution with a long tail shown in Figure 2.2. A small number of products account for most of the selling activities, but many products have a very low demand. Running a marketplace allows the online retailer to outsource some products, especially the slow-moving products and new products with unknown demands, to third-party sellers. In this way, the online retailer can provide a one-stop shopping experience without owning the inventory of all the products.

2. **To test new products:** Many online retailers make use of their marketplace to observe the popularity of some new products sold by third-party sellers. Once a popular product has been identified, the online retailers can sell the product by themselves (sometimes even in the same marketplace).

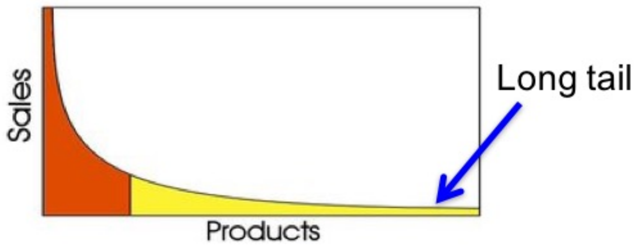


Figure 2.2: The sales (or demand) distribution in retailing typically has a long tail with many slow-moving products

3. **To adapt their business model using the data from the marketplace users:** Since the marketplace operator has a unique ability to obtain seller data, product or service data, personal data, transaction data, social data, and location data, the operator can use this data for their economic decision making and to adapt their business model.

2.3 Advantages of selling on a marketplace

If sellers operate their own e-commerce websites, they have full control, larger profits, and higher scalability. However, promoting niche brands (their websites) requires high investments and can become costly for the sellers. In contrast, on a marketplace, the sellers can sell their products online with a certain level of control but will be able to leverage the marketplace's global reach and services. In general, sellers have the following advantages when selling on a marketplace.

1. **Can tap on the traffic of the online marketplace:** Popular online marketplaces have a constant flow of visits to their websites. Tapping on the heavy traffic can help third-party sellers gain visibility on their products.

2. **Can leverage the reputation of the marketplace:** Shoppers are more comfortable and confident with major marketplaces because of their reliability and trust-

worthiness. By selling on these marketplaces, third-party sellers can leverage the reputation of the online marketplaces.

3. **Can control risks:** The sellers are under the protections by the marketplace against the risks of unpaid bills, fraud, disputes, etc.

4. **It is cheaper and quicker to begin:** Since the marketplace takes care of much of the hassle of selling online such as website design, hosting of servers, processing of orders, e-payment, financial transactions, and possibly even fulfillment, the sellers might save significant costs. By selling on the marketplace, third-party sellers do not need to make advance investments into the set-up, design, and marketing of their own websites.

5. **It is easier to access the international market:** If the marketplace operates internationally, then selling products on the marketplace will allow the sellers to expand their reach with minimal effort to other countries. For example, Figure 2.3 shows that Amazon has 11 international marketplaces.

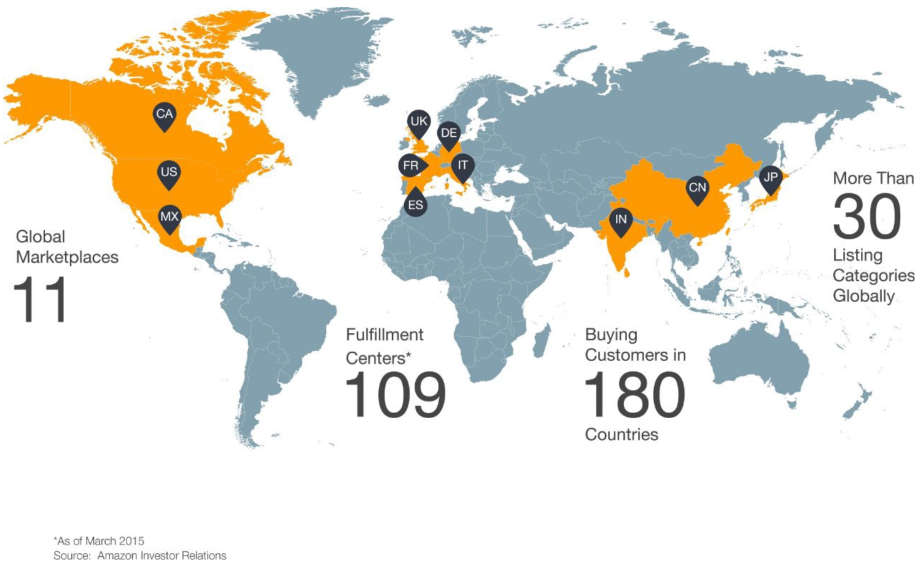


Figure 2.3: Amazon's international marketplaces

2.4 Disadvantages of selling on a marketplace

On the other hand, sellers have the following disadvantages when selling on a marketplace.

1. **Rules and regulations:** The sellers need to comply with many rules and regulations when selling on the marketplace. For example, the sellers may not be able to brand themselves in the way they wish or they may not be allowed to sell certain products. In addition, it can be a hassle for the sellers to add products to the marketplace as they need to meet many criteria.

2. **Fees:** In general, the sellers need to pay fees to the marketplace. These fees may include a monthly subscription fee and a commission for each successful transaction. Selling on a marketplace generally leads to a lower profit margin compared to selling on the sellers' own websites.

3. **Limited personalization options:** There are limited personalization options determined by the marketplace operator. The sellers have less control of their brands and customers. Furthermore, communication with the customers about their purchases are generally handled by the marketplace operator.

4. **Fierce competition:** The sellers may face a fierce competition on the marketplace. In some cases, the marketplace operator also sells the same products to compete with the sellers.

5. **Less control on pricing:** The marketplace may force the sellers to offer discounts for their products during promotion periods to attract more customers.

2.5 Online marketplaces with fulfillment service

Some marketplaces provide fulfillment service for their sellers. For example, to save logistics costs, sellers on the Amazon's marketplace can enroll in the Fulfillment by Amazon (FBA) program (see http://services.amazon.com). Under the FBA program, sellers store their products in a fulfillment center managed by Amazon. Upon receiving a customer order from her website, Amazon picks, packs, and ships the order to the customer. In addition, the FBA program also provides customer service that includes handling customer inquiries, refunds, and returns to shoppers for the listed products.

Under the FBA program, each seller determines the retail price of his product and its number of units to list for sale. Amazon charges only when a unit of the product is sold. For each unit of the product sold, Amazon keeps a certain percentage of its retail price and deposits the remaining balance to the seller's account. Units that are not sold after a period of time will be returned to the seller and the listing is closed. Figure 2.4 illustrates the business model of an online marketplace with fulfillment service.

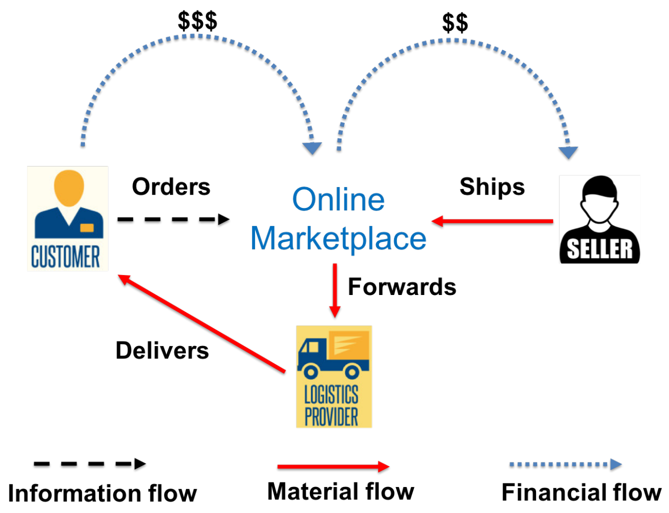


Figure 2.4: The business model of an online marketplace with fulfillment service

Formally, the marketplace operator (Amazon) offers a *consignment contract with revenue sharing* to each seller. The marketplace operator prefers this type of contract because of the following reasons: (i) The marketplace operator bears no overstocking risk. (ii) Unlike in traditional wholesale-price contracts, the marketplace operator does not need to negotiate with the individual sellers or to determine the retail price and production quantity for every product, which could be tedious when there are many sellers. (iii) Although a consignment contract with revenue sharing requires every seller to monitor his sales, the implementation is straightforward in an online setting because every transaction is tracked, and so splitting the revenue can be done automatically.

A marketplace operator typically prefers to provide fulfillment service for their sellers because of the following reasons:

1. The marketplace operator owns all the detailed data of the products and the sellers including consumer demography, shopping behavior, delivery time, trends, etc.

2. The marketplace operator can maintain her brand image by delivering the products to the customers.

3. It becomes harder for the sellers to detach from the marketplace as they rely on the marketplace's fulfillment service.

Other marketplace operators that provide fulfillment service for their sellers include Lazada.com in Southeast Asia and VIP.com in China.

2.5.1 Model

We consider a model illustrated in Figure 2.5. A marketplace operator (or retailer) with limited storage space sells n independent products over a single period. The total demand for each product over the selling period is price sensitive and uncertain. Each product is produced by a distinct manufacturer (seller) before the start of the selling period. The marketplace operator offers a consignment contract with revenue sharing to each manufacturer. Under each contract, the ownership of a product belongs to its manufacturer when it is stored in the marketplace operator's warehouse. No money is transacted until a unit of the product is sold. For each unit of any product sold, the marketplace operator keeps a fraction $r \in [0, 1)$ of the revenue for herself and remits the rest $1 - r$ to the corresponding manufacturer. The marketplace operator first specifies the common *revenue share* r for

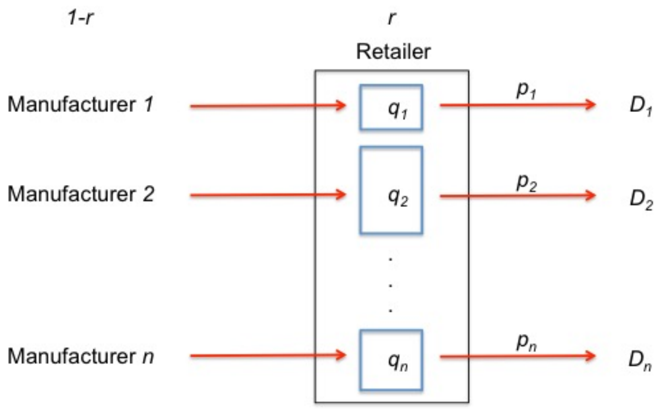


Figure 2.5: A capacitated retailer serving multiple manufacturers (sellers)

all the products (for example, Amazon publishes the revenue share on its website). After that each manufacturer i determines the retail price p_i and the production quantity q_i for his product.

We make the following assumptions.

1. This is a single-period problem.

2. The demand for product i is price sensitive and random: $D_i(p_i) = a_i p_i^{-b_i} \epsilon_i$, where a_i represents the base demand, b_i represents the price elasticity of product i, and ϵ_i is a random variable.

3. For each unit of product i, the marketplace operator charges manufacturer i a storage fee sv_i, where s is the storage fee per unit volume and v_i is the volume of each unit of product i. For each unit of product i, let $M_i = m_i + sv_i$ and $R_i = d_i - sv_i$ denote the costs incurred to manufacturer i and the marketplace operator respectively, where m_i is the manufacturing cost per unit of product i and d_i is the distribution cost per unit of product i. Thus, each unit of product i incurs a total cost $c_i = M_i + R_i$.

2.5.2 Stackelberg game

We model the decision process as a Stackelberg game where the marketplace operator is the leader and the manufacturers are followers. In this game, we assume that the marketplace operator can also set the storage fee s per unit volume. The marketplace operator first decides and announces the revenue share r and the storage fee s. Based on the announced revenue share and storage fee, each manufacturer i then chooses the retail price p_i and the production quantity q_i for his product to maximize his own profit. We will solve the overall problem backward: We first solve each manufacturer's problem to find his optimal response (price and quantity) to any revenue share and storage fee offered by the marketplace operator. Plugging each manufacturer's optimal response into the marketplace operator's profit function, we then find the revenue share and the storage fee that maximize the marketplace operator's profit subject to her storage capacity constraint.

We first solve each manufacturer's problem. Given r and s, each manufacturer i chooses p_i and q_i to maximize his expected profit. That is,

$$\max_{p_i, q_i} \quad \text{expected profit of manufacturer } i.$$

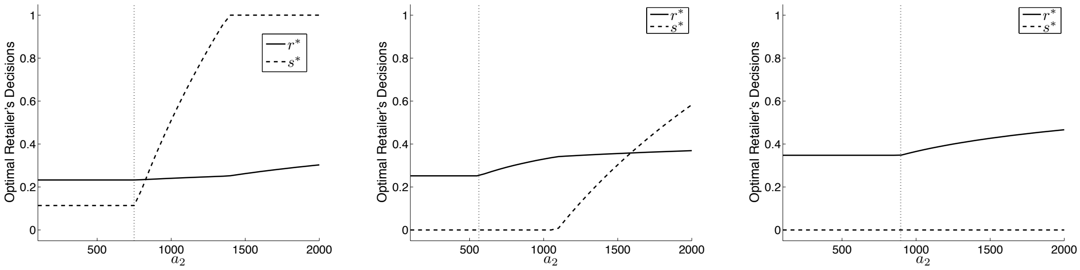
Plugging each manufacturer's optimal response into the marketplace operator's profit function, we then solve the marketplace operator's problem by optimizing the revenue share r and the storage fee s to maximize her expected profit subject to her storage capacity constraint. That is,

$$\begin{aligned} \max_{r,s} \quad & \text{expected profit of the marketplace operator} \\ \text{subject to} \quad & q_1 v_1 + q_2 v_2 + \ldots + q_n v_n \leq V, \end{aligned}$$

where V represents the operator's capacity (total storage volume of her warehouse).

