PRICING AND MATCHING IN THREE-SIDED ON-DEMAND DELIVERY SERVICES

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Abstract

On-demand delivery services allow customers to browse suppliers to choose their desired product, considering some criteria for receiving at the door. Crowd-sourced drivers pick-up orders from suppliers and deliver to customers. The three players, including customers, suppliers, and drivers, form a three-sided market where successful orders depend on all players' adequate presence. The platform balances the market towards certain profit-generating outcomes by optimally matching the orders and implementing a pricing strategy by charging customers and suppliers a fee and paying drivers a wage. A heuristic algorithm is proposed, comprising matching and pricing modules: one matches customer orders to suppliers and drivers, while the other optimizes the platform's profit by selecting pricing parameters. The findings demonstrate that the platform can influence market dynamics by strategically setting these parameters, satisfying the players' utility, and maximizing profit. The platform's success relies on regulating these parameters to attract the most players and generate profit.

Dedication

I am deeply thankful to everyone who supported and encouraged me to achieve this significant milestone in my life. I dedicate my thesis to my parents for their boundless love, support, and encouragement while they were far from me these years. I also want to acknowledge my brother and my partner for their constant presence and the moral support they provided during this important era of my life. Lastly, I extend my gratitude to all my family, friends, and colleagues who have supported me consistently throughout my journey and are truly the greatest blessing I have. To all of you, my heartfelt thanks.

Acknowledgements

I would like to express my deep gratitude to my supervisors, Dr. Mehdi Nourinejad and Dr. Peter Park, for their consistent guidance and support during my research. I am thankful for the trust they placed in me over these years and their invaluable expertise. The topics we explored in this thesis made the process very engaging. Without their insights, this document would not have been as comprehensive.

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Abbreviations

GIS	Geographic Information Systems
ILP	Integer Linear Programming
LMD	Last Mile Delivery
LP	Linear Programming
MILP	Mixed Integer Linear Programming
MNL	Multinomial Logit Model
SDD	Same Day Delivery

Chapter 1

Introduction

1.1 Overview

In this chapter, the motivation behind the research endeavors is first outlined, followed by an overview of the research goals, objectives, and the scope of the study. Subsequently, a summary of the thesis structure is presented, providing insight into the topics addressed.

1.2 Motivation

Growing e-commerce and online shopping tendencies have made on-demand delivery services, such as food delivery, a highly advantageous industry [1]. Service providers such as UberEats, DoorDash, HelloFresh, and Instacart offer platforms allowing customers to browse supplier products differentiated in terms of quality, price, location, and delivery time. In the case of Uber Eats, take-out restaurants are an example of suppliers that post their menus on the platform with their respective prices. Uber Eats ranks restaurants according to a star-rating system, giving customers a sense of the supplier's popularity/quality. It also posts an expected waiting time based on the customer's geographical location, supplier, and available nearby drivers [2]. When an order is placed, the service provider assigns an available crowd-sourced driver to pick it up from the supplier and drop it off at the customer.

The three players (customers, suppliers, and drivers) form a three-sided market with cross-side interactions (Figure 1.1), indicating that the number of processed orders depends on the adequate presence of the three players and each player expects a specific utility from the platform. For example, customers are more willing to join the platform if they have a wide range of supplier options with reasonable prices, which leads to fewer waiting times. Likewise, they benefit from a lower waiting time when more drivers are in the system waiting to be assigned an order to deliver. Suppliers profit from more customers if they can sell more products, and more drivers (delivery capacity)lead to more supplier partners. Similarly, drivers benefit from more customers and suppliers, giving them plenty of delivery job options with shorter driving times.

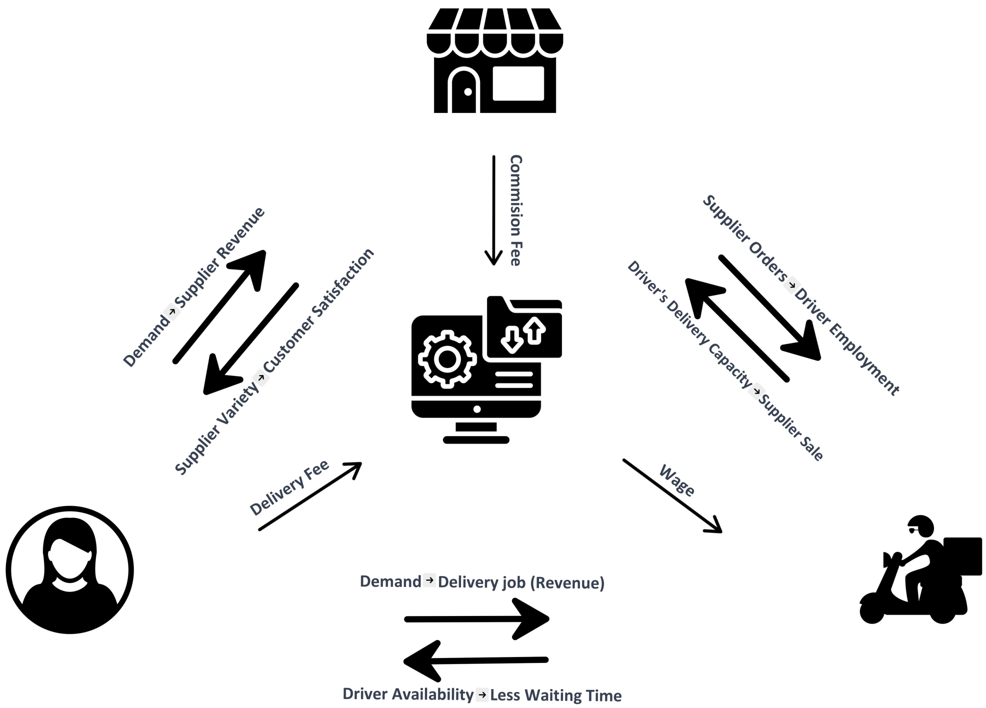


Figure 1.1: The conceptual model of a three-sided market platform

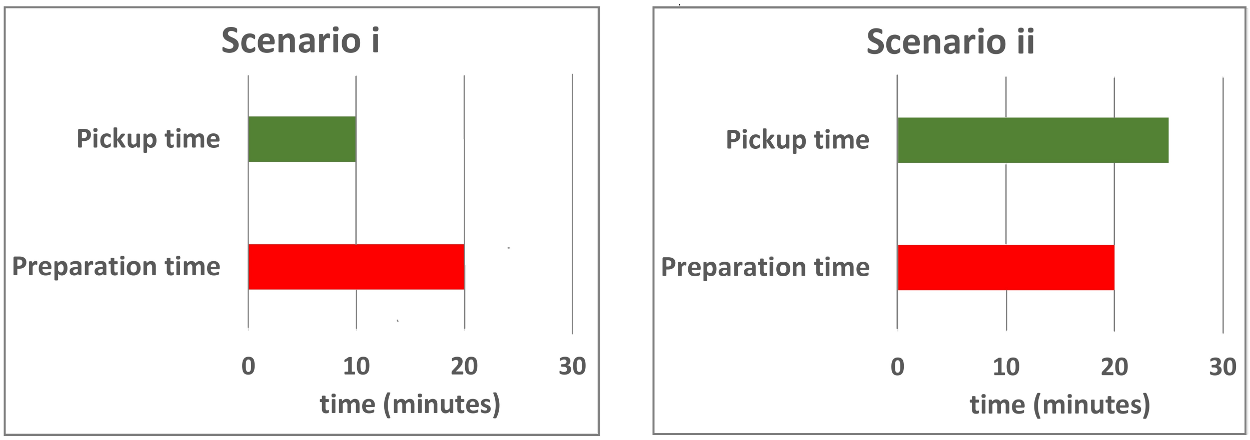
Three-sided markets have more interaction amongst the players than conventional two-sided markets, such as ride-sourcing services that match passengers with drivers [3]. A three-sided market service provider can manipulate the market towards profit-generating outcomes by implementing optimal pricing and matching strategies. Pricing strategy requires choosing an optimal delivery fee to charge customers, a commission fee for suppliers advertising their products on the platform, and a wage for drivers offering their delivery service. The matching process occurs in two stages. In the first stage, each customer places an order with the highest quality supplier, the desired price, and the desired waiting time. Some customers may opt out if they cannot find the desired order. Then, in the second stage, the platform matches each placed order with an available driver in the system to perform the delivery job.

Breaking the process into two stages ensures a more effective and simplified workflow. By focusing first on matching customers with restaurants, the system can optimize based on customer preferences, restaurant availability, and menu options. Once an order is placed, the system can then focus on matching the order with the most suitable driver. This allows the platform to consider factors such as driver availability, location, and delivery time, optimizing the delivery process separately. Splitting the process into two sublayers also allows the system to handle more orders. Each layer can be scaled independently to manage spikes in customer activity or driver availability.

Further complicating the matching process is the existence of the following three operational conditions of *preparation time*, *delivery scheduling*, and *promised* waiting times. Preparation time expresses how long it takes a supplier to prepare an order. For example, many empirical studies show that the average food preparation time in restaurants (especially fast foods) depends on the number of orders in queue given their limited serving capacity [4]. The preparation time affects delivery schedules, leading to two possible scenarios: i) the driver arrives at the supplier but has to wait for the order to become ready for delivery, and ii) the order is ready at the supplier and is waiting for the driver to pick it up. Two scenarios are shown in Figure 1.2, but they will be explained in detail in Section 3.2.1.

1.3 Research goal

The primary goal of this research is to develop and validate a comprehensive analytical framework for optimizing pricing and matching strategies in three-sided on-demand delivery markets. Optimizing pricing strategy means setting the customers' delivery fee, suppliers' commission fee, and drivers' wage to maximize the platform's profit while satisfying all players. By integrating Linear Programming and Integer Linear Programming with heuristic algorithms, this framework aims to facilitate efficient interactions among customers, suppliers,



(a) (b)

Figure 1.2: Two possible scenarios based on the preparation time and pickup time

and drivers, enhancing the overall performance of the delivery platform. The objective is to develop a model that maximizes the platform's profitability and ensures equitable utility distribution among all players, increasing participation and satisfaction.

This research aims to bridge the gap between theoretical mathematical models and practical applications in real-world market conditions (some examples of on-demand delivery services). It pursues to provide actionable insights that on-demand delivery platforms can directly apply to navigate the complexities of dynamic market environments. Through simulation and sensitivity analysis, the study examines the stability of the developed strategies against various operational challenges, including demand variability and supply constraints.

In order to better align the proposed algorithm with its use case in the industry, the proposed algorithm introduces features that enhance its practical application, including utility-based decision-making and sensitivity analysis framework:

- **Utility-Based Decision Making:** The algorithm incorporates player utilities beyond simple distance or demand-based driver matching. It considers customers' sensitivity to waiting times, suppliers' constraints, and drivers' earnings expectations, offering a more comprehensive and balanced approach to ensuring satisfaction for all three players.

- **Sensitivity Analysis Framework:** The developed framework allows the three-sided platforms to perform sensitivity analysis on key parameters like customers' and drivers' sensitivity to waiting times, which helps predict the impact of different pricing and operational scenarios. This feature adds a strategic planning dimension, enabling the platforms to proactively adjust their policies to improve performance.

1.4 Research objectives

This research sets three objectives to examine pricing and matching strategies in on-demand delivery services. The three objectives include:

1. Investigate players' interactions in three-sided on-demand delivery markets to capture the impact of key factors on the platform's performance.

2. Propose pricing and matching strategies that optimize the profit of the service provider while maintaining the equilibrium of the market and analyze the impact of these strategies on the balance between all players, ensuring adequate utilities for them and maximizing the attraction and profit of the platform.

3. Develop a framework for performing sensitivity analysis on key parameters, including drivers' and customers' sensitivity to waiting time and pricing strategies. Assess how fluctuations in these factors influence platform efficiency and profitability across various scenarios.

The pricing strategy refers to increasing or decreasing the pricing parameters to optimize the platform's profit. This strategy ensures a balance between maximizing profitability and maintaining sufficient satisfaction and participation from all market players. This includes determining:

- **Delivery Fees for Customers:** The fee that customers pay in addition to the product price for the convenience of having their orders delivered. This fee impacts customer satisfaction and willingness to place orders.

- **Commission Fees for Suppliers:** The percentage of the order price that suppliers (such as restaurants or retailers) pay to the platform for advertising their products. This affects the suppliers' decision to participate in the platform and offer competitive prices.

- **Wages for Drivers:** The amount paid to drivers for delivering the products. This influences driver availability and willingness to accept delivery tasks.

This research develops a framework that employs heuristic algorithms alongside mathematical methods such as linear programming and integer linear programming. The framework is designed to dynamically adjust pricing and matching strategies based on data input, including order volume, driver availability, and customer demand patterns. This approach aims to enhance the platform's responsiveness and operational efficiency, maximizing the platform's income and optimizing resource allocation while maximizing all players' satisfaction across the three-sided market structure.

1.5 Scope and thesis organization

This thesis investigates the structure of three-sided on-demand delivery markets, focusing on cross-side interactions between customers, suppliers, and drivers. This study helps to understand players' behavior on three-sided on-demand delivery platforms and explores methods that platforms can employ to optimize performance and user satisfaction. It also examines the impact of pricing strategy on the platform's profitability through a mathematical model and contributes to a deep understanding of the factors that drive decisions in on-demand delivery services. As an example of pricing strategy, the platform increases the wage for drivers to attract them to the market and incentivizes them to accept delivery jobs.

Figure 1.3 presents the flowchart of the developed model. Initially, simulated data for the players, including customers, suppliers, and drivers, are generated. Subsequent steps involve calculating the travel times between these players using road network data and network analysis (origin-destination cost matrix) tools. Then, the problem is divided into two subproblems as it is not straightforward. Some constraints are nonlinear; moreover, matching the orders and determining the pricing parameters simultaneously is difficult to solve. Thus, a heuristic Matching and Pricing Algorithm processes the inputs to solve the problem and generate outputs. Following this, a comprehensive sensitivity analysis is conducted to examine the impact of key factors on an on-demand delivery platform. The findings of this analysis are discussed in the conclusion section of the thesis.

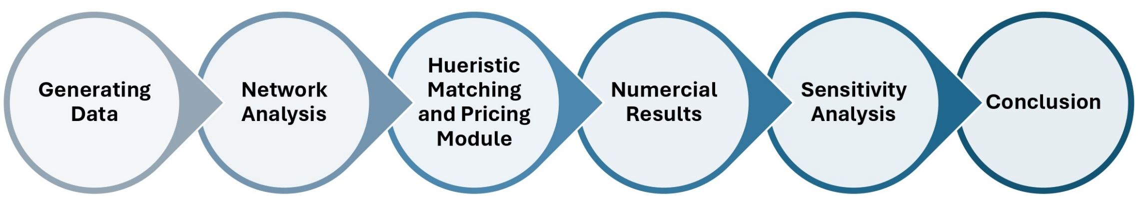


Figure 1.3: The research flowchart

The remainder of the thesis is organized as follows. A review of the related works is presented in Chapter 2. The developed model and solution algorithm are given in Chapter 3. The results from the developed model are presented in Chapter 4. Lastly, the study's conclusions are presented in Chapter 5.

Chapter 2

Literature Review

2.1 Overview

In this chapter, the literature on three-sided on-demand delivery services is reviewed. Two-sided markets have become prevalent in the last two decades as they leverage the sharing economy, allowing users to use shared resources and consequently decreasing costs. This section has categorized the related works as 1) Same-Day Delivery (SDD) and Next-Day Delivery Services, 2) Two-sided market pricing and matching, 3) Three-sided and multisided markets, 4) Crowd-sourced deliveries, 5) Linear Programming (LP) and Integer Linear Programming (ILP), and 6) Recent transportation research using LP and ILP.

2.2 Same day delivery and next day delivery services

Same-day delivery is a premium service that provides customers with the opportunity to buy merchandise online and get it the same day they bought (before the end of the day) [5], which is a fast-growing service and is predicted to surpass 26.4 billion U.S. dollars in 2027 [6]. Next-day delivery customers receive their orders the day after purchase [7]. The demand for same-day delivery is growing as 80% of online shoppers expressed expectations for same-day delivery options at checkout [8]. This widespread consumer demand has encouraged a diverse spectrum of businesses, from e-retail giants like Amazon and Walmart to specialized services in food and groceries, office supplies, and pharmaceuticals, to adopt SDD, underlining its significance and potential impact across various industry sectors.

SDD services have a *time window* constraint (determined time deadline for completing an order) for receiving an order on the same day. If an order is placed before a specific time, it will be received the same day. For instance, Amazon customers should place orders before a specific deadline (cut-off time) for same-day delivery. A countdown timer on the checkout page indicates the time window in which a customer must complete the order to receive it the same day. Nonetheless, the changes in inventory or fleet capacity while the customer is completing his/her order may affect the delivery date and time.

Amazon offers same-day delivery in selected cities with specific cut-off times, typically between 9 AM and 12 PM, depending on the city. If customers place their orders within this time frame, they can expect their packages by the evening, often between 6 PM and 10 PM. Amazon also helps customers by displaying a countdown timer during checkout to let them know how much time they have left to place an order for same-day delivery. The exact cut-off and delivery times can vary based on the customer's location and item availability [9]. BestBuy, an electronic and home appliance retailer, offers its same-day delivery service seven days a week. If the products are eligible and customers place their orders by 3 PM, they will see the same-day delivery option on the checkout page and receive their orders by 9 PM. Customers who order after the deadline will receive orders on the next day. FreshDirect Co. provides grocery delivery service in some limited cities in the U.S and has two SDD services, including Standard and Express delivery. Standard service guarantees shipment of items by 9 PM. In contrast, the Express service can deliver orders in 2 hours, which has a more expensive service fee [10, 11].

While Amazon and BestBuy have a four to five-hour cut-off time, AmazonFresh provides various delivery options, including four-hour, two-hour, and one-hour. Costco offers a two-hour same-day delivery option, and Walmart promises to deliver items in two hours or one hour. Woolworths, the largest grocery retailer in Australia, has three-hour and one-hour same-day delivery options. In contrast, ASDA, a famous retailer in Europe, provides 1-hour delivery if a customer orders 1-70 items and 4 hours if a customer buys more than 70 items. Alibaba's logistics arm, Cainiao, has introduced same-day delivery services in China as part of its effort to improve e-commerce logistics. The service, branded under Cainiao Express, allows customers in over 300 cities to receive packages either the same day or the next day. Orders placed before noon can be delivered by 9 PM the same day, while those placed before midnight will be delivered by noon the next day [12].

Food delivery platforms such as UberEats, DoorDash, and Foodora generally offer two-hour and one-hour deliveries because food must be delivered fast and fresh. Third-party companies provide delivery services to retailers and hypermarkets, including Instacart, Cornershop, GoPeople, and Eleme. Since they use volunteer drivers (who want to work on their schedule), there is a widespread fleet, and most orders can be delivered in two hours or one hour by Instacart and two hours by Cornershop. Besides, GoPeople delivers 80% of orders within three hours and 95% within four hours [13]. Eleme promises to deliver items in one hour and even food in 20 minutes by drones in Shanghai [14]. Table 2.1 shows the same-day delivery services of major retailers in countries of operation.

Table 2.1: Same-day delivery service provided by large retailers.

Region Company	USA	Canada	Europe	Australia	China
Amazon [15, 16]	Most cities (eligible residential ZIP code)	Vancouver, Calgary	France, Germany, Italy, the Netherlands, Spain, Belgium, Sweden, Turkey, U.K.	Sydney, Melbourne, Brisbane, Adelaide, Canberra, Perth, New South Wales, Victoria, South Australia	Beijing, Shanghai, Guangzhou.
Amazon Fresh [17]	Most cities (eligible postal code)	N/A	Italy (Milan), Spain (Madrid), France, U.K., Germany (Berlin, Potsdam, Hamburg)	N/A	N/A
Walmart [18, 19]	Most cities (eligible postal code)	✓	N/A	N/A	+180 cities (438 stores)
Costco [20, 21]	Most cities (eligible postal code)	N/A in Quebec	France (1 warehouse), Iceland (1 warehouse), Spain (3 warehouses), UK (29 warehouses)	Kilburn; Epping, Docklands, Ringwood, Moorabbin Airport ; Canberra Airport ; Perth Airport ; Marsden Park, Casula, Lidcombe ; Bundamba, North Lakes ; Boolaroo	Shanghai, Suzhou
Alibaba [22, 23]	Most cities	Most cities	Most countries	Most cities	Most cities
Best Buy [24, 25]	✓	Greater Toronto, Vancouver, Edmonton, Calgary, Montreal, Quebec City, Ottawa, Gatineau	N/A	N/A	N/A
FreshDirect[26]	New York, Washington, Philadelphia	N/A	N/A	N/A	N/A
ASDA [27]	N/A	N/A	United Kingdom (633 points).	N/A	N/A
DoorDash [28]	✓	✓	N/A	Sydney; Geelong, Melton, Sunbury, and Melbourne	N/A
Foodora [29]	N/A	N/A	Sweden, Finland, Norway	N/A	N/A
Uber Eats [30]	✓	✓	Belgium, France, Germany, Ireland, Italy, Netherland, Poland, Portugal, Spain, Sweden, Switzerland, United Kingdom	Most main cities in Australian Capital Territory, New South Wales, Northern Territory, Queensland, South Australia, Tasmania, Victoria, Western Australia	Hong Kong
Instacart [31]	Most cities (eligible postal code)	✓	N/A	N/A	N/A
CORNERSHOP [32]	✓	✓	N/A	N/A	N/A
GoPeople [13]	N/A	N/A	N/A	Sydney, Melbourne, Brisbane, Perth, and Adelaide.	N/A
Ele.me [14]	N/A	N/A	N/A	N/A	Most cities in China (+2000).

2.2.1 Delivery mechanisms

Delivery mode directly affects the cost. Some SDD service providers prefer to own their fleet, whereas others either outsource or crowd-source the deliveries. Delivery modes include crowd-sourcing, outsourcing, or privately owned fleet routing, each of which has its distinct features that make them cost-effective under certain conditions. Therefore, SDD service providers should precisely set the delivery cost based on the delivery mode on the checkout page to convince customers to order a product with the SDD service. However, SDD customers generally pay more to receive their orders faster than the regular delivery service. Consequently, choosing a suitable delivery mechanism allows SDD service providers to effectively balance cost efficiency with high service quality and achieve high customer satisfaction.

Fleet ownership: Owing a fleet of delivery vehicles requires the appropriate number and types of vehicles to meet the expected demand for deliveries in a cost-effective way. This strategy reduces the dependency on third-party providers but requires the fleet owners to incur additional drivers, storage, and fuel costs. Amazon has an extensive network and has developed its own fleets, especially for last-mile delivery (same-day delivery services) [33]. FreshDirect also has a fleet that includes refrigerated trucks, which deliver fresh food and groceries on the same day of purchase.

Outsourcing: Some SDD service providers outsource their delivery operations to another company to reduce costs and complex scheduling challenges. In this delivery strategy, an SDD service provider only transfers the orders in the internal supply chain, and another service provider takes responsibility for the SDD delivery. For instance, Alibaba, the biggest retailer in China, delivers orders using other services such as FedEx, UPS, and DHL [34].

Crowd-sourcing: Crowdsourcing generally refers to using a large group of individuals, typically through online platforms, to obtain input, ideas, or services. In the context of last-mile delivery, the final phase of the delivery process, where orders are transported to the end customers, individuals can provide the same-day delivery service. This delivery strategy involves enlisting independent drivers to perform delivery tasks, improving flexibility and scalability while reducing operational costs [35]. In crowd-sourced delivery, drivers register in an application, receive delivery offers with the route and price and decide to take over the delivery. Amazon Flex, DoorDash, Foodora, UberEats, Instacart, GoPeople, and Eleme use crowdsourcing for their delivery operations, leveraging the flexibility and scalability of independent drivers.

Outsourced Crowd-sourcing: In the outsourced crowdsourcing delivery mechanism, an SDD service provider contracts with a delivery service provider that uses crowdsourcing and individuals' participation in delivery jobs. These SDD service providers do not manage their own fleet of delivery vehicles but rather rely on the infrastructure and labor force provided by third-party services, which operate on a crowdsourcing model. For example, BestBuy agreed with Instacart to use its fleet of part-time drivers to deliver the goods. Cornershop, Woolworths, and ASDA use Uber drivers to deliver to customers [36].

2.2.2 Product categories with same-day delivery options

Same-day delivery services quickly deliver items customers need within a day. Perishable food is one of the most commonly purchased items through same-day delivery services. Lead times and inventory levels also affect the suitability of some products for delivery within a day. For example, Amazon offers same-day delivery service on only about 3 million of its approximately 250 million products on its website. Groceries are another category of items that SDD users prefer to receive on the same day.

The most commonly purchased items using SDD services were classified into eight categories: Food, Groceries, Healthcare, Personal Care, Household, Clothing, Home Appliances, and Electronic Devices. Table 2.2 presents the availability of these products from some of the world's largest retailers that offer same-day delivery services.

Table 2.2: Product types

Company	**Grocery**	**Healthcare**	**Personal Care**	**Food**	**Household**	**Clothing**	**Home Appliances**	**Electronic Devices**
Amazon [16]	✓	✓	✓		✓	✓		
Amazon Fresh [17]	✓			✓				
Walmart [18, 19]	✓	✓			✓			
Costco [20, 21]	✓				✓			
Alibaba [22, 23]	✓	✓		✓				
Best Buy [24]			✓				✓	✓
Fresh Direct [26]	✓			✓				
ASDA [27]	✓				✓	✓		
DoorDash [28]				✓				
Foodora [29]				✓				
Uber Eats [30]				✓				
Instacart [31]	✓	✓			✓			
Cornershop [32]	✓	✓	✓			✓		
GoPeople [13]	✓	✓		✓		✓		✓
Ele.me [14]	✓	✓	✓	✓				

As mentioned above, most SDD service providers can only offer limited items to customers since SDD service requires more complicated logistics and fleets. For example, Amazon generally sells about 250 million items (types), while it can only offer the SDD service for 3 million product types.