2.5.3 Results and insights

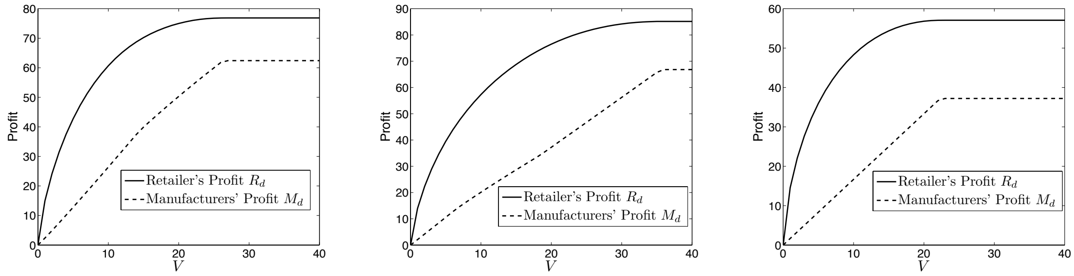
How to simultaneously set the revenue share r and the storage fee s? Figure 2.6 shows that r and s generally increase with the base demand a_2 for a system with two products. However, under some situations (such as the right-most case of Figure 2.6), it is sufficient to set $s = 0$. We find that, in general, if the manufacturing costs of the products are similar, then it is sufficient to set $s = 0$ (Lim et al., 2015). In other words, if the products have similar values, then the marketplace operator does not need to differentiate them by charging a storage fee. On the other hand, if the product manufacturing costs are very different, then the marketplace operator should set $s > 0$. Consider two products with very different values (manufacturing costs). For example, one is diamond that is expensive but occupies a small space, and the other is diaper that is much cheaper but occupies a large space. In this situation, the marketplace operator should charge a positive storage fee s to "penalize" the diaper so that she can make more space for the diamond.



(a) $b_1 = 6$, $m_1 = 15$, $a_1 = 30{,}000a_2$ (b) $b_1 = 6$, $m_1 = 10$, $a_1 = 5{,}000a_2$ (c) $b_1 = 4$, $m_1 = 5$, $a_1 = 2a_2$

Figure 2.6: Optimal revenue share r^* and storage fee s^* with $b_2 = 4, m_2 = 5$

Is it always beneficial to the firms if the marketplace operator expands her capacity? Figure 2.7 shows that expending the marketplace operator's capacity V can benefit both the marketplace operator and the manufacturers (Lim et al., 2015).



(a) $b_1 = 6$, $m_1 = 15$, $a_1 = 30{,}000a_2$ (b) $b_1 = 6$, $m_1 = 10$, $a_1 = 5{,}000a_2$ (c) $b_1 = 4$, $m_1 = 5$, $a_1 = 2a_2$

Figure 2.7: Expending capacity V benefits both the retailer and the manufacturers ($b_2 = 4, m_2 = 5$)

2.6 Different types of online marketplaces

Besides an online marketplace that sells products, there are other types of online marketplaces. For example, Amazon has developed different types of marketplaces over years:

- Sell on Amazon,
- Sell Your Services on Amazon,
- Sell on Amazon Business (B2B),
- Sell Your Apps on Amazon.

There are other marketplaces that provide different kinds of services to customers. These marketplaces match service providers with customers. Below are some examples:

1. Foodpanda, Deliveroo, and GrabFood for food delivery;
2. Airbnb and Tujia for accommodation;
3. Uber, Didi, Grab, and Gojek for transportation service;
4. Amazon Mechanical Turk for individuals and businesses to outsource their tasks to a distributed workforce who can perform these tasks virtually.

2.7 Online retailing and marketplaces

Different forms of online retailers and marketplaces exist in terms of the types of sellers and buyers. Table 2.1 shows some examples.

Table 2.1: Different seller-to-buyer types of online retailers and marketplaces

Seller-to-buyer Type	**Retailer/Marketplace**	**Examples**
B2B	online retailer	Office Depot, Nippon Paint
B2B	marketplace	Alibaba, Amazon
B2C	online retailer	JD, Amazon
B2C	marketplace	Lazada, Amazon
C2C	marketplace	eBay, Taobao

2.8 Problems

1. Which business model is better for Amazon: Sell on Amazon or Fulfillment by Amazon?

2. Which business model is better for a third-party seller: Sell on Amazon or Fulfillment by Amazon?

References

Lim, Y.F., Wang, Y., Wu, Y. 2015. Consignment contracts with revenue sharing for a capacitated retailer and multiple manufacturers. *Manufacturing and Service Operations Management* **17**(4), 527–537.

Chapter 3

Analytics and AI for Online Retailing

3.1 Introduction

Predictive commerce is getting increasingly common. Online retailers are trying to help customers to find products precisely when their need arises, or even before the customers perceive that need. To achieve that, the online retailers need to design a customer experience that leverages data analytics and large-scale automation (often called *artificial intelligence (AI)* or *machine learning*) with knowledge of human behavior. We will illustrate this idea using an example from online flash sales as follows.

3.2 Online flash sales

Online flash sales were pioneered by Vente Privée in France in 2001. Each online flash sale sells products at a discount for a short period (often less than one week). To hold flash sales, online retailers change assortment of products every week or even multiple times a day (in contrast, traditional retailers typically change their assortment only a few times a year). This is to create a sense of urgency among customers to induce impulse purchases.

By 2015, the industry of online flash sales in USA was worth approximately 4 billion USD (McKitterick, 2015). Zulily had the largest market share at 39%, followed by Gilt

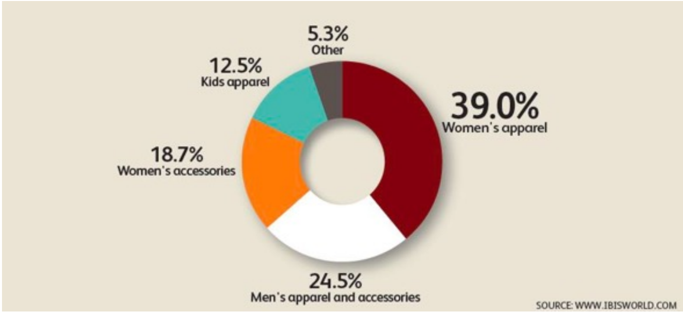


Figure 3.1: Product segmentation of the online flash sales industry in USA in 2015

Groupe at 18%, and Rue La La at 14%. Figure 3.1 shows the product segmentation of the online flash sales industry in USA in 2015.

Typically, online flash sales are organized as "events". For example, an event can be selling a collection of products from the same designer or a collection of men's sweaters. Some online retailers display a countdown timer showing the time remaining until the event is no longer available. Figure 3.2 shows different events on Gilt.com.

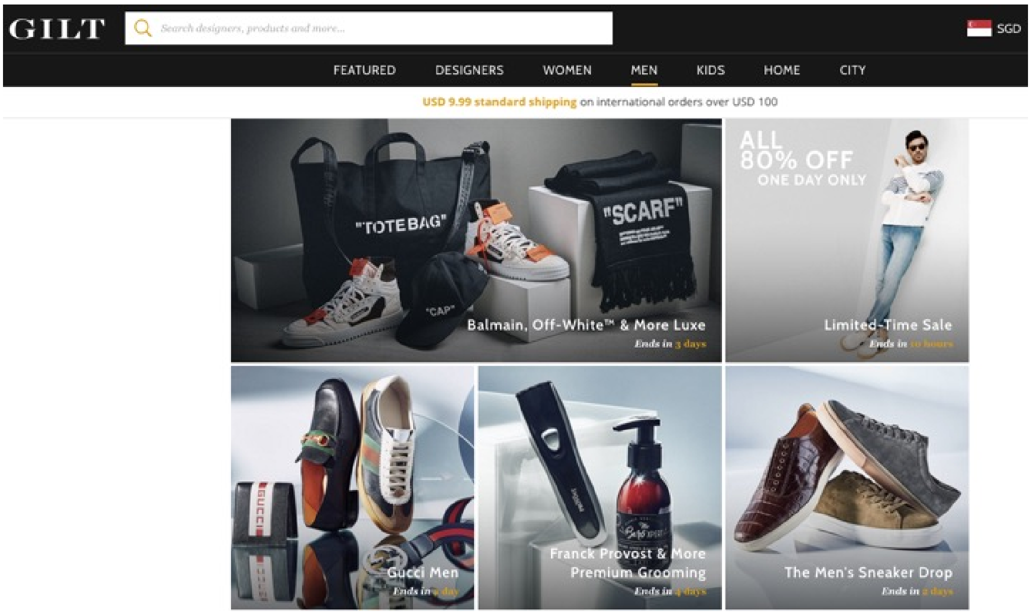
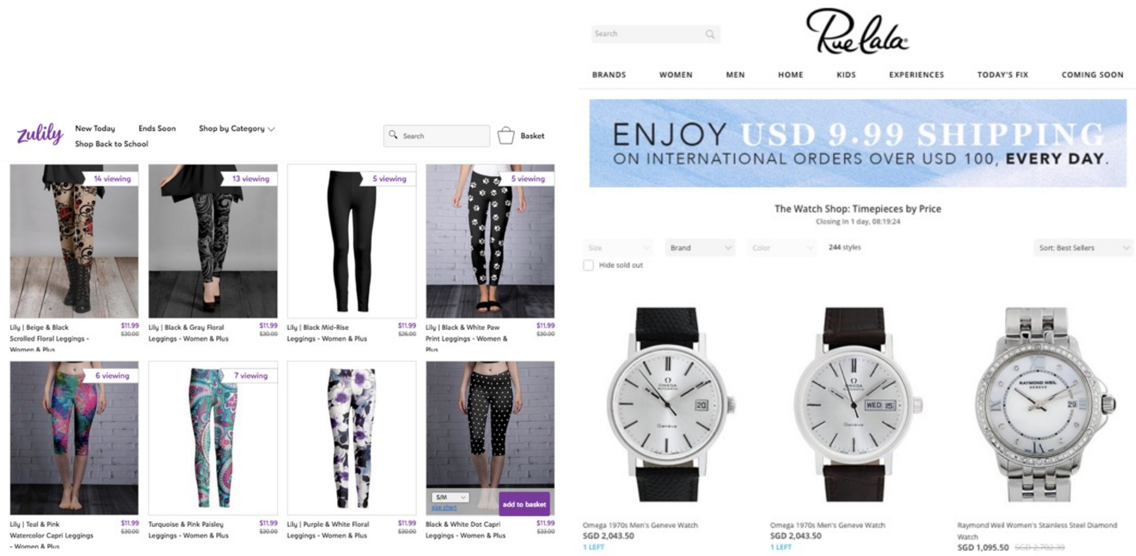


Figure 3.2: Different "events" on Gilt.com

An event consists of "styles". Each style is an aggregation of all available sizes of otherwise identical items. For example, a style could correspond to "CK men's red sweaters with sizes S, M, L, XL". All items belonging to the same style have the same price. Since the duration of each event is short, the price of each style typically does not change during the event. Figure 3.3 shows the styles in an event on Zulily.com and Ruelala.com.



(a) (b)

Figure 3.3: Different styles in an event on (a) Zulily.com and (b) Ruelala.com

3.3 Operations of online flash sales

In this section, we describe the operations of flash sales by online retailers. "Buyers" of an online retailer procure items from designers who typically ship the items immediately to the retailer's warehouse. On a frequent periodic basis, the buyers identify opportunities for future events based on available styles in inventory, customer needs, etc. When an event starts, customers place orders, and the retailer ships items from her warehouse to the customers. When the event ends or a product runs out of inventory, customers may no longer place an order for that product. If there is remaining inventory at the end of the event, then the buyers will plan a subsequent event where they will sell the same style.

Figure 3.4 illustrates the operations of online flash sales.

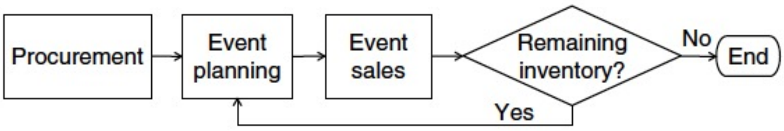


Figure 3.4: The operations of online flash sales (Ferreira et al., 2016)

We refer to styles being sold for the first time as *first exposure styles.* Historical sales data indicates that a majority of revenue may come from the first exposure styles. Hundreds of first exposure styles may be offered on a daily basis. The main challenge of many online retailers who hold flash sales is to predict demand for these first exposure styles and to determine their prices. Figure 3.5 shows an example of the sell-through distribution of the first exposure styles of an online retailer. The figure suggests that about 50% of the first exposure styles sell out before the end of the event, and approximately 15% of the first exposure styles sell less than 25% of their inventory. Since a large percentage of the first exposure styles sell out before their event is over, it may be possible to raise the prices on these styles while still achieving high sell-through. Meanwhile, many other first exposure styles sell less than half of their inventory by the end of the sales period, suggesting that their prices may have been too high. How should we price the first exposure styles properly?