2.2.3 Scheduling

Self-scheduling: All crowdsourced same-day delivery service providers offer flexible working hours to attract drivers. However, the level of flexibility varies between providers. In pure self-scheduling systems, drivers do not need to preannounce their availability. Instead, they log into the mobile app when they are ready to work and wait for delivery requests within a specific radius. The app notifies drivers by showing them the available requests, which they can accept or decline. This approach is also implemented in ride-sharing services of Uber and Lyft [37].

Centralized scheduling: Some other SDD service providers apply a centralized scheduling strategy to match supply and demand. These platforms ask drivers to announce their availability to the system, receive delivery offers, or choose desired shifts that operate on a first-come, first-served basis. Shifts are typically announced well in advance, up to several days ahead. These scheduling platforms are similar to conventional delivery services with a fleet of predetermined supply and capacity. Some systems give a minimum pay to drivers, even if they are not matched. Such programs further decrease uncertainty in supply and cause the system to be similar to traditional scheduling, matching, and routing problems.

2.2.4 Pricing in same-day delivery services

SDD pricing is influenced by factors such as product type, physical properties of the package, waiting time, distance, retailer's profit, and driver wages [38]. To encourage the use of SDD services, common pricing strategies, such as determining a delivery fee and subscription programs, are used. For example, Amazon Prime offers Prime members FREE Same-Day Delivery by placing orders before the cutoff time. While price adjustments are often made to control revenue, it is crucial to keep service costs low to maintain the profitability of premium delivery services.

Driver Compensation: Determining the driver's payment method is another essential part of each delivery system, which attracts drivers to it. Each SDD service provider seeks to hire more drivers by providing better working conditions and job benefits to expand its market and increase its income. The different driver compensation methods are compared and explained below:

- **Hourly compensation**: In an SDD system, driver wages are often based on hourly compensation. This hourly wage method guarantees fair compensation for drivers' time, regardless of delivery volumes, providing a steady and predictable income. This compensation stability can enhance employee performance and satisfaction [39].

- **Per delivery compensation**: The other convenient way to compensate drivers is based on the number of delivered packages. In this method, the fee calculation considers factors including tour distance, waiting time, traffic, and parking costs. The package size also impacts the fee. Although this is a reliable payment method for SDD service providers, it may decrease the attraction of drivers to work. Because drivers mostly want an anticipated minimum income, they may leave the platform if they do not find matched requests.

- **Customer - driver compensation**: The other drivers' wage method is a multi-sided agreement system in which the driver's wage for delivery is calculated based on an agreement between the customer and the driver. This method is a two-sided agreement, and some platforms have a three-sided market in which the platform receives a commission to establish a delivery request. The main challenge in this payment method is the lack of guarantee for matching requests because these systems are community-based, and there is less supervision of upper levels of delivery providers.

2.2.5 Capacity rationing

Each delivery vehicle has a specific capacity to carry the packages. Loading a large number of items onto a delivery vehicle can lead to extended tour lengths, higher operational costs, and increased delivery times. Furthermore, a retailer cannot consider most of its fleet's capacity for SDD service because they may not complete the deliveries on time. Moreover, if a retailer offers fewer products with SDD and uses a small portion of its fleet's capacity for SDD, it loses the potential income of this service. Thus, there is a vital balance between the capacity of the SDD fleet (along with the standard delivery items) and the company's revenue, which should be regulated using optimization methods [40, 41].

2.3 Two-sided market pricing and matching

Two-sided markets are considerably investigated with applications such as crowd-sourced ride-hailing services between riders and drivers ([42]; [43]). [44] proposed a model for a two-sided market pricing considering the suppliers' revenue and cost and desired time of customers. In this study, the utility function of each side is impacted by the number of players on the other side. [45] examined a model for a multi-sided market for pricing, while each side has an equal role in the utility function. This model proposed a general theory simplifying the real-world status while each market has a specific situation with different pricing policies.

[46] studied the cost-share of different players in two-sided markets, and shown that players could be subject to subsidization. Many two-sided markets use this mechanism in order to gain additional value to the market, such as real estate, operating systems, publication and newspaper distribution, and credit cards ([47]; [46]; [48]). As an example, in the journalism industry, the market subsidizes the readers, and publishers earn their income from advertising as well. The results indicate that increased demand on the reader side raises the advertisement fees, whereas increased demand on the advertiser side lowers the prices [49].

[50] examined the pricing of academic journals as a two-sided market. In this paper, the studied open access academic journals are free to download for users while authors are charged instead. In fact, users are subsidized and have unlimited access to the journal and authors should pay in order to publish their works. A study in Norway on large-scale vehicle registry data as a two-sided market demonstrates the non-neutrality of various subsidization policies and evaluates their effect on electric vehicle adoption when some network externalities are taken into account. The results present a significant positive relationship between electric vehicle shopping and customer price and charging station subsidies [51].

2.4 Three-sided and multi-sided markets

Three-sided and multi-sided markets extend beyond the transportation field, containing diverse sectors where platforms facilitate interactions among multiple user groups, each deriving value from the presence of the others. YouTube, a video-sharing platform, is a three-sided market [52]: 1)Internet Users (looking for content to watch/listen to), 2) Content Providers (YouTubers, bloggers, ... trying to attract users to view their videos), and 3) Advertisers (looking for users that fall into their buyer personas). Figure 2.1 shows three players of this market [53].

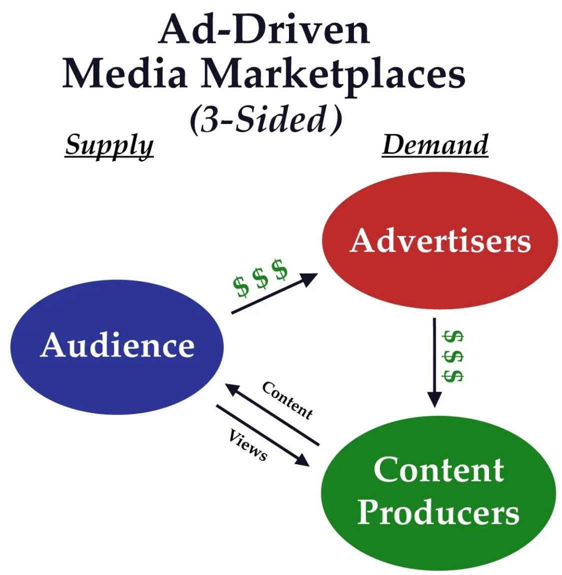


Figure 2.1: Three players forming the Youtube as a three-sided market [54]

User-generated contents attract viewers, viewers attract content producers who want audiences, and access to viewers can then be sold to advertisers [55]. Compared to the two-sided market, a third player—advertisers—joins users (customers) and producers (suppliers) in a three-sided structure. Advertisers provide additional services alongside suppliers, acting as intermediaries and catalysts within the system [56]. [56] provides valuable insights into the complexities of three-sided markets, such as on-demand delivery platforms, distinguishing them from simpler two-sided models. While two-sided markets involve direct interactions between two groups—such as creators and viewers on traditional media platforms—three-sided markets like YouTube or on-demand delivery platforms introduce a third party that significantly influences interactions and revenue distribution. Inspired by [56], this model highlights that, in a three-sided market, the platform's role becomes more complex, balancing the needs of customers, suppliers, and drivers. The presence of drivers (or advertisers in the case of YouTube) introduces logistical and economic layers absent in two-sided structures, requiring unique pricing and matching strategies to maintain equilibrium across all three groups.

These three players are tightly bonded since the satisfaction of each one of them is strictly related to the satisfaction of the members of the other two groups. Each group has a Value Proposition, which leads to making a three-sided market: i) Internet users are supplied with a platform for linking people by distributing content, ii) Advertisers are provided with a way to connect to a relevant audience, and iii) Content Producers are supplied with a scene where they can perform.

Generally, multi-sided markets are platforms providing direct interactions between two or more distinct players (sides), while each player (side) is affiliated with the platform [57]. For instance, the Android platform has five sides (Figure 2.2): 1) app developers and media publishers, 2) OEMs (Original Equipment Manufacturer), 3) Mobile device users, 4) Network operators, and 5) Marketers. These players (sides) join the market based on their utility and each side benefit from the presence of other sides [58]. The characteristics of these players are explained below:

1. App developers and media publishers make money from their apps and content through downloads, subscriptions, and ads.

2. Original Equipment Manufacturers (OEMs) benefit from the smartphone market and

attract many app developers without developing their own Operating System (OS).

3. Mobile device users enjoy the many apps available, which make their devices more useful and provide lots of media content.

4. Network operators or phone carriers benefit from a large number of subscribers using their services and data plans. More media content leads to higher demand for unlimited data plans.

5. Marketers see the large and specific user base on mobile devices as a perfect audience for their ads and services.

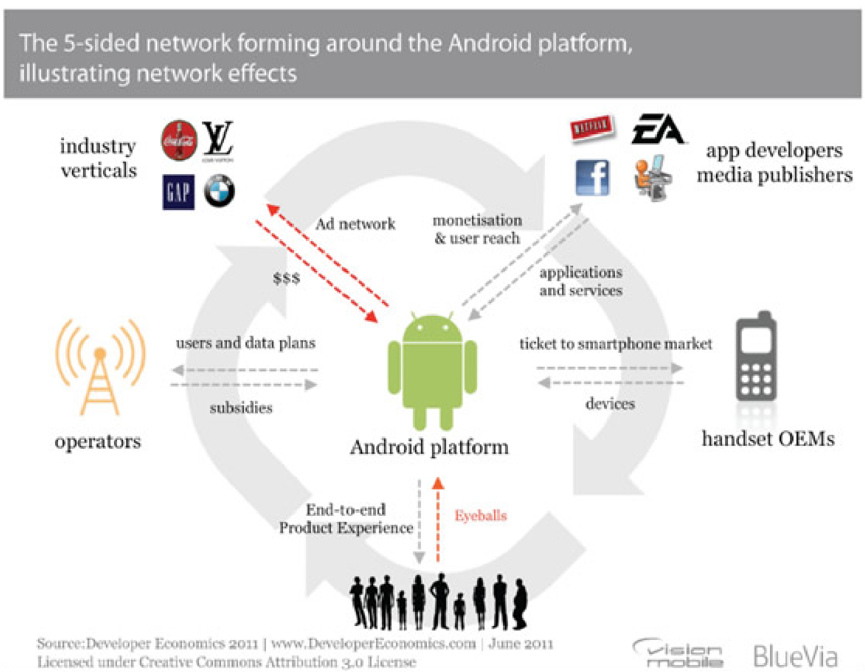


Figure 2.2: Android platform as a five-sided market

In the following, the three-sided market in transportation applications is investigated. The study of on-demand delivery services (three-sided market) is rapidly expanding. Recent research has explored a range of operational challenges within this sector. For instance, [59] examined how delivery performance affects customers' probability of using the service again soon. Analyzing data from a Chinese online food delivery platform revealed that deliveries arriving early significantly boost customer loyalty, while late deliveries deter future orders. [60] looked at how such delivery services (like DoorDash, Grubhub, and Uber Eats) impact restaurant sales. [61] used a game theory approach to explore whether restaurants should handle deliveries themselves or partner with delivery platforms. [62] created a model to examine customer types, distinguishing between those comfortable using online platforms and those who are not, such as some elderly individuals. They found that while food delivery services increase the proportion of tech-savvy customers, they only sometimes increase overall restaurant demand. [63] criticized the industry's typical revenue-sharing contracts for failing to manage the system effectively. They proposed a new type of contract that combines a fixed fee with a revenue share, offering a more flexible and effective way to distribute earnings between delivery platforms and restaurants.

The closest work to this research, [56] investigated the dynamics of three-sided on-demand delivery markets, especially concentrating on online food delivery services that connect customers, suppliers (restaurants), and crowd-sourced drivers. This study explored the complexities of such markets and proposed pricing strategy allowing platforms to optimize either their profits or social welfare. The study considers various factors, including earning-sensitive independent drivers, price-sensitive customers, and price-sensitive suppliers. It models the endogenous dependence of the number of participants from each side on the platform's price, wage, and commission. The research demonstrates that, in both profit and social welfare maximization scenarios, suppliers internalize a portion of the driver wage while customers internalize the supplier commission. In social welfare maximization, customers also internalize part of the driver wage. Notably, the platform charges lower commissions and offers higher wages in social welfare optimization than profit maximization, even though this results in negative profits for the platform in the former case.

For comparison, this research focuses on pricing and matching mechanisms in three-sided markets by developing heuristic methods for matching and pricing optimization, emphasizing capacity constraints and operational details. Meanwhile, [56] presents a theoretical framework using continuum approximation to estimate customer waiting times and driver routing, addressing commissions and wages to balance profit maximization and social welfare. While this thesis incorporates real-world constraints such as preparation times and delivery schedules, [56] takes a broader view of on-demand delivery services, analyzing varying population sizes and commission schemes to understand market dynamics.

[64] investigated how online food delivery platforms compete in pricing and service quality, clarifying the complex dynamics and incentives among these stakeholders. It introduced a game-theoretic model to analyze optimal strategies, including pricing and service quality decisions made by online food delivery platforms using to mitigate competition and optimize either profit or social welfare. It indicated that the three-sided nature of an online food delivery affects the platforms' incentive to leverage it and can soften consumer price competition while intensifying restaurant price competition. The paper also considered the impact of minimum wage regulations on gig labour and their implications for consumers and platforms.

[65] explored the optimization of crowdsourced shipping systems by developing pricing and compensation schemes (Flat Price/Flat Compensation (FPFC), Flat Price/Individual Compensation (FPIC), Individual Price/Flat Compensation (IPFC), and Individual Price/Individual Compensation (IPIC)) that balance the needs and preferences of senders, couriers, and platform providers. The study introduced an integrated framework combining matching and routing models with dynamic pricing and compensation strategies. The research demonstrated that platforms maximize profits with the Individual Price/Individual Compensation (IPIC) scheme, which allows both the pricing for the senders and the compensation for the couriers to be customized individually based on factors like distance, delivery complexity, and time. It provides more flexibility and adaptability, enabling platforms to set different prices for each

sender and assign varying compensations to couriers.

2.5 Crowd-sourced deliveries

Crowd-sourced deliveries leverage the potential of large groups of independent drivers and enhance flexibility and scalability in last-mile delivery services. [66] evaluated crowdsourcing the last-mile delivery of online orders using the social networks of retail store customers. They used the outcome of a questionnaire of the respondent's views about joining social network-reliant parcel delivery for modelling and analyzing the possible advantages of crowdsourcing last-mile delivery by utilizing customers' social network contacts. The paper indicated that allowing friends/neighbours to pick up and transfer online orders to each other during their routine trips to the store/work/home decreases the last-mile delivery times and costs.

[67] investigated crowd shipping in stochastic last-mile delivery where a professional delivery fleet is supported with crowd shipping. Crowd shipping involves ordinary people in delivering online orders to the customers. In this study, in-store shoppers, as occasional couriers, carry some packages on their way home and receive compensation. The aim is to use crowd shipping to decrease the total costs of a same-day delivery platform by introducing a bi-level methodology for matching and routing. [68] proposed an event-based rolling horizon framework that dynamically matches the delivery tasks with time windows with ad-hoc drivers who registered their information such as their routes, vehicle capacity, and schedule on the platform. The computational results depicted that this system can reduce delivery times and costs and save up to 37% compared to a conventional delivery method with a dedicated fleet.

[69] proposed a platform that in-store customers support company drivers and deliver online orders on their way to their destination. They developed a model considering two variants: 1) static: having complete knowledge about the request and delivery capacity, and

2) dynamic: having uncertainty about future requests. The in-store customers are shopping, the system can assign one or more online orders to the in-store customers, who will deliver on their way home. Although using in-store customers to deliver online orders is beneficial when the delivery system is under pressure, there are some limitations: 1) the coverage area of an in-store customer willing to make a delivery, and 2) some in-store customers may be reluctant to reveal their destinations since the systems' coverage depends on customer's destinations; thus, it creates uncertainty.

[70] studied public transport-based crowd-shipping for sustainable city logistics. They evaluated both the economic and environmental impacts of a crowd-shipping delivery system on the city of Rome, Italy. They proposed a platform for passengers as crowd-shippers to do a delivery job (pick-up and drop-off) using the public transportation system and some automated parcel lockers located in transit stations or their surroundings. They evaluated the costs and pollution that delivery jobs produce if they are completed by regular delivery cars. Their results show that if such a platform is implemented in Rome, it will reduce 239 kg of particulates (emissions) per year. However, they refer to some operational challenges that should be considered, including technical requirements such as parcel lockers' location and size and coordination between shippers.

[71] proposed a public transport-based crowd-shipping model in which travellers deliver packages using public transportation systems, e.g., subway and bus lines. They designed a system including several locations for pick-up/drop-off boxes outside the public transport network named satellite. Some sites within the network for entering/exiting the packages to the system are called PT (public transport) connections. Boxes are supposed to be carried by passengers from satellites to PT connections and then delivered to the final destinations from PT connections to satellites, and finally, customers come and pick their packages up.

This research is closely related to the literature on crowd-shipping, which attempts to match drivers with package delivery requests. It is also related to the literature on two-sided markets, with the difference of the additional player in on-demand delivery markets.

2.6 Transportation research using LP and ILP

Linear Programming (LP) and Integer Linear Programming (ILP) have been widely applied in engineering [72, 73, 74, 75, 76, 77], especially transportation systems, to optimize various operational aspects. [78] proposed a novel approach to last-mile delivery (LMD) challenges in urban areas through a crowdsourced model using parcel lockers. This approach leverages the crowd for LMD, utilizing parcel lockers as exchange points to minimize trip detours and enhance geographical coverage. To optimize the location of parcel lockers and the assignment of delivery tasks, the authors developed an Integer Linear Programming (ILP) model. This model facilitates efficient job allocation to crowdshippers and strategic parcel locker placement, aiming to increase delivery rates and reduce operational costs. The study's findings suggest that enabling joint delivery with a minimal number of strategically located parcel lockers can significantly improve the success rate of deliveries. The "joint delivery" refers to a delivery task being completed by more than one crowdshipper. This process involves using parcel lockers as intermediate exchange points, where one crowdshipper picks up the parcel from the origin, drops it at a parcel locker, and another crowdshipper retrieves it from the locker to deliver it to the final destination. This method minimizes trip detours, improves geographical coverage, and increases delivery success rates.

[79] presented an innovative demand-driven approach for shared mobility operations, integrating machine learning and mathematical programming. It specifically employs a deep Q-learning model for system performance optimization, addressing real-time demand, service rebalance, and charging station use. Additionally, the study explores the application of Integer Linear Programming (ILP) for solving complex vehicle routing problems in high-capacity ride-pooling systems, enhancing route efficiency and operational efficacy. This combination of

ILP and machine learning showcases a significant advancement in optimizing shared mobility systems, particularly in real-world applications like New York City's case study.

[80] proposed an innovative approach to optimizing ride assignments in ride-sharing systems using Integer Linear Programming (ILP). It addresses the computational challenges of existing batching-based methods by introducing a learning model to efficiently prune the search space for ILP, thus enhancing both efficiency and efficacy. This approach, termed Learn2Pool, leverages pointer networks for learning the priority order of ride requests, significantly reducing the computational expense associated with ILP optimizations. The experimental results demonstrate Learn2Pool's superior performance in balancing efficacy and efficiency over traditional methods, offering practical solutions for real-world ride-sharing challenges.

[81] explored the concept of fairness in income distribution for drivers in ride-hailing platforms such as Uber and Lyft using Integer Linear Programming (ILP). It aims to balance the income among drivers over time, considering the inherent inequality and potential discrimination within these platforms. By implementing ILP models, the study seeks to ensure that drivers receive equitable income proportional to their activity on the platform, thus addressing critical issues such as driver exploitation and income disparity. This approach marks a significant step towards achieving fairness in dynamic and complex matching markets like ride-hailing services.

[82] focused on equitable work distribution among couriers in the food delivery industry using Integer Linear Programming (ILP). It addresses the challenge of ensuring fair order assignments among gig economy couriers, contrasting with the traditional goal of minimizing total delivery time or cost. The study introduces a multi-objective ILP model that aims at balancing workload fairly among couriers while also considering efficiency metrics. The model efficiently solves small to medium-sized problems and uses a Variable Neighbourhood Search (VNS) algorithm for larger datasets, demonstrating the practical applicability of

combining ILP with advanced heuristics to achieve fairness in dynamic and competitive market conditions.

In conclusion, Linear programming and Integer Linear programming are indispensable tools for optimization in various domains. LP provides solutions to continuous optimization problems, while ILP extends this capability to handle discrete decision variables. These optimization techniques have been extensively studied and applied in diverse fields, demonstrating their versatility and effectiveness in solving complex decision-making problems [83]. However, alternative optimization techniques include Non-Linear Programming (NLP), which handles problems with non-linear relationships, and Dynamic Programming (DP), used for optimization problems that can be broken down into simpler sub-problems. Additionally, metaheuristic methods like Genetic Algorithms or Simulated Annealing [84] offer solutions for complex problems where methods like LP or ILP may struggle due to non-convexity or multiple local optima. Throughout this thesis, LP and ILP serve as essential tools for addressing the specific challenges of pricing and delivery assignments, demonstrating their relevance in solving complex logistics problems.

Chapter 3

Methodology

3.1 Overview

This chapter outlines the methodology for optimizing pricing and matching strategies in three-sided on-demand delivery platforms, focusing on interactions among customers, suppliers, and drivers. It describes the model structure, including operational elements such as pickup, preparation, and delivery times, alongside utility functions that capture economic and operational satisfaction for all players. A comprehensive mathematical formulation integrates key variables, parameters, and constraints to balance platform profitability and market equilibrium. The chapter concludes with a heuristic solution algorithm, utilizing linearization and step-by-step procedures to address the complexities of the optimization problem, setting the stage for the empirical analysis in the following chapter.

3.2 Model structure

Consider a set of three players in an on-demand delivery platform: customers, suppliers, and crowd-sourced drivers, presented by sets I, J, and K, respectively (Figure 3.1). The three players create a network $G(N, A)$ with node set $N = \{I, J, K\}$ and arc set $A = \{K \times J, J \times I\}$ that connects every driver node to every supplier node, and every supplier node to every customer node. Time is discretized into same-length epochs, and a framework is proposed to match and price the three players in each epoch. The primary decision variable is x_{ijk}, equal to 1 if customer i places an order from supplier j and is to be delivered by driver k.

3.2.1 Pickup, preparation, and delivery times

This section expresses the operational conditions of the proposed match and price model as a set of constraints. Although the platform strictly chooses and displays the promised delivery time for each potential order, the total waiting time depends on matching drivers to orders

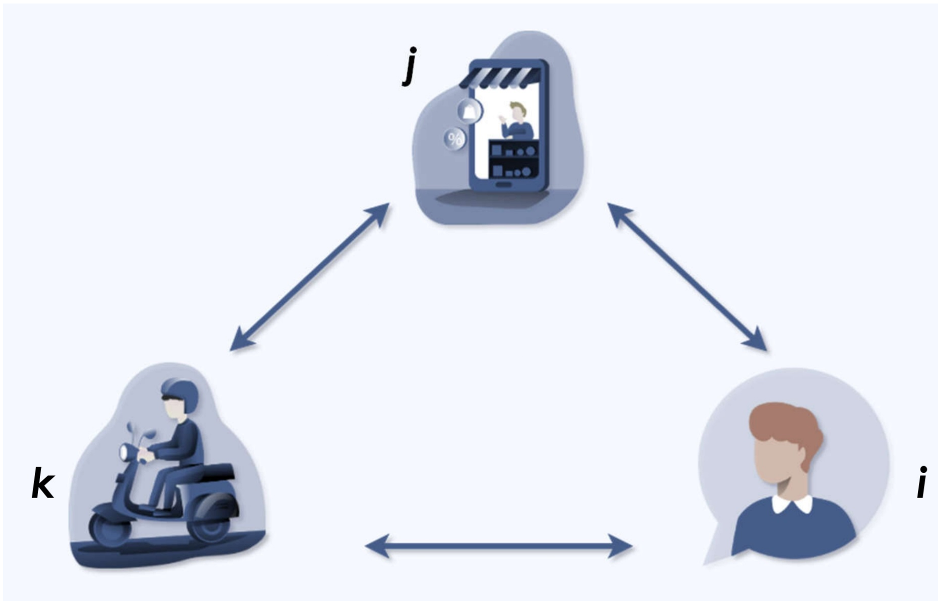


Figure 3.1: The three players forming the market

(between customers and suppliers). The waiting time consists of three parts: i) pickup time from the driver k's location to supplier j expressed as t_{kj}, ii) a potential *preparation time* at the supplier's location until the product is ready, and iii) delivery from the supplier j to the customer k expressed as t_{ji}. The concept of these three components of time is displayed in Figure 3.2 .

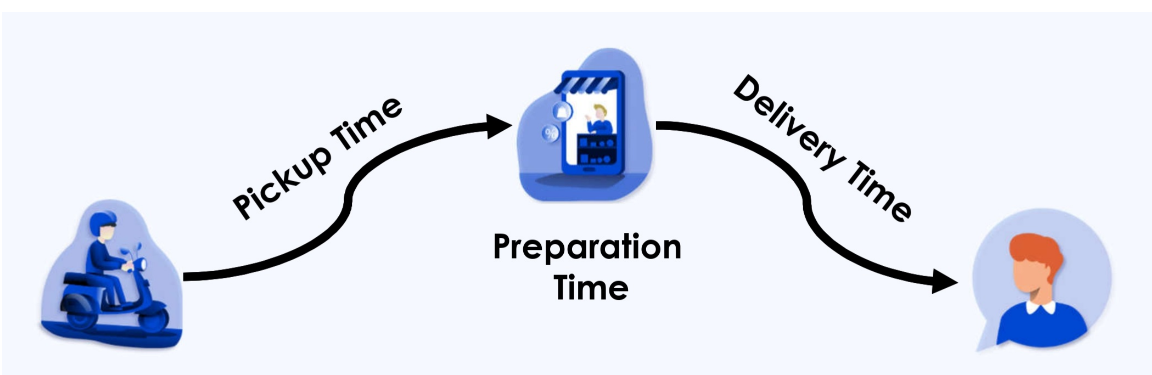


Figure 3.2: The components of waiting time

The preparation time typically occurs delivering of customized perishables such as food.

It can be expressed as the average waiting time of a queue system that receives a given number of orders and has a finite number of servers for preparation. Each supplier's average waiting time is considered proportional to the number of orders received in each epoch and the previously accepted orders in the queue. Assuming that supplier j has O_j (number of current orders) in the queue, the average preparation time of supplier j is

$$R_j = \mu(O_j + \sum_{ik} x_{ijk}), \qquad \forall j \in J \qquad 3.1$$

where μ is the average time per order and $\sum_{ik} x_{ijk}$ is the number of newly received orders.

Supplier orders enter the preparation queue when the order is received. Thus, the preparation time and pickup time always overlap unless the driver is already present at their assigned supplier location, which would make the pickup time zero. In general, when $t_{kj} > R_j$, the customer does not experience an explicit preparation time because the driver is en-route to the supplier location during this time. In contrast, when $t_{kj} < R_j$, the driver waits at the supplier $t_{kj} - R_j$ time units until the order is ready for delivery. In fact, the preparation time affects delivery schedules, leading to two possible scenarios:

i. Driver arrives at the supplier but has to wait for the order to become ready for picking-up (Figure 1.2(a)).

ii. The order is ready and the supplier is waiting for the driver to pick up (Figure 1.2(b)).

Figure 1.2 shows the two possible scenarios. Following this logic, the total waiting time between customer i and supplier j is

$$T_{ijk} = \max(\mu(O_j + \sum_{ik} x_{ijk}), t_{kj}) + t_{ji}. \qquad 3.2$$

3.2.2 Players' utilities

Before examining player utilities in the three-sided market model, utility is defined from both economic and transportation standpoints. Utility is a measure of the satisfaction, benefit, or value derived from the consumption of goods and services in exchange for a specific cost [85][86]. In economic terms, utility is defined as the measure of satisfaction or benefit derived from consuming goods or services [87]. In the context of transportation economics, utility often refers to the satisfaction or benefits a user gains from choosing a specific mode of transport, considering factors like cost, time, and convenience [88]. In the model, the utility for each player—customers, suppliers, and drivers—is quantified as their perceived value and satisfaction in engaging with the platform. Customers' utility might involve evaluating price, quality, and delivery time, while suppliers and drivers assess profitability and cost-benefit ratios.

Customers pay a fee for access to suppliers and delivery services. Suppliers also pay a fee for posting their products on the platform and benefiting from the provided delivery system. Drivers earn a wage for offering their delivery service. The platform's objective is to maximize profit by setting optimal fees and rewards and matching drivers with existing order requests between customers and suppliers.

The proposed matching and pricing strategies express the reactive behaviour of the three players in terms of the utilities they obtain from the platform. It is assumed that each supplier sells a single product and that each customer i's valuation of supplier j's product is v_{ij}. This valuation (v_{ij}), which is different for each customer, is the outcome of several factors, such as price, quality, and type of supplier. For instance, in an online food delivery system, there are several types of restaurants, including steakhouses, fast foods, vegetarian, seafood, Asian foods, etc.

The price of the product sold by supplier j is p_j, which is preset by the supplier and often equivalent to the supplier's in-store price. The platform charges a rate α of the product's price as the delivery fee, therefore requesting customers to pay $(1+\alpha)p_j$ for supplier j's product. This linear pricing scheme is common in practice, where delivery fees and tips are proportional to the total purchase price.

Customers experience the discomfort of waiting, which is the time between placing an order and receiving it at the door. The waiting time is displayed for each supplier when customers browse. Customers are probably less likely to order from suppliers with excessively long waiting times. Let T_{ijk} be the displayed (promised) waiting time for customer i who wishes to place an order with supplier j. The actual waiting time is not always the same as the promised waiting time due to various reasons such as logistical challenges or unpredictable traffic conditions. It was assumed that the platform ensures the actual delivery time is always less than the promised delivery time as a gesture of goodwill and to support customer loyalty. The utility of customer i ordering from supplier j on the platform is as follows, where η is a marginal waiting cost (a multiplier to transform time to value/cost).

$$U^c_{ijk} = v_{ij} - (1+\alpha)p_j - \eta T_{ijk}. \qquad 3.3$$

Suppliers gain revenue from selling their products on the platform. Let U^s_{ijk} be the profit (utility) of supplier j, which the platform charges a proportion β of the order price p_j. An alternative simpler pricing structure is to charge each supplier a fixed fee for using the platform. Given its ability to impose customer-specific fees rather than a single fee for all, the focus is placed on the former variable pricing structure. Let x_{ijk} be a binary decision variable equal to one if driver k is assigned to pick up an order from supplier j and deliver it to customer i. The profit of supplier j per each placed order (when x_{ijk}=1) can be defined as the revenue less the cost of using the platform, expressed as follows where v_j is the expected valuation of the market for suppliers, which is similarly assigned with a random number:

$$U^s_{ijk} = p_j(1 - \beta) - v_j. \tag{3.4}$$

The drivers earn a wage from the platform for delivering each order. It is assumed that the wage per delivery is a proportion of the product's price, as this pricing structure is common in food delivery platforms such as Uber Eats, which request customers to pay a tip proportional to the product's price. Let γ be the wage proportion indicating that if a product is priced p_j by supplier j, a driver receives γp_j, where $\gamma > 0$, for delivering that product. It is assumed that each product is delivered in a single trip, with no pooling of products during delivery. Each driver k expects an earning of at least v_k from the platform as v_k represents the opportunity earning of the driver k from an outside job option. A driver partakes in the delivery service if the earning exceeds the outside option. Thus, the utility of a driver with valuation v_k (similarly assigned with a random number for simplification) on the platform per each delivery job is as follows, where ω is a multiplier to transform time to value/cost:

$$U^d_{ijk} = \gamma p_j - v_k - \omega T_{ijk} \tag{3.5}$$

where the first term is their earnings per delivery and the second term is the opportunity cost. Moreover, the third term illustrates how delivery time affects the utility of drivers. The longer the waiting time, the more gas the driver will be required to consume, which will negatively impact the driver's utility and the decision to accept or reject an order. Other costs that can be considered in equation 3.5 are the operation and maintenance costs of the vehicle, which are left for future research.

3.2.3 Overview of mathematical notation of model

The following subsections provide a comprehensive overview of the model's notations, detailing the importance of each variable and parameter in the model context. This foundational understanding is essential for exploring the strategic pricing and matching mechanisms that the platform can utilize to enhance its service delivery and operational efficiency. Table 3.1 shows the notation of the variables and parameters used in the model.

Table 3.1: Overview of mathematical model notation

Notation	Description
U^c_{ijk}	Utility of a customer i
U^s_{ijk}	Utility of a supplier j
U^d_{ijk}	Utility of a driver k
v_{ij}	Valuation of the supplier j for the customer i
v_j	Valuation of the market for the supplier j
v_k	Valuation of the market for the driver k
p_j	Product price of the supplier j
O_j	Current orders of the supplier j
R_j	Preparation time of supplier j
α_i	Delivery fee paid by the customer i to the platform
β_j	Commission fee paid by the supplier j to the platform
γ_k	Wage paid by the platform to the driver k
η	Customer's marginal waiting time cost
ω	Driver's marginal waiting time cost
t_{ji}	Delivery time from supplier j to customer i
t_{kj}	Pickup time from driver k to supplier j
T_{ijk}	Total waiting time (which is equal for customer and driver)
x_{ijk}	Decision variable (binary) for the order of customer i from supplier j delivered by driver k

U^c_{ijk} : The utility of a customer i when choosing a supplier j and matched with a driver k. This utility captures the customer's satisfaction or net benefit from the transaction, factoring in the product's value, the delivery fee, and the cost of waiting. The model assumes customers consider the product's price, the additional delivery cost, and the inconvenience of waiting against the inherent value they place on the product from a specific supplier.

U^s_{ijk} : The utility of a supplier j when an order is placed by customer i and delivered by driver k. It represents the profit or net benefit the supplier gains from selling through the platform after accounting for the product's price and the commission fee paid to the platform. This parameter is crucial for understanding how suppliers evaluate their participation in the platform, balancing the opportunity for increased sales against the costs associated with platform commissions.

U^d_{ijk} : The utility of a driver k for delivering an order from supplier j to customer i. It captures the driver's earnings from the delivery job after considering their opportunity cost (the value of alternative job opportunities) and the cost associated with the delivery time. This utility reflects the attractiveness of delivery jobs to drivers, incorporating the platform's payment, the driver's alternative earnings, and the impact of delivery times on driver satisfaction.

v_{ij}, v_j, v_k : Valuations are assigned by customer i to supplier j, by the market to supplier j, and by the market to driver k, respectively. These valuations mean the expectation of the market for each player. These valuations reflect the perceived quality or desirability of the suppliers and drivers on the platform, influencing customer choices and market dynamics. They are foundational for modelling how different actors in the market perceive each other and make decisions based on these perceptions.

p_j, O_j, R_j : The price of the product offered by the supplier j, the current orders of the supplier j in the current epoch which is to be calculated, and the preparation time of supplier j, respectively. These parameters are essential for calculating the costs associated with each transaction, including how the price affects customer utility, how existing orders impact delivery times, and how preparation times can affect the overall efficiency of the supply chain.

α, β, γ : Fees and commissions charged by the platform: α is the delivery fee paid by the customer, β is the commission fee paid by the supplier, and γ is the wage paid to the driver. These rates are critical for understanding the platform's revenue model and how it balances the interests of all parties involved to maximize participation and profitability.

η, ω : The marginal waiting time cost for customers (η) and drivers (ω). These parameters quantify the cost of waiting, reflecting how delays in the delivery process detract from the utility of customers and drivers. They are crucial to optimizing the matching and scheduling process to minimize waiting times and enhance customer and driver satisfaction.

t_{ji}, t_{kj}, T_{ijk} : These represent the delivery time from supplier j to customer i, the pickup time from driver k to supplier j, and the total waiting time for an order involving customer i, supplier j, and driver k. Let T_{ijk} represent the total waiting time, starting from the moment a customer places an order and the platform assigns it to a driver. This time is identical for both the driver and the customer, as it accounts for the maximum value between the pickup time and the preparation time, plus the delivery time from the supplier to the customer's door. Effectively, the customer's waiting time corresponds to the time taken for the driver to travel from their initial point to the final destination, including any waiting time at the supplier.

x_{ijk} : A decision variable indicating whether driver k is assigned to deliver an order from supplier j to customer i. This binary variable is central to the model's matching algorithm, determining the optimal allocation of drivers to orders to maximize the platform's profit while considering the utilities of all participants.

3.2.4 Non-linear integer programming formulation

This section introduces the non-linear integer programming model, an essential advancement in analyzing three-sided on-demand delivery services. It formalizes customer, supplier, and driver interactions using the previously established mathematical framework. By incorporating each participant's utilities and decision-making parameters, the model provides a structured methodology for optimizing the platform's profit while ensuring that the utility of all three parties is satisfied and maximizing the number of participants in the market.

The following mathematical model maximizes the platform's revenue, which satisfies a set of conditions. The model is presented as

$$\max_{\alpha,\beta,\gamma,x_{ijk}} \pi = \sum_{i,j,k} x_{ijk} p_j (\alpha + \beta - \gamma) \quad 3.6$$

$$\text{s.t.} \quad \sum_{j,k} x_{ijk} \leq 1 \qquad \forall i \in I \quad 3.7$$

$$\sum_{i,j} x_{ijk} \leq 1 \qquad \forall k \in K \quad 3.8$$

$$x_{ijk} U^c_{ijk} \geq U^c_{ij'k'} - M(1 - x_{ijk}) \qquad \forall i \in I, j \in J, j' \in J, k \in K, k' \in K' \quad 3.9$$

$$\sum_{j,k} x_{ijk} U^c_{ijk} \geq 0 \qquad \forall i \in I \quad 3.10$$

$$\sum_{i,j} x_{ijk} U^d_{ijk} \geq 0 \qquad \forall k \in K \quad 3.11$$

$$\sum_{i,k} x_{ijk} U^s_{ijk} \geq 0 \qquad \forall j \in J \quad 3.12$$

$$\alpha, \beta, \gamma \geq 0 \quad 3.13$$

$$\alpha, \beta, \gamma < 1 \quad 3.14$$

$$\alpha + \beta > \gamma \quad 3.15$$

$$x_{ijk} = \{0, 1\} \qquad \forall i \in I, j \in J, k \in K \quad 3.16$$

The objective function (3.6) maximizes the platform's profit by optimizing the pricing parameters and matching decisions between customers, suppliers, and drivers. It focuses on determining the ideal delivery fees, commission fees, and wages. The objective function works by calculating the total profit based on successfully matched orders between customers, suppliers, and drivers. It sums up all the matched orders and multiplies them by the product price. The resulting value is then adjusted by adding the delivery fee (α) and the commission fee (β) that the platform receives from customers and suppliers, respectively. From this, the driver's wage (γ) is deducted, reflecting the platform's payment to the drivers.

Constraint (3.7) regulates that each customer can only place an order for one supplier, while constraint (3.8) allows drivers to accept only one order from a supplier for a specific customer. Constraint (3.9) ensures that the model finds the highest utility for each customer by comparing all available options. The use of M, a large number, helps enforce this selection by deactivating the constraint for non-chosen suppliers and drivers (i.e., when x_{ijk}=0) and keeping it active for the chosen ones (when x_{ijk}=1). The big-M technique ([89, 90]) guarantees that the model efficiently finds the maximum utility for each customer, which is explained with an example in the following.

The constraints (3.10) and (3.11) ensure that the utility functions of drivers and customers are positive. Constraint (3.12) regulates a positive utility for suppliers, which guarantees suppliers' income. Finally, α , β, and γ should be positive to make revenue for drivers and suppliers (constraint (3.13) and (3.14)), constraint (3.15) guarantees the [positive] profit for the platform, and constraint (3.16) expresses that the x_{ijk} can only be 0 or 1.

As explained, M is a large constant commonly used in optimization models to ensure the correct enforcement of the constraints. To clarify how the constraint works, consider the example where a customer has two utility options: $U_{111} = 100$ and $U_{112} = 90$. The decision variables are x_{111} and x_{112}, where one will be 1 (chosen) and the other 0 (not chosen). The constraint is written as:

$$x_{111} \cdot U_{111} \geq U_{112} - M \cdot (1 - x_{111})$$

With $U_{111} = 100$ and $U_{112} = 90$, the constraint becomes:

$$x_{111} \cdot 100 \geq 90 - M \cdot (1 - x_{111})$$

If $x_{111} = 1$ (indicating option 1 is chosen), the constraint simplifies to:

$$1 * 100 \geq 90 - M \cdot (1 - 1)$$

$$100 \geq 90$$

Which holds true, meaning option 1 is selected. To further clarify, consider the scenario where the algorithm tests x_{112}, meaning it evaluates option 2 for the customer. The constraint in this case would be written as:

$$x_{112} \cdot U_{112} \geq U_{111} - M \cdot (1 - x_{112})$$

With $U_{112} = 90$ and $U_{111} = 100$, the constraint becomes:

$$x_{112} \cdot 90 \geq 100 - M \cdot (1 - x_{112})$$

Now, if $x_{112} = 0$ (since option 2 will not be chosen due to lower utility), the equation simplifies to:

$$0 * 90 \geq 100 - M \cdot (1 - 0)$$

$$0 \geq 100 - M$$

For example, if $M = 10^{18}$, this becomes:

$$0 \geq 100 - 10^{18}$$

which simplifies to:

$$0 \geq -10^{18}$$

This is obviously true. The large M ensures that when $x_{112} = 0$, the constraint is always satisfied, meaning the algorithm correctly disregards option 2 in this case. In this way, the algorithm is forced to find the highest possible utility for each customer by ensuring that only the best matches (those with the highest utility) are selected, while lower-utility options are automatically excluded.

3.3 Solution algorithm

The solution to the proposed model is challenging to solve straight away due to the nonlinearity of constraints (3.9) to (3.11). Therefore, there is a need to linearize those equations and develop a heuristic method to break the model down into simpler sub-problems and transform those constraints into linear ones, which is easier to solve. Consequently, first, a linearization technique is introduced to change the equations to a linear system; then, a detailed description of a heuristic algorithm is given below. It divides the model into two parts: the Matching module, which tries to match the customers and suppliers with drivers based on their utilities, and the Pricing module, which tries to optimize the model's pricing parameters to maximize the platform's profit. In addition, another heuristic method is developed only for the matching module, dividing it into two parts, including the Ordering module and the Delivering module. Finally, a differentiated pricing parameters policy is proposed to make the model more realistic, which is explained in detail in the related section. For example, the algorithm assigns a distinct delivery fee, α_i, to each customer based on their waiting time. This means that customers located further from the supplier are charged a higher delivery fee, reflecting the longer distance and increased service time required.

3.3.1 Linearization of the matching problem

As mentioned earlier, the equations (3.9) to (3.11) in the first part of the solution algorithm, Matching module, are nonlinear, which is difficult to solve; thus, there is a need for linearization of these constraints. For a better understanding of the nonlinearity, the constraint (3.10) is expanded:

$$\begin{aligned}
&\sum_{j,k} x_{ijk} U^c_{ijk} \\
&= \sum_{j,k} x_{ijk}(v_{ij} - (1+\alpha)p_j - \eta T_{ijk}) \\
&= \sum_{j,k} x_{ijk}(v_{ij} - (1+\alpha)p_j - \eta(\max(\mu(O_j + \sum_{ik} x_{ijk}), t_{kj}) + t_{ji}))
\end{aligned}$$

When $t_{kj} \geq \mu(O_j + \sum_{i,k} x_{ijk})$, the constraint is equal to $\sum_{j,k} x_{ijk}(v_{ij} - (1+\alpha)p_j - \eta(t_{kj} + t_{ji}))$ which is linear. But, when $t_{kj} < \mu(O_j + \sum_{i,k} x_{ijk})$, the constraint is equal to:

$$\sum_{j,k} x_{ijk}(v_{ij} - (1+\alpha)p_j - \eta(\mu(O_j + \sum_{ik} x_{ijk}) + t_{ji})) \tag{3.17}$$

$$= \sum_{j,k} (x_{ijk} v_{ij} - x_{ijk}(1+\alpha)p_j - \eta\mu O_j x_{ijk} - \eta\mu x_{ijk} \sum_{i,k} x_{ijk} - \eta t_{ji} x_{ijk}) \tag{3.18}$$

All the above terms are linear except the fourth one, $\eta\mu x_{ijk} \sum_{i,k} x_{ijk}$, which is nonlinear as the decision variable, x_{ijk}, is multiplied by itself. In fact, the term, $x_{ijk} \sum_{i,k} x_{ijk}$ makes the problem non-linear. There are different ways to change a nonlinear equation to a linear one. The linearization technique introduced by [91] and used by [92] is applied by replacing each $x_{ijk} \sum_{i,k} x_{ijk}$ with a new variable Z_{ijk}. This modifies the constraint to:

$$\sum_{j,k}(x_{ijk}v_{ij} - x_{ijk}(1+\alpha)p_j - \eta\mu O_j x_{ijk} - \eta\mu Z_{ijk} - \eta t_{ji}x_{ijk}) \geq 0 \quad \forall i \in I \qquad 3.19$$

which can be written in the simplified form:

$$(v_{ij} - (1+\alpha)p_j - \eta(\mu O_j + t_{ji}))\sum_{j,k} x_{ijk} - \eta\mu \sum_{j,k} Z_{ijk} \geq 0 \qquad \forall i \in I \qquad 3.20$$

For $\forall i \in I$, $\forall j \in J$, and $\forall k \in K$ a set of new constraints are applied to the model to impose $Z_{ijk} = x_{ijk}\sum_{i,k} x_{ijk}$:

$$Z_{ijk} \leq x_{ijk} \cdot M \qquad \forall i \in I, j \in J, k \in K \qquad 3.21$$

$$Z_{ijk} \leq \sum_{i,k} x_{ijk} \qquad \forall i \in I, j \in J, k \in K \qquad 3.22$$

$$Z_{ijk} \geq \sum_{i,k} x_{ijk} + (x_{ijk} - 1) \cdot M \qquad \forall i \in I, j \in J, k \in K \qquad 3.23$$

$$Z_{ijk} \geq 0 \qquad \forall i \in I, j \in J, k \in K \qquad 3.24$$

Where M is a large number (at least greater than $\sum_{i,k} x_{ijk}$). The constraints (3.9) and (3.11) also have the same situation since the decision variable, x_{ijk} is multiplied by the utility functions (customer and driver utility functions), including the waiting time, T_{ijk} which has the x_{ijk} inside. Therefore, there is the same term, $x_{ijk}\sum_{i,k} x_{ijk}$ in all three nonlinear constraints, and this linearizaion technique ($Z_{ijk} = x_{ijk}\sum_{i,k} x_{ijk}$) works for all three nonlinear constraints.

Consequently, the first part of the algorithm is rewritten for the case when $t_{kj} < \mu(O_j +$

$\sum_{ik} x_{ijk}$), leading to $T_{ijk} = \mu(O_j + \sum_{i,k} x_{ijk}) + t_{ji}$ as follows:

$$\max_{x_{ijk}} \pi = \sum_{i,j,k} x_{ijk} p_j (\alpha + \beta - \gamma) \tag{3.25}$$

$$\text{s.t.} \quad \sum_{j,k} x_{ijk} \leq 1 \qquad \forall i \in I \tag{3.26}$$

$$\sum_{i,j} x_{ijk} \leq 1 \qquad \forall k \in K \tag{3.27}$$

$$(v_{ij} - (1+\alpha)p_j - \eta(\mu O_j + t_{ji}))x_{ijk} - \eta\mu Z_{ijk} \geq U^c_{ij'k'} - M(1 - x_{ijk}) \quad \forall i \in I, j, j' \in J, k \in K, k' \in K' \tag{3.28}$$

$$(v_{ij} - (1+\alpha)p_j - \eta(\mu O_j + t_{ji})) \sum_{j,k} x_{ijk} - \eta\mu \sum_{j,k} Z_{ijk} \geq 0 \qquad \forall i \in I \tag{3.29}$$

$$(\gamma p_j - v_k - \omega\mu O_j - \omega t_{ji}) \sum_{i,j} x_{ijk} - \omega\mu \sum_{i,j} Z_{ijk} \geq 0 \qquad \forall k \in K \tag{3.30}$$

$$\sum_{i,k} x_{ijk} U^s_{ijk} \geq 0 \qquad \forall j \in J \tag{3.31}$$

$$Z_{ijk} \leq x_{ijk} \cdot M \qquad \forall i \in I, j \in J, k \in K \tag{3.32}$$

$$Z_{ijk} \leq \sum_{i,k} x_{ijk} \qquad \forall i \in I, j \in J, k \in K \tag{3.33}$$

$$Z_{ijk} \geq \sum_{i,k} x_{ijk} + (x_{ijk} - 1) \cdot M \qquad \forall i \in I, j \in J, k \in K \tag{3.34}$$

$$Z_{ijk} \geq 0 \qquad \forall i \in I, j \in J, k \in K \tag{3.35}$$

$$x_{ijk} = \{0, 1\} \qquad \forall i \in I, j \in J, k \in K \tag{3.36}$$

The linearization technique and decomposition approach (dividing the model into two modules, as detailed in the following section) play distinct roles in the proposed model. Linearization serves as a technique to enhance the representation and solvability of a specific class of mixed-integer linear programs. The model becomes more compatible with standard optimization methods by converting non-linear components into a linear format, thereby improving computational efficiency. However, the primary algorithmic contribution lies in the decomposition approach, which further increases computational power by breaking down complex problems into smaller, more manageable sub-problems. This decomposition enables the algorithm to address large-scale, three-sided market scenarios effectively.

3.3.2 Heuristic matching and pricing algorithm

Since the solution to equations mentioned above (3.25 to 3.36) is not straightforward due to the constraints' non-linearity, the formulation can be divided into two parts using a heuristic method. The first part involves fixing α, β, and γ and using only x_{ijk} for decision variables; then, nonlinear equations can be transformed into linear equations by a linearization technique explained in the section 3.3.1. Afterward, the linearized equations can be solved, and x_{ijk}'s are calculated. The second part assumes that all the x_{ijk} variables are determined and fixed, with α, β, and γ as variables to be derived. Notably, some constraints are deleted in each part due to their fixed values since x_{ijk} or α, β, and γ are not considered decision variables. In this heuristic solution algorithm, the two parts are repeatedly solved, and their answers are sent back and forth until the optimal solution is found.