3.4 Predicting value of fashion apparel

3.4.1 Art versus science

Can we use a data-and-analytics approach to predict the value of fashion apparel?

The answer may be “no” because of the following reasons:

- It is difficult to quantify trends.
- There is little data on competitors’ pricing and demand.

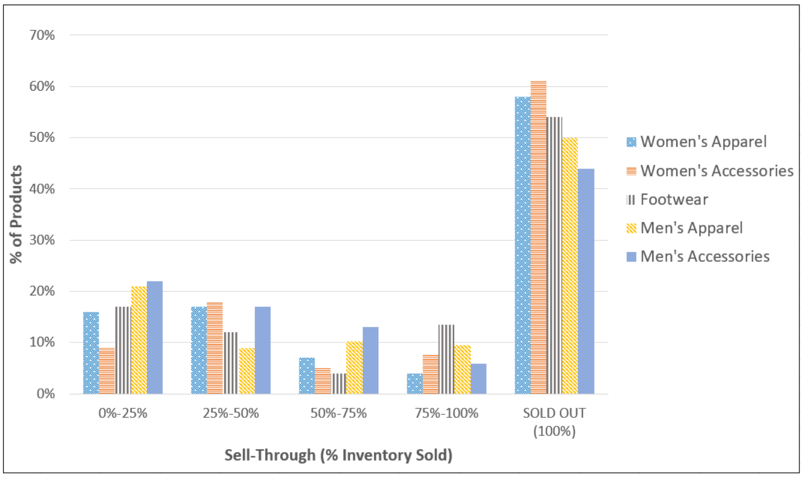


Figure 3.5: The sell-through distribution of first exposure styles

- It is hard to specify some metrics such as color popularity, style, quality, etc.
- The value of a product is different for different people.

People who support the above view may think pricing for fashion apparel is a kind of art.

On the other hand, the answer may be "yes" because of the following reasons:

- E-commerce data from clickstream, website traffic, etc. is rich.
- Some metrics such as price, discount, product category, etc. can be specified.
- There is a clear criterion of what makes a product successful: Large demand.
- Getting only a few predictions wrong has less of an impact.

People supporting the above view may think pricing for fashion apparel is a study of science.

3.4.2 Predicting the demand

To determine the price of a style, we first predict its demand. We can predict the demand for the style by looking at the demand data in the past. Figure 3.6 shows the past demands of similar styles under different prices. Each dot in the figure represents the demand for a style (Y axis) under a certain price (X axis). We can fit these data points in the figure using a straight line by *linear regression.* The solid line in Figure 3.6 suggests that the demand Y can be expressed as a linear function of the price X. That is $Y = f(X) = a + bX$, where a and b represent the intercept and the slope, respectively, of the linear function. The linear regression helps us to determine the coefficients a and b. We can predict the demand for a style based on this linear function. For example, the demand is d if a style is priced at p (dollars).

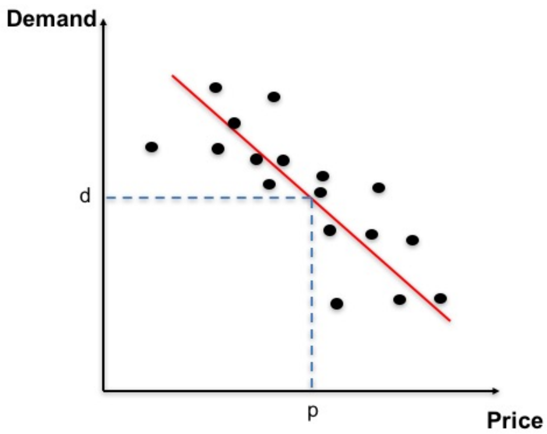


Figure 3.6: A linear demand model that predicts the demand based on the price

Generally, the demand for a style has a more complicated form. For example, the demand may depend on multiple factors such that $Y = f(X_1, X_2, X_3, \ldots)$. Given the historical values of $Y, X_1, X_2, X_3, \ldots$, we can use *multi-dimensional* linear regression to determine the coefficients of the function f. For example, the demand may depend on two factors X_1 and X_2 such that $Y = a + bX_1 + cX_2$, where X_1 represents the price set by the retailer and X_2 represents the price set by a competitor. The multi-dimensional linear regression helps us to determine the coefficients a, b, and c.

However, what are $X_1, X_2, X_3, \ldots$? In other words, what factors should we consider to forecast the demand? The following relevant factors usually have data available:

- Price

- Manufacturer suggested retail price (MSRP)
- Timing of event (month, day, time)
- Competitors' prices
- Sales (quantity sold)

Some other relevant factors may be *derived* from the available data:

- Discount
- Number of styles in an event
- Relative price
- Weekend or weekday

Some other factors may be relevant but are missing from the data:

- Lost sales (including the time of stockout, traffic to site)

Considering the above factors together with their data allows us to perform multi-dimensional linear regression to find the function f. The main idea here is to first collect relevant data, and then use AI or machine learning techniques (such as linear regression) to do demand prediction (that is, to find the coefficients of f).

What we have seen here is a rather scientific approach to demand prediction, but it is not completely void of art. There is art in deciding the features (that is, $X_1, X_2, X_3, \ldots$), and recognizing the derived and the missing data.

3.4.3 Optimizing the price

After determining the demand function $Y = f(X)$, we can optimize the price of a style to improve our revenue (or profit). Some key considerations are:

- Demand

- Competitors' pricing
- Fashion trends (for example, colors)
- Product assortment
- Inventory (what you have, how much you have)
- Target margins
- Target sell-through
- Economic factors or macro changes (including industry growth rate, recession, more new flash sales sites, etc.)
- Own inventory versus drop-shipping (that is, directly ship the products from the suppliers)
- Promotions and advertisements
- Discount price point (for example, minimum $9)

Incorporating some of the above considerations, we can determine the price of a style using the optimization framework in Figure 3.7.

Decision variable:
price (X)

Objective:
maximize revenue $XY = Xf(X) = X(a + bX)$

Constraints on decision:
price (X) $\leq$ competitor's price
margin $\geq$ x%
constraint on discount price point

Figure 3.7: Price optimization framework

3.4.4 Summary of price optimization

A retailer can use the following procedure to determine the price of a style to maximize her revenue (or profit):

1. Collect relevant data.

2. Use AI or machine learning techniques (such as linear regression) to predict the demand $Y = f(X)$.

3. Perform price optimization using the framework in Figure 3.7.

3.5 AI and the importance of data

3.5.1 Two approaches in AI

In the 1980s the AI field consisted of two camps: the *rule-based* approach and the *neural networks* approach (Lee, 2018). The rule-based approach attempts to instruct computers to think by providing many logical rules in its programs. For example, to identify whether there is a panda in a picture, the rule-based approach would lay down many "if-then" rules to help a computer make a decision. An example of such rules is "if there are black and white patches on an object, then it is probably a panda." This approach can be used to solve simple problems, but breaks down as the complexity of the problems increases.

In contrast, the neural networks approach does not instruct the computer with the rules created by a human brain. Instead, this approach attempts to emulate the functionality of the human brain. Researchers in this camp try to reconstruct the structure of the network of neurons in the human brain. They emulate the human brain's neural network structure with layers of *artificial neurons* that can receive and transmit signals. Instead of giving rules to the artificial neural networks for decision making, this approach provides an enormous number of samples of a phenomenon for the networks to identify patterns within the data. For example, instead of telling the computer the "if-then" rules to determine whether there is a panda in a picture, researchers in this camp simply feed many, many images labeled "panda" or "no panda" to the computer program and let the program figure out for itself what features are linked to the "panda" label.

The neural networks approach requires large amounts of data and computing power. The data (for example, images, texts, or clicks) is used to train the networks to identify patterns and the computing power is needed to process the data. As these two key ingredients become more and more available nowadays, the neural networks approach (now called *deep learning*) becomes increasingly promising. The approach has real-world applications (Lee, 2018) including face recognition, deciphering speech, language translation, identifying credit-card fraud, approving insurance applications, predicting consumer behavior, navigating robots, and driving vehicles.

3.5.2 The importance of data

So, why is data important in the era of AI? Figure 3.8 shows a few articles in the media stating that data is becoming like a natural resource.

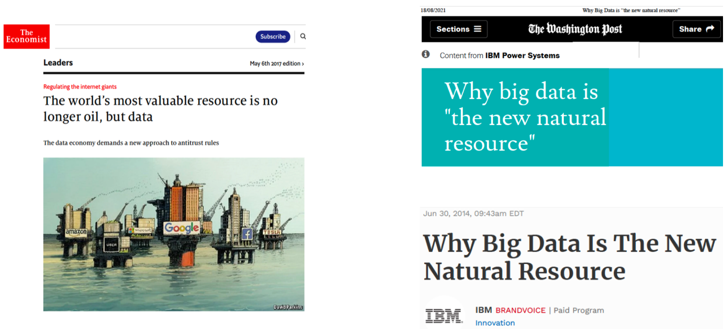


Figure 3.8: Data is becoming like a natural resource

As computing power and engineering talent attain a certain threshold, the amount of data becomes a critical factor in determining the accuracy of a deep-learning algorithm. More data will make a neural network recognize patterns more accurately, and will generally lead to better performance of the algorithm. In general, given more data, a deep-learning algorithm designed by an average AI engineer can usually outperform that designed by a world expert of deep learning (Lee, 2018). The importance of data in the era of AI is best illustrated by the following analogy: *If we imagine AI as the electricity that revolutionized the industry, then data is the oil that generates the electricity.*

References

Ferreira, K.J., B.H.A. Lee, D. Simchi-Levi. 2016. Analytics for an online retailer: Demand forecasting and price optimization. *Manuf. Serv. Oper. Manag.* **18**(1): 69–88.

Lee, K.-F. 2018. *AI Superpowers: China, Silicon Valley, and The New World Order*. Houghton Mifflin Harcourt, New York.

McKitterick, W. 2015. Online Fashion Sample Sales in the U.S.. *IBISWorld Industry Report OD5438*, p. 12.

Chapter 4

Supply Chain Management for Online Retailing

4.1 Introduction

Supply chain management is a core competency of almost all online retailers. Online retailers need to control not only their supply of inventory, but also the allocation of the inventory to different warehouses, the demand fulfillment for different zones, and the last-mile delivery to the customers in each zone.

The difference between fulfillment for offline and online demands

Figure 4.1 shows the difference between fulfilling offline (brick-and-mortar) and online demands.

Fulfillment for offline (brick-and-mortar) demands: Each warehouse ships products to brick-and-mortar retail stores (for example, Walmart). The warehouse receives a smaller number of orders per day, but a large quantity for each order. In general, there is no fulfillment flexibility: The retailer does not retrieve products from other warehouses if one warehouse is out of stock.

Fulfillment for online demands: Each warehouse ships products directly to end consumers. The warehouse receives a large number of orders per day, but a small quan-

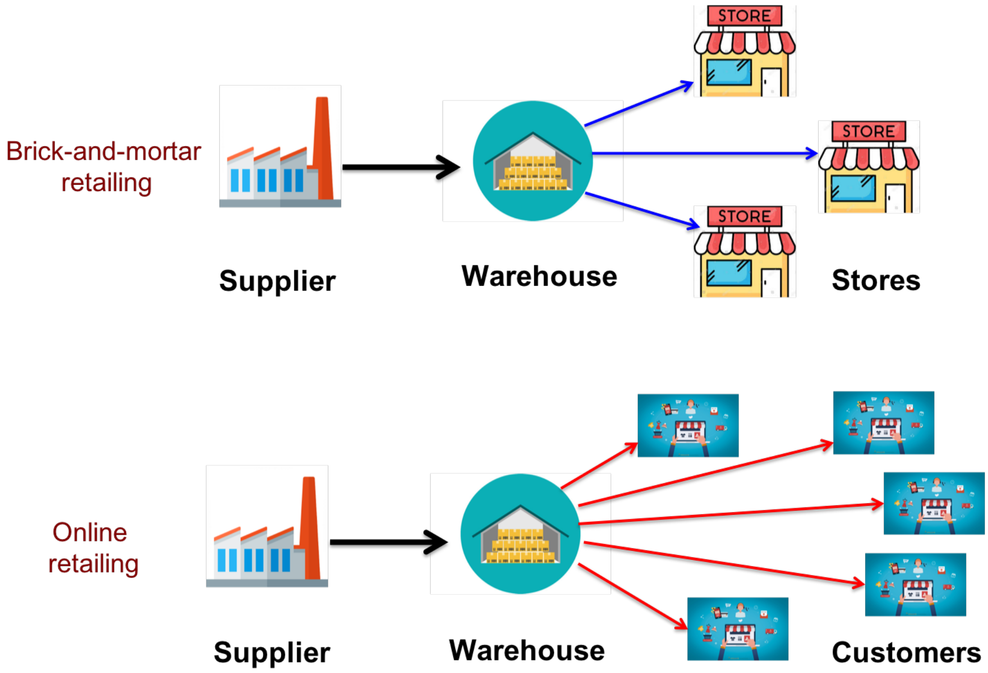


Figure 4.1: Brick-and-mortar retailing versus online retailing

tity for each order. In general, there is fulfillment flexibility: The retailer retrieves products from other warehouses if one warehouse is out of stock.

4.2 Aggregate supply chain planning for online retailing

Figure 4.2 shows the supply chain of a typical online retailer. The online retailer orders products from different suppliers. These products are then stored in different warehouses located in different cities to serve the demands of different zones. Depending on the scale of the network, a zone can be a district, a city, a state, or even a country. After a customer from a zone orders a product online, the retailer retrieves the product from one of the warehouses and sends it to a local sortation center near the zone. At the sortation center, this shipment is consolidated with shipments for other customers in the same zone before they are delivered to the customers.

An online retailer makes several key decisions for aggregate supply chain planning:

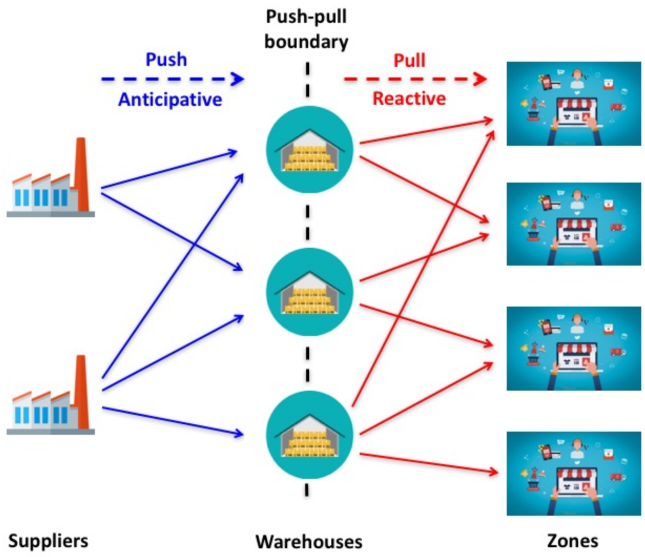


Figure 4.2: The supply chain of an online retailer

(i) When and how much to order from each supplier for each product? This decision deals with the trade-off between the (fixed) cost to order the product from the supplier and the cost of holding the inventory.

(ii) How much to store in each warehouse for each product? The goal of this decision is to allocate the inventory to different warehouses such that the inventory of each product is close to its demand.

(iii) Which warehouse to retrieve the products from? After the demand for a product of a zone (represented by a sortation center in Figure 4.2) is realized, the online retailer chooses a warehouse to fulfill the demand such that the shipping (transportation) cost is minimized.

We formulate the problem of aggregate supply chain planning for an online retailer in the following sections.

4.2.1 Problem description

We consider a common challenge faced by an online retailer selling multiple products to different demand zones over a multi-period horizon. The retailer replenishes the products from different suppliers and stores the products at multiple warehouses or fulfillment centers (FCs) to satisfy demand. In each period, the retailer makes three types of decisions: (i) At the start of the period, the retailer determines how much to replenish for each product from each supplier given a lead time and a limited production capacity. (ii) The retailer then decides how to allocate the inventory to the different FCs, given that each FC has a limited storage capacity and different allocation and fulfillment costs. (iii) At the end of the period, the demands are realized and the retailer decides on which FCs to fulfill the demands of each zone. In case a product is out of stock, the retailer requests the product to be *drop-shipped* from suppliers to satisfy the demands (for example, CleoCat Fashion in Singapore offers drop-shipping services for fashion products). The retailer's objective is to minimize the expected total operating cost over the multi-period horizon.

In contrast to brick-and-mortar retailing, a distinct characteristic of online retailing is that the retailer has the flexibility to satisfy the demands of a zone from any FC that holds the inventory. This fulfillment flexibility improves service levels, but may also increase the retailer's outbound shipping cost, which is a main operating cost of online retailing (Dinlersoz and Li, 2006). The fulfillment flexibility further complicates the inventory allocation to the FCs and the product replenishments from the suppliers. To address these issues in an effective manner, the retailer needs to optimize the replenishment, allocation, and fulfillment decisions *jointly*.

The problem is especially challenging because replenishment and allocation of inventory are typically done before the demand is known in each period. Thus, the replenishment and allocation decisions are made in an *anticipative* manner. In contrast, the fulfillment decisions are made in a *reactive* manner as order fulfillment for online retailing is usually performed after the actual demand is realized in each period. In other words, an online retailer typically adopts a "push" strategy for inventory replenishment-allocation and a "pull" strategy for order fulfillment in each period. We propose a multi-period optimization model that delicately integrates the anticipative replenishment-allocation decisions with the reactive fulfillment decisions to minimize the retailer's expected total cost. These two kinds of decisions (anticipative versus reactive) can be determined seamlessly by our model.

4.2.2 Deterministic optimization model

Consider an online retailer selling products $n = 1, \ldots, N$ to customers in demand zones $k = 1, \ldots, K$. The retailer replenishes her inventory from suppliers $i = 1, \ldots, I$ and allocates the inventory to FCs $j = 1, \ldots, J$, where she retrieves the inventory to fulfill the demand of each zone. If the retailer is out of stock for a certain product, the product is drop-shipped directly from the suppliers to the customers. For notational convenience, we denote the drop-shipping channel as FC $J+1$, which incurs significantly higher production and transportation costs.

We divide the planning horizon into periods $t = 1, \ldots, T$. In each period t, the retailer makes the following three decisions in the specified sequence: (1) At the start of period t, the retailer determines the replenishment quantity for each product from each supplier (called the *replenishment decisions*). (2) The retailer then chooses the FCs to store the product (called the *allocation decisions*). (3) At the end of period t, the demand of each zone for each product is realized, the retailer selects the FCs to retrieve the product to fulfill the demand (called the *fulfillment decisions*). For convenience, define $\mathcal{N} = \{1, \ldots, N\}$, $\mathcal{I} = \{1, \ldots, I\}$, $\mathcal{J} = \{1, \ldots, J\}$, $\mathcal{J}^+ = \{1, \ldots, J+1\}$, $\mathcal{K} = \{1, \ldots, K\}$, $\mathcal{T} = \{1, \ldots, T\}$, and $\mathcal{T}^+ = \{1, \ldots, T+1\}$.

For the sake of simplicity, we consider a deterministic model in which all demand information throughout the entire planning horizon is available at the start of period $t = 1$. Let y_j^{nt} denote the on-hand inventory level of product n in FC j at the start of period t, for $n \in \mathcal{N}$, $j \in \mathcal{J}$, $t \in \mathcal{T}$. Based on these inventory levels, the retailer replenishes a quantity

x_i^{nt} of product n from supplier i at the start of period t. This incurs a fixed *setup cost* S_i^{nt} and a variable *production cost* $p_i^{nt} x_i^{nt}$, where p_i^{nt} is the corresponding unit production cost. Each supplier i has a production capacity $\bar{x}_i^t$ in period t such that $\sum_{n \in \mathcal{N}} x_i^{nt} \leq \bar{x}_i^t$, for $i \in \mathcal{I}, t \in \mathcal{T}$. We assume a constant lead time l_i^n such that a replenishment order for product n from supplier i placed at the start of period $t - l_i^n$ will be received by the retailer at the start of period t. We assume the replenishment quantities $\left\{x_i^{n,1-l_i^n}, \ldots, x_i^{n0}\right\}$ and the initial inventory levels y_j^{n1}, for $n \in \mathcal{N}$, $i \in \mathcal{I}$, $j \in \mathcal{J}$, are given at the start of period $t = 1$.

Define v_{ij}^{nt} as a decision variable representing the quantity of product n from supplier i allocated to FC j in period t, for $n \in \mathcal{N}$, $i \in \mathcal{I}$, $j \in \mathcal{J}$, $t \in \mathcal{T}$. This incurs an *allocation cost* $a_{ij}^{nt} v_{ij}^{nt}$, where a_{ij}^{nt} is the corresponding unit allocation cost. Since all the received quantity $x_i^{n,t-l_i^n}$ at the start of period t must be allocated to the FCs, we have $\sum_{j \in \mathcal{J}} v_{ij}^{nt} = x_i^{n,t-l_i^n}$, for $n \in \mathcal{N}, i \in \mathcal{I}, t \in \mathcal{T}$. The total inventory of each FC j cannot exceed its storage capacity $\bar{y}_j$ such that $\sum_{n \in \mathcal{N}} \left(y_j^{nt} + \sum_{i \in \mathcal{I}} v_{ij}^{nt}\right) \leq \bar{y}_j$, for $j \in \mathcal{J}$, $t \in \mathcal{T}$. Let d_k^{nt} denote the realized demand of zone k for product n in period t, for $n \in \mathcal{N}$, $k \in \mathcal{K}$, $t \in \mathcal{T}$. Define w_{jk}^{nt} as a decision variable representing the quantity of product n retrieved from FC j to fulfill the demand of zone k in period t, for $n \in \mathcal{N}$, $j \in \mathcal{J}^+$, $k \in \mathcal{K}$, $t \in \mathcal{T}$. This incurs a *fulfillment cost* $f_{jk}^{nt} w_{jk}^{nt}$, where f_{jk}^{nt} is the corresponding unit fulfillment cost. Note that $w_{J+1,k}^{nt}$ is the drop-shipping quantity of product n to fulfill the demand of zone k in period t and $f_{J+1,k}^{nt}$ is the corresponding unit drop-shipping cost. We do not allow backlog or lost-sales of demands such that $\sum_{j \in \mathcal{J}^+} w_{jk}^{nt} = d_k^{nt}$, for $n \in \mathcal{N}, k \in \mathcal{K}, t \in \mathcal{T}$, and $y_j^{nt} \geq 0$, for $n \in \mathcal{N}$, $j \in \mathcal{J}$, $t \in \mathcal{T}^+$.

After the demands are fulfilled, the inventory level of product n in FC j at the start of period $t+1$ is $y_j^{n,t+1} = y_j^{nt} + \sum_{i \in \mathcal{I}} v_{ij}^{nt} - \sum_{k \in \mathcal{K}} w_{jk}^{nt}$. Since the leftover inventory at the end of period t is carried over to period $t+1$, a holding cost $h_j^{nt} y_j^{n,t+1}$ is incurred, where h_j^{nt} is the corresponding unit holding cost. Figure 4.3 illustrates the integration of replenishment-allocation with fulfillment for the online retailer. The objective is to minimize the online retailer's total cost over the planning horizon. We formulate the *joint replenishment-allocation-fulfillment* (JRAF) problem as the following optimization model:

$$
\begin{aligned}
(\mathrm{P_D})\quad \min\ & \sum_{t\in\mathcal{T}}\sum_{n\in\mathcal{N}}\left[\sum_{i\in\mathcal{I}}\left(S_i^{nt}\delta_i^{nt}+p_i^{nt}x_i^{nt}\right)+\sum_{j\in\mathcal{J}}h_j^{nt}y_j^{n,t+1}+\sum_{i\in\mathcal{I}}\sum_{j\in\mathcal{J}}a_{ij}^{nt}v_{ij}^{nt}+\sum_{j\in\mathcal{J}^+}\sum_{k\in\mathcal{K}}f_{jk}^{nt}w_{jk}^{nt}\right] \\
\text{s.t.}\ & \sum_{n\in\mathcal{N}} x_i^{nt}\le \bar{x}_i^t, && i\in\mathcal{I},t\in\mathcal{T}; && (4.1.1)\\
& \sum_{j\in\mathcal{J}} v_{ij}^{nt}=x_i^{n,t-l_i^n}, && n\in\mathcal{N},i\in\mathcal{I},t\in\mathcal{T}; && (4.1.2)\\
& \sum_{n\in\mathcal{N}}\left(y_j^{nt}+\sum_{i\in\mathcal{I}}v_{ij}^{nt}\right)\le \bar{y}_j, && j\in\mathcal{J},t\in\mathcal{T}; && (4.1.3)\\
& \sum_{j\in\mathcal{J}^+} w_{jk}^{nt}=d_k^{nt}, && n\in\mathcal{N},k\in\mathcal{K},t\in\mathcal{T}; && (4.1.4)\\
& y_j^{n,t+1}=y_j^{nt}+\sum_{i\in\mathcal{I}}v_{ij}^{nt}-\sum_{k\in\mathcal{K}}w_{jk}^{nt}, && n\in\mathcal{N},j\in\mathcal{J},t\in\mathcal{T}; && (4.1.5)\\
& x_i^{nt}\ge 0, && n\in\mathcal{N},i\in\mathcal{I},t\in\mathcal{T}; && (4.1.6)\\
& v_{ij}^{nt}\ge 0, && n\in\mathcal{N},i\in\mathcal{I},j\in\mathcal{J},t\in\mathcal{T}; && (4.1.7)\\
& w_{jk}^{nt}\ge 0, && n\in\mathcal{N},j\in\mathcal{J}^+,k\in\mathcal{K},t\in\mathcal{T}; && (4.1.8)\\
& y_j^{nt}\ge 0, && n\in\mathcal{N},j\in\mathcal{J},t\in\mathcal{T}^+; && (4.1.9)\\
& x_i^{nt}\le \bar{x}_i^t\delta_i^{nt},\ \delta_i^{nt}\in\{0,1\}, && n\in\mathcal{N},i\in\mathcal{I},t\in\mathcal{T}. && (4.1.10)
\end{aligned}
$$