The flowchart of the solution algorithm is displayed in Figure 3.3, demonstrating two parts, including the Matching and Pricing modules. These modules obtain and send their answers to each other to maximize the platform's profit. This cycle continues so that the difference in the platform's profit generated from the two parts does not exceed a specific threshold. Importantly, a hat sign was used on the parameters in Figure 3.3 to indicate that these values are fixed. For example, in the Pricing module, as the matches are already obtained from the previous step, x_{ijk} is displayed as $\hat{x}_{ijk}$.

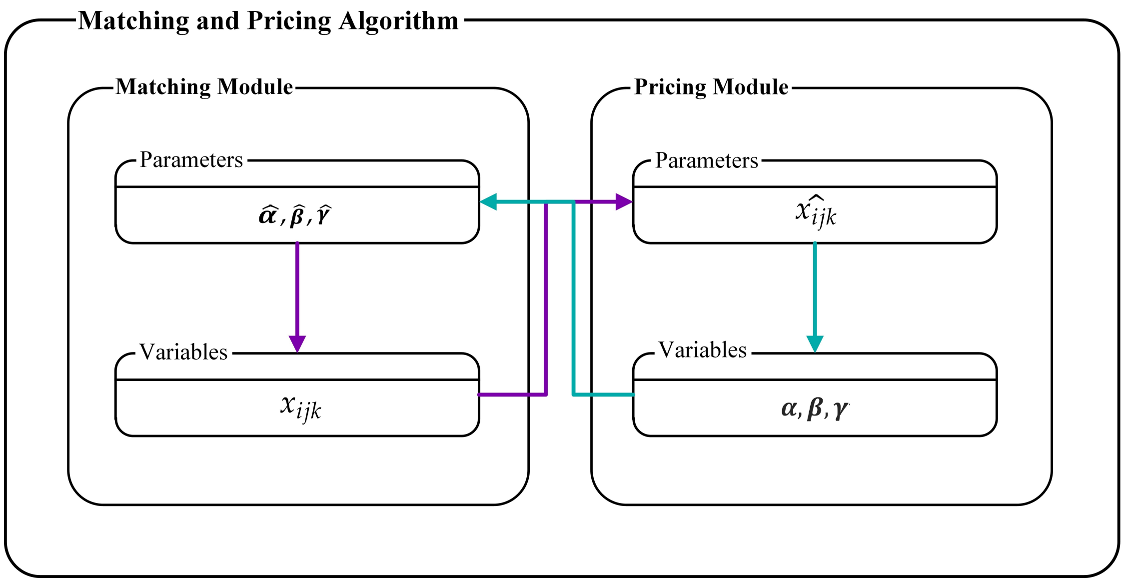


Figure 3.3: The flowchart of heuristic matching and pricing algorithm

3.3.2.1 The matching module

The Matching problem is responsible for finding the matches between customers, suppliers, and drivers. In the Matching step, customers select their desired suppliers to place orders, and orders are matched with drivers. This process is done based on the three players' utilities. As this step is related to finding the matches, the matching module considers α, β, and γ (pricing parameters) as fixed by initial values; accordingly, the related constraints are deleted. Therefore, the objective function and the remaining constraints are presented as:

$$\max_{x_{ijk}} \pi = \sum_{i,j,k} x_{ijk} p_j (\hat{\alpha} + \hat{\beta} - \hat{\gamma}) \qquad 3.37$$

$$\text{s.t.} \quad \sum_{j,k} x_{ijk} \leq 1 \qquad \forall i \in I \qquad 3.38$$

$$\sum_{i,j} x_{ijk} \leq 1 \qquad \forall k \in K \qquad 3.39$$

$$x_{ijk}\hat{U^c_{ijk}} \geq \hat{U^c_{ij'k'}} - M(1 - x_{ijk}) \qquad \forall i \in I, j \in J, j' \in J, k \in K, k' \in K' \qquad 3.40$$

$$\sum_{j,k} x_{ijk}\hat{U^c_{ijk}} \geq 0 \qquad \forall i \in I \qquad 3.41$$

$$\sum_{i,j} x_{ijk}\hat{U^d_{ijk}} \geq 0 \qquad \forall k \in K \qquad 3.42$$

$$\sum_{i,k} x_{ijk}\hat{U^s_{ijk}} \geq 0 \qquad \forall j \in J \qquad 3.43$$

$$x_{ijk} = \{0, 1\} \qquad \forall i \in I, j \in J, k \in K \qquad 3.44$$

However, the equations remain nonlinear because the decision variable, x_{ijk}, is multiplied by utilities in constraints (3.40) to (3.42), where utility functions have T_{ijk}, and T_{ijk} has the variable x_{ijk}. To ease the solving of the equations, they will be changed to linear ones, presented in the section 3.3.1. The linear equation system can be solved using algorithms such as the Simplex method [93].

The Matching Module pairs customers with suppliers and drivers. This step, pivotal for the platform's functionality, operates on a framework considering all players' utility and optimizes these pairings, ensuring that each matched order is feasible and favourable for customers, suppliers, and drivers alike. In this module, the algorithm works with fixed values for the pricing parameters, allowing it to focus primarily on matchmaking without the added complexity of variable pricing.

3.3.2.2 The pricing module

The Pricing problem's responsibility is focusing on maximizing the platform's profit by setting the optimal values for pricing parameters, α, β, and γ. This part of the solution algorithm assumes that all delivery jobs are determined and drivers are matched with orders. It means all x_{ijk}'s are determined (considered as fixed values), and the algorithm tries to find the optimal value of α, β, and γ as the decision variables to maximize the platform's profit. By assuming x_{ijk}'s as fixed values, R_j and T_{ijk} (equations (3.1) and (3.2)) are turned to fixed terms since they include x_{ijk}. It should be noted that, in this part of the algorithm, x_{ijk}'s are treated as fixed values and are denoted as $\hat{x}_{ijk}$ in the notation, as they are fixed values. Eventually, the objective function and remaining constraints are expressed in the following:

$$\max_{\alpha,\beta,\gamma} \pi = \sum_{i,j,k} \hat{x}_{ijk} p_j (\alpha + \beta - \gamma) \tag{3.45}$$

$$\text{s.t.} \quad \sum_{j,k} \hat{x}_{ijk} U^c_{ijk} \geq 0 \qquad \forall i \in I \tag{3.46}$$

$$\sum_{i,j} \hat{x}_{ijk} U^d_{ijk} \geq 0 \qquad \forall k \in K \tag{3.47}$$

$$\sum_{i,k} \hat{x}_{ijk} U^s_{ijk} \geq 0 \qquad \forall j \in J \tag{3.48}$$

$$\alpha, \beta, \gamma \geq 0 \tag{3.49}$$

$$\alpha, \beta, \gamma < 1 \tag{3.50}$$

$$\alpha + \beta > \gamma \tag{3.51}$$

The Pricing Module's task is to set these parameters to maximize platform profit while maintaining market competitiveness and operational sustainability. For instance, α is a direct influencer of customer demand. A higher α could potentially increase the platform's immediate profit; however, it must be cautiously balanced against the risk of reducing order volume due to increased cost to the customer. Likewise, β needs to be set at the right level so that the platform keeps a good share of the revenue from each order without making it unattractive for suppliers by charging them excessively high commission fees. Finally, γ, the wage for drivers, is critical to maintaining a satisfied and motivated fleet of drivers, and must be optimized to be competitive enough to attract drivers and maintain a robust supply without deteriorating the platform's profit margins.

3.3.2.3 The heuristic matching module

In the existing Matching module, the complex challenge of simultaneously finding suitable matches among customers, suppliers, and drivers is addressed. Given a scenario with 20 customers, 4 suppliers, and 20 drivers, the module must sift through an extensive array of $20 \times 4 \times 20 = 1600$ feasible solutions, which demands processing large matrices using an Integer Linear Programming (ILP) model. To streamline this process, it is proposed to divide the Matching module into two more manageable components: Ordering and Delivering. In real-world conditions, when a customer wants to place an order from a supplier, the customer first selects the desired supplier based on some criteria. At this point, drivers do not influence the process, and only the matching between the customer and the supplier takes place. After placing an order from a supplier by the customer, the platform matches the order with a driver. Therefore, these two steps—ordering and delivering—can be separated (Figure 3.4).

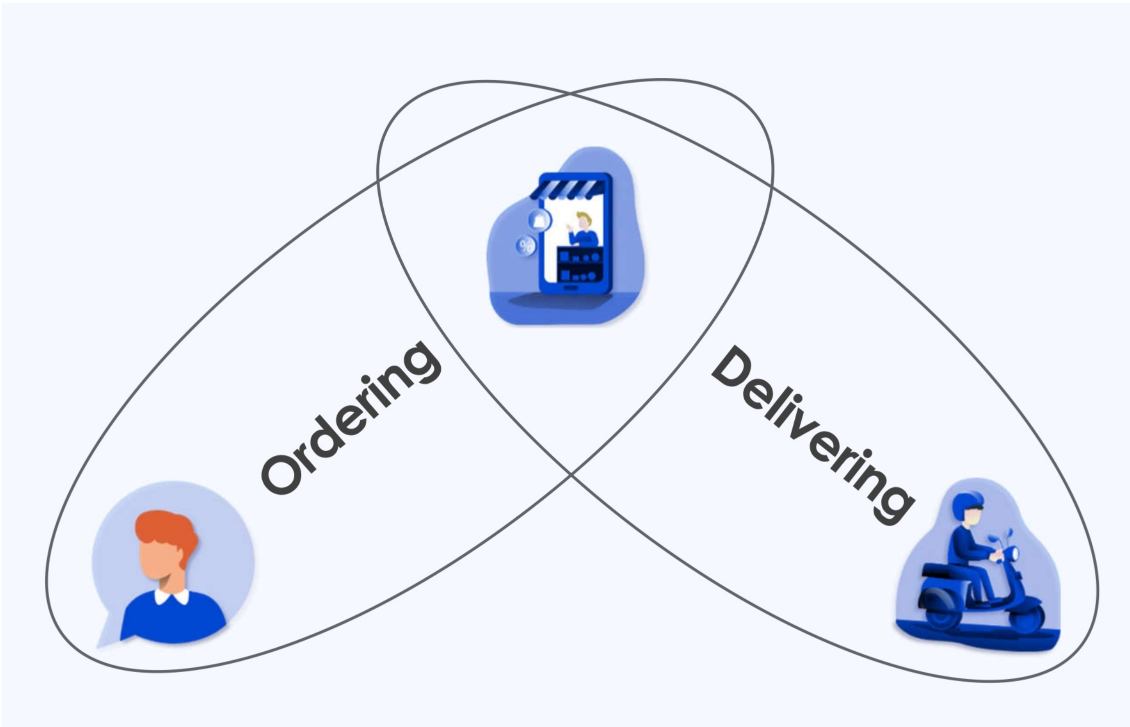


Figure 3.4: The heuristic matching module's components

The Ordering Module: In this step, customers select their preferred suppliers, as explained earlier. This step is simplified by focusing solely on the travel time between customers and suppliers. This travel time is used to calculate the T_{ij}, which is essentially a measure of the match's suitability. The value of T_{ij} is determined by selecting the greater of the supplier's preparation time (R_j) and the delivery time (t_{ji}) between the customer and the supplier. Once T_{ij} is established, the utilities of both customers and suppliers can be quickly calculated. At this stage, the objective function only considers two pricing parameters: α and β. This process leads us to identify the initial set of **orders** – the matches between customers and suppliers among only $20 \times 4 = 80$ possible ones. Thus, in this step, only the variables x_{ij}'s are considered.

The Delivering Module: A list of orders (customer-supplier matches) is already available following the completion of the ordering module. Now, drivers' utilities are calculated, and the objective function considering all pricing parameters (α, β, and γ) pairs these orders with available drivers. This step involves another round of matching, this time focusing on aligning the orders with the drivers to ensure efficient delivery. Once the final matches are achieved, the T_{ijk} values are updated to reflect the new customer-supplier-driver configurations. Therefore, in this step, the variables x_{ijk}'s are considered. Considering 20 orders obtained from the ordering module and 20 drivers, there are only $20 \times 20 = 400$ feasible solutions, which is extremely less than $20 \times 4 \times 20 = 1600$ possible initial answers.

The iterative nature of this revised approach significantly enhances its effectiveness. After completing the Delivering module, the process cycles back to the Ordering module. This time, however, the updated T_{ijk} values are used to find potentially more optimized pairings. This iteration –alternating between ordering and delivering– continues until the algorithm finds the most suitable matches across all three parties involved: customers, suppliers, and drivers.

Figure 3.5 shows the flowchart of heuristic matching and pricing algorithm, including this new heuristic for matching modules (ordering and delivering modules). In the following, a summary captures the essence of the proposed Ordering and Delivering modules in a structured and transparent manner.

Ordering module:

1. Calculate $T_{ij} = R_j + t_{ji}$,

2. Calculate utilities of customers and suppliers, U^c_{ij} , U^s_{ij} using T_{ij},

3. Solve the objective function, $\max_{x_{ij}} \pi = \sum_{i,j} x_{ij} p_j(\hat{\alpha} + \hat{\beta})$, to find orders (desired suppliers for customers),

4. Update suppliers' queue, O_j, and suppliers' preparation time, R_j, using determined orders,

Delivering module:

5. Calculate utilities of drivers, U^d_{ijk}, using T_{ij},

Table 3.2: Formulations for ordering and delivering modules

Ordering	Delivering
$\max_{x_{ij}} \pi = \sum_{i,j} x_{ij} p_j (\hat{\alpha} + \hat{\beta})$ $\text{s.t.} \sum_{j} x_{ij} \leq 1 \forall i \in I$ $x_{ij} \hat{U^{c}_{ij}} \geq \hat{U^{c}_{ij'}} - M(1 - x_{ij})$ $\sum_{j} x_{ij} \hat{U^{c}_{ij}} \geq 0 \forall i \in I$ $\sum_{i} x_{ij} \hat{U^{s}_{ij}} \geq 0 \forall j \in J$ $x_{ij} = \{0,1\} \forall i \in I, j \in J$	$\max_{x_{(ij)k}} \pi = \sum_{(i,j),k} x_{(ij)k} p_j (\hat{\alpha} + \hat{\beta} - \hat{\gamma})$ $\text{s.t.} \sum_{i,j} x_{(ij)k} \leq 1 \forall k \in K$ $\sum_{k} x_{(ij)k} \leq 1 \forall ij \in IJ$ $\sum_{i,j} x_{(ij)k} \hat{U^{d}_{ijk}} \geq 0 \forall k \in K$ $x_{(ij)k} = \{0,1\} \forall ij \in IJ, k \in K$

6. Solve objective function, $\max_{x_{ijk}} \pi = \sum_{i,j,k} x_{(ij)k} p_j (\hat{\alpha} + \hat{\beta} - \hat{\gamma})$, to find matches between orders and drivers (then, t_{kj}'s can be determined),

7. Update T_{ijk} using final matches, x_{ijk}'s: $T_{ijk} = \max(R_j, t_{kj}) + t_{ji}$,

8. If the best matches are found, stop the algorithm; otherwise, $T_{ij} = T_{ijk}$, and go back to line 2.

‘

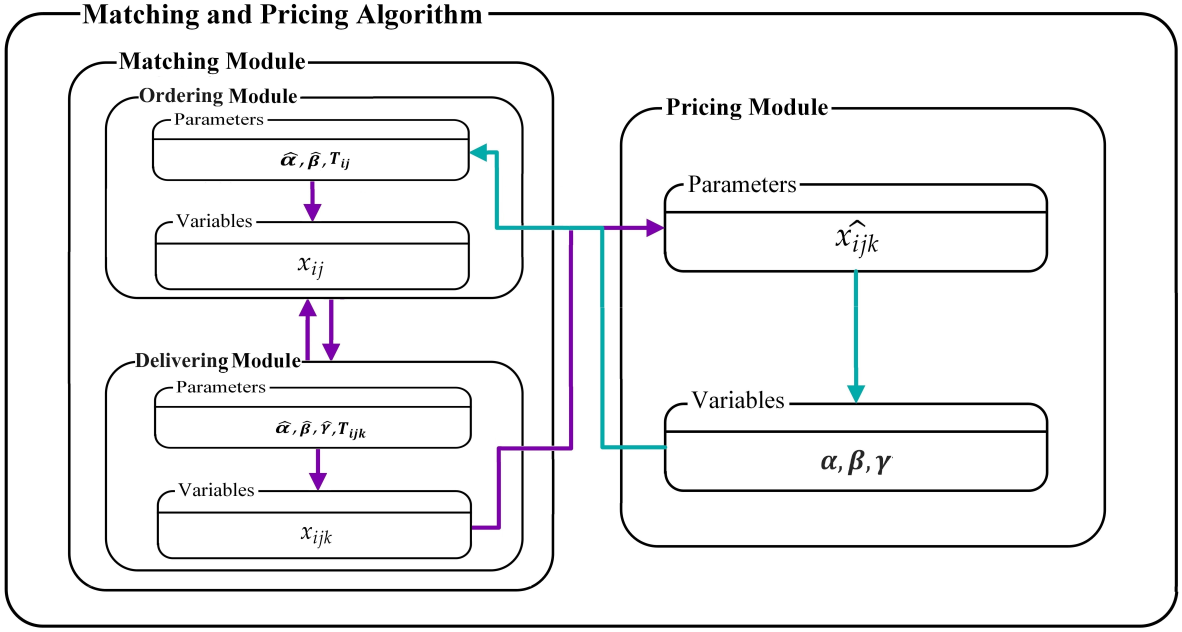


Figure 3.5: The flowchart of improved heuristic matching and pricing algorithm

By breaking down the complex Matching module into these two sequential yet interlinked modules, the efficiency of the matching process is enhanced. This approach simplifies the computational burden and allows for a more dynamic and responsive matching system, adapting to changes and optimizing matches more effectively and realistically.

3.3.2.4 Differentiated pricing parameters

In the model's current framework, considering fixed pricing parameters for all instances of players does not reflect real-world characteristics. For example, a fixed delivery fee, α, for all customers, regardless of their different waiting times, may not accurately provide fairness. Specifically, customers with longer waiting times are likely to value the delivery service more and have to pay a higher delivery fee due to the longer delivery time that the driver has to travel. This suggests a need for a differentiated α that increases with the waiting time, ensuring the pricing module captures the true value customers place on faster delivery (Figure 3.6).

Similarly, a fixed γ for all drivers ignores the complexities of their experiences. Drivers engaged in longer delivery routes confront more operational challenges and costs, justifying a higher wage. Therefore, adjusting γ in proportion to the delivery time can more accurately align driver incentives with their efforts, promoting a fairer and more efficient distribution of orders within the platform. On the other hand, there is a need to differentiate the β parameter for restaurants, particularly in terms of their operational characteristics, such as average preparation times and order volumes. This differentiation plays a crucial role in managing and balancing order loads across the network of restaurants.

A pivotal element of this strategy is the introduction of a constraint that guides the determination of β for each restaurant. Specifically, the constraint ensures that restaurants with longer preparation times and higher order volumes are considered for higher commission fees. This approach strategically influences the market dynamics. It inherently discourages the platform from accepting new orders from these busy restaurants, as the increased commission fees reduce the overall profitability or attractiveness of orders from these establishments. Consequently, this leads to redistributing new orders towards less busy restaurants with shorter preparation times. In effect, the model manipulates the market to prevent overburdening restaurants with already high order volumes and lengthy preparation times, thereby promoting a more balanced and efficient allocation of orders across the network. By differentiating β in this manner and applying the related constraint, the pricing model can dynamically determine appropriate commission fees for each restaurant, enabling a balanced and efficient delivery service that adapts to the evolving operational landscape.

These refinements in modelling α, β, and γ will enhance the model's realism, allowing for more effective pricing strategy that better reflect the dynamics of the three-sided market in on-demand delivery services. In the refined model, a more dynamic approach to the calculation of utility parameters is introduced by considering α_i for each customer i and γ_k for each driver k, which are now directly influenced by waiting time. This change allows for a more precise representation of utility, where α_i increases with longer customer waiting times, T_{ijk}, reflecting higher delivery fees for longer waits. Similarly, γ_k is adjusted upward for drivers as the delivery time increases, ensuring fairer compensation for longer or more complex delivery routes. This modification ensures that the pricing and wage structures within the model are more closely aligned with the real-time demands and efforts of the market participants. Thus, the modified utilities and pricing formulations are as follows.

$$U_{ijk}^{c} = v_{ij} - (1 + \alpha_i)p_j - \eta T_{ijk} \quad 3.52$$

$$U_{ijk}^{s} = p_j(1 - \beta_j) - v_j \quad 3.53$$

$$U_{ijk}^{d} = \gamma_k p_j - v_k - \omega T_{ijk} \quad 3.54$$

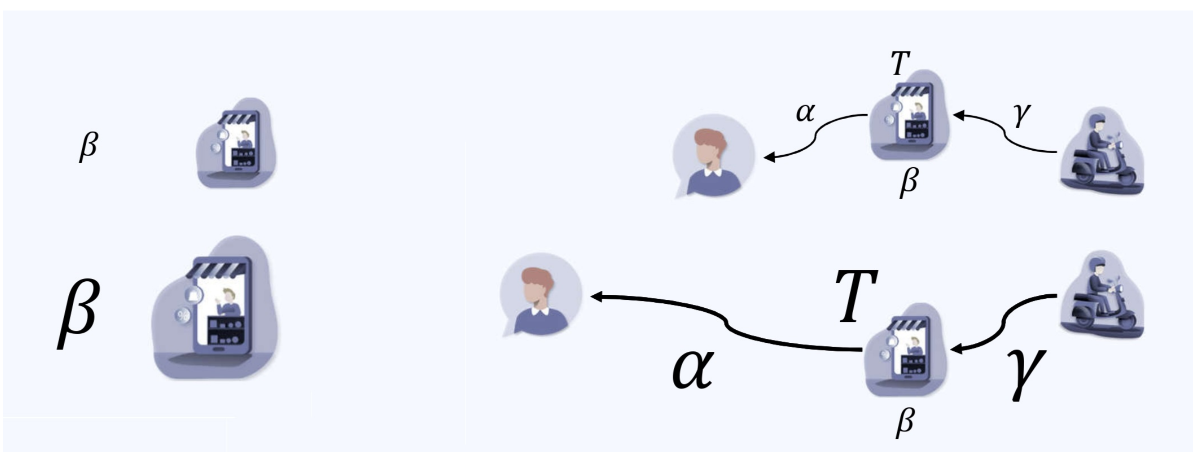


Figure 3.6: Differentiated pricing parameters

Chapter 4

Experiments and Analysis

4.1 Overview

This section details the implementation of the solution algorithm for the three-sided on-demand delivery platform. MATLAB was utilized, benefiting from its powerful Integer Linear Programming (ILP) and Linear Programming (LP) functions. The solution algorithm consists of two modules: the Matching module, where customers, suppliers, and drivers are optimally paired, and the Pricing module, which optimizes the pricing parameters. The combination of ILP (for solving the Matching module) and LP (for solving the Pricing module) functions allows us to effectively solve the complexity of the problem, resulting in a Mixed-Integer Linear Programming (MILP) approach.

4.2 Empirical results

This section presents the detailed results of the experiments conducted on the proposed three-sided on-demand delivery platform using simulated data, including the location of customers, suppliers, and drivers. The process begins by specifying the travel time calculations, followed by the presentation of numerical results that highlight the platform's performance, with a focus on key metrics such as platform profits and pricing parameters. The findings from these analyses provide a comprehensive understanding of the platform's operational capabilities.

4.2.1 Travel time calculation

A critical aspect of the modelling is accurately simulating the travel times between different players within the three-sided market—specifically, the drivers and restaurants and between the restaurants and customers. To achieve this, the ArcGIS Network Analyst toolbox is used, an advanced GIS tool that facilitates comprehensive spatial analysis and routing solutions. The specific tool used in the Network Analyst Toolbox is the OD (Origin-Destination) Cost

Matrix tool. This tool calculates the costs of time and distance between multiple origins and destinations within a network [94, 95]. The OD Cost Matrix is a fundamental concept in GIS and transportation planning, providing a method to evaluate travel costs between origins and destinations within a network. This matrix is instrumental in logistics and route optimization as it calculates the least-cost paths along network lines based on travel time, distance, or other cost metrics. The result is a matrix that lists the cost from each origin to each destination, which can be critical for making decisions about resource allocation, delivery routing, and network analysis [96].

Using the OD Cost Matrix, a detailed matrix of travel times was generated, providing a realistic basis for optimizing the matching and delivery processes within the simulated model. The location data for customers, suppliers, and drivers, along with the road network of the study area, are imported into the GIS toolbox. The road network is categorized into four types: Highway, Arterial, Collector/Distributor, and Local roads. Maximum speed limits are assigned to each road type within the OD Cost Matrix to generate more realistic travel times. This classification and speed specification ensures that the travel time calculations reflect the actual conditions drivers would encounter on different types of roads, enhancing the accuracy of the model's output.

4.2.2 Numercial results

A set of data points was generated, including 20 points for customers, 4 for suppliers, and 20 for drivers, to implement and test the model. With this data, essential parameters of the model, such as v_{ij}, v_j, and v_k were initialized with random values in the range of 1 to 100. Calculating the exact values of these parameters is outside the scope of this research, but they can be calculated using methods such as Discrete Choice Modeling.

The Matching and Pricing modules are implemented as separate functions. In the

Matching module, pricing parameters (α, β, and γ) are considered fixed values, and the function finds optimal matches (x_{ijk}'s) among the customers, suppliers, and drivers using the ILP toolbox, thereby calculating the resulting platform profit. The Matching module does this duty using two modules: the Ordering and Delivering modules. The Ordering module tries to match the customers with suppliers based on utility, sending the orders to the Delivery module to match the orders with drivers. These two modules send their answers back and forth till the best matches (x_{ijk}'s) are found. These matches are then passed to the pricing function.