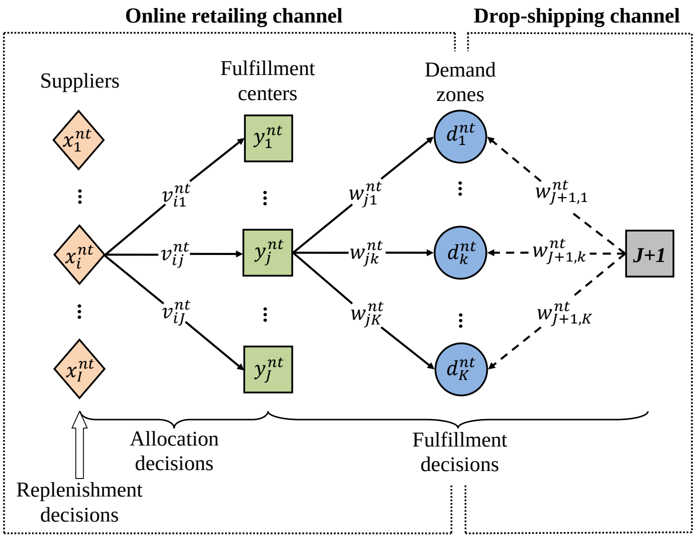


Figure 4.3: Integrating replenishment-allocation with fulfillment for an online retailer

The first term of the objective function is the total replenishment cost, the second term is the total holding cost at the FCs, the third term is the total allocation cost to the FCs, and the last term is the total fulfillment cost to the zones. We relax the integrality constraints on the decision variables x_i^{nt}, y_j^{nt}, v_{ij}^{nt}, and w_{jk}^{nt} so that we have a mixed-integer program. Problem $\mathrm{P_D}$ is always feasible because the retailer can always request drop-shipping if necessary (for example, one feasible solution is $x_i^{nt} = v_{ij}^{nt} = w_{jk}^{nt} = 0$, for $n \in \mathcal{N}$, $i \in \mathcal{I}$, $j \in \mathcal{J}$, $k \in \mathcal{K}$, $t \in \mathcal{T}$, and $w_{J+1,k}^{nt} = d_k^{nt}$, for $n \in \mathcal{N}$, $k \in \mathcal{K}$, $t \in \mathcal{T}$). Problem $\mathrm{P_D}$ can be solved using off-the-shelf, commercial or open-source, optimization software.

For a version of the above model with stochastic demands and the methodology to solve it, please refer to Lim et al. (2020).

4.3 Last-mile delivery

After the shipments arrive at a sortation center, the online retailer performs last-mile delivery of the shipments to the customers. For the last-mile delivery, the online retailer needs to decide the sequence of visits to every customer so that her transportation cost (including fuel cost, driver's pay, toll charge, etc.) is minimized, subject to constraints on delivery time windows (for example, customer X may request that his shipment to be delivered between 2–4PM).

Within the supply chain of an online retailer, the main "bottlenecks" occur at the order-picking operation in the warehouses and the last-mile delivery to the customers. We will address these two challenges in the following chapters.

References

Bartholdi JJ III, Hackman ST (2018). *Warehouse and Distribution Science*. `http://www.warehouse-science.com/`.

Dinlersoz EM, Li H (2006). The shipping strategies of internet retailers: Evidence from internet book retailing. *Quant. Marketing Econom.* **4**(4): 407–438.

Lim YF, Jiu S, Ang M (2020). Integrating anticipative replenishment-allocation with reactive fulfillment for online retailing using robust optimization. *Manufacturing and Service Operations Management*, forthcoming.

Chapter 5

Logistics Equipment and Technologies for Online Retailing

5.1 Introduction

A unique product is called a *stock-keeping unit* (sku) in retailing. For example, two shirts with the identical brand, model, and size, but with different colors are labelled as two different skus. When an online customer places an order for a sku, the customer can order a *pallet* of the sku (for example, a pallet of soft toys), a *case* of the sku (for example, a case of Coca-Cola), or a *piece* of the sku (for example, a bottle of shampoo). Figure 5.1 shows these three types of demands, which lead to three different ways of order-picking in a warehouse: pallet picking, case picking, and piece picking.

Figure 5.1: Three types of demands in online retailing

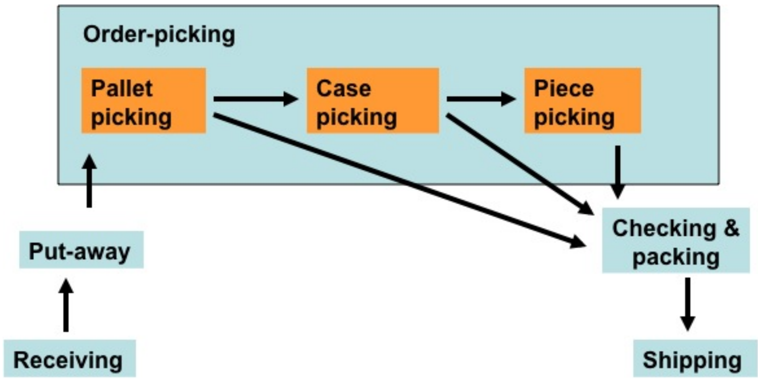


Figure 5.2: The basic operations of a warehouse

Figure 5.2 shows the basic operations of a warehouse for online retailing. Among the basic operations, order-picking is the most costly operation, making up about 55% of the total operating expense (Bartholdi and Heckman, 2018). Within order-picking, traveling is the most time consuming. Each type of order-picking (that is, pallet picking, case picking, or piece picking) requires different storage and handling equipment in the warehouse.

5.2 Storage equipment

5.2.1 Single-deep pallet racks

Single-deep pallet racks (also called selective racks) are for pallet picking (see Figure 5.3(a)). Pallets are easily accessible in such a rack.

5.2.2 Pallet flow racks

Pallet flow racks are for case picking (see Figure 5.3(b)). Their shelves are tilted with rollers so that pallets at the back can roll to the front easily. Picking and restocking of skus are performed from different aisles so that the restocking process does not interrupt order-picking. Thus, pallet flow racks are suitable for high-throughput skus.

(a) (b)

Figure 5.3: (a) Single-deep pallet rack (b) Pallet flow rack

5.2.3 Bin-shelving

Bin shelves are for piece picking (see Figure 5.4). Their shelves are shallow and so they cannot hold a lot of inventory in a section. This requires frequent restocking if a high-throughput sku is stored in a section of a bin shelf. Furthermore, both picking and restocking of skus must be done from the pick face along the same aisle. This causes order-picking to be frequently interrupted by the restocking process. Therefore, bin shelves are suitable only for low-throughput (slow-moving) skus.

Figure 5.4: Bin-shelving

5.2.4 Gravity flow racks

Gravity flow racks are for piece picking. They have deep shelves so that a section can hold a lot of inventory (see Figure 5.5(a)). Typically, only one case of a sku is presented on the pick face. This leads to high density of skus on the pick face. The shelves are tilted with rollers so that cases at the back can roll to the front easily. Restocking of skus is done from the back of a rack, and so does not interrupt order-picking. Therefore, gravity flow racks are suitable for high-throughput (fast-moving) skus. Some gravity flow racks are supported by a pick-to-light system to increase pick accuracy and productivity (see Figure 5.5(b)).

(a) (b)

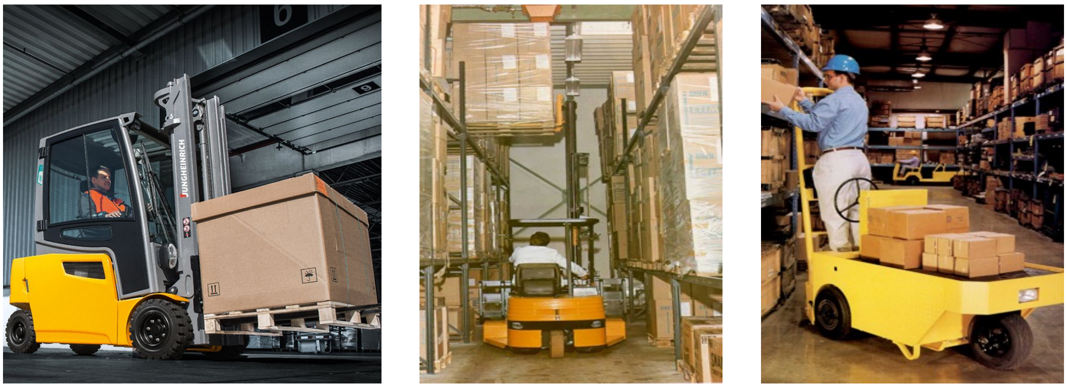
Figure 5.5: (a) Gravity flow rack (b) Pick-to-light system

5.3 Handling equipment and technologies

The following handling equipment and technologies are commonly used in e-commerce warehouses.

5.3.1 Counterbalance lift trucks

Counterbalance lift trucks or forklifts (see Figure 5.6(a)) are the most commonly used vehicles to carry pallets from the receiving area to the storage area, and then from the



(a) (b) (c)

Figure 5.6: (a) Counterbalance lift truck (b) Turret truck (c) Order-picker truck

storage area to the shipping area in a warehouse. Typically, one forklift carries one pallet at a time.

5.3.2 Turret trucks

Each turret truck (see Figure 5.6(b)) has a turret that can turn 90 degrees (left or right) to put-away or retrieve pallets. The truck itself does not need to turn within an aisle. Thus, turret trucks are suitable for very narrow aisles with a width of only 5-7 feet (1.5-2.1 meters). Very narrow aisles are adopted when space is very limited.

5.3.3 Order-picker trucks

Order-picker trucks are usually used to perform case picking (see Figure 5.6(c)). Since the travel distance is typically long between picks for case picking, order-pickers can drive these trucks to speed up the picking process. Furthermore, this type of trucks also allows the order-pickers to carry multiple cases in one trip.

5.3.4 Automated storage and retrieval systems

An automated storage and retrieval system (AS/RS) can put-away or retrieve unit loads in high racks (see Figure 5.7(a)). Depending on the system, each unit load can be a pallet or a standard-size bin. If each unit load is a pallet, then the AS/RS is typically used for pallet picking. If each unit load is a standard-size bin, then the AS/RS is typically used for piece picking. To perform piece picking, each bin is retrieved by the AS/RS from a rack and moved to a picking station. Pieces are picked from the bin at the picking station to fulfill demand, and the bin with the remaining inventory is returned by the AS/RS to the rack.

(a) (b)

Figure 5.7: (a) AS/RS (b) Conveyor

5.3.5 Conveyors

Conveyors are used to carry pallets or cases (see Figure 5.7(b)). They partition a warehouse into zones because it is difficult for workers and products to cross the conveyors. This may create issues of workload balance. Some conveyors are integrated with a sortation system that can sort cases to their destinations. This is useful for case picking but is expensive.

5.3.6 Robots

Various forms of robots are becoming increasingly common in e-commerce warehouses. These include Kiva robots (see Figure 5.8(a)) that move racks to a picking station for piece picking. Autostore robots (see Figure 5.8(b)) move on the top surface of a three-dimensional structure, carrying bins to a picking station for piece picking. Boston Dynamics robots (see Figure 5.8(c)) can move cases from one location to another location in a warehouse, and stack the cases on a pallet.

(a) (b) (c)

Figure 5.8: (a) Kiva robots (b) Autostore robots (c) Boston Dynamics robots

References

Bartholdi JJ III, Hackman ST (2018). *Warehouse and Distribution Science*. http://www.warehouse-science.com/.

Chapter 6

Order Fulfillment for Online Retailing

6.1 Introduction

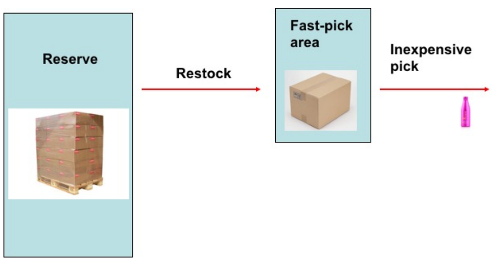
After a customer places an order, an online retailer first determines which warehouse (fulfillment center) to satisfy the demand using her decision support system. If the order requests products from different warehouses, the order might be split into multiple (usually two) parts. Each part is fulfilled by a single warehouse.

Once an order is received by a warehouse, it first goes through the *order-picking* process within the warehouse. After all the requested items have been picked and packed, the order departs from the warehouse for a sortation center near the customer. At the sortation center, the order is consolidated with other orders before it departs from the sortation center for the *last-mile delivery* to the customer.