Subsequently, the Pricing module considered the matched x_{ijk}'s as fixed values and pricing parameters as decision variables. Using the LP toolbox, this function determined the optimal pricing parameters, maximizing the platform's profit. This process of exchanging answers between the two modules continued iteratively until convergence. The stopping criterion is set such that the difference between the profits obtained from the Matching and Pricing modules does not exceed 1 dollar.

The developed MATLAB code executed both parts of the algorithm, allowing back-and-forth communication between the modules, ultimately converging to the best value for the platform's profit. Figure 4.1 displays the location of example data produced randomly in a road network for testing the model. The following results can be considered a one-minute epoch of a platform like Uber Eats. This means that twenty customers trying to place their orders in a one-minute epoch out of a whole day are simulated using the model.

Table 4.1: The parameters value of the first results

α_0	β_0	γ_0	η	μ	ω	p_1	p_2	p_3	p_4	O_1	O_2	O_3	O_4
0.35	0.25	0.35	0.45	3	0.20	23	20	15	17	3	0	1	2

Table 4.1 shows the values of the parameters of the first produced results, which are

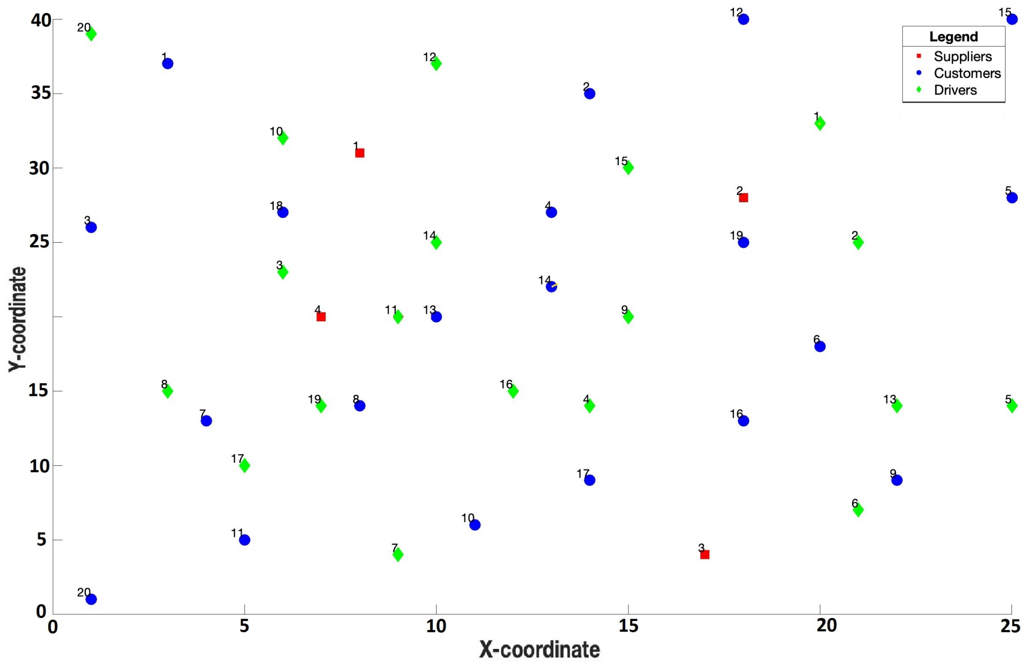


Figure 4.1: The location of customers, suppliers, and drivers

entirely random but in a rational range. α_0, β_0, and γ_0 are the initial values for pricing parameters that will be optimized in the algorithm. Also, p_j and O_j are each supplier's product price and current number of orders (queue), respectively.

Figure 4.2 depicts the results achieved using the specified parameter settings. Simultaneously, the chart provides a view of the profits obtained from both parts of the algorithms and the pricing parameters. The left displays the platform's profit values, and the right presents the values of the pricing parameters. The two solid lines represent the profit generated by two modules, Matching (blue line) and Pricing (green line). Also, the three dashed lines represent pricing parameters, red, light blue, and purple line for α, β, and γ, respectively. The diagram displays the average values for pricing parameters, while different pricing parameters were considered for each player instance in section 3.3.2.4. Thus, the diagram represents α as an average value of α_1 to α_{20} (20 customers), β as an average value of β_1 to β_4 (4 restaurants), and γ as an average value of γ_1 to γ_{20} (20 drivers).

As described in the previous section, the solution algorithm resolves both the Matching and Pricing modules, yielding a profit value. The algorithm terminates when the difference between profits obtained from these modules is less than 1 dollar. As illustrated, 13 out of 20 orders are matched, the profits converged to \$279, and the average values of α, β, and γ reached 1.00, 0.48, and 0.41, respectively. Additionally, Figure 4.3 illustrates the matches, indicating that suppliers 1, 2, 3, and 4 received 4, 4, 5, and 0 orders, respectively.

The average delivery fee is set to 1.00 by the model, meaning that the platform charges the customers a delivery fee equal to the original product's price. This can be explained by two reasons: First, the model's objective function is to maximize the platform's profit; therefore, the platform increases the delivery fee to the maximum possible value, which is 1.00 (equal to the upper bound of pricing parameters in the pricing module's LP model). Secondly, in real-world conditions, online food delivery applications usually show higher prices for the foods rather than in-store prices to profit for themselves and also pay a wage to the drivers. Thus, the obtained delivery fee almost reflects real-world situations. In contrast, the average commission fee for the suppliers determined by the model is equal to 0.48, meaning around half of the product's price goes to the platform. This is again due to the model's objective function, which maximizes the platform's profit. Furthermore, drivers receive an average wage of 0.41, indicating that 41% of each product's price is paid to the driver. The details of the average wage is discussed in the following sections.

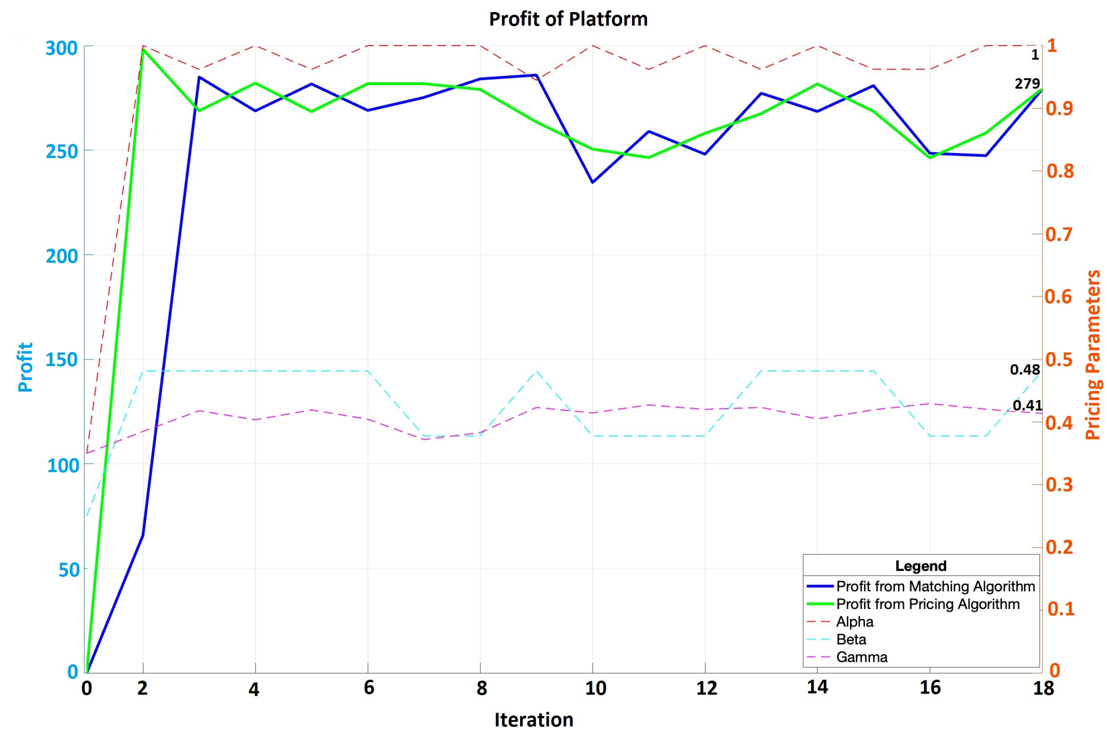


Figure 4.2: The result of profit and pricing parameters

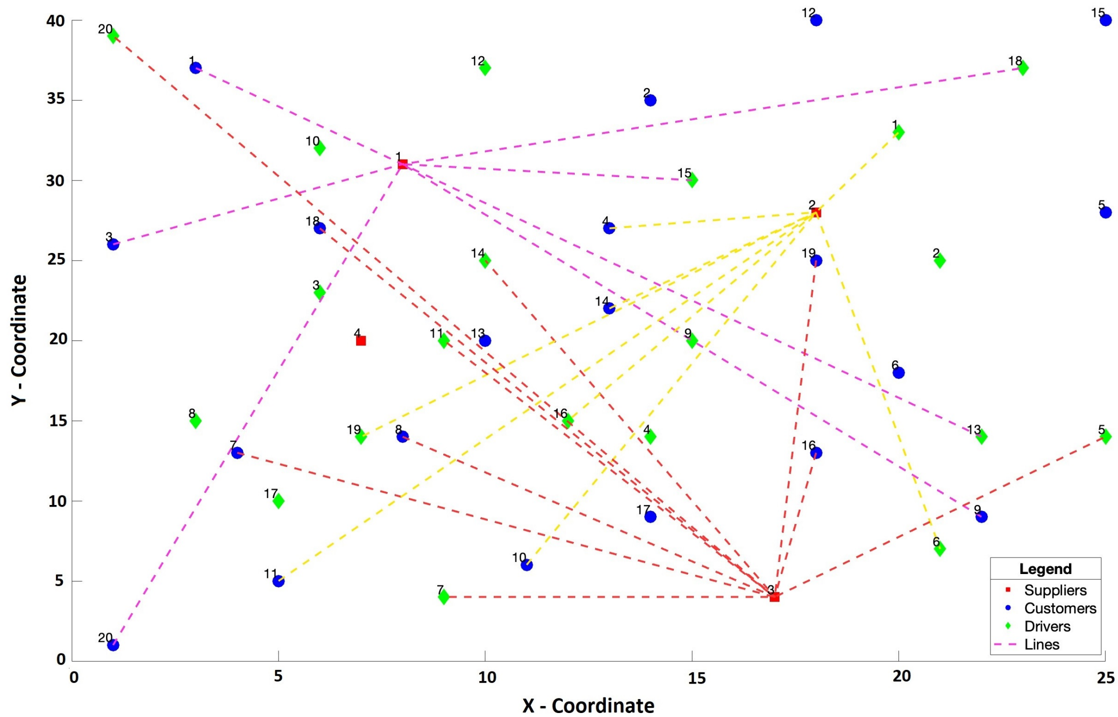


Figure 4.3: The matches (driver-supplier-customer)

For an experiment, the constraints on the pricing parameters' range were removed to observe how far the algorithm would go in maximizing the platform's profit by charging customers a delivery fee. Figure 4.4 displays the results of this test, with all other parameters being the same as those depicted in figure 4.2. As can be seen, both β and γ have the same values of 0.48 and 0.41, respectively. However, α reached 2.48, indicating that the algorithm charged customers two and a half times the original price of the product, which resulted in a profit of 650 dollars for the platform. Therefore, this restriction for pricing parameters seems necessary since people will only be willing to pay a certain amount based on how much they value the product.

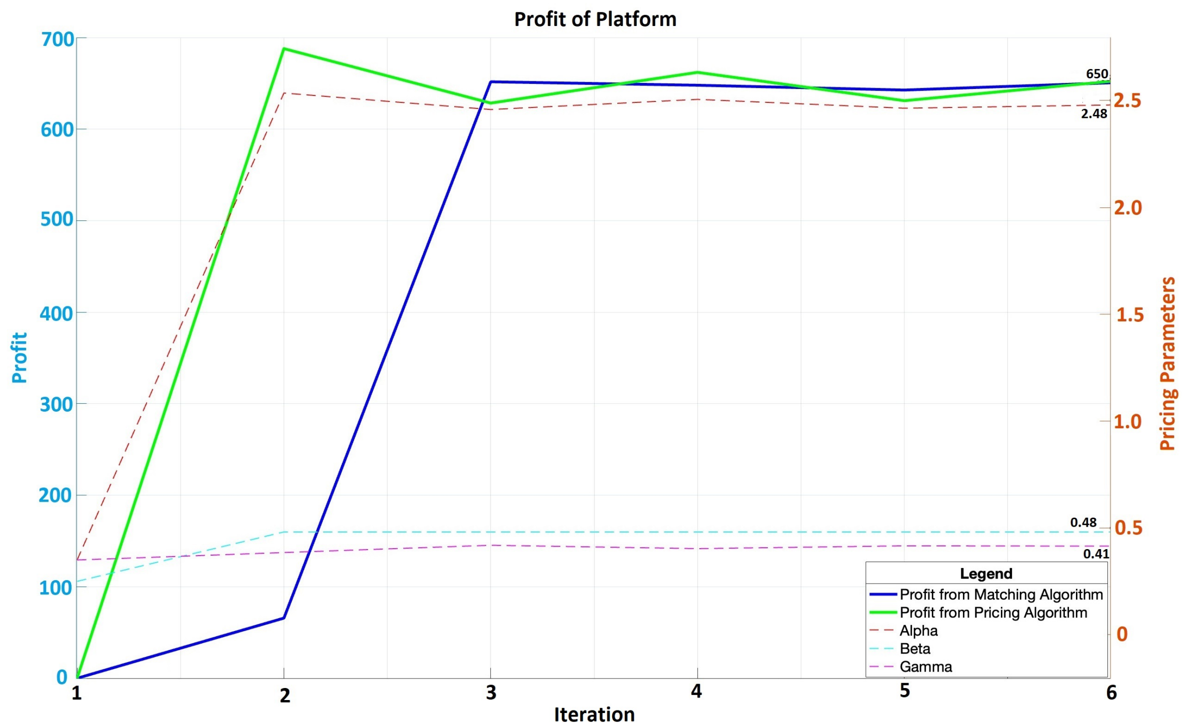


Figure 4.4: The result of profit without limitation for pricing parameters

4.3 Calibration

The calibration process aims to align model parameters with realistic market conditions in the on-demand delivery market. It involves adjusting the model to reflect observed operational data and fine-tuning elements such as driver availability, customer demand, and supplier capacity to match typical market behaviors. The following sections show that the model is calibrated effectively, as the delivery fee, commission fee, and driver wage closely align with real-world values. This calibration process ensures that the model can realistically simulate the dynamics encountered in actual delivery operations.

The calibration procedure involved setting key parameters—delivery fees, commission fees, and driver wages—to values that reflect real-world standards observed in on-demand delivery platforms. This process utilized industry benchmarks and available data to approximate these fees, ensuring the model accurately represents typical market conditions. Additionally, driver availability and customer demand patterns were adjusted based on observed fluctuations in similar platforms, allowing the model to simulate realistic operational dynamics. This calibration approach provides a more accurate reflection of the platform environment, enabling reliable assessment of the model's performance under practical conditions.

One limitation of the calibration exercise is that it relies on data samples collected from the app, which may not accurately reflect the full operational state of the entire system. Since calibration is based on a subset of data, it may miss differences in the larger system's dynamics, such as variations in driver availability, fluctuating customer demand, or changing supplier capacity. Additionally, there is no opportunity to access comprehensive order data from companies such as Uber Eats or DoorDash, which could have provided a more complete perspective on demand patterns and system behavior. This lack of access is also noted in Chapter 5, under the "Research limitations" section. Moreover, this calibration method does not account for real-time external factors such as traffic or weather, which could impact delivery and waiting times. Consequently, while calibration provides an approximation, it may not fully capture the real-world variability that affects on-demand delivery operations.

4.3.1 Delivery fee calibration

The calibration of the delivery fee is a critical step, ensuring that the model's assumptions and outcomes closely mirror the practical, real-world results in on-demand delivery services. The model strategically sets the average delivery fee at 1.00, a value chosen to maximize the platform's profit while mirroring the realistic pricing strategy prevalent in the industry. This fee aligns with the upper limit of the pricing parameters in the model's linear programming framework, thereby supporting the objective of enhancing platform profitability.

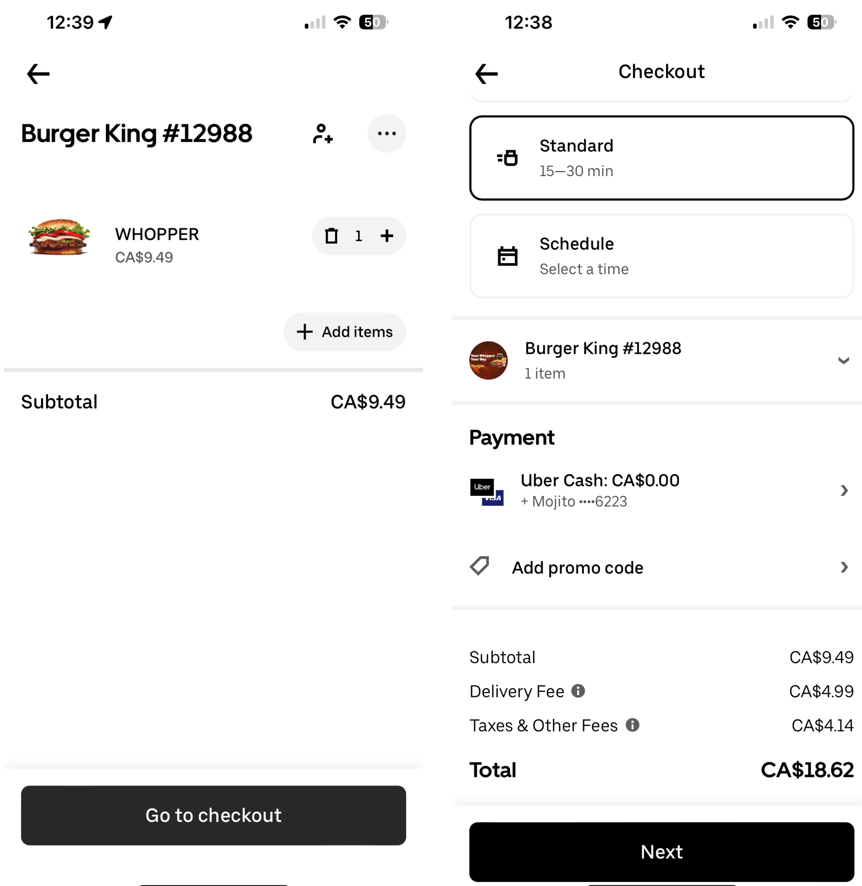
Figure 4.5 presents the delivery fee (α) calibration through a comparative analysis between the original (Figure 4.5(a)) and final product's price after adding the delivery fee in a real example of an online food order (Figure 4.5(b)). The original product price is 9.49, and after adding the delivery fee, it reaches 18.62, which is 0.96 times more than the original price (although the in-store price of that specific product is only 6.49). The model considered the final cost to be 1.00 times more than the original price for the customers. This comparison demonstrates that the modeled delivery fee accurately captures the typical pricing adjustments in real-world online food delivery platforms. The platforms often increase product prices to cover logistical costs, such as providing a resource to pay drivers' wages, and to ensure profitability.

4.3.2 Commission fee calibration

The commission fee in our model, represented by β, is set at 0.48 (Figure 4.2), equivalent to 48% of the product's price. This relatively high rate reflects a scenario in which the platform maximizes profitability while maintaining a competitive edge through high-value services provided to suppliers. To calibrate this approach, the real-world commission fees of leading delivery platforms, as reported in recent industry analyses ([97]), were referenced. The diversity of commission rates, ranging from 15% to 40% on platforms such as Uber Eats, GrubHub, and DoorDash (Table 4.2), illustrates that our 48% fee is close to the standard range of the industry, depending on the level of service and market strategy of each platform. The example of DoorDash, which extends up to 40% in commission fees under certain conditions, supports our model's use of a 48% fee under a specialized market scenario.

Table 4.2: Different delivery platforms' commission fees for suppliers

Delivery Platforms	**Uber Eats**	**GrubHub**	**DoorDash**
Commissions	15%-30%	15%-25%	15%-40%



(a) Original product's price

(b) Final product's price plus delivery fee

Figure 4.5: Calibration of α by comparing original product's price and final price by adding delivery fee.

4.3.3 Wage calibration

According to the results displayed in Figure 4.6, the average wage rate for drivers set by the model is 0.41 of the order amount. Screenshots from the Uber Eats driver app show that the app offers a wage rate similar to that of drivers. As shown in the Table 4.1, the product prices of four suppliers in this simulation are 23, 20, 15, and 17 dollars, with an average amount of 18.75. Thus, the wage calculated by the model would be $0.41 \times 18.75 = 7.66$, which is similar to the wage offered by the Uber Eats app for drivers based on the Figure 4.6.

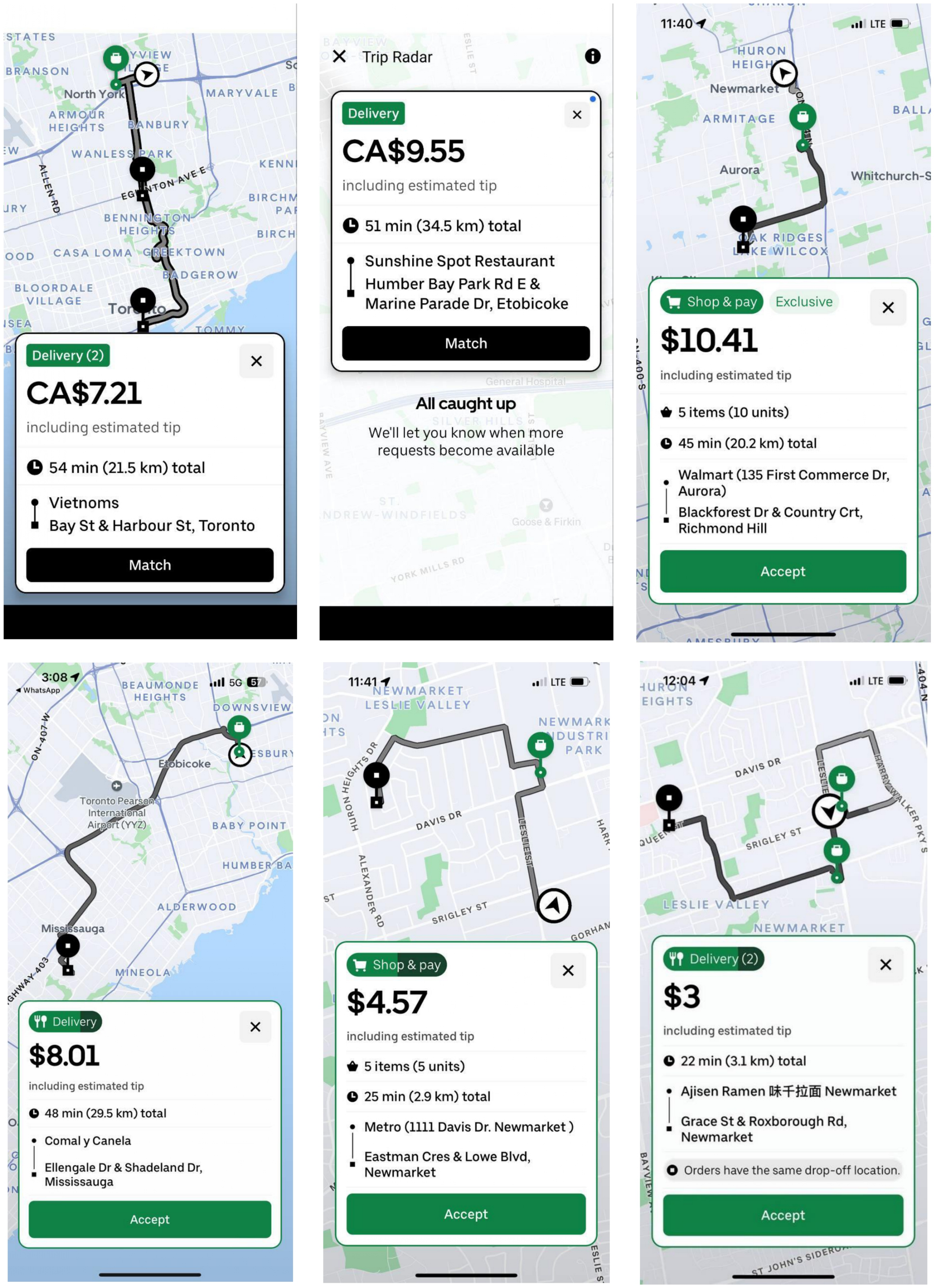


Figure 4.6: Calibration of the algorithm's wage by comparing with UberEats offered wages

This tight alignment between the simulated wage and the actual data reveals that the model accurately captures the wage-setting mechanisms typical in real-world on-demand delivery services. It highlights the algorithm's capability to replicate the pricing dynamics observed in the industry, reinforcing the model's accuracy and relevance.

4.3.4 Operational distances calibration

The model employs actual distance data between drivers and restaurants and between restaurants and customers, which vary from 3 to 36 kilometers for distances between drivers and restaurants and from 2 to 38 kilometers for distances between restaurants and customers. These distances reflect realistic travel ranges observed in urban and suburban areas where on-demand delivery services operate. In addition, the distances shown in the real-world delivery job examples (Figure 4.6) range from 3 to 34 kilometres, similar to the distances used in our model. By incorporating these actual distances, the simulated travel times and associated costs become representative of real-world conditions, providing a practical and reliable tool for decision-making. Calibrating the critical elements of the model demonstrates its practical applicability and supports its credibility.

4.4 Sensitivity analysis

Sensitivity analysis, a vital statistical tool in modeling, allows us to determine how different values of an independent variable influence a specific dependent variable under a set of assumptions. This analysis is particularly significant in simulation and forecasting models, as it aids in comprehending the model's robustness in diverse conditions [98]. By altering parameters, sensitivity analysis can specify which inputs substantially impact the outcome, revealing the most critical factors requiring close monitoring.

In this section, sensitivity analysis explores the stability and reliability of the algorithm's outputs by systematically varying the parameters η and ω, which are key factors in the model. This analysis is performed by holding η constant while varying ω, and then incrementally increasing η and repeating the process with ω. This approach generates a series of results, revealing how changes in these parameters influence the number of successful orders, the profit of the platform, and the pricing parameters. Table 4.3 shows the different result of platform's profit ($) by changing η (columns) and ω (rows).

This sensitivity analysis validates the model's capacity to handle realistic market fluctuations. It provides deep insights into the dynamics that control interactions within the three-sided market, ensuring the proposed model effectively demonstrates adaptability under diverse and fluctuating market conditions.

Table 4.3: Platform profit sensitivity to changes in η and ω

$\omega \setminus \eta$	**0**	**0.05**	**0.1**	**0.15**	**0.2**	**0.25**	**0.3**	**0.35**	**0.4**	**0.45**	**0.5**
0.00	431	431	431	431	431	407	431	431	356	341	359
0.05	288	288	288	306	436	436	436	372	339	399	382
0.10	286	287	287	303	384	384	344	401	293	370	357
0.15	269	238	238	233	303	318	353	320	254	312	300
0.20	198	235	235	153	180	180	271	203	216	279	286
0.25	191	41	41	41	41	41	166	97	107	186	181
0.30	22	96	96	98	101	101	37	37	37	71	155
0.35	41	20	20	20	20	20	48	48	120	97	99
0.40	19	39	39	N/A	39	39	71	71	N/A	116	N/A

4.4.1 Impact of η on platform's profit and pricing parameters

One such parameter is η, which is a significant factor in the utility of customers (Equation (3.3)). By varying the value of η, changes were observed in the generated profits and pricing parameters.

4.4.1.1 Impact of η on platform's profit

Figure 4.7 provides insights into how adjustments to η impact the platform's profit. This figure shows the result of platform's profit by changing the amount of η when ω is 0.15. As η

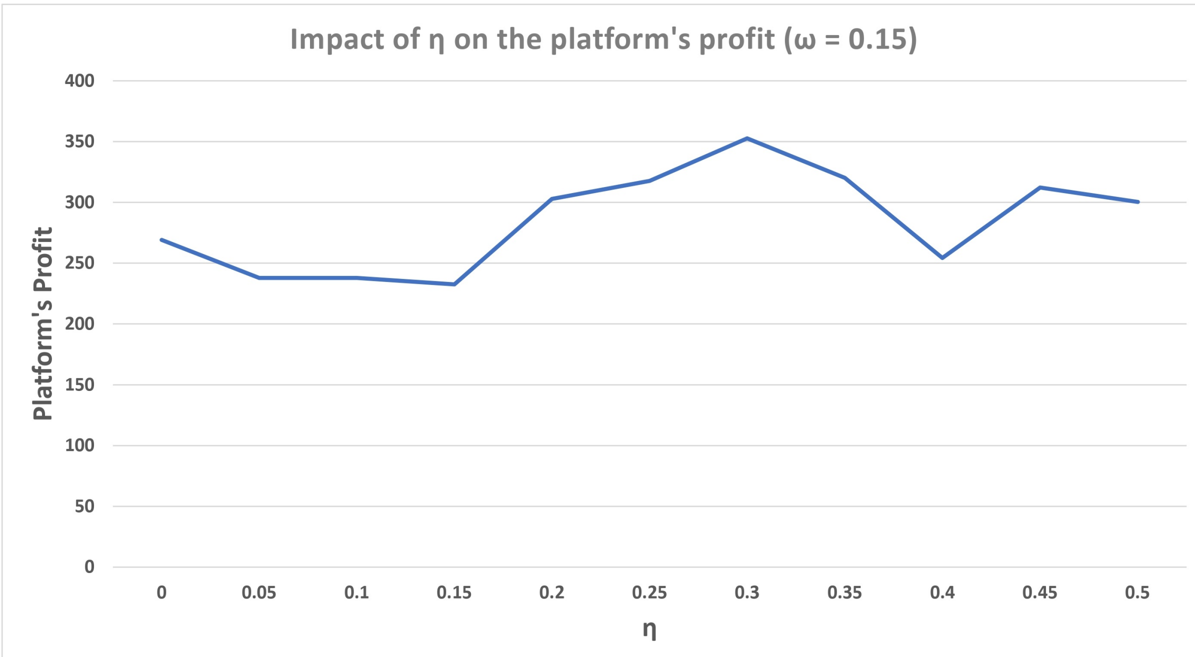


Figure 4.7: Impact of η on the platform's profit ($\omega = 0.15$)

increases, the value of U^c_{ijk} decreases due to the negative effect on the term ηT_{ijk}, where T_{ijk} represents the total waiting time from supplier j to customer i by driver k. When examining the fluctuations in revenue as η increases, the key aspect to consider is how changes in the customer waiting time sensitivity impact the platform's operations and customer behaviour. As a reminder, the utility of customer i placing an order from supplier j by driver k is:

$$U^c_{ijk} = v_{ij} - (1 + \alpha)p_j - \eta T_{ijk}. \qquad 4.1$$

This formula depicts that as η increases, the negative effect of waiting time T_{ijk} on customer utility becomes more evident. Initially, this might not drastically affect customer choices if T_{ijk} is within acceptable limits, but as η increases further, even small waiting times become significantly more effective to customer satisfaction.

- **Initial Phase of Increasing η:** Initially, as η increases, the platform might see an increase in revenue if it can keep T_{ijk} relatively low. This is because the increase in η is insufficient to offset the value provided by v_{ij} and the current price settings. Customers are still willing to engage with the platform due to the perceived value exceeding the increased sensitivity to waiting time.

- **Middle Phase of Increasing η:** As η increases further, customers become significantly more sensitive to waiting time. If the platform cannot improve delivery speeds accordingly or if doing so is cost-prohibitive, customers might start opting for alternatives or less frequent use of the service after an increase in profit at the beginning. This behaviour change can lead to a drop in revenue as orders decrease, even if prices per order remain unchanging.

- **Later Phase of Increasing η:** At high levels of η, even very short delivery times become a critical service feature and make a difference. Thus, there is a decrease in the number of orders and, consequently, a slight drop in the platform's profit. The platform may need to invest heavily in logistics to reduce waiting time dramatically; for instance, decreasing orders' preparation time, R_j by increasing operators in the suppliers. If these costs cannot be fully passed on to customers through higher prices due to competitive pressures or price sensitivity, the platform might experience a more noticeable revenue drop. The risks of not meeting these high expectations efficiently are significant. It could lead to decreased customer usage, potentially destabilizing or even decreasing revenue.

In conclusion, the non-linear fluctuation in revenue as η increases can be attributed to the increasing cost (in utility terms) of customer waiting time. Initially, moderate increases in η might not significantly disrupt customer behaviour if the platform maintains reasonable delivery times. However, as η continues to rise and make the waiting time more effective for customer utility, the platform's ability to meet these expectations becomes critical. If it fails to keep up without imposing prohibitive costs, revenue drops as customers turn away. Successfully managing these expectations with effective logistical strategies could mitigate or reverse revenue decrease trends. This analysis emphasizes the importance of balancing operational efficiency with customer expectations in a dynamic market environment.

With this analysis in hand, examining the impact of η on the platform's profit when ω is 0.15, a comprehensive analysis can be performed to evaluate the effect of η on the platform's profit across all values of ω. Figure 4.8 indicates the changing trend of the platform's profit by changes in η in all ω scenarios.

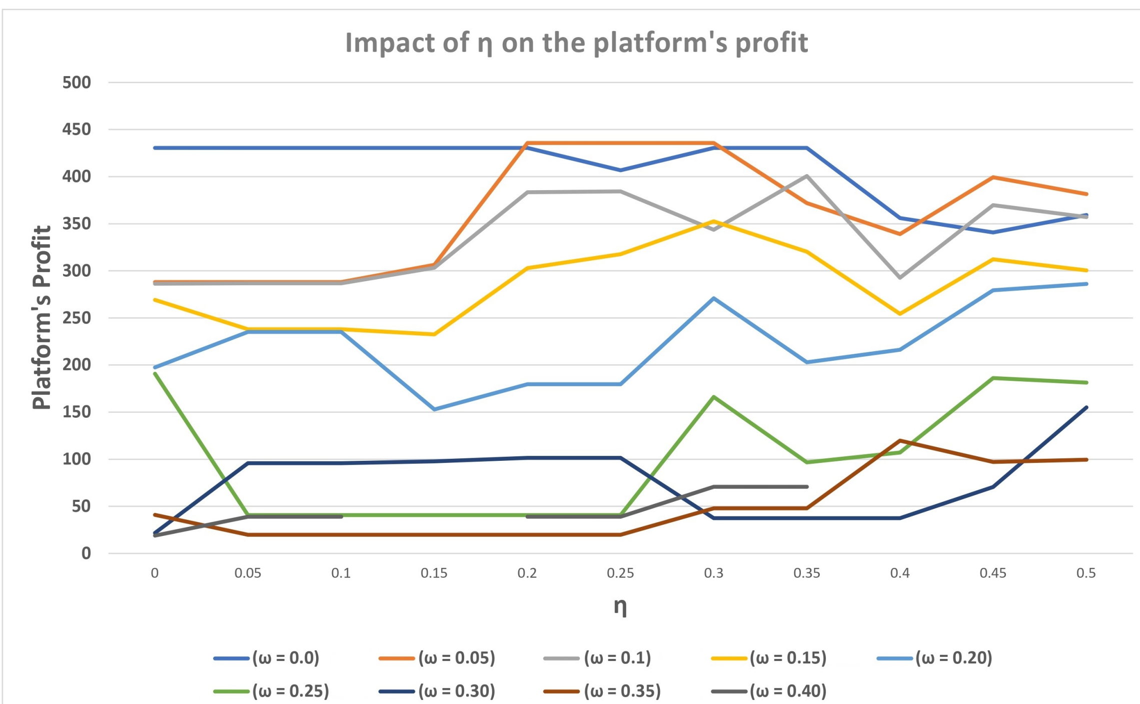


Figure 4.8: Impact of η on the platform's profit

Each line in the provided figure corresponds to a specific value of ω, allowing us to observe how profit changes with increments in η under constant driver waiting time sensitivity. When $\omega = 0.0$, the platform's profit remains constant at higher values for lower η levels, gradually declining after η=0.25. It means that when driver cost sensitivity is non-existent ($\omega = 0$), the platform can initially absorb the increased costs from higher customer sensitivity without affecting profit. However, as η increases beyond 0.25, even slight increases in waiting times become significantly undesirable to customers, leading to reduced usage or higher operational costs to meet faster service expectations.

When $\omega = 0.05$ and $\omega = 0.1$, an initial stable profit is observed, followed by a peak around $\eta = 0.2$, after which the profit begins to fluctuate. With a slight sensitivity of drivers to waiting time, the platform seems capable of optimizing operational strategies to handle moderate increases in η. The peak at $\eta = 0.2$ suggests an optimal balance between revenue from customers willing to pay more for faster service and the cost of providing that service.

In the range of $\omega = 0.15$ to $\omega = 0.25$, profits start higher but show a sharper decline as η increases. As ω increases, the compounding effect of paying drivers more to reduce their waiting time and the need to minimize customer waiting time drives up costs. These conditions create a scenario where maintaining profits becomes increasingly difficult as η increases, especially beyond $\eta = 0.2$.

Finally, when $\omega = 0.3$ and $\omega = 0.35$, profit starts relatively low and initially increases or stabilizes before declining again. In these high ω scenarios, initial profits suggest that the platform can still find short-term efficiencies or pricing strategy to counteract high ω, while generally, higher values of ω lead to lower profit (regardless of η). But I don't see this summary listed clearly here. However, continuous increases in η eventually make it cost-prohibitive to maintain service standards without significant financial impact.

This detailed analysis provides a deep understanding of the impact of η on profit, which varies significantly depending on the level of ω. While profits can initially resist increases in η, there is a clear pattern where the costs to accommodate faster service expectations affect profitability. This deep understanding of how changing η impacts profit across different ω settings reveals critical insights into cost management and the importance of strategic adjustments in pricing parameters.

4.4.1.2 Impact of η on pricing parameters

Figure 4.9, presenting values of pricing parameters by varying η, illustrates how the platform's pricing parameters— α (delivery fee), β (commission fee for suppliers), and γ (wage for drivers)—respond to changes in η, which measures customer sensitivity to waiting times.

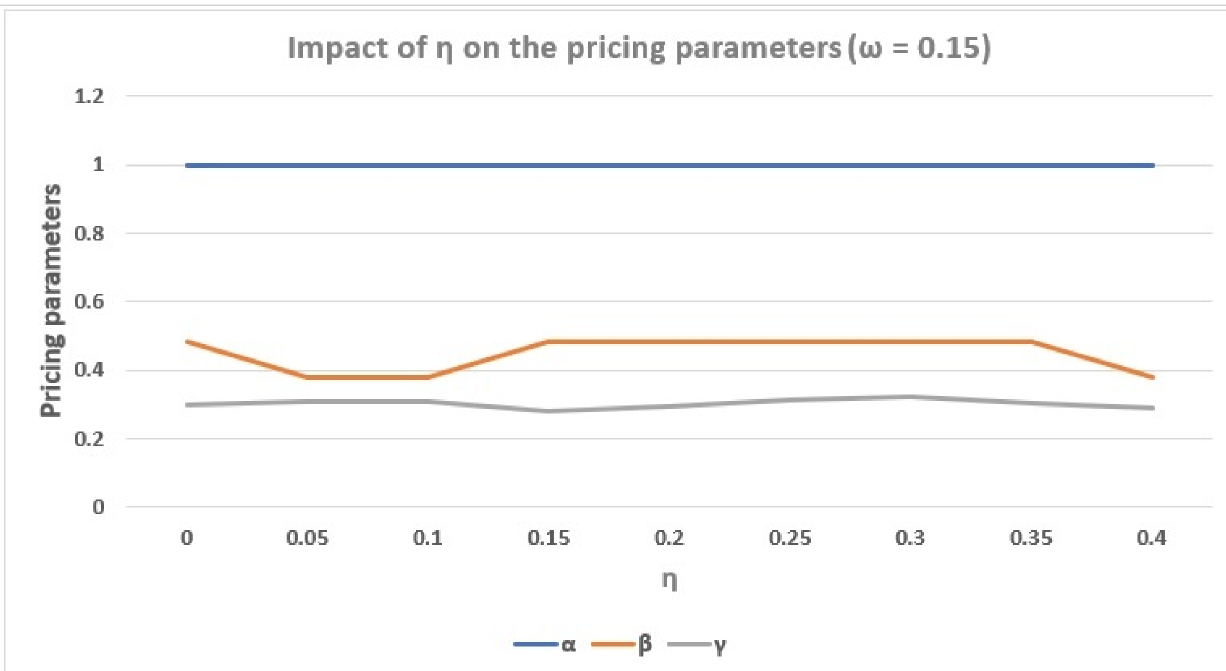


Figure 4.9: Impact of η on the pricing parameters

- α, **Delivery fee for customers:** Notably, α remains constant across all scenarios, which suggests that the delivery fee is optimally set to balance revenue generation without impeding customer orders due to high fees. This stability in α indicates that the platform maintains a consistent strategy for delivery charges to generate its profit, which is crucial for maintaining customer satisfaction and avoiding variability in customer cost perceptions.

- β**, Commission fee for suppliers:** The commission fee β shows variability with changes in η. Initially, as η increases from 0 to 0.1, β decreases, suggesting an adjustment to reduce the burden on suppliers, possibly encouraging them to improve service speed, aligning with the increased customer sensitivity to waiting times. However, as η further increases, β returns to higher levels and stabilizes, which might reflect a need to balance the platform's revenue against the decrease in orders and costs incurred in facilitating faster deliveries.

- γ**, Wage for drivers:** The wage parameter γ generally increases with η, peaking at η=0.3. This behaviour indicates that drivers are compensated more as customer sensitivity to waiting time increases, which is likely to incentivize quicker deliveries. The trend in γ aligns with the need to ensure driver motivation aligns with the urgency demanded by customers.

This analysis (Figure 4.9) relates to the impact of η on pricing parameters in only one scenario when $\omega = 0.15$. Figure 4.10 and 4.11 shows the impact of η on β and γ in all values of ω, respectively. The similar figure for α was omitted since its pattern is identical to Figure 4.9, and the value of α consistently equals 1.00.

Figure 4.10 highlights how the commission fee for suppliers (β) is influenced by changes in η across various levels of ω. A key observation is that β remains relatively stable at lower ω values, consistently around 0.48, regardless of changes in η. This stability means that when driver waiting time sensitivity is low, the platform maintains a steady commission rate, likely because the operational costs associated with driver waiting are manageable.

As ω increases, however, β reveals more significant fluctuations, especially noticeable at certain η levels (e.g., a drop to 0.38 at $\eta = 0.15$ and $\omega = 0.15$). These fluctuations

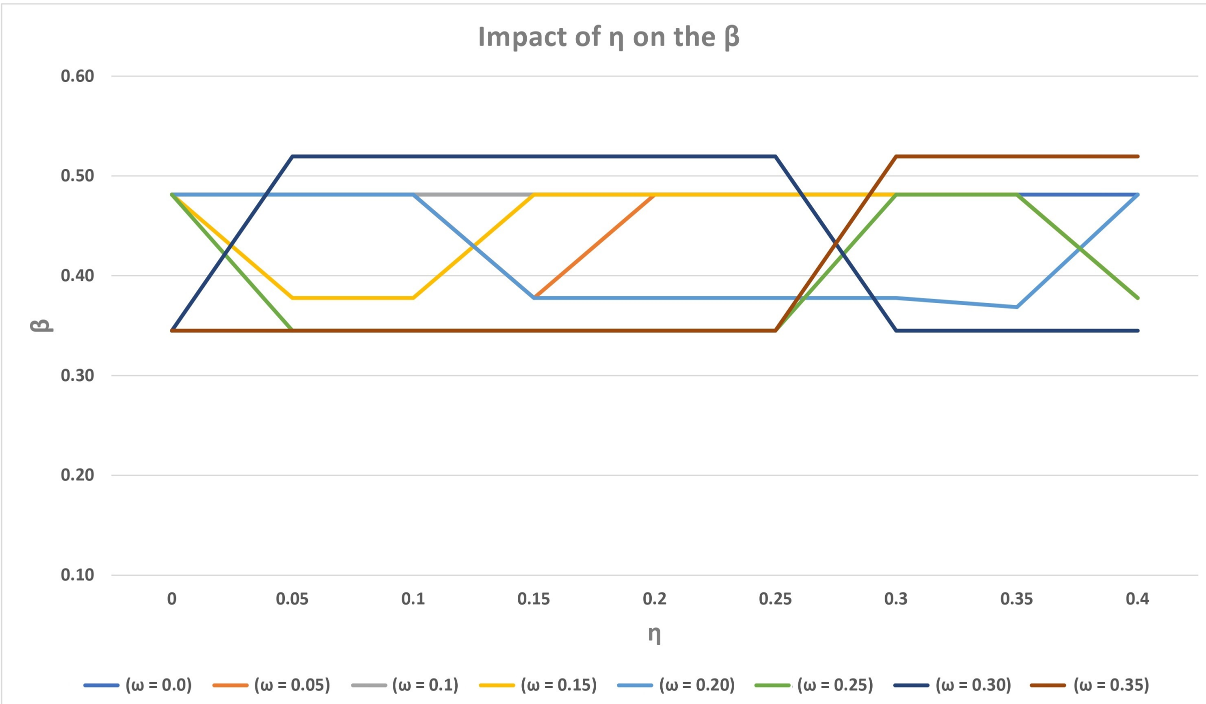


Figure 4.10: Impact of η on β

indicate strategic adjustments in commission rates, possibly to balance the increased costs of compensating drivers for longer wait times. At high ω values, the platform sometimes decreases β to manage profitability by incentivizing suppliers, keeping drivers interested in the market, and accepting delivery jobs. This dynamic adjustment of β highlights the platform's strategy to align supplier incentives with varying market pressures and cost structures.

Also, Figure 4.11 illustrates how γ is adjusted in response to changes in η across different levels of ω. At lower ω levels (0.0 to 0.15), γ remains relatively constant across various η values, indicating a stable wage policy when driver waiting time sensitivity is minimal. This denotes that the platform can maintain driver satisfaction without significant wage adjustments to meet service levels, as the impact of waiting time on operational costs is lower. Stability in γ under these conditions implies the platform's commitment to its drivers, even despite changes in customer expectations.

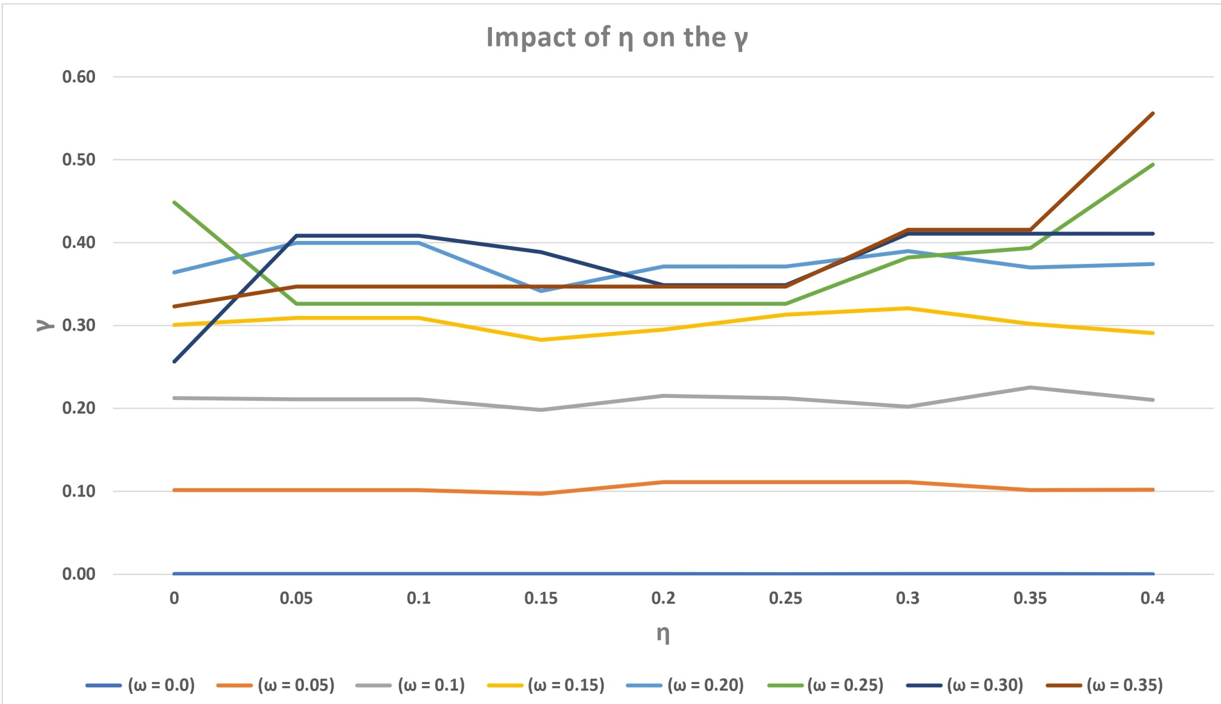


Figure 4.11: Impact of η on γ

As ω increases (0.20 and higher), γ exhibits more noticeable fluctuations, particularly at higher η values. This pattern indicates the platform's strategic approach, where it takes proactive measures, adjusting wages more aggressively to align with the increased sensitivities of both drivers and customers to waiting times. In scenarios where both ω and η are high, substantial increases in γ are observed, reflecting the platform's strategic effort to incentivize drivers to meet accelerated service demands. This strategic adjustment is a key element in maintaining service quality and operational efficiency in high-pressure environments, instilling confidence in the platform's operations.

Overall, the adjustments in γ across varying η and ω levels demonstrate the platform's dynamic approach to managing driver wages, aiming to balance customer service expectations with the economic realities of driver satisfaction and operational costs.

4.4.2 Impact of ω on platform's profit and pricing parameters

The second sensitivity analysis can investigate the impact of different values of ω on the platform's profit and its influence on the pricing parameters. ω is a crucial factor in the utility of drivers (Equation (3.5)).

4.4.2.1 Impact of ω on platform's profit

Figure 4.12 shows the impact of varying levels of ω (the sensitivity of drivers' costs to waiting time) on the platform's profit, with η fixed at 0.15. This analysis provides insights into how changes in the compensation strategy for drivers, as they become more sensitive to delays, affect overall platform profitability.