Order-picking and last-mile delivery are the most labor-intensive and costly activities for an online retailer to satisfy demands. Specifically, order-picking costs about 55% of the total operating expense of a warehouse (Bartholdi and Heckman, 2018), whereas last-mile delivery comprises up to 28% of the total delivery cost in a supply chain (Wang et al., 2016). We discuss order-picking in this chapter and last-mile delivery in Chapter 7.

6.2 How to prepare inventory

How to store the products in a warehouse to minimize the response time of fulfillment? A common strategy is to store the products in a *fast-pick area*. A fast-pick area is a premier region in a warehouse (typically near the shipping department) where the products can be picked quickly. The inventory of the fast-pick area can be restocked from the *reserve* area of the warehouse. Thus, a fast-pick area is like "a warehouse within a warehouse". Figure 6.1(a) illustrates the idea of a fast-pick area. Figure 6.1(b) shows an example of a reserve (the pallet racks at the back) and a fast-pick area (the gravity flow rack at the front).



(a)

(b)

Figure 6.1: (a) The idea of a fast-pick area (b) An example of a reserve (the pallet racks at the back) and a fast-pick area (the gravity flow rack at the front)

Figure 6.2 provides two examples of fast-pick areas. Gravity flow racks in Figure 6.2(a) are typically used for faster-moving products. Figure 6.2(b) shows bin-shelving that is commonly used for slower-moving products.

6.3 How to pick faster-moving products

Figure 6.2(a) shows an order-picking line in a fast-pick area for faster-moving products. Each order is released from one end of the line (typically by a printer) and is progressively


(a) (b)

Figure 6.2: (a) A fast-pick area using gravity flow racks (b) A fast-pick area using bin-shelving

assembled by workers (called order-pickers) along the line until all the products for the order are picked. The completed order is then placed on an active conveyor that brings it to a shipping department of the warehouse.

One way to coordinate workers along an order-picking line is by forming a *bucket brigade* (Bartholdi and Eisenstein, 1996a,b). In a bucket brigade, each worker follows a simple rule:

> Continue to assemble a job along an order-picking line until either your colleague downstream takes over your work or you finish your work at the end of the line (if you are the last worker); then you walk back to get more work, either from your colleague upstream or from a buffer at the start of the line (if you are the first worker).

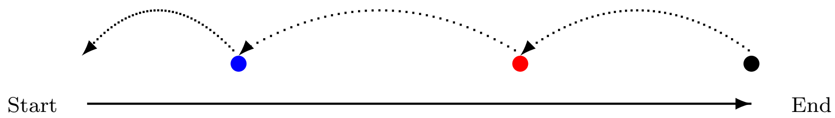


Figure 6.3: Workers walk back to get more work from their colleagues in a bucket brigade

Note that a job can represent an order or a batch of orders. Figure 6.3 shows how each worker walks back to get more work from his colleague in a bucket brigade.

Bucket brigades are notably used not only for order-picking, but also in other industrial environments that require intensive labor. Table 6.1 shows various applications of bucket brigades in different industries.

Table 6.1: Applications of bucket brigades

Order-picking	**Sewing**	**Assembly**
CVS	Coach Leatherware	Mitsubishi
Walgreen's	Champion Products	Tug Manufacturing
Reader's Digest		Subway
The Gap		
McGraw-Hill		
Time Warner		
Ford		
Anderson Merchandisers		

Source: `www.bucketbrigades.com`

Bartholdi and Eisenstein (1996a) consider a model with deterministic work content. They assume that each worker has a deterministic, finite work velocity and an infinite walk-back velocity. They show that if the workers are sequenced from slowest to fastest according to their work velocities in the direction of the production flow, then a bucket brigade will *self-balance* such that the hand-offs between any two neighboring workers will converge to a fixed location. Eventually, every worker will repeatedly work on a fixed segment of the order-picking line. Furthermore, if the work content is continuously and uniformly distributed along the line, then the long-run average throughput (the number of jobs completed per unit time) will achieve the maximum possible value for the system.

Specifically, Bartholdi and Eisenstein (1996a) make the following assumptions in their model of a bucket brigade with n workers:

1. The work content of a job is a constant that is normalized to 1. The work content is distributed continuously and uniformly along the order-picking line such as shown in Figure 6.4.

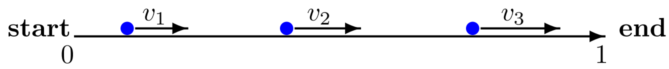


Figure 6.4: A model of a bucket brigade

2. Each worker has a constant work (forward) velocity v_i, for $i = 1, \ldots, n$.

3. Each worker walks back instantaneously.

4. No passing is allowed among the workers so that they maintain a fixed sequence along the order-picking line.

A bucket brigade is *balanced* if it satisfies the following conditions:

Repetition condition: Each worker repeats the same portion of work content on each successive job.

Efficiency condition: Workers are utilized to their fullest without creating additional work-in-process.

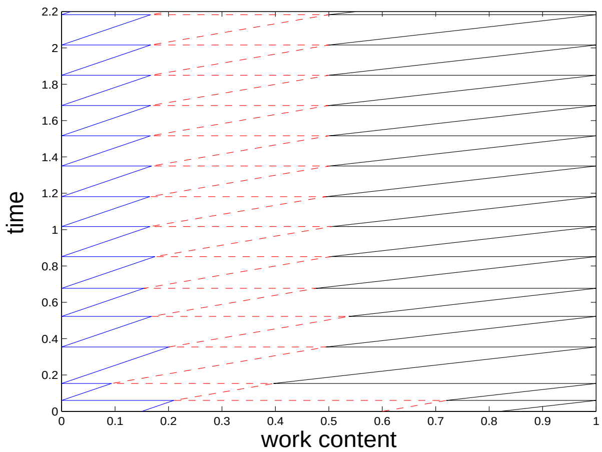


Figure 6.5: Self-balance of a bucket brigade

As illustrated in Figure 6.5, if the workers are sequenced from *slowest to fastest* according to their work velocities in the direction of the production flow (from the start to the end of the line), then the bucket brigade will self-balance. When a bucket brigade with n workers is balanced, it satisfies the above two conditions as follows.

Repetition condition: Each worker i repeats the interval of work content

$$\left[\frac{\sum_{j=1}^{i-1} v_j}{\sum_{j=1}^{n} v_j}, \frac{\sum_{j=1}^{i} v_j}{\sum_{j=1}^{n} v_j}\right].$$

Efficiency condition: Workers are utilized to their fullest. The system's throughput is

$$TH = \sum_{j=1}^{n} v_j.$$

A bucket brigade has the following advantages:

1. It is a pure *pull* system. Thus, work-in-process is under control.
2. Workers carry the jobs from section to section. Thus, no special material handling equipment is required.
3. It is self-balancing if the workers are sequenced from slowest to fastest in the direction of the production flow. Thus, no accurate measurement of task times is required.
4. It is consistent with the trend of *team work*.
5. The protocol is *simple and identical* for all the workers and no management intervention is required.

6.4 How to pick slower-moving products

Figure 6.2(b) shows a fast-pick area for slower-moving products in a warehouse. The slower-moving products are typically stored on bin shelves. These bin shelves are arranged in multiple lines separated by aisles. Figure 6.6 shows the top view of a fast-pick area comprising bin shelves. Products requested by an order are located at different shelves in the fast-pick area. To pick the products for an order (or a batch of orders), a worker needs to visit multiple locations in the fast-pick area. To minimize the total travel time (or distance), one needs to optimize the pick route of a trip. This problem is known as the *traveling salesman problem*, which is computationally very challenging. Figure 6.6 shows a pick route (in red) of a worker to pick all the products ordered (in blue).

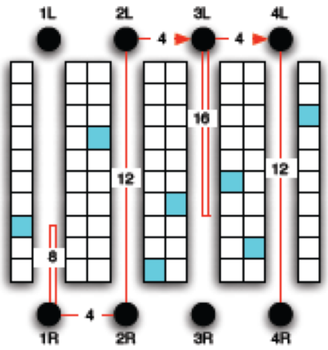


Figure 6.6: A fast-pick area comprising multiple lines of bin shelves [Source: Bartholdi and Heckman (2018)]

In practice, most online retailers use simple heuristics to determine the pick route of each worker. Figure 6.7 illustrates a few simple heuristics for routing each worker (de Koster et al., 2007). The simplest one is the *S-shape* heuristic. Under this heuristic, a worker will traverse entirely any aisle containing at least one pick, skipping aisles with no picks. After picking the last item, the worker returns to the depot from the last visited aisle. The *return* heuristic is another simple routing method, in which a worker enters and leaves each aisle from the same end. The worker only enters aisles with picks.

The *mid-point* heuristic divides the fast-pick area into two parts (see Figure 6.7). A worker accesses from the front cross aisle to pick items in the front half, and accesses from the back cross aisle to pick items in the back half. The worker traverses to the back cross aisle by either the first or the last aisle visited. When the number of picks per aisle is small, this method can outperform the S-shape heuristic.

Within an aisle, define a gap as the separation between the first pick and the front cross aisle, between any two adjacent picks, or between the last pick and the back cross aisle. Instead of reaching the mid-point, each worker under the *largest gap* heuristic continues on an aisle until he reaches the largest gap within the aisle, which is the portion of the aisle that the worker does not traverse. If the largest gap is between two adjacent picks, the worker performs a return route from both ends of the aisle. Otherwise, the worker performs a return route from either the front or the back cross aisle. Note that the back cross aisle can only be accessed through either the first or the last visited aisle. Although it is more efficient than the mid-point heuristic, the largest gap heuristic is more difficult to implement in practice (de Koster et al., 2007).

Under the *combined* heuristic, a worker either entirely traverses an aisle with picks or performs a return route. For each visited aisle, the choice is determined by an optimization method called dynamic programming. Based on numerical experiments by Petersen (1997) that compare the above five routing heuristics with an optimal method for a warehouse with random storage, the best heuristic solution is on average 5% less efficient than the optimal solution.

6.5 Problems

1. Do you think the following variant of bucket brigades can improve the productivity further? Why?

    - Allow a blocked worker to drop his incomplete job in a buffer before the busy section and walk back

2. Do you think the following variant of bucket brigades can improve the productivity further? Why?

    - Allow the workers to circle through the order-picking line

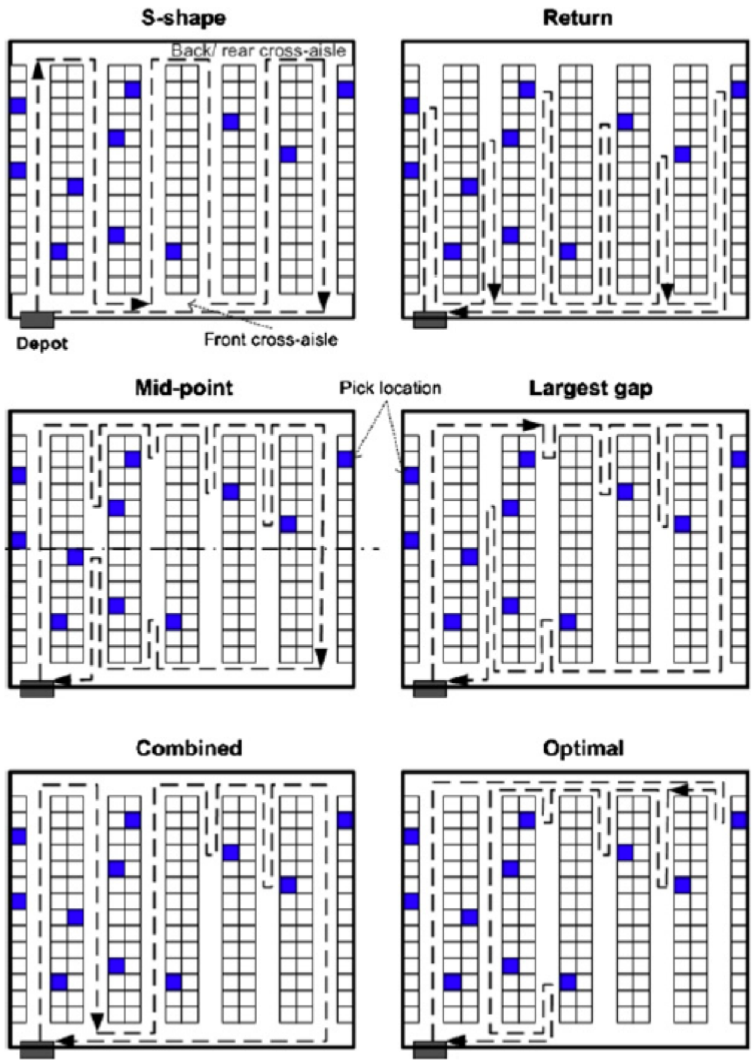


Figure 6.7: Routing methods for order-picking [Source: de Koster et al. (2007)]

References

Bartholdi JJ III, Eisenstein DD (1996a) A production line that balances itself. *Operations Research* **44**(1): 21–34.

Bartholdi JJ III, Eisenstein DD (1996b) The bucket brigade web page. `http://www.BucketBrigades.com`.