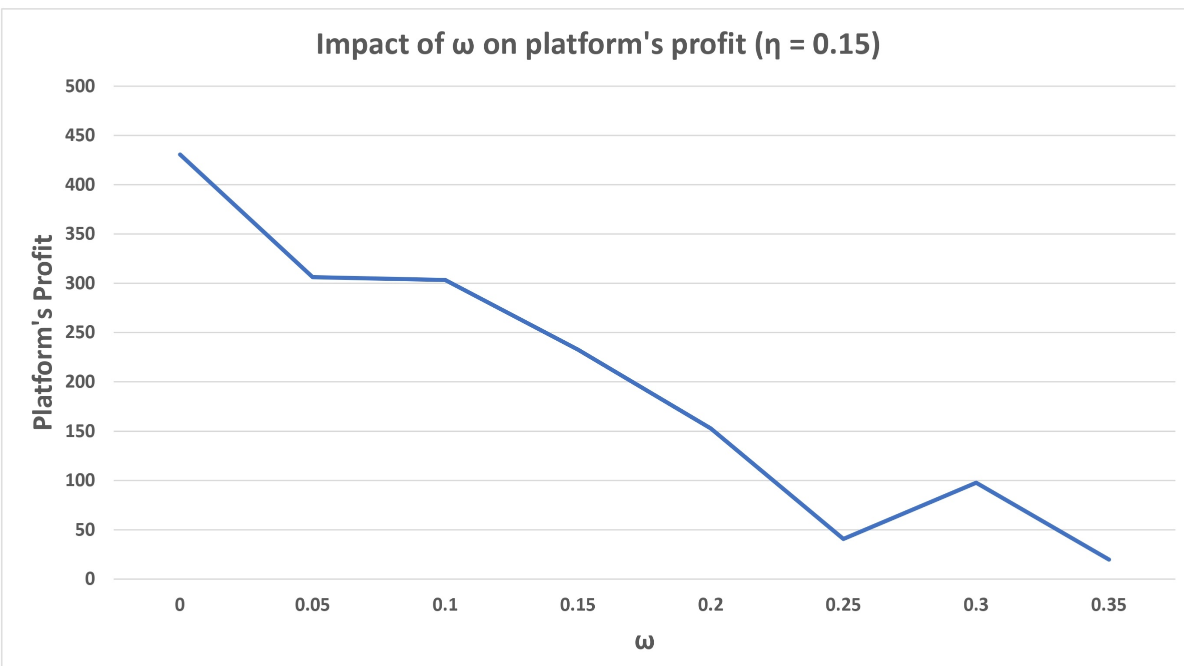


Figure 4.12: Impact of ω on the platform's profit ($\eta = 0.15$)

As a reminder, the utility of driver k delivering the order placed by customer i from supplier j is as follows, which is a key to understanding the economic interplay within the platform's operations as ω, the sensitivity of drivers to waiting time, varies:

$$U_{ijk}^{d} = \gamma p_j - v_k - \omega T_{ijk} \qquad 4.2$$

As ω increases from 0 to 0.35, the graph indicates a general trend of decreasing profit, with some fluctuations. This pattern suggests that as the platform adjusts driver wages to account for their increased sensitivity to waiting time, it incurs higher operational costs, which affects profitability.

- **Initial Phase of Increasing ω:** As ω increases from 0 to 0.1, the platform sees a significant profit drop from 430.59 to 303.30. This substantial decrease indicates that even slight increases in the driver's sensitivity to waiting times significantly elevate the platform's operational costs. The drivers demand higher compensation for delays directly impacting the platform's cost structure.

- **Middle Phase of Increasing ω:** The profit trend continues to decline intensely as ω increases from 0.1 to 0.25, with a notable low at ω=0.25, where profit dips to 40.75. The growing value of ω amplifies the driver's cost per unit of waiting time, which even efficient operational adjustments struggle to mitigate. This demonstrates the sensitive balance between driver compensation and operational profitability.

- **Later Phase of Increasing ω:** At ω=0.3, there is a temporary improvement in profit to 97.65 before it falls again at ω=0.35 to 19.96. This fluctuation could indicate adaptive or compensatory mechanisms temporarily overcoming the costs imposed by higher ω values. However, the general trend indicates that when driver waiting time sensitivity is high, sustaining profitability becomes increasingly challenging.

In addition, a sensitivity analysis was conducted to assess the impact of ω on the platform's profit across all values of η. Figure 4.13 indicates the changing trend of the platform's profit by changes in ω in all η scenarios. As ω increases, there is a general trend of decreasing profit across almost all values of η. This trend indicates that higher driver cost sensitivity to waiting time significantly impacts the platform's operational costs, reducing overall profitability.

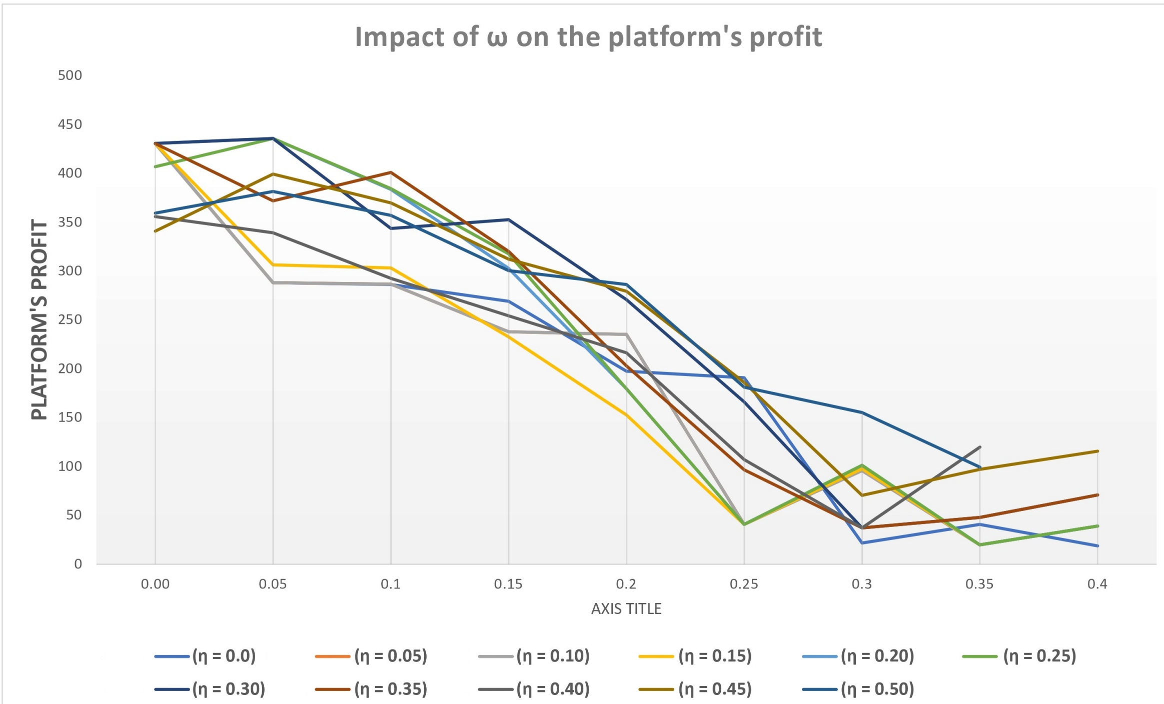


Figure 4.13: Impact of ω on the platform's profit

The increasing costs associated with compensating drivers for their waiting time (ω) directly decline profit margins, particularly as ω reaches moderate levels (around 0.2 and higher). This reflects the platform's increased financial responsibility to ensure drivers are not disadvantaged by longer wait times, which becomes unsustainable at higher ω values.

High values of ω are particularly destructive to profit across all η levels. Strategic measures to mitigate these effects are crucial, especially when both η and ω are high. Implementing dynamic pricing that can adjust more finely in response to changes in ω may help. Additionally, revising driver compensation models to more efficiently handle increased costs without drastically impacting profit could be beneficial.

The analysis demonstrates that ω significantly and generally negatively impacts platform profit, particularly as it increases. This trend highlights the importance of managing driver costs effectively to maintain profit margins, especially in market conditions where both η and ω are elevated. The platform must carefully consider balancing these costs with revenue strategies to sustain profitability in a competitive service environment.

4.4.2.2 Impact of ω on pricing parameters

Figure 4.14, presenting values of pricing parameters by varying ω, explains how the platform's pricing parameters— α (delivery fee), β (commission fee for suppliers), and γ (wage for drivers)—react to changes in η, which measures driver sensitivity to waiting times.

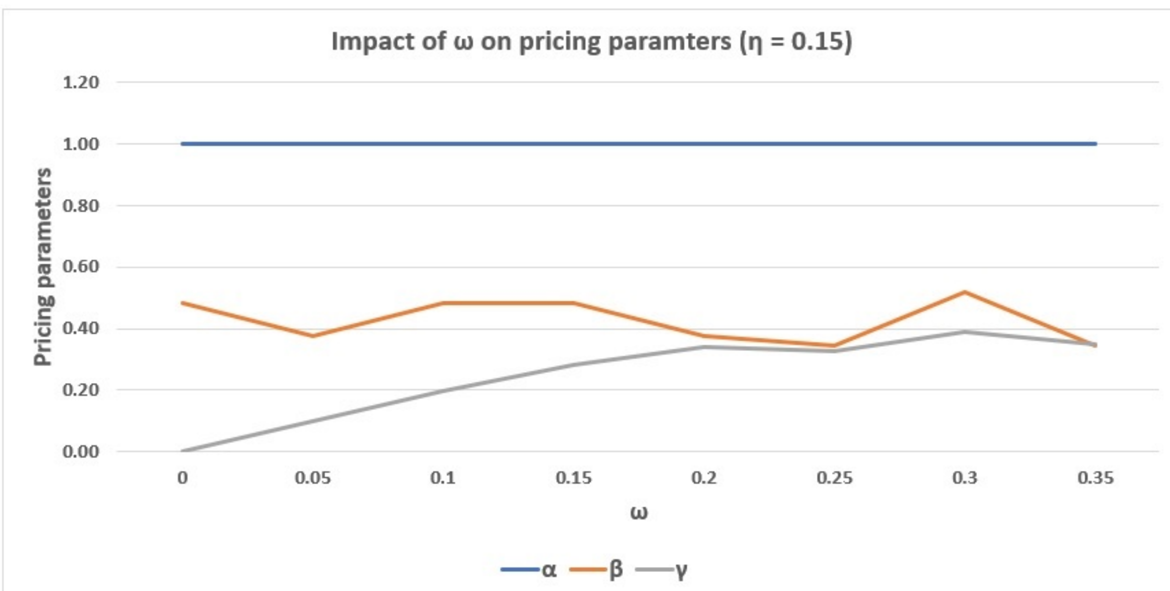


Figure 4.14: Impact of ω on the pricing parameters

Figure 4.14 reveals that α remains constant at 1.00 across all ω values. This consistency indicates that the delivery fee charged to customers does not vary with driver sensitivity to changes in waiting times. It suggests that the platform is dedicated to maintaining a stable pricing strategy for customers despite varying costs associated with driver waiting times. The commission fee for suppliers (β) and the wage for drivers (γ) show variability with changes in ω. These fluctuations reflect the platform's adjustments to balance the cost implications of increased driver sensitivity and to manage the interactions among the three market sides—customers, suppliers, and drivers.

- α**, Delivery fee for customers:** The fixed value of across different levels of ω indicates that the platform shields customers from cost variations due to driver waiting time sensitivity changes. This approach likely aims to maintain customer satisfaction and predictable pricing.

- β**, Commission fee for suppliers:** β shows fluctuations that do not follow a simple linear trend, suggesting complex interactions between supplier costs and platform revenue strategies. Decreases in β at certain ω levels (0.05, 0.2, 0.25, and 0.35) could ease the burden on suppliers to maintain their cooperation and satisfaction when driver costs increase.

- γ**, Wage for drivers:** The trend in γ, which generally increases with ω and peaks at ω=0.3, highlights the platform's strategic approach. It aims to compensate drivers more generously as their sensitivity to waiting time increases. This strategy potentially incentivizes quicker deliveries, thereby reducing overall waiting times. Such a reduction in waiting times can significantly enhance customer satisfaction.

The utility of drivers, given by the formula, is crucial for understanding the impact of ω on γ. As ω increases, the negative impact of waiting time (T_{ijk}) on driver utility becomes more significant, justifying higher wages (γ) to keep drivers interested in working on the platform and willingness to complete deliveries quickly.

The platform should continue to adjust β and γ dynamically in response to changes in ω to balance the market forces optimally. Adjusting these parameters helps manage the cost pressures suppliers and drivers face, ensuring that all parties remain incentivized to participate in the platform. Additionally, regularly reviewing the impact of these pricing adjustments on market participation rates and satisfaction levels across all three sides is crucial to ensure that the adjustments have the intended effects. This analysis highlights the platform's key role in managing driver waiting times (ω) and influencing the pricing strategy toward suppliers and drivers. By carefully managing β and γ, the platform can effectively navigate the complexities of a three-sided market, maintaining balance and operational efficiency even as external conditions change. This emphasis on the platform's management instills confidence in its ability to adapt and thrive.

This sensitivity analysis (Figure 4.14) relates to the impact of ω on pricing parameters in only one scenario when $\eta = 0.15$. Figure 4.15 and 4.16 shows the impact of ω on β and γ in all values of η, respectively. The similar figure for α was omitted since its pattern is identical to Figure 4.14, and the value of α remains consistently at 1.00. Reviewing the Figure 4.15 and the patterns in how β adjusts across different ω levels, it appears that β is not significantly influenced by ω across a broad range of η. The fluctuations in β seem more slight and do not exhibit a clear, consistent pattern of change directly proportional to increases in ω.

β remains relatively stable at lower ω levels (up to 0.20), consistently varying around 0.48 across various η values. This indicates that the platform does not feel pressured to adjust supplier commissions dramatically in response to changes in driver waiting time sensitivities within this range. Even at higher ω levels, while there are some fluctuations in β, these do not follow a strong or clear trend that shows an explicit response to increasing ω. Instead, adjustments in β seem unsteady and possibly influenced more by other operational or market considerations than by ω alone.

The relative stability and limited changes in β across changes in ω point that the platform may prioritize maintaining consistent commission rates to ensure stability and predictability for suppliers, which could be crucial for long-term supplier relationships and market stability. The lack of a strong correlation between ω and β adjustments might also signify that the

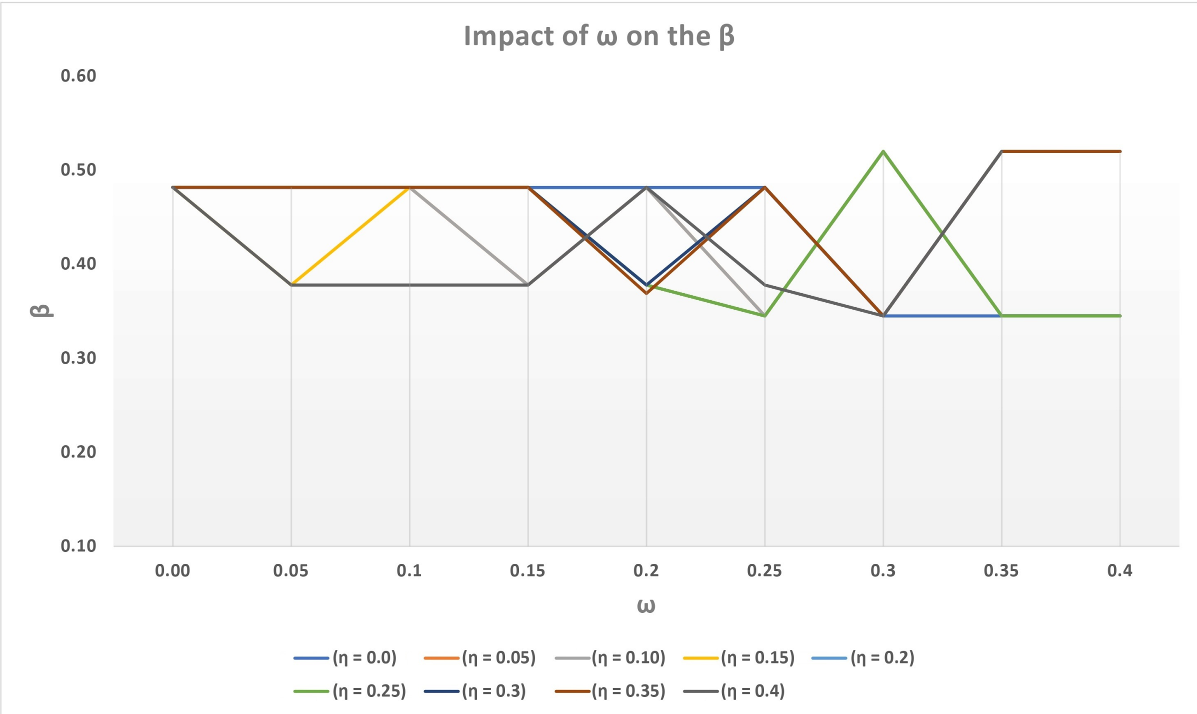


Figure 4.15: Impact of ω on β

platform has effective cost management strategies that mitigate the impact of increased driver waiting time sensitivities without significantly adjusting supplier commissions.

Figure 4.16 provides a detailed analysis of how γ changes in response to various levels of ω across different fixed values of η. This analysis indicates how the platform strategically adjusts driver wages to keep drivers and customers interested in joining the market and increasing its profit.

Increasing Trends: As ω increases, there is a clear trend of increasing γ across most η levels. This denotes that higher driver sensitivity to waiting time pushes the platform to offer greater compensation to ensure driver retention and motivation. For example, at η=0.0, γ starts at 0.00 and rises to 0.40 by ω=0.4. This increase is consistent across other η levels, indicating a robust response to ω.

Impact of Higher η: At higher η values, the increment in γ becomes more apparent

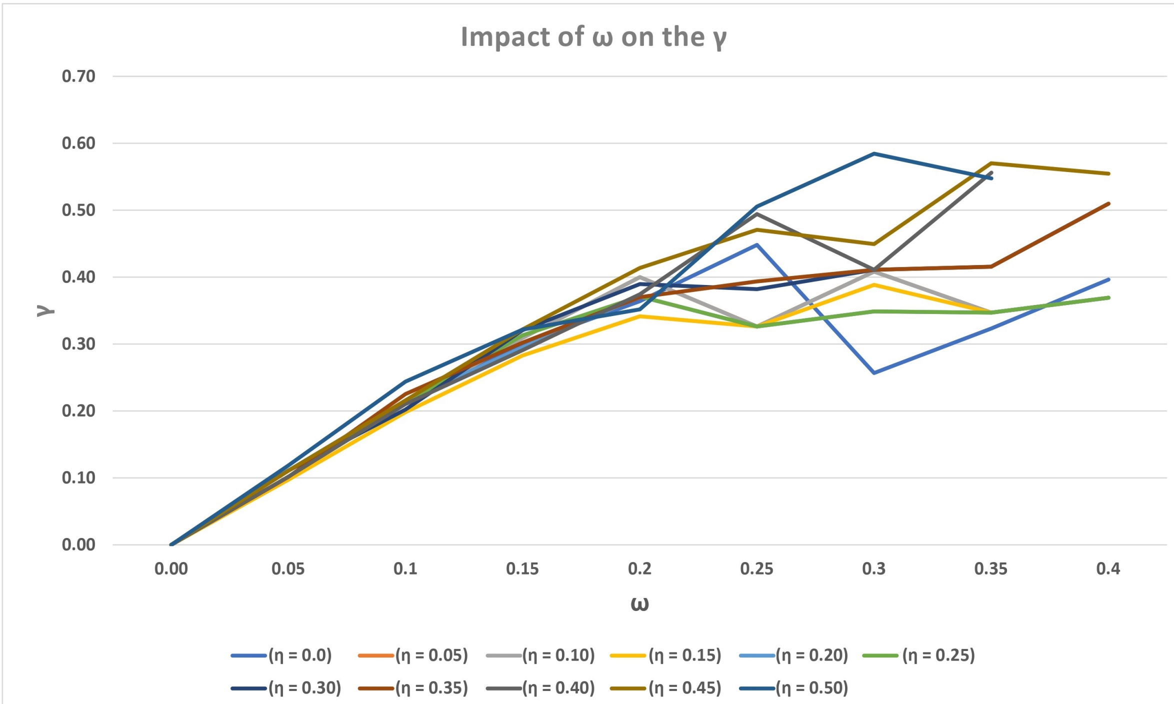


Figure 4.16: Impact of ω on γ

with increasing ω, demonstrating that the platform potentially faces compounded pressures to maintain service efficiency. Drivers are compensated not only for their increased waiting sensitivity but also for meeting customer expectations for quicker service, as seen with η values from 0.35 to 0.50, where γ often rises in the higher ω ranges.

Stability in Low ω: At the lowest ω settings, γ remains at zero or increases very slightly, reflecting minimal or no need for additional compensation due to low driver cost sensitivity. This pattern shifts dramatically as ω rises, emphasizing the platform's adaptive compensation strategy in response to changing operational dynamics.

The consistent increase in γ across rising ω levels, regardless of η, highlights a dynamic compensation strategy to maintain driver satisfaction. The platform adjusts wages to ensure that drivers are adequately compensated for longer wait times, which is crucial for sustaining service quality in the face of increasing operational challenges. In general, the results illustrate that the platform uses γ to effectively manage its workforce, ensuring that driver wages align with external market pressures and internal operational needs. This approach not only supports driver enthusiasm and retention, but also aligns with broader strategic objectives to meet customer expectations.

4.4.3 Impact of product price

This section explains the influence of product pricing on the distribution of orders among restaurants by examining the algorithm's preference for higher-priced products. The trend is substantiated through a comprehensive sensitivity analysis, focusing on the impact of ω on restaurant orders. To visualize this dynamic, 11 figures were produced, each corresponding to a fixed value of η. These figures illustrate the variations in the order volume associated with each restaurant as the value of ω changes, providing a clear depiction of the algorithm's operational behavior.

Figure 4.17 to Figure 4.20 allows us to focus on key trends, highlighting the algorithm's strategic assignment of orders to restaurants with higher price points and emphasizing the direct correlation between product pricing and order distribution. This approach not only confirms the algorithm's preference towards more expensive restaurants but also serves as a foundation for discussing strategic implications and potential adjustments to enhance market equity and customer satisfaction. As mentioned earlier, the algorithm's objective function is intricately designed to maximize the platform's overall profitability:

$$\max_{\alpha,\beta,\gamma,x_{ijk}} \pi = \sum_{i,j,k} x_{ijk} p_j (\alpha + \beta - \gamma) \tag{4.3}$$

Where α, β, and γ represent the delivery fee, commission fee, and wage rate, respectively, each scaled by the price p_j of products from restaurant j, and x_{ijk} is a binary decision variable that is one if an order is placed by customer i from restaurant j and delivered by driver k, indicating active transactions facilitated by the platform.

High-Priced Restaurants: Restaurants like Restaurant 1, with a price of 23$, consistently see less fluctuation in orders with varying ω, illustrating an algorithmic tendency towards securing higher revenue per transaction. This aligns with the platform's utility functions described in Section 3.1 of the thesis, which emphasize maximizing platform's profit.

Mid to Low-Priced Restaurants: Restaurant 2 (20$) and Restaurant 3 (17$) show decreasing orders as ω increases, suggesting a diminishing preference as the profit margin per order decreases. Restaurant 4 (15$), consistently receiving few or no orders, is a clear indicator of being below the profitability threshold set by the algorithm's parameters.

The analysis presented in this subsection clearly demonstrates that the platform's algorithm strategically assigns orders to restaurants offering higher-priced products. This preference is naturally embedded in the algorithm's objective function, which aims to maximize the platform's profitability by optimizing the balance between revenue from fees and the operational costs associated with driver wages. The empirical evidence drawn from sensitivity analyses supports this observation, showing a consistent pattern where restaurants with higher price tags possess a greater volume of orders across varying market conditions.

As another analysis to prove the above-mentioned tendency of the model, a detailed analysis of the experimental data of 97 scenarios, with ω and η parameter variations, provided clear insights into the algorithm's operational preferences. The first restaurant, consistently maintaining the highest price point at 23$, showcased a dominant performance in the order allocation process. Specifically, it received an equal or greater number of orders than other participating restaurants in 44 out of 97 scenarios, approximately 45% of the cases. Even more evident, in 27 out of 97 scenarios—equating to 28% —the first restaurant not only matched but surpassed the order volume of its competitors.

This significant portion of scenarios where the highest-priced restaurant led in order allocations unequivocally demonstrates the algorithm's intended strategy to favour higher-priced products, presumably to increase the platform's profit, while a higher price decreases the customer's utility and probably its willingness to participate in the market and place an order. This behaviour highlights the algorithm's role in shaping market dynamics, potentially driving a pricing strategy that could influence restaurant pricing behaviours and market positioning within the competitive landscape of on-demand food delivery services.

While the current pricing strategy effectively maximizes profits, it could lead to a less diverse and competitive marketplace, deterring price-sensitive customers. However, by implementing adaptive adjustments to the algorithm's parameters, the platform can encourage a more equitable distribution of orders. This enhances the platform's service appeal to a broader customer base and promotes a more competitive restaurant environment. Maintaining a competitive marketplace is crucial for the platform's profitability and customer satisfaction.

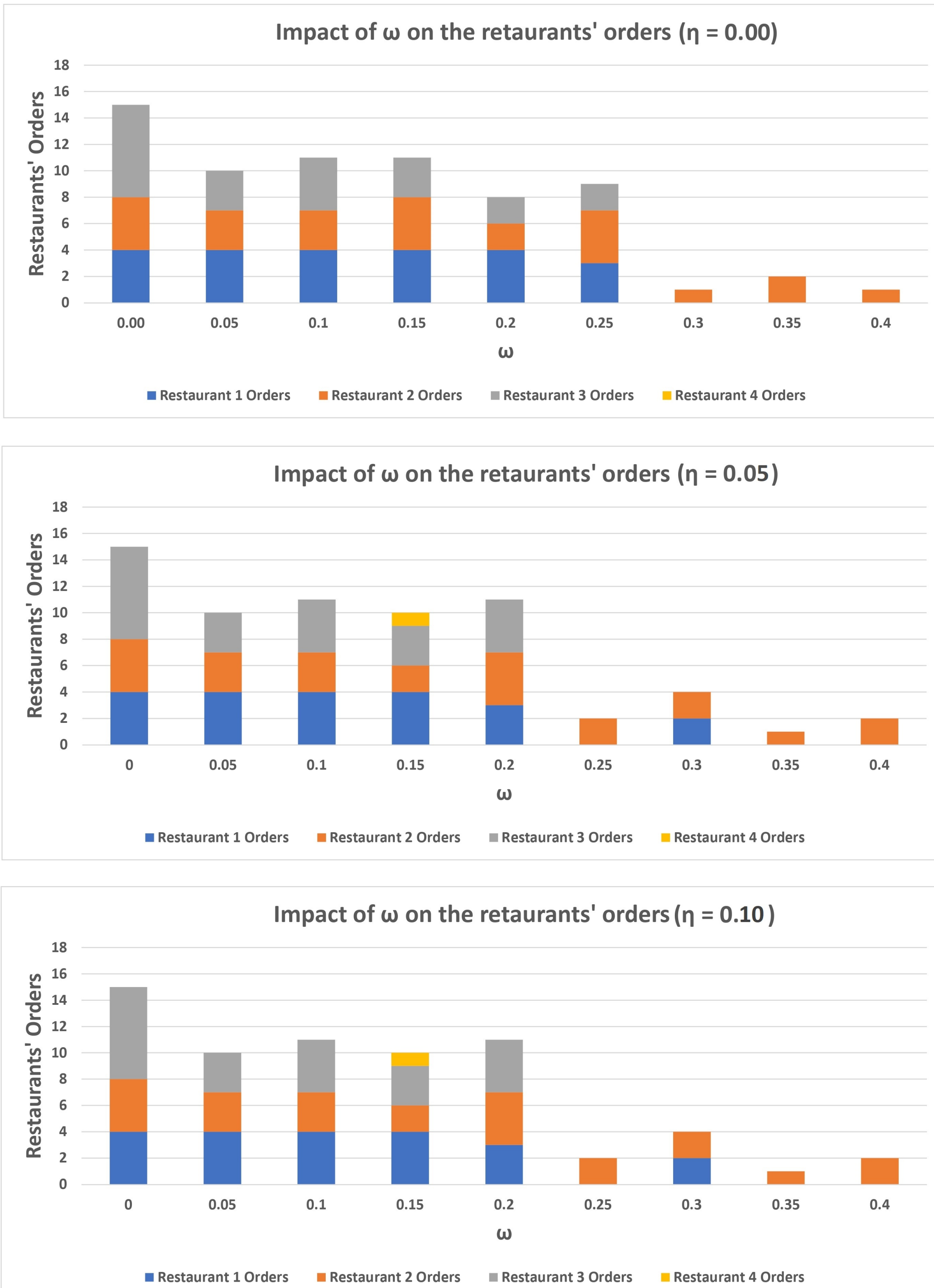


Figure 4.17: Impact of ω on the restaurants' orders for η between 0.00 to 0.10

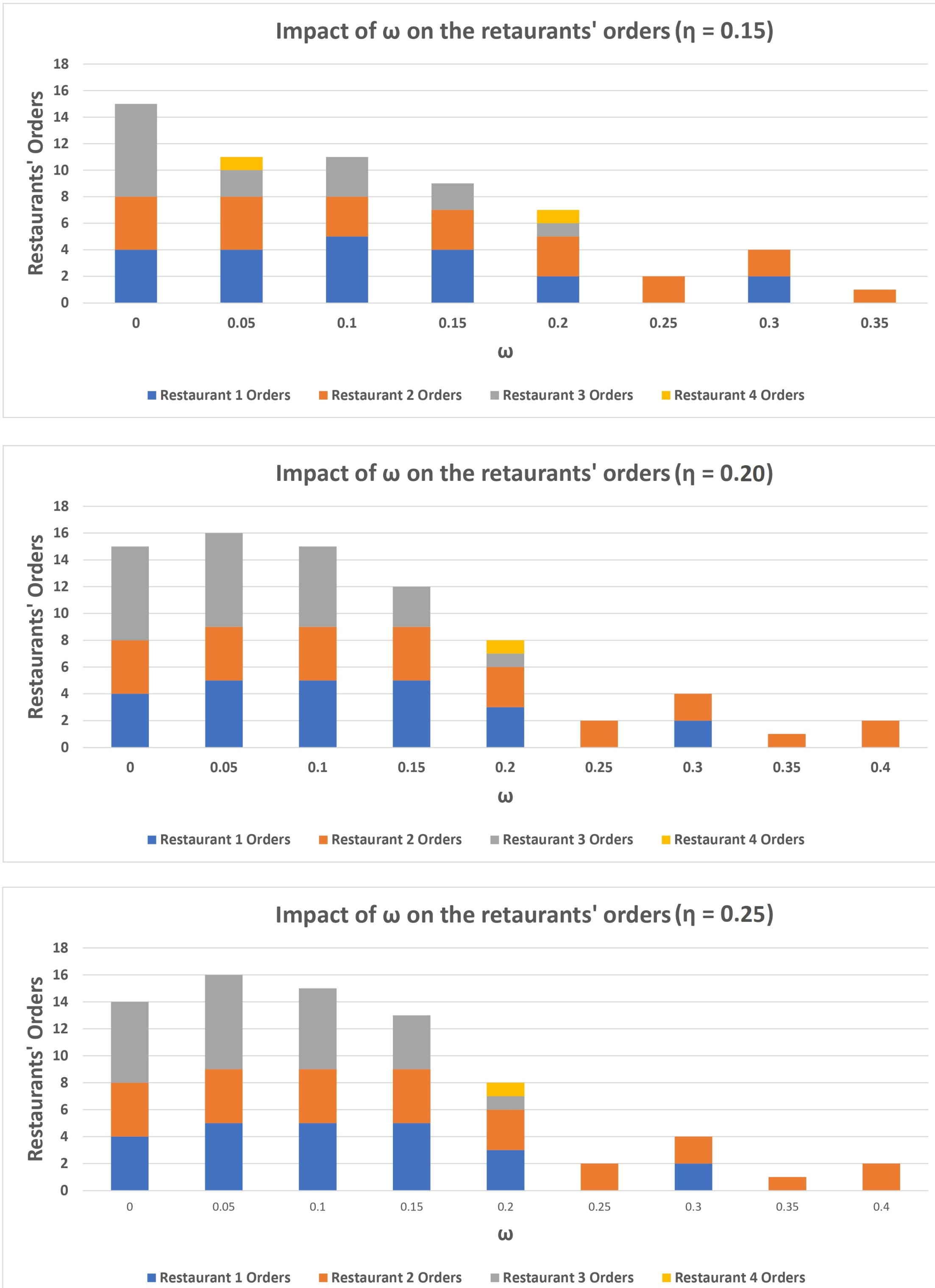


Figure 4.18: Impact of ω on the restaurants' orders for η between 0.15 to 0.25

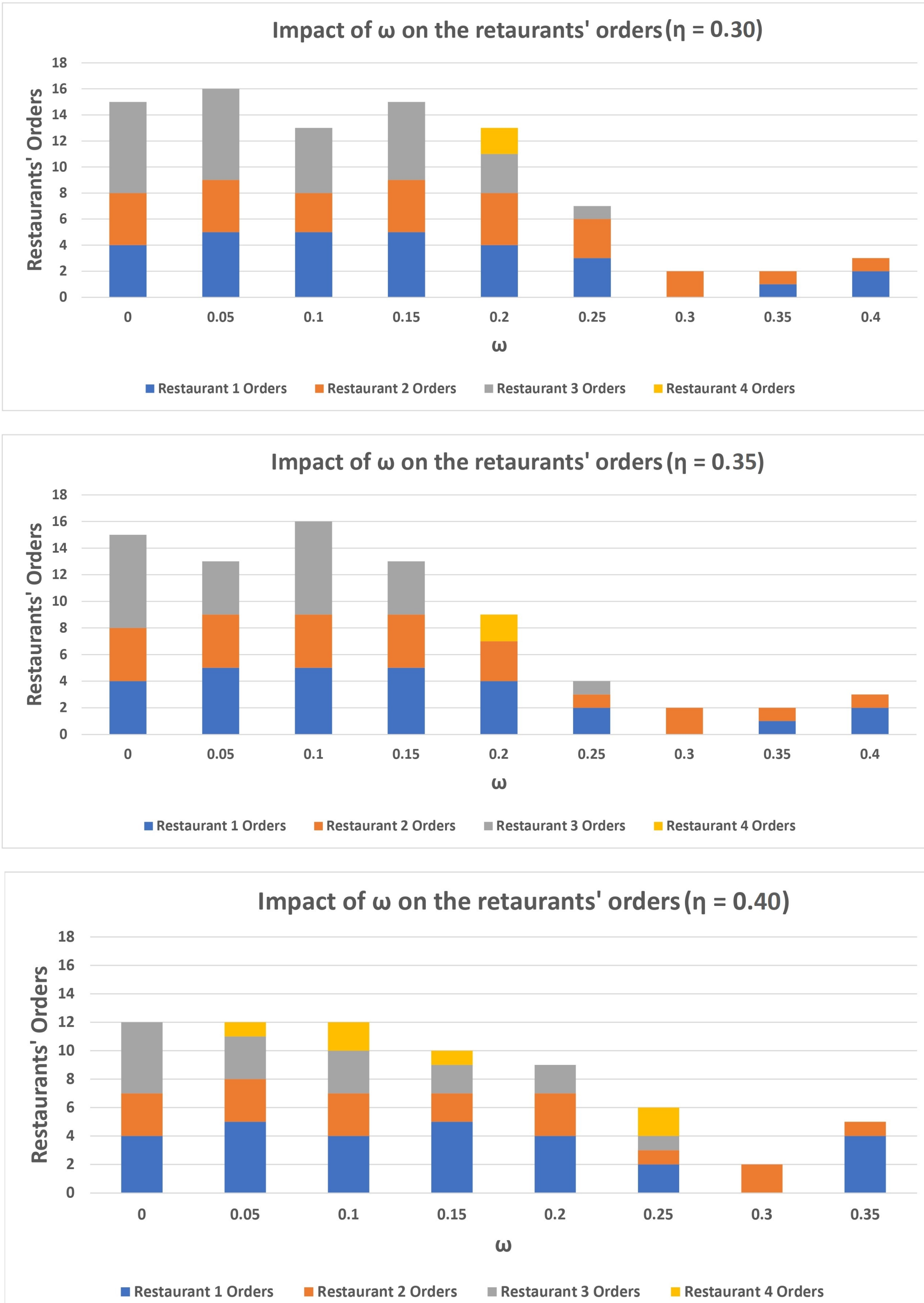
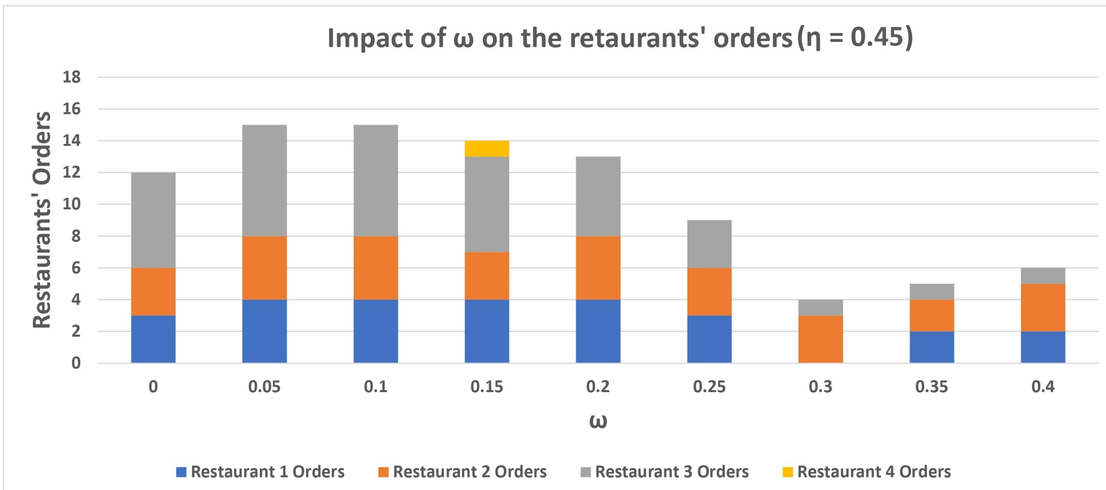


Figure 4.19: Impact of ω on the restaurants' orders for η between 0.30 to 0.40



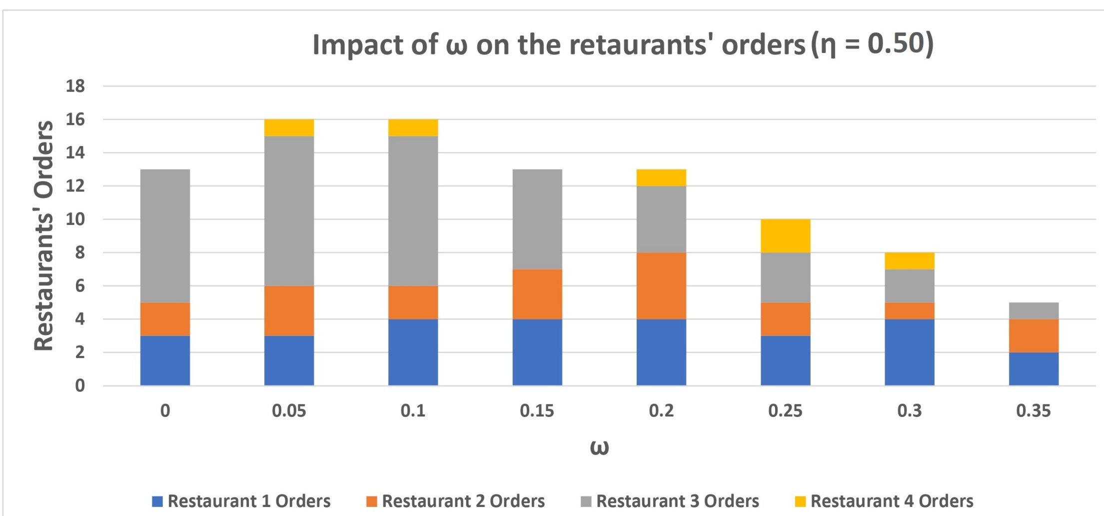


Figure 4.20: Impact of ω on the restaurants' orders for η between 0.45 to 0.50

Chapter 5

Conclusion

5.1 Overview

This chapter provides a summary of the entire thesis, reviewing the key aspects of the proposed model and its approach to addressing three-sided market dynamics. It also discusses the limitations of the model, offering insights into the challenges and considerations associated with its use. The chapter concludes by identifying potential areas for future research to further refine and improve the model's effectiveness in complex market environments.

5.2 Summary

This section analyzes the structure of a three-sided on-demand delivery service model, providing a deep understanding of how pricing and matching strategies can influence the behavior of all players in the market. Combining Mixed Integer Linear Programming (MILP) with heuristic techniques, the research highlighted the sensitivity of the platform's profitability and service efficiency to various parameters.

The analysis demonstrated that the platform's profitability is highly sensitive to the strategic setting of pricing parameters. By adjusting these parameters, the platform can manipulate the market equilibrium effectively. For instance, higher commission fees might reduce the attractiveness of the platform for suppliers. The optimal balance achieved in these parameters ensures a competitive edge in the market without sacrificing participant satisfaction.

The model also highlighted the critical role of driver compensation in maintaining an adequate supply of drivers while ensuring their satisfaction. The platform can provide a reliable delivery service by optimizing the wage rates, which is crucial for maintaining customer satisfaction and timely deliveries.

The sensitivity analysis related to customer and driver waiting times revealed that longer waiting times have a direct negative impact on the utility of both customers and drivers, thus affecting their loyalty and retention. This relationship between waiting time and utility is helpful for the platform in designing better job assignment algorithms that minimize waiting times, thereby enhancing overall service quality. Analyzing the behavior of each participant in a three-sided market—customers, suppliers, drivers, and the platform itself—provides a comprehensive understanding of the entire ecosystem.

Customers in on-demand delivery platforms primarily pursue convenience, speed, values, and quality. The sensitivity analysis indicates that customers are particularly responsive to waiting times (η), as longer waiting times directly impact their satisfaction and likelihood of repeating business. However, when η is high, suggesting increased sensitivity to waiting time, customers may prioritize faster service over other factors, such as cost or supplier diversity. Platforms might need to adapt by prioritizing quicker suppliers or optimizing driver assignments to minimize waiting times.

In the proposed model, demand loss can occur due to limitations in the availability of drivers or suppliers. When the number of available suppliers is insufficient, customers may experience fewer order options, reducing their willingness to engage with the platform. Similarly, a shortage of drivers can lead to longer wait times and consequently decrease the utility, further decreasing customer satisfaction and, ultimately, demand. These scenarios illustrate how supply constraints indirectly reduce demand by increasing waiting times and limiting choice.

Suppliers are concerned with maximizing their sales volumes and maintaining profitability. The commission fee is a significant factor for them as it directly affects their earnings. Adjustments in commission rates can influence their participation and competitive pricing. When commission fees are adjusted, it reflects the platform's strategy to incentivize supplier participation during high demand or optimize profit margins when the customer base is stable. Lower commissions can encourage suppliers to join or remain on the platform, which is crucial for maintaining a diverse and attractive service offering to customers.

Drivers value consistent earnings and reasonable working conditions. Their sensitivity to waiting time (ω) affects their satisfaction with the job, as longer waiting times at pickup or delivery points decrease their effective hourly wage and can lead to job dissatisfaction. The variability in wages in response to changes in ω indicates the platform's efforts to compensate drivers adequately for their time, especially under conditions of high waiting time sensitivity. This adjustment helps maintain a reliable fleet of drivers by aligning their earnings with the expected effort, thereby reducing turnover and ensuring capacity meets demand.

Platform aims to maximize profitability while balancing the needs and satisfaction of all market players. It must strategically manage delivery fees, commission rates, and wages to optimize its operations and competitive position. The platform's decision to keep delivery fees stable despite changes in η and ω focuses on customer experience and market competitiveness. Variations in commission and wages are used as tools to adjust the market dynamics—reducing commission rates can boost supplier participation while adjusting wages helps manage driver availability and satisfaction. These tools allow the platform to respond dynamically to fluctuations in market conditions and participant sensitivities. Also, the platform tends to assign orders to more expensive restaurants since more expensive restaurants typically translate to higher order values for the platform, which can lead to higher absolute commissions if the platform's fee structure includes a percentage of the order total. The platform can maximize its revenue per transaction by directing customers to these restaurants.

Each market player's behaviour is influenced by different factors, and the platform's role is to adjust these factors to create a sustainable business model. The sensitivity analysis for each group (η for customers and ω for drivers) and the strategic adjustments in pricing parameters (commission for suppliers and wages for drivers) are crucial for maintaining this balance. By understanding and responding to these dynamics, the platform can enhance overall efficiency, satisfaction, and profitability, thereby securing its position in the competitive on-demand delivery market.

In conclusion, the results provide robust evidence that the developed model can significantly enhance the operational efficiency of on-demand delivery services. The platform can balance maximizing profits and maintaining high service quality and player satisfaction by combining pricing adjustments and optimal matching strategies. These findings validate the model's effectiveness in a simulated environment and suggest its potential for adaptation in real-world applications, offering on-demand delivery platforms a strategic tool to optimize their operations dynamically in response to market changes.

This thesis marks a significant advancement in studying three-sided markets, providing theoretical and empirical insights that could shape the future of on-demand delivery services. As this sector continues to develop, the flexibility and depth of analysis provided by this research will undoubtedly serve as a base for further explorations into optimizing multi-sided platforms. Understanding the interdependencies within such markets paves the way for more sophisticated models that could include real-time data integration and adaptive learning mechanisms, promising even greater efficiencies and market responsiveness.

5.3 Literature contribution

This thesis contributes significantly to the three-sided on-demand delivery markets literature by introducing a comprehensive analytical framework that integrates pricing and matching strategies. This thesis develops novel heuristic algorithms for solving matching and pricing problems in three-sided on-demand delivery markets. This is a notable advancement over existing models, which often focus exclusively on two-sided markets. While most existing research focuses on two-sided markets, this thesis explores the complex dynamics of three-sided on-demand delivery systems involving customers, suppliers, and drivers. This unique focus addresses a significant gap in the literature, offering foundational insights into a market structure. This approach provides a more detailed understanding of the interactions between customers, suppliers, and drivers, which are critical to the dynamics of these platforms.

The combination of Integer Linear Programming (ILP) and Linear Programming (LP) used in this study is a methodological advancement in solving complex problems within the three-sided market. This robust methodological approach allows for a detailed exploration of the strategic decisions that platforms must make to effectively balance the utility of all market participants.

The research extends existing knowledge on dynamic pricing strategy by addressing the unique complexities of three-sided markets. This includes developing a pricing model that considers the interdependencies between market players and their interactions. The sensitivity analysis provides a deeper understanding of how changes in key parameters like customer and driver sensitivity to waiting time affect platform profitability.

5.4 Research limitations

This thesis has successfully developed and analyzed pricing and matching strategies within a three-sided on-demand delivery market. However, several limitations should be noted, which might affect the generalizability and applicability of the findings.

Access to proprietary data: The first and most significant limitation relates to the accessibility of real-world data from major on-demand delivery platforms such as Uber Eats and DoorDash. These companies maintain proprietary rights over their operational data, which includes sensitive information about users, transaction details, and business operations. As a result, such data is not readily available for academic research due to commercial confidentiality and privacy concerns. This restriction significantly limits the ability to test and validate the proposed models against actual market behaviours and can affect the robustness and applicability of research findings. Addressing this limitation requires either the development of partnerships with these platforms for research purposes, which are often challenging to secure, or the use of publicly available or synthetic data that may not capture the full complexity of real-world operations.

Therefore, the experiments conducted as part of this research primarily utilized simulated data. While this allows for controlled manipulation of variables and clean testing of the model, it does not account for the unpredictable nature of real-world data. Factors such as unanticipated user behaviour, external economic impacts, and varying market conditions are difficult to simulate with high dedication.

Computational and infrastructure limitations: Another essential limitation encountered during this study relates to computational resources. The processing capacity of the available hardware, imposed significant constraints on the scale of the experimental model. The MATLAB simulations were restricted to scenarios involving only 20 customers, 4 restaurants, and 20 drivers due to these limitations. Even at this limited scale, the models were time-consuming, requiring several hours to solve each instance in MATLAB. This scale is considerably smaller than real-world operations managed by platforms like UberEats and DoorDash, which handle daily transactions involving thousands of users. The inability to test the model under more expansive and varied conditions due to hardware constraints may affect the generalizability of the results. Future research would benefit from access to higher-performance computing resources, allowing for simulations that more accurately mirror the complexity and scale of real on-demand delivery operations.

Model assumptions: The mathematical model used in this thesis relies heavily on assumptions that simplify real-world complexities. For instance, the model assumes that drivers, customers, and suppliers respond rationally to price changes, which may not always reflect actual human behaviour. Such assumptions are necessary for computational feasibility but may limit the model's accuracy in predicting real-world behaviours.

5.5 Future works

In this section, potential future aspects of the research are proposed. The proposed directions aim to enhance the applicability and complexity of our model, more accurately reflecting real-world scenarios and offering actionable insights for on-demand delivery platforms. By pursuing the suggested future works, the model can be continuously adapted to meet evolving technological and market demands, ensuring sustained competitiveness and efficiency in on-demand delivery services.

Advanced queue management with queuing theory: To enhance the accuracy of supplier-side operations, integrating more sophisticated queuing theory models would help in understanding queue dynamics under different conditions, such as varying arrival rates and service mechanisms [99]. Applying the queue management model by incorporating stochastic queuing models could allow for more realistic simulations of customer and supplier interactions during peak and variable demand periods. This refinement could include priority queues and multi-channel service systems, more reflective of real-world operations [100].

Stochastic order and delivery dynamics: Introducing randomness in order placements and driver availability can make the model more reflective of real-world uncertainties. Techniques for modelling stochastic systems in operations research can be applied to this aspect [101]. Integrating uncertainty in both order placement and fulfillment could provide insights into operational resilience. Stochastic modelling could also include random cancellations or no-shows by drivers, offering a deeper understanding of the risks in planning [102].

Peak/off-peak demand modelling and dynamic pricing: Analyzing demand variability through time-dependent modelling would enable the platform to implement dynamic strategies based on peak and off-peak periods. Implementing dynamic pricing based on real-time demand and supply analytics could optimize platform profitability and customer satisfaction. This model would adjust prices and fees during peak times, special events, or in response to competitor pricing strategies [103].

Predictive analytics and machine learning: Predictive models such as the Markov Decision Process ([104]) or machine learning techniques can provide foresight into demand patterns and help optimize resource allocation efficiently [105]. Employing machine learning algorithms to predict order volumes, customer preferences, and delivery blockages could help preemptively reallocate resources and optimize delivery schedules [106].

Integration of external data: Future models could integrate external data sources such as traffic conditions, weather, and local events, significantly influencing delivery times and order volumes. This integration would improve the accuracy of the delivery time predictions and the robustness of the scheduling algorithms [107].

Behavioral economics in platform design: Exploring how different economic incentives influence the behaviour of market participants could lead to better-designed service platforms that ensure higher satisfaction of all players and the platform's profitability [108]. This research could focus on loyalty programs, gamification, and personalized marketing strategies to enhance user engagement and platform loyalty [109].

The model can be expanded by developing these future research directions to address current challenges and adapt to future technological and market developments. These proactive approaches will enable service providers to continuously evolve and maintain a competitive advantage in a rapidly changing industry.

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