Bartholdi JJ III, Hackman ST (2018) *Warehouse and Distribution Science*. `http://www.warehouse-science.com/`.

de Koster R, Le-Duc T, Roodbergen KJ (2007) Design and control of warehouse order picking: A literature review. *Eur. J. Oper. Res.* **182**(2): 481–501.

Petersen CG (1997) An evaluation of order picking routing policies. *International Journal of Operations & Production Management* **17**(11): 1098–1111.

Wang Y, Zhang D, Liu Q, Shen F, Lee LH (2016) Towards enhancing the last-mile delivery: An effective crowd-tasking model with scalable solutions. *Transortation Research Part E* **93**: 279–293.

Chapter 7

Last-mile Delivery for Online Retailing

> *"We pay a lot of money to acquire a customer and if they have that bad experience on their first delivery they are not going to use us again and they are going to tell everyone how terrible we are. We couldn't afford this to happen. Delivery was our touch point with the customer. We learned that, especially with groceries, you need to control that last mile."*

— Roger Egan III, co-founder and founding CEO of RedMart

7.1 Introduction

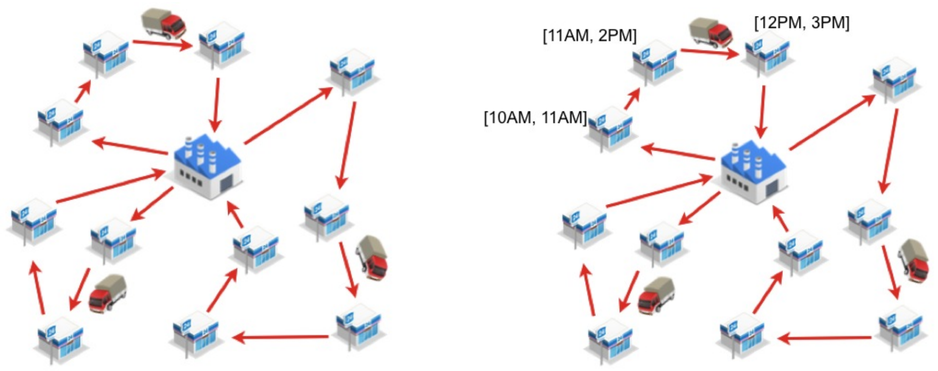
Last-mile delivery is the last leg of a supply chain that transfers products from a sortation center to a receiver. The latter can be a retail store, a restaurant, a consumer's home, or a carrier-designated pickup station, such as a UPS Store or an Amazon locker (Lopez, 2017). Last-mile delivery comprises up to 28% of the total delivery cost in a supply chain (Wang et al., 2016). Furthermore, last-mile delivery is the most expensive and critical operation for companies engaged in e-commerce (Lee and Whang, 2001).

7.2 Vehicle routing problem

An online retailer can deliver the goods to the customers either by herself or by engaging a third-party logistics service provider. To perform the last-mile delivery to the customers, one needs to solve a *vehicle routing problem* (VRP):

> Given a fleet of vehicles and a set of locations, find a set of routes, beginning and ending at a depot, that minimizes the total travel cost of visiting every location once.

Figure 7.1(a) shows a set of three routes delivering the products to the customers. In reality, some online retailers allow their customers to specify a delivery time window. This leads to a more complicated problem called the *vehicle routing problem with time windows* (VRPTW). See Figure 7.1(b) for an example. Both the VRP and VRPTW are computationally challenging.



(a) (b)

Figure 7.1: (a) The vehicle routing problem (b) The vehicle routing problem with time windows

7.3 Challenges of last-mile delivery

In practice, last-mile delivery is costly because of the following additional challenges.

1. Digital maps may not be available for some countries or regions.

2. It is hard to navigate in some complex neighborhood.

3. It takes time to park the vehicle, to find the right elevator, and to locate the final destination. It is hard to estimate the time.

4. The customer may not be around. In that case, shall we leave it at the doorstep or revisit? If we revisit, what is the maximum number of attempts?

5. The delivery time is subject to weather and traffic conditions. Thus, it is challenging to maintain the given delivery schedule.

6. Some online retailers allow rescheduling and adding new orders during the delivery. This gives rise to the need of *dynamic routing*, which is more complex.

7. It is hard to maintain a consistent service level and customer experience if the labor turnover rate is high.

7.4 Solutions to last-mile delivery

To overcome these challenges, companies have developed the following potential solutions to last-mile delivery.

1. **Pick-up stations:** A common approach to last-mile delivery is to set up pick-up stations at some convenient locations for customers to pick up their parcels by themselves. Figure 7.2 shows examples of PopStation and Ninja Van.

2. **Autonomous vehicles:** A promising approach to last-mile delivery is to use autonomous vehicles. Many autonomous vehicles are powered by electricity. Figure 7.3 shows some examples. The adoption rate of autonomous vehicles in a city depends on its infrastructure and traffic regulations.

3. **Drone delivery:** Some companies, such as Amazon, have been using drone technology (see Figure 7.4) to deliver orders to their customers. This technology is more

Figure 7.2: Various forms of pick-up stations

Figure 7.3: Autonomous vehicles

suitable for sparse areas that facilitate drone maneuver and for low-density delivery that typically requires a long-distance travel between two customers.

4. **Buy online pick up in stores:** Some online retailers allow customers to purchase online and later pick up their orders from convenient stores such as 7 Eleven, Cheers, etc. For retailers that also operate brick-and-mortar stores, they allow their customers to purchase online and then pick up their orders from the brick-and-mortar stores. Figure 7.5 shows some examples. This approach integrating the offline and the online channels gives rise to the ideas of *omni-channel retailing*.

Figure 7.4: Drone delivery

Figure 7.5: Buy online pick up in stores

5. **"Uberization" of last-mile delivery:** Online retailers can outsource the last-mile delivery to individuals such as part-timers, retirees, or students, who are willing to perform the delivery tasks for a fee. This is especially common for food delivery such as the examples shown in Figure 7.6.

7.5 Significance of online platforms for services

In recent years, many online platforms have been established for various kinds of services. These online platforms create various kinds of jobs:

- Drivers: Uber, Didi, Lyft
- Delivery persons: Deliveroo, Ele.me
- Handicrafts producers: Etsy, eBay
- App developers: Apple store, Google play

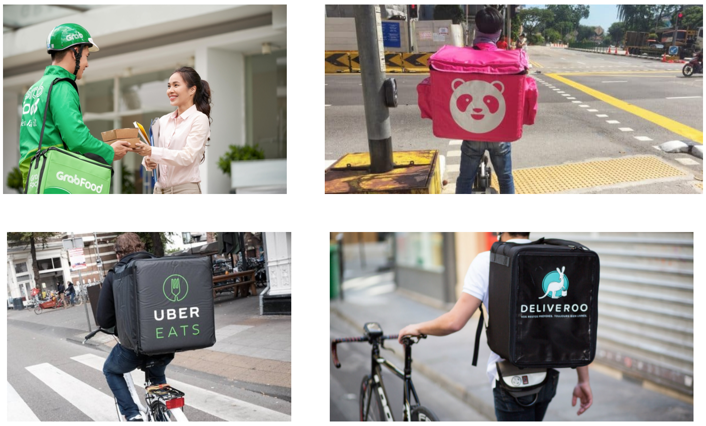


Figure 7.6: Uberization of last-mile delivery

- Job seekers: Innocentive, Indeed

Specifically, meal delivery platforms have a huge market in many countries. For example, in 2018 the meal delivery platform Meituan in China handled 20M orders per day. Figure 7.7 shows the significance of the meal delivery platforms.

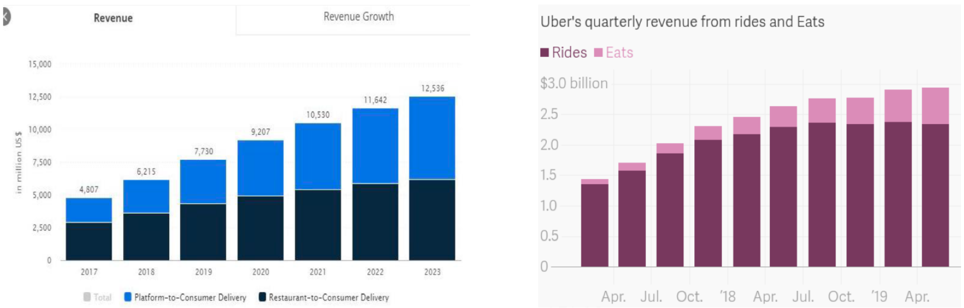


Figure 7.7: Significance of meal delivery platforms

The meal delivery platforms are based on a business model for a *three-sided* market in which (i) customers place orders with a platform, (ii) restaurants post menus, prepare food, and share revenue with the platform, and (iii) drivers pick up and deliver assigned orders. In contrast, the platform determines the "required times" of deliveries, manages the order process flow, and assigns orders to drivers.

Figure 7.8 illustrates the operations of a meal delivery platform, which include the following activities:

1. Customers place orders with the platform.
2. The platform sends the orders to restaurants.
3. The platform assigns the orders to drivers.
4. The drivers pick up the orders from the restaurants.
5. The drivers deliver the orders to the customers.

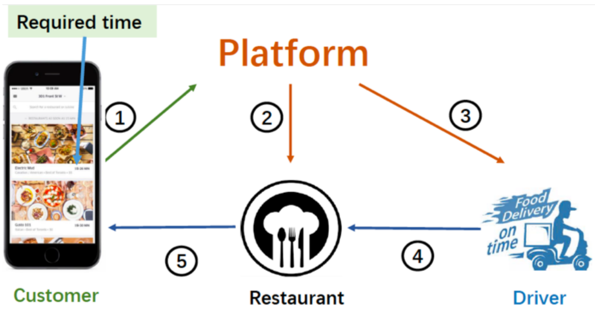


Figure 7.8: The operations of a meal delivery platform [Source: Mao et al. (2019)]

Figure 7.9 illustrates the process flow of handling customer orders on a meal delivery platform.

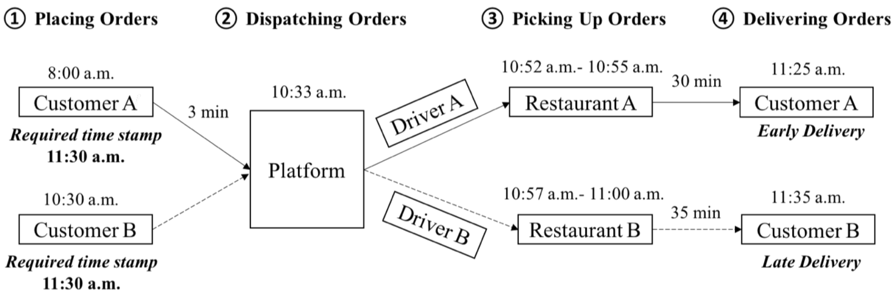


Figure 7.9: The process flow of handling customer orders on a meal delivery platform [Source: Mao et al. (2019)]

7.6 Uberization: US versus China

Although Uber was the first that used cell phones and personal vehicles to revolutionize how people get around cities in the United States, it was arguably Chinese companies that would generalize this business model and apply it to transforming many other industries.

7.6.1 The O2O Revolution in China

Chinese internet companies have creatively applied the ideas of Uberization in various forms to many real-world services. “The O2O Revolution” was coined by analysts to describe the blossom of internet services across Chinese cities. The term “O2O” is a short form of “online-to-offline”, which means *turning online actions into offline services* (Lee, 2018). Examples of O2O services include delivery of a hot meal, pickup and delivery of a parcel, a haircut or manicure at home, and a ride to the bar. People who are sick can use Apps to hire someones to queue in the long lines outside of famous hospitals. Pet owners can use Apps to hail someones to come and clean their pets. All these economic activities create a rich set of data of daily life that is invaluable in building an AI-driven society.

7.6.2 “Go light” versus “go heavy”

It is interesting to see that American internet companies tend to adopt a “light” approach. They will build information platforms but let others to deal with the on-the-ground logistics (Lee, 2018). In contrast, companies in China tend to adopt a “heavy” approach. They not only want to build platforms, but also want to recruit sellers, handle the goods, operate logistics teams, supply and maintain scooters, and control e-payment. Below are a few examples (Lee, 2018).

Yelp versus Dianping: Yelp is an American platform founded around 2004 for posting restaurant reviews. It essentially serves as an information platform that mainly depends on advertisements. Its Chinese counterpart, Dianping (now called Meituan

Dianping after merging with the group-buying platform Meituan) however chooses a vertically integrated business model. In addition to restaurant reviews, Dianping goes very heavily into food delivery. It hires and manages teams of scooter riders to deliver meals from restaurants to customers' doorstep. By 2017, Meituan Dianping was valued at 30 billion USD, more than triple that of Yelp.

Airbnb versus Tujia: Airbnb is an American platform that lists homes and rooms for rent. It operates as a light platform that matches supply with demand for houses, apartments, and rooms. In contrast, its Chinese rival, Tujia offers various services including cleaning after each visit, stocking supplies, and installing smart locks.

Uber versus Didi: After Uber created one of the first O2O models for ride-hailing, a Chinese company called Didi copied the business idea and quickly adapted it to the local environment. Didi went one step further by acquiring gas stations and car workshops to service its fleet. This builds trust of drivers in the Didi brand and makes Didi better understand the drivers. Didi eventually drove Uber out of the Chinese market. By late 2017, Didi was valued at 57.6 billion USD, higher than that of Uber.

References

Lee H, Whang S (2001) Winning the last mile of e-commerce. *MIT Sloan Management Review* **42**(4):54–62.

Lee, K.-F. 2018. *AI Superpowers: China, Silicon Valley, and The New World Order*. Houghton Mifflin Harcourt, New York.

Lopez E (2017) Why is the last mile so inefficient? *Supply Chain Dive*.

Mao W, Ming L, Rong Y, Tang CS, Zheng H (2019) Faster deliveries and smarter order assignments for an on-demand meal delivery platform. `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3469015`.

Wang Y, Zhang D, Liu Q, Shen F, Lee LH (2016) Towards enhancing the last-mile delivery: An effective crowd-tasking model with scalable solutions. *Transortation Research Part E* **93**:279–293.

Chapter 8

Omni-channel Retailing

8.1 Introduction

Omni-channel retailing is an integrated sales approach that blends the advantages of brick-and-mortar stores with the convenience of online shopping. This approach seeks to provide customers with a seamless shopping experience across multiple channels, whether the customers are shopping online from a desktop or mobile device, by telephone, or in a brick-and-mortar store. To discuss the need for omni-channel retailing, we first consider the advantages of shopping in brick-and-mortar stores and shopping online.

8.2 Advantages of shopping in brick-and-mortar stores

From a consumer's perspective, the advantages of shopping in brick-and-mortar stores include:

1. Provide face-to-face interaction with store personnel and personal service.

2. Allow instant access to products and gratification of all senses.

3. Allow customers to try on products.

4. Provide help with initial setup and ongoing repairs.

5. Facilitate convenient returns.

6. Provide social experience of shopping as an event.

Figure 8.1: Shopping in a brick-and-mortar store provides gratification of all senses

8.3 Advantages of shopping online

From a consumer's perspective, the advantages of shopping online include:

1. The selection is broad yet remarkably easy to search.
2. The prices are transparent and can easily be compared.
3. It is convenient to shop online wherever the customers are.
4. Many firms provide free deliveries and returns.
5. Product information is rich (see Figure 8.2).
6. Product reviews and recommendations are extensive (see Figure 8.3).

8.4 Information-fulfillment matrix

Bell et al. (2014) propose a customer-focused framework that can be expressed as an information-fulfillment matrix in Figure 8.4 to help retailers navigate in an omni-channel

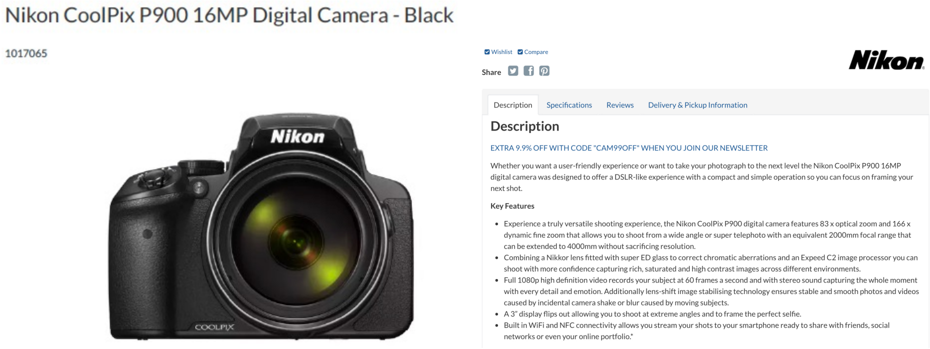


Figure 8.2: Product descriptions are usually more comprehensive online than offline

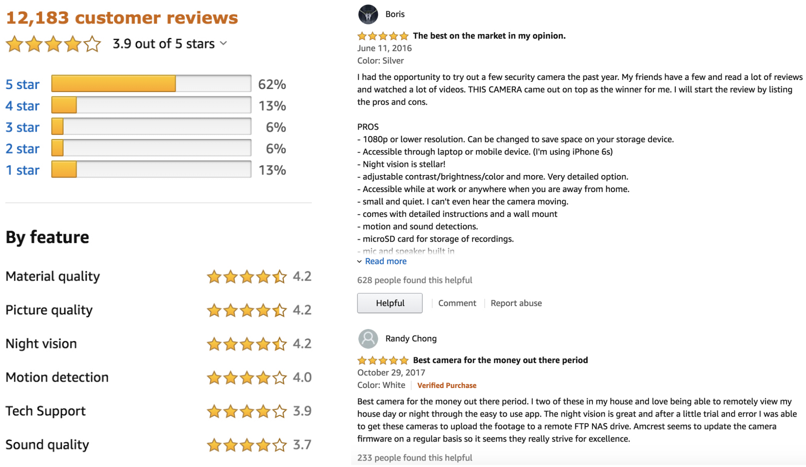


Figure 8.3: Online customer reviews can influence the purchasing behavior of future customers

environment. They ask two fundamental questions: (i) How should a retailer channel the product information to the customers (online or offline)? (ii) How should a retailer fulfill a customer order (pickup or delivery)?

The authors argue that a brick-and-mortar retailer in quadrant 1 of Figure 8.4 with an online channel can consider enhancing its overall performance by adopting a strategy in quadrant 2. This allows the customers to *buy online and pickup in store* or *research online and purchase offline*. Similarly, a pure-play online retailer in quadrant 4 can adopt a strategy in quadrant 3 to offer the customers to first try the products in physical showrooms and purchase them online later. The authors foresee that the strategies in quadrants 2 and 3, which provide hybrid experiences for the customers, are becoming "must-have" features in the omni-channel revolution.

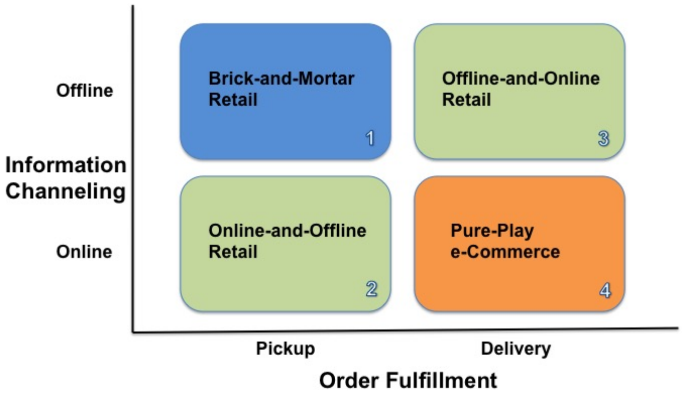


Figure 8.4: Information-fulfillment matrix

Examples of quadrant 2 (Online-and-offline retail) include:

- Buy online, pick up in (return to) store
- Research online, buy in store

Examples of quadrant 3 (Offline-and-online retail) include:

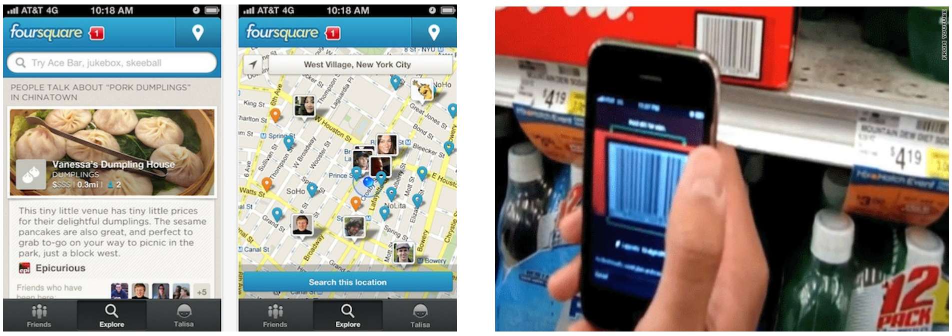
- Buy in store, deliver to home
- Try in store, buy online (also known as "showrooming")

8.5 Ways for brick-and-mortar stores to compete against online retailing

In order to compete against online retailing, brick-and-mortar stores adopt various omni-channel strategies. These include:

- Location-based apps (such as Foursquare) to offer electronic coupons or goodies

- Apps (such as RedLaser) that provide online product reviews, prices, video content on fashion trends, advices, and tips



(a) (b)

Figure 8.5: (a) Foursquare (b) RedLaser

- Apps that allow consumers to search for products and prices available at local stores (for example, Wal-Mart, Target, and Macy's)
- Allow buy online and pick up in store
- Collect offline sales data, promote online group buying
- Utilize mobile network
- Provide interactive and good service experience
  - Leverage social media to interact with consumers
  - Products and services must be consistent across online and offline channels
- Not just sell products, but also sell curated contents
  - Good contents can be better than good advertisements
  - Build up positive energy among consumers
- Provide flexible and convenient e-payment methods

8.6 Integrating retail and logistics

Many companies expand from brick-and-mortar retailing to online retailing. For example, Tesco, a giant grocery chain in UK, creates attractive catalogs on the platforms of subway stations, at bus stands, and in airports (see Figure 8.6). While waiting for the trains, buses, or flights, customers can order products by scanning a QR code (or bar code) using their mobile phones. Tesco will then deliver the orders to the customers' homes.

Figure 8.6: Tesco catalogs

Instead of just integrating online and offline channels, some companies even integrate their businesses in different industries. For example, Shun Feng (SF) Express is a major third-party logistics provider in China. Besides providing logistics services, SF has opened many small-size *SF stores* (see Figure 8.7) in different cities in China. Customers can browse the catalogs in the stores, which contain no inventory. They can order products by scanning a QR code with their mobile phones, and SF will deliver the products to the customers' homes.

Figure 8.8 illustrates some examples where firms expand from one industry to another. Amazon has evolved from a pure-play e-commerce retailer to a company that has businesses in logistics (Fulfillment by Amazon) and brick-and-mortar retail (Amazon Go). By contrast, SF Express transformed themselves from a logistics service provider to a retailer with both online and offline channels. Tesco expands from traditional brick-and-mortar retail to online (mobile) retail. Through these examples, we can see that as the customers' omni-channel shopping experience becomes more seamless, the integration of retail and

Figure 8.7: SF stores

logistics becomes more unavoidable.

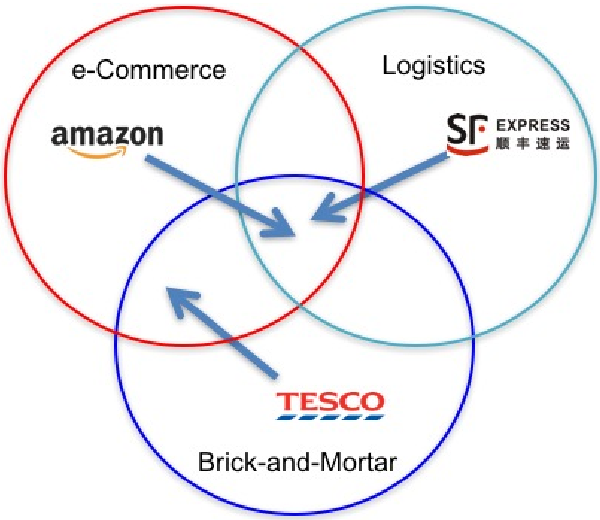


Figure 8.8: Integration of retail and logistics

In fact, the following different industries are being integrated in the Internet economy:

1. e-commerce and online marketplaces,
2. logistics,
3. brick-and-mortar retailing,
4. web services and cloud computing,

5. e-payment and financing,
6. AI and autonomous technology.

Companies that provide these services and products include Alibaba, Amazon, and JD.com.

References

Bell DR, Gallino S, Moreno A. 2014. How to win in an omnichannel world. *MIT Sloan Management Review* **56**(1): 45–53.

About the author

Yun Fong Lim is Associate Professor of Operations Management and MPA Research Fellow at the Lee Kong Chian School of Business, Singapore Management University (SMU). He is also Academic Director of the MSc in Management (MiM) Program at SMU. He has been a Chang Jiang Chair Professor, a Lee Kong Chian Fellow, and an NOL Fellow. Yun Fong's research has appeared in *Operations Research*, *Management Science*, *Manufacturing and Service Operations Management*, and *Production and Operations Management*. He has delivered keynote and plenary speeches in several international conferences. In addition, his work has received funding by MOE, A*STAR, and NNSF, and media coverage by The Business Times, CNA938, and Channel 8. His current research interests include e-commerce and marketplace analytics, inventory management, warehousing and fulfillment, sustainable urban logistics, and flexible workforce and resource management. Yun Fong serves as Associate Editor for *Naval Research Logistics* and Guest Editor for *Production and Operations Management*.

Yun Fong is a recipient of the SMU Teaching Excellence Innovative Teacher Award. He teaches both undergraduate and postgraduate courses in Operations Management. He has provided consulting service and executive development to corporations such as Alibaba, Maersk, McMaster-Carr Company, Resorts World Sentosa, Schneider Electrics, Temasek Holdings, and Zalora. Yun Fong obtained both his PhD and MSc degrees in Industrial and Systems Engineering from the Georgia Institute of Technology.